



HAL
open science

Beta herding through overconfidence: A behavioral explanation of the low-beta anomaly

Soosung Hwang, Alexandre Rubesam, Mark Salmon

► **To cite this version:**

Soosung Hwang, Alexandre Rubesam, Mark Salmon. Beta herding through overconfidence: A behavioral explanation of the low-beta anomaly. *Journal of International Money and Finance*, 2021, 111, pp.102318. 10.1016/j.jimonfin.2020.102318 . hal-03275894

HAL Id: hal-03275894

<https://hal.science/hal-03275894v1>

Submitted on 15 Dec 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

Beta herding through overconfidence: A behavioral explanation of the low-beta anomaly [☆]

Soosung Hwang^{*}

College of Economics, Sungkyunkwan University, Seoul, Korea

Alexandre Rubesam^{#,◇}

Department of Finance, IESEG School of Management, Paris, France
LEM-CNRS 9221

Mark Salmon[♦]

Faculty of Economics, University of Cambridge

Abstract

We investigate asset returns using the concept of beta herding, which measures cross-sectional variations in betas due to changes in investors' confidence about their market outlook. Overconfidence causes beta herding (compression of betas towards the market beta), while under-confidence leads to adverse beta herding (dispersion of betas from the market beta). We show that the low-beta anomaly can be explained by a return reversal following adverse beta herding, as high beta stocks underperform low beta stocks exclusively following periods of adverse beta herding. This result is robust to investors' preferences for lottery-like assets, sentiment, and return reversals, and beta herding leads time variation in betas.

Keywords: Beta, Herding, Overconfidence, Low-beta Anomaly.

JEL Classifications: C12, C31, G12, G14

[☆] We would like to thank the seminar participants at the FMA European Conference, Glasgow, The Eastern Finance Association Meeting, Miami, the International Conference on the Econometrics of Financial Markets, the PACAP/FMA Finance Conference, Faculty of Economics, University of Cambridge, University of New South Wales, the Bank of England, Saïd Business School, Oxford, University of Copenhagen, Imperial College, London, Australian Conference of Economists, Perth for their comments on this paper.

^{*} Department of Economics, Sungkyunkwan University, 25-2 Sungkyunkwan-ro, Jongno-Gu, Seoul 03063, Korea., Tel: +82 (0)2 760 0489, Fax: +82 (0)2 744 5717, Email: shwang@skku.edu.

[#] Department of Finance, IESEG School of Management, 1 Parvis de La Défense - F-92044 Paris La Défense, France. Tel: +33 (0)1435 882622, Fax: +44 (0) 320 545 892, Email: a.rubesam@ieseg.fr.

[◇] LEM-CNRS 9221.

[♦] Faculty of Economics, Austin Robinson Building, Sidgwick Avenue, Cambridge CB3 9DD, UK. Tel: +44 (0)1435 882622, Fax: +44 (0)24 76523779, Email: markhsalmon@gmail.com

Beta herding through overconfidence: A behavioral explanation of the low-beta anomaly [☆]

Abstract

We investigate asset returns using the concept of beta herding, which measures cross-sectional variations in betas due to changes in investors' confidence about their market outlook. Overconfidence causes beta herding (compression of betas towards the market beta), while under-confidence leads to adverse beta herding (dispersion of betas from the market beta). We show that the low-beta anomaly can be explained by a return reversal following adverse beta herding, as high beta stocks underperform low beta stocks exclusively following periods of adverse beta herding. This result is robust to investors' preferences for lottery-like assets, sentiment, and return reversals, and beta herding leads time variation in betas.

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

1. Introduction

Herding is widely believed to be an important behavioral element in financial markets, and yet, empirical evidence of herding on cross-sectional asset pricing remains inconclusive.¹ Empirical results do not necessarily indicate whether asset prices are biased such that the efficient allocation of assets is disturbed, nor do they clearly differentiate between a common rational reaction to changes in fundamentals and the actions of investors who suppress their own information and herd. In this study, we fill the gap in the literature by investigating the bias in cross-sectional asset pricing when individual asset prices move together regardless of their fundamentals.

We propose a mechanism of irrational herding that explains co-movements in asset returns, caused by a well-known behavioral bias in finance, investor overconfidence, defined as investors' biased perceptions about the precision of their signals as in Daniel et al. (1998) (DHS).² We demonstrate that both expected returns and betas of individual assets are biased (compressed) towards their respective cross-sectional means when investors are overconfident about signals of the market outlook. The opposite case is also possible: when investors are under-confident about the signals, individual betas and expected returns are biased (dispersed) away from their respective cross-sectional means. The compression or

¹ The majority of studies find evidence of herding by observing the clustering behavior of market experts such as analysts or institutional investors (see Welch, 2000; Barber et al., 2009; Choi and Sias, 2009), whereas other studies demonstrate that informed traders can herd to a significant degree on a daily basis (Cipriani and Guarino, 2014).

² For studies on overconfidence, see Barberis et al. (1998), Daniel et al. (1998, 2001), Daniel and Hirshleifer (2015), and Antoniou et al. (2016). Our study does not directly investigate if or why investors' confidence changes over time, but focus on biases in cross-sectional asset pricing when investors are over- or under-confident about signals of the market outlook.

dispersion of betas reflects, in aggregate, micro models of irrational herding or adverse herding, respectively, and gives rise to cross-sectional distortion in asset returns.

This type of cross-sectional bias through investor overconfidence is referred to as “beta herding” in this study because individual betas are biased (herd) towards the market beta, regardless of their equilibrium risk-return relationship.³ When individual betas are biased together with the bias in the expected excess market return (the slope of the Security Market Line, SML), cross-sectional asset prices can become significantly biased. For example, when investors are under-confident about negative signals, the return difference between high and low beta stocks increases significantly (positively biased), because the difference in betas between these stocks increases. The impact of this bias in betas on cross-sectional asset prices increases even further because the expected market return is positively biased by investors’ under-confidence about negative signals. On the contrary, when investors are overconfident, the return difference between high and low beta stocks decreases (negatively biased) with their beta difference.

Our explanation of biases in cross-sectional asset returns is consistent with the argument of Kozak et al. (2018). When investors are overwhelmed by their beliefs about the market outlook, their demand will be related to the main factor (the market) and thus arbitrageurs might not be willing to take on the additional risk, giving rise to mispricing.

³ Simple cross-sectional variability of returns, a popular measure of herding (Christie and Huang, 1995; Chang et al., 2000), may not be indicative of irrational herding in the market, as it may just reflect fundamental changes in common factors. Beta herding focuses on deviations from the equilibrium risk-return relationship, rather than on the clustering behavior of market experts such as analysts or institutional investors (Lakonishok et al., 1992; Wermers, 1999; Welch, 2000; Sias, 2004; Barber et al., 2009; Choi and Sias, 2009). The effects of beta herding on asset returns could be significant in financial markets because the true betas are not known and their estimates are noisy (Damodaran, 2012), and moreover, because overconfidence is a widespread psychological phenomenon in financial markets (Daniel and Hirshleifer, 2015).

Consequently, low (high) beta stocks appear relatively cheap (expensive) compared with the market outlook, and thus expected returns of low (high) beta stocks become upwardly (downwardly) biased. On the other hand, during periods of market uncertainty, investors become under-confident about the market outlook (Gervais and Odean, 2001; Kim and Nofsinger, 2007) and their opinions about the market outlook differ significantly (Miller, 1977; Barberis et al., 1998; Baker and Wurgler, 2007). In this case, expected returns of low (high) beta stocks become biased downward (upward).

These effects of beta herding on asset returns differ from the norm in much of the literature, in that the effects of overconfidence or sentiment are more pronounced for assets with greater valuation uncertainties, e.g., Baker and Wurgler (2006), Kumar (2009), Stambaugh et al. (2012), and Antoniou et al. (2016). In our model, high and low beta stocks are equally affected by investor overconfidence about the overall market outlook, and thus, we measure beta herding using the cross-sectional variance of standardized betas, which are equivalent to the t -statistics of beta estimates (Bring, 1994). The standardized beta provides information on the precision of the beta estimate in addition to its magnitude, and more importantly, makes it possible to compare the dynamics of beta herding over different periods, because it is homoscedastic.

Our empirical results over the sample period from January 1967 to June 2016 show that this measure of beta herding varies significantly through time and increases during periods of high volatility. However, its dynamics are not explained by various macroeconomic and fundamental factors, business cycles, or the instrumental variables that Cederburg and O'Doherty (2016) use to proxy for time-varying betas. These empirical results

are consistent with our view that the changes in beta herding arise when investors are over- or under-confident about their market outlook.

Beta herding provides an opportunity to investigate the low-beta anomaly, whereby low beta stocks outperform high beta stocks on a risk-adjusted basis (Baker et al., 2011; Baker et al., 2014; Frazzini and Pedersen, 2014), because beta herding directly measures bias in cross-sectional betas. Our hypothesis is that the low-beta anomaly arises due to return reversals following periods of adverse beta herding, identified by a large cross-sectional variance of standardized betas. According to our model, when investors are under-confident about negative signals of the market outlook, betas of high (low) beta stocks are upwardly (downwardly) biased and thus, when this bias is subsequently corrected at the arrival of new signals, high beta stocks underperform low beta stocks. The bias and the subsequent return reversals increase even further because the expected excess market return is also upwardly biased due to investors' under-confidence about the negative signals. According to this explanation, the low-beta anomaly should be observed after adverse beta herding that arises during turbulent periods.

Our empirical results confirm this hypothesis: for value-weighted decile portfolios formed on standardized betas, the risk-adjusted return of the high-minus-low beta portfolio over the 12 months following adverse beta herding is -11.4% per year, whereas the risk-adjusted returns are not significantly different from zero following periods of no beta herding or high beta herding. The effects of adverse beta herding on standardized-beta sorted portfolios are quite persistent and remain significant over two years. Similar results are also found for portfolios formed on OLS betas or for different holding periods. We also find that

adverse beta herding arises during periods of market uncertainty when returns are low with high volatility.

Our behavioral explanation for the low-beta anomaly, i.e., a bias in cross-sectional asset pricing triggered by investor overconfidence, is quite different from the economic mechanisms proposed in the literature. Previous studies suggest that investors are poorly diversified and tend to tilt on high risk stocks, rather than increasing leverage on the market portfolio. According to this explanation, the low-beta anomaly can be explained by investors' preference for stocks with higher risk, measured either by idiosyncratic volatility, idiosyncratic skewness (Kumar, 2009), maximum returns (Bali et al., 2011), or beta (Frazzini and Pedersen, 2014).

Beta herding as an explanation of the low-beta anomaly is closely related to the well-documented link between market conditions and the negative unconditional CAPM alpha. Lewellen and Nagel (2006), Boguth et al. (2011), and Cederburg and O'Doherty (2016) demonstrate that the low-beta anomaly arises because beta is positively related to market volatility. However, we find that the positive relationship between beta and market volatility contributes to the low-beta anomaly when the market return is positive after adverse beta herding. Moreover, beta herding leads time-variation in betas by more than 36 months, but not the other way around. Therefore, we argue that the time-variation in betas in Cederburg and O'Doherty (2016) reflects lagged beta herding through overconfidence, in addition to the economic drivers underlying the observed changes in betas.

Finally, the effects of beta herding on cross-sectional asset returns are distinct from those of sentiment, which are based on over-responses of difficult-to-value stocks to sentiment (Baker and Wurgler, 2006; Kumar, 2009; Stambaugh et al., 2012). In particular,

Antoniou et al. (2016) show that the low-beta anomaly arises when the overvaluation of stocks with greater valuation uncertainty is reversed following high sentiment, the effects of which are intensified by investor overconfidence. However, our empirical results show that sentiment does not fully explain the low-beta anomaly. Moreover, the firm characteristics of high standardized-beta stocks reported in the Internet Appendix show differences from those of stocks that are more difficult to price (Baker and Wurgler, 2006): high standardized-beta stocks are not necessarily unprofitable nor illiquid and are growth stocks.

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 assessing its robustness to fundamentals, we then analyze the implications of beta herding in cross-sectional asset pricing in Section 4. Finally, we draw some conclusions in Section 5.

2. Beta herding through overconfidence

2.1. The effects of overconfidence on asset returns

We explain the effects of investor overconfidence about the overall market outlook in the context of the CAPM. Specifically, we assume, as in DHS, that there are uninformed investors, who are risk averse, and informed investors, who are risk neutral. The informed investors receive a private, noisy signal about the next period's market return. Based on the private signal, they update their expectations of the market return using Bayes' rule, and use their expectations to forecast next period's individual stock betas and returns. Our model shows that the predicted asset returns and betas are cross-sectionally biased by investors'

overconfident beliefs about the information they receive for the prediction of the overall market return.

DHS (1998) investigate the effects of investors' overconfidence on asset returns when the precision of a signal is overestimated. Let us assume that the excess market return follows $r_{m,t+1} = \mu_m + \varepsilon_{t+1}$, where μ_m is the unconditional market risk premium and $\varepsilon_{t+1} \sim N(0, \sigma_{\varepsilon,t+1}^2)$ is a shock. Informed investors receive a private noisy signal $s_{m,t}$ to predict the market return. As in DHS (1998, 2001) and Epstein and Schneider (2008), the signal is presented as $s_{m,t} = \varepsilon_{t+1} + v_t$, where v_t is noise, $v_t \sim N(0, \sigma_{v,t}^2)$, and ε_{t+1} and v_t are uncorrelated. The quality of the signal is measured by the signal precision $1/\sigma_{v,t}^2$ in the Bayesian framework. In this setting, the investors' prediction of $r_{m,t+1}$ is decided by their posterior about ε_{t+1} given $s_{m,t}$. Uninformed investors (who do not receive this signal) do not affect the market return as far as they are not risk neutral. DHS (1998) show that upon receiving $s_{m,t}$, informed overconfident investors predict the excess market return with their posterior expectation $E_t^b(r_{m,t+1}|s_{m,t}) = \mu_m + w_{b,t}s_{m,t}$, where $w_{b,t}$ is larger than $w_t = \frac{\sigma_{\varepsilon,t+1}^2}{\sigma_{\varepsilon,t+1}^2 + \sigma_{v,t}^2}$ (the weight of the rational investors),⁴ because investors are overconfident about their signal and thus the precision of the signal ($1/\sigma_{v,t}^2$) is overestimated. Therefore, when investors believe that the signal is more precise than it actually is, $w_{b,t}$ approaches one. On

⁴ The results come from the properties of the bivariate conditional expectation as in Daniel et al. (1998). Suppose that two jointly normally distributed random variables X and Y have their variances and covariance represented by σ_X^2 , σ_Y^2 and σ_{XY} , respectively. Then, the conditional expected value of X given Y is $E(X|Y) = E(X) + \frac{\sigma_{XY}}{\sigma_Y^2}\{Y - E(Y)\}$. Our results can be obtained by replacing X and Y with $r_{m,t+1}$ and $s_{m,t}$, respectively. Similarly, if investors are overconfident about the precision of their signals, we obtain the biased estimate as in the paper.

the other hand, when investors do not have any confidence about the signal, $w_{b,t}$ would approach zero, *i.e.* investors would disregard the signal.

We now investigate how individual asset returns are affected by the overconfidence of informed investors. Let a positive parameter γ_t be the perceived quality of the signal $s_{m,t}$ such that the precision of the signal perceived by overconfident investors is measured by $\frac{1}{\gamma_t \sigma_{v,t}^2}$. When investors believe that the signal is more (less) precise than it actually is, γ_t decreases (increases). Therefore, for overconfident investors, the weight on the signal can be represented as $w_{b,t} = \frac{\sigma_{\varepsilon,t+1}^2}{\sigma_{\varepsilon,t+1}^2 + \gamma_t \sigma_{v,t}^2}$. This parameter γ_t lies between 0 and 1 for overconfident investors. 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 $w_t = \frac{\sigma_{\varepsilon,t+1}^2}{\sigma_{\varepsilon,t+1}^2 + \sigma_{v,t}^2}$ with $\gamma_t = 1$. Note that the parameter γ_t represents informed investors' overconfidence regarding the signal about the market portfolio (henceforth, market signal), not about individual assets.

The effects of investor overconfidence on individual betas and expected excess returns can be summarized as follows.

Lemma 1: *When investors are over- or under-confident about their market signal ($s_{m,t}$) and thus their biased posterior expectation of the excess market return is given by $E_t^b(r_{m,t+1}|s_{m,t}) = \mu_m + w_{b,t}s_{m,t}$, the cross-sectional difference between the beta of an individual asset i and the market beta is*

$$\beta_{i,t+1|t}^b - E_c(\beta_{i,t+1|t}^b) = \gamma_t^*(\beta_{i,t+1|t} - 1), \quad (1)$$

where $E_c(\cdot)$ represents cross-sectional expectation and $\gamma_t^* = \frac{\sigma_{\varepsilon,t+1}^2 + \gamma_t \sigma_{v,t}^2}{\sigma_{\varepsilon,t+1}^2 + \sigma_{v,t}^2}$. The cross-sectional

difference between the expected excess return of asset i and that of the market portfolio is

$$\begin{aligned} & E_t \left(r_{i,t+1} \left| E_t^b(r_{m,t+1} | s_{m,t}) \right. \right) - E_c \left(E_t \left(r_{i,t+1} \left| E_t^b(r_{m,t+1} | s_{m,t}) \right. \right) \right) \\ &= \gamma_t^* (\beta_{i,t+1|t} - 1) (\mu_m + w_{b,t} s_{m,t}). \end{aligned} \quad (2)$$

where $\beta_{i,t+1|t}^b = \gamma_t^* \beta_{i,t+1|t}$, $\beta_{i,t+1|t} = \frac{\text{cov}_t(\varepsilon_{t+1}, r_{i,t+1})}{\sigma_{\varepsilon,t}^2}$, and $w_{b,t} = \frac{w_t}{\gamma_t^*} = \frac{\sigma_{\varepsilon,t}^2}{\sigma_{\varepsilon,t}^2 + \gamma_t \sigma_{v,t}^2}$.

Proof of Lemma 1: See the Internet Appendix.

The lemma shows that when investors are over- or under-confident, both betas and expected excess returns are biased by a factor of γ_t^* , regardless of the sign of $s_{m,t}$. The bias factor, γ_t^* , decreases as investor overconfidence increases in a similar way to the parameter γ_t , but has the lower bound at w_t when $\gamma_t = 0$: i.e., $w_t < \gamma_t^* < 1$ for overconfident investors, and $\gamma_t^* > 1$ for under-confident investors.⁵

When betas are biased by γ_t^* because of investor under-confidence, the betas of high-beta assets ($\beta_{H,t+1|t}$) are biased more than those of low-beta assets ($\beta_{L,t+1|t}$) in absolute values:

$$[\beta_{H,t+1|t}^b - \beta_{L,t+1|t}^b] - [\beta_{H,t+1|t} - \beta_{L,t+1|t}] = (\gamma_t^* - 1)(\beta_{H,t+1|t} - \beta_{L,t+1|t}), \quad (3)$$

For example, if investors are under-confident with $\gamma_t^* = 1.4$, a beta of 1.5 increases to 2.1 (0.6 increase in beta) while a beta of 0.5 increases to 0.7 (only 0.2 increase in beta). This effect is shown in Figure 1. When investors are under-confident ($\gamma_t^* > 1$), both high betas

⁵ 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 (Kelly and Pruitt, 2013), noise in $s_{m,t}$ should be much larger than the shock, and the lower bound of the bias factor in beta, $\gamma_t^* > w_t = \frac{\sigma_{\varepsilon,t}^2}{\sigma_{\varepsilon,t}^2 + \sigma_{v,t}^2}$, would be close to zero.

($\beta_{it} > 1$) and low betas ($\beta_{it} < 1$) increase, as does the difference between them. We use this property to measure the cross-sectional bias in asset returns through investor over- or under-confidence, because this bias can be easily measured by the cross-sectional variance of betas, i.e. $var_c(\beta_{i,t+1}^b|t) = (\gamma_t^*)^2 var_c(\beta_{i,t+1}|t)$, which decreases as overconfidence increases.⁶

The expected excess returns of individual assets are affected by the compression or dispersion of betas but also by the bias in the expected excess market return: investor overconfidence changes the expected excess market return, i.e., the slope of Security Market Line (SML).⁷ Note that the difference in the expected excess market return between rational and overconfident investors is $E_t^b(r_{m,t+1}|s_{m,t}) - E_t(r_{m,t+1}|s_{m,t}) = (w_{b,t} - w_t)s_{m,t}$, which depends on the level of investor confidence and the signs of signals. Figure 1 shows three dashed SMLs for rational investors: the unconditional SML when there is no signal, and two SMLs when the signal is either positive or negative. When investors are over- or under-confident, the excess market returns are predicted differently for the positive or negative signals because the slope of the SML ($\mu_m + \frac{w_t}{\gamma_t^*} s_{m,t}$) depends on the confidence level. For example, when investors are overconfident, they over-respond to the market signal, and thus the slopes of the SML appear higher or lower than those of rational investors (solid black lines in Figure 1). On the other hand, when investors are under-confident about the market signal, the slopes do not move as much as those of the rational investors (solid grey lines in Figure 1).

⁶ The details of the effects of investor overconfidence on expected returns and betas of individual assets are summarized in Table IA.1 of the Internet Appendix.

⁷ We thank an anonymous referee for suggesting a further explanation of the changes in the risk-return relationship when investors are over- or under-confident about market signal, and their implication in asset returns.

We calculate the bias in the cross-sectional asset returns by combining the bias in the slope of SML with the compression or dispersion of betas. The bias in the return difference increases when investors are under-confident about the market signal and vice versa:

$$\begin{aligned}
& \left[E_t \left(r_{H,t+1} \middle| E_t^b(r_{m,t+1} | s_{m,t}) \right) - E_t \left(r_{L,t+1} \middle| E_t^b(r_{m,t+1} | s_{m,t}) \right) \right] \\
& \quad - \left[E_t \left(r_{H,t+1} \middle| E_t(r_{m,t+1} | s_{m,t}) \right) - E_t \left(r_{L,t+1} \middle| E_t(r_{m,t+1} | s_{m,t}) \right) \right] \\
& = \gamma_t^* (\beta_{H,t+1|t} - \beta_{L,t+1|t}) (\mu_m + w_{b,t} s_{m,t}) - (\beta_{H,t+1|t} - \beta_{L,t+1|t}) (\mu_m + w_t s_{m,t}) \\
& = (\beta_{H,t+1|t} - \beta_{L,t+1|t}) (\gamma_t^* - 1) \mu_m. \tag{4}
\end{aligned}$$

A graphical explanation in Figure 1 (thick arrows) is that when investors are under-confident about negative signals, expected excess returns are calculated by the betas that are biased by γ_t^* times for the biased slope of SML. Interestingly, the cross-sectional bias in asset prices depends on the level of investor confidence, not the signals.

These results are summarized in the following proposition.

Proposition 1: *If investors are overconfident and overestimate the precision of their signals for the overall market outlook, individual betas and expected excess returns are biased towards the market beta and the expected excess market return, respectively. On the other hand, when investors are under-confident about their signals for the market, individual betas and expected excess returns are biased away from the market beta and the expected excess market return, respectively. In both cases, the slope of the Security Market Line (the expected excess market return) is upwardly or downwardly biased depending on the signs of signals.*

This bias in asset returns does not disappear in the presence of rational investors as far as they are not risk-neutral (DHS, 1998), and could become serious because the true betas are unknown and can only be estimated with a degree of inaccuracy (Damodaran, 2012).⁸

2.2. Beta herding and its effects on asset returns

Intuitively, the bias in betas reflects the behavior of investors who irrationally herd towards the performance of the market portfolio. When investors give too much weight to their private signal about the market outlook, the market outlook appears excessively convincing while firm characteristics such as betas are suppressed. Thus, investors will tend to buy assets whose returns are lower than the market return because these assets appear relatively cheap. Likewise, they may sell assets whose returns increase more than the market because these assets appear relatively expensive and the opportunity for taking apparent profits might be hard to resist (Shefrin and Statman, 1985). In both of these two cases, the more overconfident the investors are of their market signal, the more likely they are to trade at a price close to their view (Deaves et al., 2009). When investors are overwhelmed by their biased view about the overall market outlook, assets' returns are compressed towards the market return, regardless of their betas.

On the other hand, individual firm characteristics become far more important than the market outlook when investors are under-confident regarding the overall market direction. When markets are uncertain with high volatility, investors have less consensus on their

⁸ The proposition also holds for other factors in a multi-factor model. As long as factors are not correlated, the factor loadings on a factor and predicted individual asset returns are affected in a similar way by investors' overconfident beliefs about the information they receive for the prediction of the factor.

market outlook and their opinions about asset prices are diverse even for the same information (Miller, 1977). Our results show that the dispersion in betas between these stocks increases.

We define this cross-sectional compression (dispersion) in betas as beta herding (adverse beta herding):

Definition *Beta herding (adverse beta herding) represents the cross-sectional compression of betas towards (the cross-sectional dispersion of betas away from) the market beta due to investors' biased perception about the market outlook.*

Beta herding differs from the effects of sentiment and overconfidence on cross-sectional asset returns in the literature. For example, Baker and Wurgler (2006), Kumar (2009), Stambaugh et al. (2012), and Antoniou et al. (2016) focus on asymmetric responses of individual assets upon investor overconfidence or sentiment because of differences in firm characteristics. Assets with greater valuation difficulties are more affected by behavioral biases. In our study, however, we focus on responses of individual assets driven by investors' overconfidence about the *overall* market outlook.

2.3. A measure of beta herding

Lemma 1 suggests the cross-sectional variance of betas as a measure of beta herding:

$$H_t = \text{Var}_c(\beta_{i,t+1|t}^b) = (\gamma_t^*)^2 \text{Var}_c(\beta_{i,t+1|t}), \quad (5)$$

which we denote by H_t . For given $\text{Var}_c(\beta_{i,t+1|t})$, the dynamics of $\text{Var}_c(\beta_{i,t+1|t}^b)$ reflect changes in irrational pricing due to overconfidence (γ_t^*): as γ_t^* decreases, beta herding intensifies. However, H_t is affected by the estimation error of $\beta_{i,t+1|t}^b$. When the estimated

betas are written as $\hat{\beta}_{i,t+1|t}^b = \beta_{i,t+1|t}^b + \eta_{i,t+1|t}$, where $\eta_{i,t+1|t} \sim N(0, \sigma_{\eta,i,t+1|t}^2)$ is the estimation error, the cross-sectional variance of estimated betas $H_t^O = \text{Var}_c(\hat{\beta}_{i,t+1|t}^b)$ is:

$$H_t^O = H_t + \text{CVEE}_t. \quad (6)$$

where $\text{CVEE}_t = E_c(\eta_{i,t+1|t}^2)$ represents cross-sectional variance of estimation errors (CVEE).

The dynamics of H_t can be recovered from H_t^O only when CVEE_t is time-invariant. However, CVEE is not constant due to the heteroscedasticity of idiosyncratic errors and market returns (Campbell et al., 2001).

Our approach to avoid this inconvenient property of H_t^O is to make each $\eta_{i,t+1|t}$ homoscedastic. We standardize $\hat{\beta}_{i,t+1|t}^b$ with its own standard error to create standardized-

betas as in Bring (1994): $\hat{\beta}_{i,t+1|t}^{b*} \equiv \frac{\hat{\beta}_{i,t+1|t}^b - \overline{\hat{\beta}_{i,t+1|t}^b}}{\sigma_{\eta,i,t+1|t}} = \frac{\beta_{i,t+1|t}^b - \overline{\beta_{i,t+1|t}^b}}{\sigma_{\eta,i,t+1|t}} + \eta_{i,t+1|t}^*$, where $\eta_{i,t+1|t}^* =$

$\frac{\eta_{i,t+1|t}}{\sigma_{\eta,i,t+1|t}} \sim N(0,1)$ for all i and t . The standardized beta, which is equivalent to the t -statistic of

the beta of asset i at time t , represents the importance of the market factor for asset i relative to other assets, because the t statistic provides information on the magnitude of the beta estimate $(\hat{\beta}_{i,t+1|t}^b - \overline{\hat{\beta}_{i,t+1|t}^b})$ relative to its precision $(1/\sigma_{\eta,i,t+1|t})$.

An important benefit of using standardized beta in this study is that it becomes possible to compare the dynamics of beta herding over different periods.⁹ The t statistic has a homoscedastic distribution and thus will not be affected by any heteroscedasticity in estimation errors. The regression phenomenon problem raised by Fama and MacBeth (1973) can be minimized by standardizing betas with their corresponding standard errors, since all

⁹ The interpretation of standardized-beta is not as straightforward as that of beta. See King (1986), Bring (1994) for general discussion about standardized regression coefficients.

standardized betas have the same distribution and less extreme values when a small number of observations is omitted. Therefore, outliers in the estimates of betas can be controlled without using Bayesian shrinkage methods, as in Vasicek (1973) and Frazzini and Pedersen (2014).¹⁰

In this study, we calculate beta herding as

$$H_t^* = E_c \left[\left(\frac{\hat{\beta}_{i,t+1|t}^b - \overline{\hat{\beta}_{i,t+1|t}^b}}{\hat{\sigma}_{\eta,i,t}} \right)^2 \right], \quad (7)$$

because $E_c \left[\left(\frac{\hat{\beta}_{i,t+1|t}^b - \overline{\hat{\beta}_{i,t+1|t}^b}}{\hat{\sigma}_{\eta,i,t}} \right)^2 \right] = E_c \left[\left(\frac{\beta_{i,t+1|t}^b - \overline{\beta_{i,t+1|t}^b}}{\hat{\sigma}_{\eta,i,t}} \right)^2 \right] + 1$ is not affected by estimation error. Henceforth, we refer to H_t^O in expression (6) as the beta-based beta herd measure, whereas $\hat{\beta}_{i,t+1|t}^{b*}$ and H_t^* in (7) are referred to as standardized beta and the beta herd measure, respectively. The following distributional result applies to (7) when the standardized betas are equally weighted.¹¹

Theorem 1 Let $\hat{\boldsymbol{\beta}}^{b*} = (\hat{\beta}_1^{b*} \quad \hat{\beta}_2^{b*} \quad \dots \quad \hat{\beta}_N^{b*})'$, where $\hat{\beta}_i^{b*} = \frac{\hat{\beta}_i^b - \overline{\hat{\beta}_i^b}}{\hat{\sigma}_{\eta,i}}$. Then

$$H^* = \frac{1}{N} \sum_{i=1}^N \hat{\beta}_i^{b*2} = \frac{1}{N} \hat{\boldsymbol{\beta}}^{b*'} \hat{\boldsymbol{\beta}}^{b*} \sim \frac{1}{N} \chi^2(R; \delta^R)$$

and

$$\text{Var}[H^*] = \frac{2}{N^2} [R + 2\delta^R]. \quad (8)$$

¹⁰ Standard errors of betas are important for investors who do not diversify their portfolios and hold only a small number of stocks (Barber and Odean, 2000; Goetzmann and Kumar, 2008). For example, an estimate of asset i 's beta, $\hat{\beta}_{i,t+1|t}^b$, does not tell much about its expected return for these investors, if its standard error is large. Estimation errors may be disregarded only when investors hold well-diversified portfolios such that idiosyncratic volatility becomes negligible. However, in reality, investors are more likely to invest in the stocks of their employers, local stocks, familiar stocks, and domestic companies, and do not fully relish the benefits of diversification.

¹¹ Time sub-scripts are abbreviated.

where R is the rank of the variance-covariance matrix \mathbf{V}^* of $\hat{\boldsymbol{\beta}}^{b*}$ and $\delta^R = \sum_{k=1}^R (\mu_{zk}^*)^2 / \sigma_{zk}^2$, where μ_{zk}^* and σ_{zk}^2 are the k th element of the vector $\hat{\boldsymbol{\beta}}^{b*'} \mathbf{C} \boldsymbol{\Lambda}^{1/2}$, where $\mathbf{C} = \boldsymbol{\Gamma} \boldsymbol{\Lambda}^{-1/2}$ is a $(N \times R)$ matrix, and $\boldsymbol{\Gamma}$ and $\boldsymbol{\Lambda}$ are the $(N \times R)$ matrix of the eigenvectors and the $(R \times R)$ diagonal matrix of the eigenvalues of the matrix \mathbf{V}^* , respectively.

Proof. See the Internet Appendix.

In practice, the non-centrality parameter δ^R would be replaced with its sample estimate. It is worth noting that this distributional result depends on the assumptions that the number of observations used to estimate $\beta_{i,t+1|t}^b$ is sufficiently large, and that $\hat{\boldsymbol{\beta}}_t^{b*}$ is multivariate normal.

2.4. The low-beta anomaly following adverse beta herding

Since beta herding through overconfidence leads to biases in betas as well as in the slope of SML, it should be closely related to the low-beta anomaly. In particular, the result in equation (4) suggests that the bias in cross-sectional asset prices depends on the level of investor overconfidence regardless of signals. For example, if investors lose confidence during turbulent periods as in Gervais and Odean (2001) and Kim and Nofsinger (2007), the return difference between high and low beta stocks would increase. During these periods, signals are more likely to be negative and the slope of the SML is upwardly biased ($\gamma_t^* > 1$); the cross-sectional difference between high and low betas is also upwardly biased by the factor of γ_t^* . As the thick arrows in Figure 1 show, the difference between the expected returns of high and low beta stocks ($\gamma_t^*(\beta_H - \beta_L)(\mu_m + (w_t/\gamma_t^*)s_{m,t})$) is positively biased

during these periods. When these biases are subsequently reversed, high beta stocks should show lower returns than low beta stocks do, explaining the low beta anomaly.¹²

In the empirical tests, we test if the low beta anomaly can be explained by return reversals following adverse beta herding. We test the relationship between the risk-adjusted return of the high-minus-low beta portfolio and the level of beta herding, and whether the low-beta anomaly appears following adverse beta herding only. We also investigate if the effects of beta herding on cross-sectional asset returns are distinct from those of sentiment, the lottery preference factor (FMAX) of Bali et al. (2017), or Cederburg and O’Doherty’s (2016) time-varying betas, which have been reported to explain the low-beta anomaly.

3. The Properties of the Beta Herd Measure

3.1. Estimation of the beta herd measure

We estimate betas every month using rolling windows of the prior 12 months of daily returns (minimum 150 valid daily returns) as in Cederburg and O’Doherty (2016) and update the beta herd measure and its confidence interval as shown in Theorem 1. Current and lagged market returns are used to minimize the impact of nonsynchronous price movements as in Lewellen and Nagel (2006):

$$r_{i,t} = \alpha_i^{K3} + \beta_{i,0}^{K3} r_{m,t} + \beta_{i,1}^{K3} r_{m,t-1} + \beta_{i,2}^{K3} [(r_{m,t-2} + r_{m,t-3} + r_{m,t-4})/3] + \varepsilon_{i,t}, \quad (9)$$

and

$$r_{i,t} = \alpha_i^{K2} + \beta_{i,0}^{K2} r_{m,t} + \beta_{i,1}^{K2} r_{m,t-1} + \varepsilon_{i,t}, \quad (10)$$

¹² A typical method to investigate the effects of behavioral biases on asset returns in the literature is to observe subsequent return reversals. For example, DHS (1998, 2001), Baker and Wurgler (2006), and Antoniou et al. (2016) demonstrate that cross-sectional asset returns are affected by return reversals following periods of optimism and overconfidence.

from which betas ($\beta_i^{K3} = \beta_{i,0}^{K3} + \beta_{i,1}^{K3} + \beta_{i,2}^{K3}$ and $\beta_i^{K2} = \beta_{i,0}^{K2} + \beta_{i,1}^{K2}$) and their heteroscedasticity-robust standard errors are calculated. We refer to these specifications as K3 and K2, respectively. For robustness, we also consider betas estimated using 60-month rolling windows (minimum 24 months) as in Fama and French (1992) and Baker et al. (2014), which is referred to as τ_{60} . Our main results are reported with K3, but they also hold for the other estimates of betas as shown in the Internet Appendix.

We use common stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ, whose market capitalizations are larger than the bottom 20% of NYSE stocks. The beta herd measure H_t^* (H_t^O) is calculated by value-weighting individual standardized-betas (betas) for the period from January 1967 to December 2016:

$$\hat{H}_t^* = \sum_{i=1}^N w_{i,t} \left(\frac{\hat{\beta}_{i,t+1|t}^b - \overline{\hat{\beta}_{i,t+1|t}^b}}{\hat{\sigma}_{\eta,i,t}} \right)^2, \quad \hat{H}_t^O = \sum_{i=1}^N w_{i,t} \left(\hat{\beta}_{i,t+1|t}^b - \overline{\hat{\beta}_{i,t+1|t}^b} \right)^2,$$

where $w_{i,t}$ is the weight of stock i at time t and $\sum_{i=1}^N w_{i,t} = 1$. For excess market returns, the CRSP value weighted market portfolio returns and 1-month treasury bills are obtained from Kenneth French's data library.

3.2. Empirical properties of the beta herd measure

The beta herd measure (H_t^*) and the beta-based herd measure (H_t^O) are plotted in Figure 2. Both measures of herding vary significantly through time.¹³ We investigate the

¹³ Table IA.2 in the Internet Appendix reports some of the basic statistical properties of H_t^O and H_t^* . All beta herd measures are highly non-normal, being positively skewed and leptokurtic. The beta herd measures calculated with K3 and K2 are highly correlated (i.e., larger than 0.9) but are less correlated with that of τ_{60} calculated with monthly returns (approximately 0.5). On the other hand, H_t^* and H_t^O are not highly correlated. When the three beta herd measures (K3, K2, and τ_{60}) are plotted, the beta herd measure with K2 is more

properties of H_t^* with respect to H_t^O and other macroeconomic variables that are reported to affect betas in the literature as follows.

First, the relationship between H_t^* and H_t^O in equation (6) can be investigated using the following regression:

$$H_t^O = \underset{(0.501)}{0.669} + \underset{(0.075)}{0.272} H_t^* - \underset{(0.121)}{0.435} M_Vol_t + \underset{(0.238)}{0.837} I_Vol_t + \underset{(0.030)}{0.877} H_{t-1}^O + e_t,$$

where H_t^O is multiplied by 100, the numbers in brackets are Newey-West standard errors, M_Vol_t is the market volatility calculated by summing squared daily market returns as in Schwert (1989), and I_Vol_t is the value-weighted idiosyncratic volatility. The adjusted R^2 value of the regression is 0.94. Although H_t^* and H_t^O do not appear strongly correlated (Table IA.2 in the Internet Appendix), the regression shows that a robust positive relationship exists between H_t^* and H_t^O in the presence of M_Vol_t and I_Vol_t (the two components of the estimation error in betas), and that H_t^O is affected significantly by the estimation error. This result corroborates the use of the beta-herd measure using standardized betas.

Second, considering the evidence that betas change in response to lagged macroeconomic variables (Jagannathan and Wang, 1996; Ferson and Harvey, 1999; Cederburg and O’Doherty, 2016), an important issue is whether the dynamics of the beta herding statistic are driven by fundamentals. We examine this by regressing the beta herd measure on various lagged macroeconomic variables. In addition to the six variables considered by Cederburg and O’Doherty (2016) – the fitted market risk premium (\hat{r}_m), initial public offering activity (IPO), heterogeneity in investment opportunities (σ_{BM}), heterogeneity

volatile than the other two, whereas the τ_{60} beta herd measure appears lagged relative to those calculated with daily returns (not reported).

in firm leverage (σ_{LEV}), idiosyncratic risk (I_Vol), and economy-wide funding conditions ($\sigma_{\Delta TED}$), we also include 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 ($NBER_t$).¹⁴ These additional variables have been frequently used in the literature to explain beta or control the effects of fundamentals on behavioral biases (Ferson and Harvey, 1991, 1999; Baker and Wurgler, 2006), and thus could affect firm investment, leverage, or funding. We also add the market volatility to investigate whether our beta herd measure varies in different market conditions. 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 1. Beta herd measures appear highly persistent but are stationary.¹⁵ The persistence of the beta herd measures is not surprising; betas are well known to be highly persistent both theoretically and empirically. For example, Gomes et al. (2003), and Ang and Chen (2007), suggest autoregressive coefficients larger than 0.95 for monthly data. In addition to the persistence of beta, the rolling windows we use to estimate betas also contribute to the persistence of H_t^* .

The dynamics of H_t^* can be interpreted as changes in behavioral forces driven by investor overconfidence regarding the market outlook. Controlling for the persistence of the

¹⁴ The fitted market risk premium is estimated using lagged 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), and the dividend yield (DY_t , the dividend yield of S&P500 index). These data are obtained from the Federal Reserve Bank of St. Louis.

¹⁵ The augmented Dickey-Fuller test rejects the null hypothesis of a unit root at 5% significance level.

beta herd measure, we find little evidence that H_t^* is affected by these macroeconomic variables.¹⁶ Moreover, the six variables proposed by Cederburg and O’Doherty (2016) to account for time-variation in betas can be explained by the lagged H_t^* , the details of which shall be discussed in Section 4.3. Therefore, the dynamics of the cross-sectional variance of standardized betas are not affected by the twelve explanatory variables. This result indicates that changes in economic conditions increase some standardized betas while decreasing others, with little impact on the level of cross-sectional dispersion of standardized betas.¹⁷

The predicted market return does not explain the beta herd measure, i.e. the impact of investor overconfidence on beta herding can occur whether the predicted market is moving up or down.¹⁸ Market volatility, on the other hand, has a positive relationship with the beta herd measure, suggesting that adverse beta herding arises when the market becomes uncertain. We return to this issue in Section 4.4.

¹⁶ Only when the lagged herd measure (H_{t-1}^*) is not included in the regression do we find that the heterogeneity in investment opportunities (σ_{BM}), idiosyncratic risk (I_Vol), and unemployment appear significant (details not reported). However, when the lagged herd measure (H_{t-1}^*) is not included, the model is not well specified because the Durbin-Watson statistic is only 0.18 indicating that the error term is positively auto-correlated at the 1% significance level.

¹⁷ We also find that 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, details of which can be found in Figure IA.1 of the Internet Appendix.

¹⁸ In untabulated robustness tests (available upon request), we also calculated an orthogonalized beta herd measure ($H_t^{*\perp}$) free from all explanatory variables, i.e., the two market variables, and the ten macroeconomic fundamentals using the regression results in Table 1. The dynamics of H_t^* and $H_t^{*\perp}$ for K3 are not different from each other: the rank correlation coefficient between the two is 0.97. These results are consistent with the marginal contribution (i.e., less than 1% of the adjusted R-square value) of these control variables. 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 asset returns

4.1. Cross-sectional asset returns conditional on beta herding

We first investigate if the low-beta anomaly holds for portfolios formed on standardized betas. Value-weighted decile portfolios are formed on standardized betas of non-microcap stocks with NYSE breakpoints. For each of the portfolios, post-formation risk-adjusted returns over the subsequent 12 months are calculated using the market model. The results in Table 2 show evidence of the low-beta anomaly for the standardized-beta sorted portfolios: the risk-adjusted return of the high-minus-low standardized-beta portfolio is negative and significant, i.e., -0.37% per month (-4.3% per year) for the period from January 1967 to December 2016.

We next investigate the performance of portfolios formed on standardized betas conditional on the level of beta herding. For this purpose, we divide the sample period into three sub-periods depending on the level of beta herding at the formation month, and then compare the post-formation performance of standardized-beta portfolios following each of the three herding states: i.e., high beta herding (bottom 20% of the herd measure), no beta herding (middle 60% of the herd measure), and adverse beta herding (top 20% of the herd measure).¹⁹ The results in Table 2 show that the risk-adjusted return of the high-minus-low standardized-beta portfolios is large and negative over the 12 months following adverse beta herding, i.e., -0.97% per month (-11.4% per year), whereas it is only -0.14% per month (-1.5% per year) following high beta herding. The difference is significant at the 5% level. The

¹⁹ We also tried top 30%, middle 40%, and bottom 30% of the beta herd measure; the main results do not change.

average betas of these two cases, 1.12 and 0.44, respectively, also show a significant difference.

The low-beta anomaly following adverse beta herding is not explained by the large difference in post-formation betas. Treynor's (1965) performance measure for the high and low standardized-beta sorted portfolios (or the betting against beta (BAB) factor proposed by Frazzini and Pedersen (2014)) is $\frac{\alpha_L}{\beta_L} - \frac{\alpha_H}{\beta_H} = 1.16\%$ per month following adverse beta herding whereas it is just 0.16% per month following high beta herding. In fact, the risk-adjusted returns are not different from zero following periods of no beta herding or high beta herding. The low-beta anomaly arises exclusively after adverse beta herding.

We further investigate under what market conditions adverse beta herding arises. The results in Table 3 report the performance of the pre-formation portfolios. We find that adverse beta herding arises during turbulent periods when market returns are low with high volatility. The average market return and return volatility are 0.14% and 6.3%, respectively, during the 12 months before the identification of adverse beta herding. Compared with these values, the average market return and return volatility during high beta herding periods are 0.31% and 2.79%, respectively.²⁰ On the other hand, the difference in betas before and after the identification of beta herding states does not show any unexpected pattern.²¹

²⁰ Large and positive risk-adjusted returns of the high-minus-low beta portfolios before high beta herding and no beta herding become negative in the post-formation period although these negative risk-adjusted returns are not significant. Therefore, positive risk-adjusted returns before the identification of beta herding states are driven by high beta herding or no beta herding. Negative risk-adjusted returns of the high-minus-low beta portfolios during the post-formation period are driven by adverse high beta herding.

²¹ All post-formation betas are lower than the pre-formation betas by approximately 25%, and the order of pre-formation betas remain unchanged after the formation of the portfolio: betas of the high-minus-low beta portfolio before and after adverse herding are higher than those before and after high beta herding, respectively.

Therefore, our empirical results in Tables 2 and 3 are consistent with our model that adverse beta herding arises during periods of higher market uncertainty when investors lose confidence (Gervais and Odean, 2001; Kim and Nofsinger, 2007) and their opinions about the market outlook differ significantly (Miller, 1977; Barberis et al., 1998; Baker and Wurgler, 2007). According to our model, when investors are under-confident about negative market signals, the slope of the SML is upwardly biased and betas are biased away from the market beta. However, the return difference between high and low beta stocks during the pre-formation period is close to zero because market returns are close to zero. The bias in asset prices is reversed subsequently, which appears as the low-beta anomaly during the post-formation period.

4.2. Beta herding, sentiment, and lottery-like risk

We further investigate if beta herding can explain the low-beta anomaly over various forecasting horizons, in the presence of other variables that have been proposed in the literature to explain the low-beta anomaly. We regress the post-formation average monthly return of the high-minus-low standardized-beta portfolio over f months on the excess market return for the same period, the lagged beta herd measure (H_{t-s}^*), Baker and Wurgler's (2006) sentiment (S_{t-s}), and Bali et al.'s (2017) lottery-like preference factor ($FMAX_{t-s}$), where s represents the number of lags:²²

²² The lottery-like preference factor represents the value-weighted return difference between high and low decile portfolios formed on the average of the five highest daily returns over the past one month. See Bali et al. (2017) for further details.

$$r_{HL,t+1,t+f} = \alpha + c_1 r_{m,t+1,t+f} + c_2 H_{t-s}^* + c_3 S_{t-s} + c_4 FMAX_{t-s} + c_5 r_{HL,t-s-f+1,t-s} + \varepsilon_{i,t+1,t+f}$$

where $r_{HL,t+1,t+f}$ and $r_{m,t+1,t+f}$ are the average monthly returns of the high-minus-low standardized-beta portfolios and the excess market portfolio for $f = 6, 12, 24,$ and 36 months, respectively: e.g., $r_{m,t+1,t+f} = \frac{1}{f} \sum_{\tau=1}^f r_{m,t+\tau}$.²³ The lags in beta herding, sentiment, and FMAX are allowed to take values, i.e., $s = 0, 6, 12,$ and 24 months, considering the persistence of the beta herd measure. The average pre-formation return of the high-minus-low standardized-beta portfolio, $r_{HL,t-s-f+1,t-s}$, is inserted to control for return reversals (Jegadeesh,1990; Lehmann, 1990) that are not created by adverse beta herding.

The results, reported in Table 4, are consistent with those in Table 2. The low-beta anomaly disappears when the lagged beta herd measure is inserted as an explanatory variable. Coefficients on H_{t-s}^* are negative for all lags and forecasting horizons, and are significant when lags are large, i.e., $s \geq 12$. Therefore, the return of the high-minus-low standardized-beta portfolio decreases following adverse beta herding (high beta herd measure), and this effect is persistent.

The negative coefficients on the lagged beta herd measure are robust in the presence of sentiment, the lottery-like preference factor (FMAX), and return reversals. According to Antoniou et al. (2016), the low-beta anomaly arises when the overvaluation of stocks with greater valuation uncertainty is subsequently reversed following high sentiment. Our results in Table 4 support this argument regardless of formation methods: the return of the high-

²³ For longer forecasting horizons, e.g., $f = 36$, we do not find evidence of the low-beta anomaly.

minus-low standardized-beta portfolio decreases following high sentiment. On the other hand, the coefficients on the lagged lottery-like preference factor of Bali et al. (2017) are negative in general, and significant when lags are less than or equal to 12 months. However, the returns of the beta-sorted portfolios still show a negative relationship with the lagged beta herd measure in the presence of these two variables.²⁴ These results hold in the presence of the pre-formation return of the high-minus-low standardized-beta portfolio and for portfolios formed on OLS betas rather than standardized-betas (not reported).²⁵

These results show that the beta herd measure explains the low-beta anomaly in a different way. The low-beta anomaly is due to return reversals following periods of adverse beta herding, and the effects of beta herding on beta-sorted portfolios are robust to those of sentiment or lottery-like preferences on high and low beta stocks. Moreover, the beta herd measure is not correlated with the two anomalies that are known to explain the low-beta anomaly: the correlation coefficients of the beta herd measure with Baker and Wurgler's (2006) sentiment index is significant but is low, i.e., -0.17, whereas its correlation with Bali et al.'s (2017) lottery-like preference factor is not significant.

²⁴ We also find that the risk-adjusted returns of the high and low standardized-beta portfolios are still significant in the presence of sentiment or the lottery-like preference factor despite their significance. It is beta herding that makes the risk-adjusted returns insignificant.

²⁵ When $s = 0$ (no lag), the results with $f = 6, 12, 24,$ and 36 show the immediate effects of the independent variables on near (from $t + 1$ to $t + 6$, $f = 6$) or on remote future (from $t + 1$ to $t + 36$, $f = 36$) monthly returns of the high-minus-low standardized-beta portfolios. The results show that the low-beta anomaly cannot be explained by momentum. We also estimate the regression by decomposing $r_{HL,t-s-f+1,t-s}$ into $r_{HL,t-s,t-s}$ and $r_{HL,t-s-f,t-s-1}$ to control the effects of short-term return reversals and momentum separately, but the results are similar to those in Table 4. These results can be obtained from the authors upon request. We thank an anonymous referee for this suggestion.

4.3. Beta herding and time-varying betas

Cederburg and O’Doherty (2016) argue that the low-beta anomaly can be explained by time-varying betas using the results of Lewellen and Nagel (2006) and Boguth et al. (2011). To capture time variation in betas, we add explanatory variables $z_{k,t-1}r_{m,t}$, $k = 1, \dots, 6$ in addition to $r_{m,t}$, where $z_{k,t-1}$ s are the six lagged instrumental variables proposed by Cederburg and O’Doherty (2016) (see section 3.2). These additional explanatory variables are calculated as $z_{k,t+1,t+f}^* = \frac{1}{f} \sum_{\tau=1}^f z_{k,t+\tau-1} r_{m,t+\tau}$ for the time-varying betas over f months following the formation of the beta portfolios. We then run the following regression:

$$r_{HL,t+1,t+f} = \alpha + c_1 r_{m,t+1,t+f} + c_2 H_{m,t-s}^* + c_3 S_{t-s} + c_4 FMAX_{t-s} + \sum_{k=1}^6 c_k^* z_{k,t+1,t+f}^* + \varepsilon_{i,t,t+f}.$$

The results in Table 5 support Cederburg and O’Doherty (2016): the low-beta anomaly disappears when the six lagged instrumental variables are used to model time-varying betas. The betas of the high-minus-low standardized-beta portfolio become negative in the presence of the six variables, although they are not significant. Therefore, the unconditional positive betas of the high-minus-low standardized-beta portfolio in Table 3 are upward biased and thus the risk-adjusted returns are negatively biased. Among the six instrumental variables, only IVOL is positive and significant in the high-minus-low standardized-beta portfolio for different forecasting horizons. When idiosyncratic risk increases, so does the dispersion of firm betas (Babenko et al., 2016). The fitted market risk premium (\hat{r}_m) and the cross-sectional standard deviation of firm-level log book-to-market ratios (σ_{BM}) are significant over longer horizons.

It is not surprising that lagged beta herding, sentiment, and FMAX become insignificant in the presence of the six lagged instrumental variables that are *contemporaneous* with the high-minus-low standardized-beta portfolio returns. We investigate the lead-lag relationship between beta herding and the other three variables using the following regressions:

$$V_t^* = c_0^b + c_1^b r_{m,t+1,t+f} + c_2^b H_{m,t-s}^* + \varepsilon_{i,t,t+f}$$

$$H_{m,t+s}^* = c_0^h + c_1^h r_{m,t+s+1,t+s+f} + c_2^h V_t^* + \varepsilon_{i,t,t+f}$$

where V_t^* is equal to $\sum_{k=1}^6 \hat{c}_k z_{k,t+1,t+f}^*$, S_t , or $FMAX_t$. Note that $\sum_{k=1}^6 \hat{c}_k z_{k,t+1,t+f}^*$ is estimated in the presence of the excess market return (without the lagged beta herd measure and sentiment). The first regression investigates whether the lagged beta herd measure ($H_{m,t-s}^*$) is useful to explain V_t^* , whereas the second regression is used to assess whether V_t^* can explain future beta herding. Note that when $s > 12$, there is no overlapping period between dependent and independent variables. Figure 3 shows the coefficients with the 95% confidence level for various lags, $s = 1, 2, \dots, 36$ when $f = 12$. Beta herding does not show any lead-lag relationship with S_t or $FMAX_t$ (i.e., the 95% confidence intervals in Panels C, D, E and F always include the value of zero). This is consistent with our earlier results in Table 3, which show that beta herding is robust in the presence of these two variables.

Interestingly, lagged beta herding affects the time-variation in beta up to two years (Panel A), whereas the time-variation in beta does not affect beta herding (Panel B). This result suggests that beta herding Granger-causes time-variation in beta, in particular over 12 months. The negative coefficients suggest that the time-varying component of beta of the high-minus-low standardized-beta portfolio decreases following adverse beta herding, and

thus the risk-adjusted return increases. However, the coefficients on the excess market return in Tables 3 and 5 show that the beta herd measure corrects the bias in the risk-adjusted return without affecting beta, whereas the additional six variables for time-varying beta make the unconditional beta negative such that the risk-adjusted return increases.

4.4. Adverse beta herding and market uncertainty

The effects of investors' behavioral biases on asset returns become more pronounced when uncertainty increases because, during these periods, investors' differences in opinion increase (Miller, 1977; Barberis et al., 1998; Baker and Wurgler, 2007) and investors lose confidence about the market outlook (Gervais and Odean, 2001; Kim and Nofsinger, 2007). However, the large beta difference does not create large return difference in the pre-formation period because market returns are close to zero. It is following adverse beta herding, when the average market return becomes over 10% per year, that the post-formation return difference between high and low beta portfolios is not large enough due to return reversals, creating the low-beta anomaly.

Adverse beta herding arises during market uncertainty when investors are underconfident about their market signals, and the bias in returns is not quickly reversed because the market still remains uncertain. Our results so far show that adverse beta herding arises when market returns are close to zero with high volatility. The average market return and volatility during the past 12 months before the identification of adverse beta herding are 0.14% and 6.3% per month, respectively, and become 0.88% and 5% per month, respectively, after

the identification of adverse beta herding.²⁶ The market volatility after the identification of adverse beta herding is still significantly higher than those of the other two beta herding states (monthly volatilities of 3.81% and 3.65%).

Following Lewellen and Nagel (2006), Boguth et al. (2011), and Cederburg and O’Doherty (2016), we approximate the unconditional risk-adjusted return as follows when beta varies over time:

$$\alpha_H - \alpha_L \approx Cov(\beta_{Ht} - \beta_{Lt}, E_{t-1}(R_{mt})) - \frac{E(R_{mt})}{\sigma_m^2} Cov(\beta_{Ht} - \beta_{Lt}, \sigma_{mt}^2).$$

Suppose that the beta difference $\beta_{Ht} - \beta_{Lt}$ can be approximated by our herding measure. The results in Table 1 show no significant relationship between beta herding and the predicted market return, indicating that the first component is close to zero. As in Boguth et al. (2011), the relationship between beta herding and the market (market timing) does not explain the low-beta anomaly. When the market timing is excluded for the explanation of the low-beta anomaly, the second component, ‘volatility timing’, should explain the low-beta anomaly.

The significant and positive relationship between the beta herd measure and the market volatility reported in Table 1 supports that volatility timing is at least partially responsible for the low-beta anomaly. However, volatility timing by itself does not contribute to the low beta anomaly. The low-beta anomaly arises only when the market volatility is high and adverse beta herding arises, i.e., the pre-formation periods before adverse beta herding in

²⁶ The change in market conditions before and after the identification of other beta herding states also appears reversed: the average market return before and after the identification of high beta herding is 1.31% and 0.83% per month, respectively. The difference is significant at the 5% level. Therefore, high beta herding is more likely to arise in bull markets, with high return and low volatility, during which time investors are overconfident and optimistic about market the outlook.

Table 3. Our results show that the market return in combination with the volatility timing is responsible for the low-beta anomaly. Only when the market return becomes positive (e.g., 10% per year) does the positive relationship between the beta herd measure and the market volatility produce the low-beta anomaly.

4.5. Robustness Checks

We have tested various other settings to check the robustness of our results, which can be found in the Internet Appendix. The following is a short summary of the robustness tests.

We first investigate whether the effects of adverse beta herding on standardized-beta sorted portfolios are robust regarding the length of the post-formation period. In our main results in section 4.1, the post-formation period is set to 12 months. The results with post-formation periods of 6, 24, and 36 months (Panel D, E, and F of Table IA.3) show that the effects of adverse beta herding on standardized-beta sorted portfolios are indeed persistent. The risk-adjusted returns of the high-minus-low standardized-beta portfolios are -0.4%, -0.37%, and -0.33% per month over 6, 12, and 24 months following the formation of the portfolios, respectively. These become -1.07%, -0.97%, -0.8% per month following adverse beta herding, respectively. The risk-adjusted return of the high-minus-low standardized-beta portfolio is -0.63% per month (-7.6% per year) for the second year alone following adverse beta herding.

Next, we investigate the robustness of our results to other estimates of standardized betas, i.e. the K2 or τ_{60} estimates discussed in section 3.1. The risk-adjusted returns over 12 months following adverse herding are equal to -0.92% per month when the K2 estimate is

used (Panel A of Table IA.3) and -0.72% per month when the τ_{60} estimate is used (Panel B of Table IA.3).

Our results are also robust to the definition of the universe of stocks considered. In our main results, we have used non-microcap stocks, defined as the set of all stocks whose market capitalization would place them above the 20th percentile of the market capitalization of all NYSE stocks. The results do not change when all stocks are used rather than only non-microcap stocks (Panel C of Table IA.3).

Finally, our main results still hold when the portfolios are formed on simple OLS betas rather than standardized betas. The post-formation risk-adjusted return of the high-minus-low (OLS) beta portfolio (Table IA.4 of the Internet Appendix) is also -0.37% per month over the subsequent 12 months, and is large and negative following adverse beta herding, i.e., -0.86% per month, similar to the results with standardized betas reported in Table 2 and discussed in section 4.1. We also find similar patterns for pre-formation returns when betas rather than standardized betas are used to form portfolios (Table IA.5 of the Internet Appendix), which confirm those reported in Table 3 and discussed in section 4.1.

5. Conclusions

We measure biases in cross-sectional asset prices due to investor overconfidence in the CAPM framework. We demonstrate that the slope of the SML and betas (and therefore, expected returns) are biased when investors are overconfident about the market signal, and we propose beta herding, defined as the cross-sectional variance of standardized betas, to measure this bias. We show that this dispersion changes over time, depending on investor over- or under-confidence in their signals about the overall market outlook. 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 the herding measures proposed by Lakonishok et al. (1992), Wermers (1999), and Park and Sabourian (2011). This type of bias can be tested by investigating the return behavior following the different levels of herding, because the risk-return relationship is not affected by beta herding.

We have applied our measure to the US stock market and found that the low-beta anomaly of Baker et al. (2014) is only observed following periods of adverse beta herding. Our behavioral explanation for the low-beta anomaly, i.e., a bias in cross-sectional asset pricing triggered by investor overconfidence, is quite different from other alternative explanations such as Baker and Wurgler's (2006) sentiment and Bali et al.'s (2017) lottery-like preference factor.

We further need to investigate the low-beta anomaly for other equity markets using our beta herding. Baker and Haugen (2012) and Baker et al (2014) show that the low-beta anomaly is found in all equity markets in the world. The concept of herding can also be easily applied to other factor loadings in multifactor models, insofar as the additional factors are orthogonal to the market factor. That is, when investors are overly influenced by their outlook regarding a factor, the cross-sectional difference in individual asset prices due to the factor is suppressed by the outlook, and thus, individual asset returns tend to have similar factor loadings on the factor. We leave for future research the investigation of the impact of herding on other factors, as well as the empirical investigation of beta herding in other markets.

References

- Admati, A.R. and Pfleiderer, P., 1997. Does it all add up? Benchmarks and the compensation of active portfolio managers. *The Journal of Business*, 70(3), 323-350.
- Ang, A., and Chen, J., 2007. CAPM over the long run: 1926-2001, *Journal of Empirical Finance* 14(1), 1-40.
- Antoniou, C., Doukas, J. A., and Subrahmanyam, A., 2016. Investor sentiment, beta, and the cost of equity capital, *Management Science*, 62, 347-367.
- Babenko, I., Boguth, O. and Tserlukevich, Y., 2016. Idiosyncratic cash flows and systematic risk. *Journal of Finance*, 71(1), pp.425-456.
- Baker, M., Bradley, B. and Wurgler, J., 2011. Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly. *Financial Analysts Journal*, 67(1), 40-54.
- Baker, M., B. Bradley, and Taliaferro, R., 2014. The low-risk anomaly: A decomposition into micro and macro effects. *Financial Analysts Journal* 70(2), 43-58.
- Baker, M. and Wurgler, J., 2006. Investor sentiment and the cross section of stock returns, *Journal of Finance* 61, 1645-1680.
- Baker, M. and Wurgler, J., 2007. Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2), pp.129-152.
- Bali, T. G., Cakici, N., and Whitelaw, R. F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns, *Journal of Financial Economics* 99, 427-446.
- Bali, T.G., Brown, S.J., Murray, S. and Tang, Y., 2017. A lottery-demand-based explanation of the beta anomaly. *Journal of Financial and Quantitative Analysis*, 52(6), 2369-2397.
- Banerjee, A.V., 1992. A simple model of herd behavior. *The Quarterly Journal of Economics*, 107(3), 797-817.
- Baker, N. L., and Haugen, R. A., 2012. Low risk stocks outperform within all observable markets of the world, SSRN: <https://ssrn.com/abstract=2055431>
- Barber, B. M., and Odean, T., 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The journal of Finance*, 55(2), 773-806.
- Barber, B. M., Odean, T., and Zhu, N., 2009. Do retail trades move markets?, *Review of Financial Studies* 22(1), 151-186.
- Barberis, N., Schleifer, A., and Vishny, R., 1998. A model of investor sentiment, *Journal of Financial Economics* 49, 307-343.
- Bikhchandani, S., Hirshleifer, D. and Welch, I., 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of political Economy*, 100(5), 992-1026.
- Boguth, O., Carlson, M., Fisher, A. and Simutin, M., 2011. Conditional risk and performance evaluation: Volatility timing, overconditioning, and new estimates of momentum alphas. *Journal of Financial Economics*, 102(2),363-389.
- Bring J., 1994. How to standardize regression Coefficients, *The American Statistician* 48(3), 209-213.
- Campbell, J. Y., Lettau, M., Malkiel, B. G., and Xu, Y., 2001. Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk, *Journal of Finance* 56(1), 1-43.

- Cederburg, S. and O'Doherty, M. S., 2016. Does it pay to bet against beta? On the conditional performance of the beta anomaly, *Journal of finance* 71(2), 737-774.
- Chang, E. C., Cheng, J. W. and Khorana, A., 2000. An examination of herd behavior in equity markets: An International Perspective, *Journal of Banking and Finance* 24, 1651-1679.
- Choe, H., Kho, B., and Stulz, R. M., 1999. Do foreign investors destabilize stock markets? The Korean experience in 1997. *Journal of Financial Economics* 54, 227-264.
- Choi, N., and Sias, R. W., 2009. Institutional industry herding. *Journal of Financial Economics* 94(3), 469-491.
- Christie, W. G., and Huang, R. D., 1995. Following the Pied Piper: Do individual returns herd around the market?, *Financial Analysts Journal* (July-August), 31-37.
- Cipriani, M. and Guarino, A., 2014. Estimating a structural model of herd behavior in financial markets, *American Economic Review* 104(1), 224-51.
- Damodaran, A., 2012. Investment valuation: tools and techniques for determining the value of any asset, 3rd Edition, Wiley.
- Daniel, K., and Hirshleifer, D., 2015. Overconfident investors, predictable returns, and excessive trading, *Journal of Economic Perspectives* 29, 61-88.
- Daniel, K., Hirshleifer, D. and Subrahmanyam, A., 1998. Investor psychology and security market under-and overreactions, *Journal of Finance* 53, 1839-1885.
- Daniel, K., Hirshleifer, D. and Subrahmanyam, A., 2001. Overconfidence, arbitrage, and equilibrium asset pricing, *Journal of Finance* 56, 921-965.
- Deaves, R., Lüders, E. and Luo, G., 2009. An experimental test of the impact of overconfidence and gender on trading activity, *Review of Finance* 13, 555-575.
- Epstein, L. G. and Schneider M., 2008. Ambiguity, information quality, and asset pricing. *The Journal of Finance*, 63(1), 197-228.
- Fama, E. F. and French, K. R., 1992. The cross section of expected stock returns, *Journal of Finance* 47, 427-465.
- Fama, E. F. and MacBeth, J.D., 1973. Risk, return and equilibrium: empirical tests, *Journal of Political Economy* 81, 607-636.
- Ferson, W. E. and Harvey, C. R. , 1991. Sources of predictability in portfolio returns, *Financial Analysts Journal* 3, 49-56.
- Ferson, W. E. and Harvey, C. R., 1999. Conditioning variables and cross-section of stock returns, *Journal of Finance* 54, 1325-1360.
- Frazzini, A. and Pedersen, L. H., 2014. Betting against beta. *Journal of Financial Economics*, 111(1), 1-25.
- Gervais, S. and Odean, T., 2001. Learning to be overconfident. *The Review of Financial Studies*, 14 (1), 1-27.
- Goetzmann, W.N. and Kumar, A., 2008. Equity portfolio diversification. *Review of Finance*, 12(3), 433-463.
- Gomes, J., Kogan L. and Zhang, L., 2003. Equilibrium cross-section of returns, *Journal of Political Economy* 111(4), 693-732.
- Jagannathan, R. and Wang, Z., 1996. The conditional CAPM and the cross-section of expected returns, *Journal of Finance* 51, 3-53.
- Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. *The Journal of Finance*, 45(3), 881-898.

- Kelly, B. and Pruitt, S., 2013. Market expectations in the cross-section of present values. *The Journal of Finance*, 68(5), 1721-1756.
- Kim, K. A., and Nofsinger, J. R. , 2007. The behavior of Japanese individual investors during bull and bear markets. *The Journal of Behavioral Finance* 8(3), 138-153.
- Kim, W. and Wei, S. J., 2002. Offshore investment funds: monsters in emerging markets? *Journal of Development Economics* 68, 205-224.
- King, G., 1986. How not to lie with statistics: Avoiding common mistakes in quantitative political science. *American Journal of Political Science*, 666-687.
- Kozak, S., Nagel, S. and Santosh, S., 2018. Interpreting factor models *The Journal of Finance*, 73(3), 1183-1223.
- Kumar, A., 2009. Who gambles in the stock market?. *The Journal of Finance*, 64(4), 1889-1933.
- Lakonishok, J., Shleifer, A. and Vishny, R. W., 1992. The impact of institutional trading on stock prices, *Journal of Financial Economics* 32, 23-43.
- Lehmann, B. N., 1990. Fads, martingales, and market efficiency. *The Quarterly Journal of Economics*, 105(1), 1-28.
- Lettau, M. and Ludvigson, S., 2001. Consumption, aggregate wealth, and expected stock returns, *Journal of Finance* 56(3), 815-849.
- Lewellen, J., and Nagel, S., 2006. The conditional CAPM does not explain asset-pricing anomalies, *Journal of Financial Economics* 82(2), 289-324.
- Miller, E.M., 1977. Risk, uncertainty, and divergence of opinion. *The Journal of Finance*, 32(4), 1151-1168.
- Park, A. and Sabourian, H., 2011. Herding and contrarian behavior in financial markets, *Econometrica* 79(4), 973-1026
- Schwert, G. W., 1989. Why does stock market volatility change over time? *Journal of Finance* 44, 1115-1153.
- Shefrin, H., and Statman, M., 1985. The disposition to sell winners too early and ride losers too long – Theory and Evidence, *Journal of Finance* 40(3), 777-790.
- Sias, R. W., 2004. Institutional herding. *Review of Financial Studies* 17(1), 165-206.
- Stambaugh, R.F., Yu, J. and Yuan, Y., 2012. The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, 104(2), 288-302.
- Treynor, J. L. 1965. How to rate management of investment funds. *Harvard Business Review* 43 (January/February): 63–75.
- Vasicek, O.A., 1973. A note on using cross-sectional information in Bayesian estimation of security betas. *The Journal of Finance*, 28(5), 1233-1239.
- Welch, I., 1992. Sequential sales, learning, and cascades. *The Journal of Finance*, 47(2), 695-732.
- Welch, I., 2000. Herding among security analysts, *Journal of Financial Economics* 58, 369-396.
- Wermers, R., 1999. Mutual fund herding and the impact on stock prices, *Journal of Finance* 54, 581-622.

Table 1 Regression of Beta Herd Measure on Various Lagged Variables

The beta herd measures (BH) are regressed on the lagged market volatility ($\sigma_{m,t-1}$), fitted market risk premium ($\hat{r}_{m,t-1}$), initial public offering activity (the number of IPOs in the prior five years divided by the total number of sample firms, IPO_{t-1}), heterogeneity in investment opportunities (the cross-sectional standard deviation of firm-level log book-to-market ratios, $\sigma_{BM,t-1}$), heterogeneity in firm leverage (the cross-sectional standard deviation of firm-level book leverage, $\sigma_{LEV,t-1}$), idiosyncratic risk (the cross-sectional average of firm-level idiosyncratic volatility computed from daily returns over the prior 12 months, I_Vol_{t-1}), and economy-wide funding conditions (the standard deviation of daily Treasury-Eurodollar (TED) spread innovations over the prior three months, $\sigma_{\Delta TED,t-1}$), as well as consumption-wealth ratio of Lettau and Ludvigson (2001) (CAY_{t-1}), the monthly inflation rate (CPI_{t-1}), the growth in industrial production (IP_{t-1}), the growth in consumption of durables, nondurables, and services ($Cons_{t-1}$), the unemployment rate ($Unemp_{t-1}$), and a dummy variable for NBER recessions ($NBER_{t-1}$) for the period from January 1967 to December 2016. The market volatility is calculated by summing squared daily returns as in Schwert (1989). The fitted market risk premium is estimated using lagged one-month Treasury bill rate, the term spread (the difference between the US ten year and one year Treasury bond rate), the credit spread (the difference between Moody's Aaa and Baa rated corporate bonds), and the dividend yield (the dividend yield of S&P500 index). The numbers in brackets are Newey-West heteroscedasticity-adjusted standard errors. The bold numbers represent significance at the 5% level.

	K3		K2		τ_{60}	
Constant	0.008	(0.519)	-0.286	(1.195)	-0.374	(0.221)
Lagged BH(-1)	0.923	(0.025)	0.944	(0.022)	0.972	(0.011)
$\sigma_{m,t-1}$	0.049	(0.015)	0.142	(0.041)	0.021	(0.009)
\hat{r}_{mt-1}	0.044	(0.073)	0.007	(0.170)	-0.042	(0.049)
IPO_{t-1}	0.037	(0.280)	-0.163	(0.616)	-0.254	(0.187)
$\sigma_{BM,t-1}$	-0.552	(0.822)	-0.681	(1.972)	0.195	(0.381)
$\sigma_{LEV,t-1}$	0.478	(0.373)	0.840	(1.015)	0.280	(0.329)
I_Vol_{t-1}	0.057	(0.037)	0.091	(0.094)	0.017	(0.012)
$\sigma_{\Delta TED,t-1}$	-0.163	(0.187)	-0.623	(0.424)	-0.125	(0.124)
CAY_{t-1}	-0.020	(0.022)	-0.009	(0.048)	0.011	(0.009)
CPI_{t-1}	-0.050	(0.063)	0.046	(0.139)	0.022	(0.049)
IP_{t-1}	0.027	(0.046)	0.169	(0.105)	-0.016	(0.035)
$Cons_{t-1}$	-0.068	(0.059)	-0.100	(0.132)	-0.005	(0.025)
$Unemp_{t-1}$	0.019	(0.030)	0.014	(0.065)	0.027	(0.015)
$NBER_{t-1}$	0.043	(0.087)	0.242	(0.196)	-0.033	(0.052)
Adj R-square	0.937		0.963		0.978	

Table 2 Post-formation average returns over 12 months conditioning on herding states

From January 1967 to December 2016, every month we form decile portfolios on standardized-betas using non-microcap stocks (larger than bottom 20% of NYSE) with NYSE breakpoints and calculate the value-weighted average return for the following 12 months after the formation. For each of the portfolios, post-formation risk-adjusted returns over 12 months from the formation are calculated using the market model. The sample period is divided into three herding states (K3), i.e., adverse beta herding, no beta herding, and high beta herding, identified by the top 20%, middle 60%, and bottom 20% of the beta herd measure, respectively. The numbers in brackets represent Newey-West robust standard errors, and bold numbers show significance at the 5% level.

		Low	2	3	4	5	6	7	8	9	High	High-Low	Monthly Market Return	Monthly Market Volatility
Unconditional Model	Raw Returns	0.503 (0.126)	0.527 (0.138)	0.594 (0.149)	0.653 (0.153)	0.616 (0.149)	0.596 (0.153)	0.645 (0.172)	0.598 (0.178)	0.589 (0.193)	0.553 (0.243)	0.050 (0.195)	0.901 (0.162)	4.011 (0.227)
	Alphas	0.206 (0.094)	0.157 (0.071)	0.182 (0.081)	0.216 (0.087)	0.177 (0.083)	0.143 (0.084)	0.128 (0.079)	0.055 (0.077)	0.015 (0.083)	-0.161 (0.089)	-0.367 (0.171)		
	Betas	0.593 (0.068)	0.738 (0.054)	0.823 (0.066)	0.873 (0.070)	0.876 (0.067)	0.905 (0.063)	1.031 (0.059)	1.084 (0.055)	1.147 (0.054)	1.427 (0.064)	0.834 (0.125)		
Adverse Herding (Top 20%)	Raw Returns	0.824 (0.224)	0.801 (0.240)	1.038 (0.278)	1.069 (0.298)	1.079 (0.266)	1.031 (0.273)	1.105 (0.308)	0.939 (0.403)	0.888 (0.373)	0.663 (0.618)	-0.162 (0.473)	0.882 (0.349)	5.012 (0.372)
	Alphas	0.444 (0.126)	0.392 (0.091)	0.552 (0.196)	0.508 (0.180)	0.565 (0.165)	0.498 (0.165)	0.465 (0.106)	0.163 (0.172)	0.140 (0.160)	-0.525 (0.250)	-0.970 (0.365)		
	Betas	0.528 (0.056)	0.568 (0.061)	0.676 (0.124)	0.780 (0.140)	0.714 (0.114)	0.742 (0.118)	0.889 (0.081)	1.078 (0.127)	1.040 (0.121)	1.651 (0.141)	1.123 (0.192)		
No Herding (Middle 60%)	Raw Returns	0.437 (0.151)	0.471 (0.161)	0.502 (0.176)	0.561 (0.180)	0.498 (0.175)	0.508 (0.183)	0.562 (0.205)	0.552 (0.192)	0.572 (0.225)	0.563 (0.274)	0.127 (0.244)	0.930 (0.188)	3.806 (0.263)
	Alphas	0.183 (0.131)	0.121 (0.088)	0.101 (0.081)	0.145 (0.092)	0.068 (0.080)	0.062 (0.087)	0.060 (0.088)	0.063 (0.087)	0.018 (0.103)	-0.106 (0.096)	-0.289 (0.207)		
	Betas	0.538 (0.107)	0.741 (0.070)	0.850 (0.071)	0.883 (0.077)	0.912 (0.072)	0.948 (0.060)	1.065 (0.072)	1.038 (0.057)	1.174 (0.061)	1.419 (0.061)	0.881 (0.155)		
Herding (Bottom 20%)	Raw Returns	0.390 (0.274)	0.430 (0.322)	0.441 (0.316)	0.525 (0.320)	0.521 (0.326)	0.439 (0.331)	0.445 (0.387)	0.405 (0.434)	0.354 (0.441)	0.418 (0.437)	0.028 (0.208)	0.834 (0.338)	3.654 (0.302)
	Alphas	0.096 (0.055)	0.087 (0.066)	0.107 (0.050)	0.177 (0.056)	0.168 (0.042)	0.080 (0.040)	0.040 (0.070)	-0.045 (0.084)	-0.095 (0.091)	-0.041 (0.091)	-0.138 (0.132)		
	Betas	0.780 (0.037)	0.910 (0.043)	0.886 (0.034)	0.925 (0.037)	0.936 (0.024)	0.950 (0.021)	1.074 (0.042)	1.193 (0.054)	1.190 (0.061)	1.218 (0.070)	0.439 (0.090)		

Table 3 Pre-formation average returns for 12 months before herding states

From January 1967 to December 2016, every month we form decile portfolios on standardized-betas using non-microcap stocks (larger than bottom 20% of NYSE) with NYSE breakpoints and calculate the value-weighted average return for 12 months before the formation. For each of the portfolios, pre-formation risk-adjusted returns for 12 months before the formation are calculated using the market model. The period before the identification of herding states is divided into three prior herding states, i.e., adverse beta herding, no beta herding, and high beta herding, identified by the top 20%, middle 60%, and bottom 20% of the beta herd measure, respectively. The numbers in brackets represent Newey-West robust standard errors, and bold numbers show significance at the 5% level.

		Low	2	3	4	5	6	7	8	9	High	High-Low	Monthly Market Return	Monthly Market Volatility
Unconditional Model	Raw Returns	0.595 (0.118)	0.776 (0.128)	0.894 (0.136)	0.966 (0.148)	1.011 (0.149)	1.092 (0.162)	1.176 (0.170)	1.280 (0.183)	1.394 (0.203)	1.547 (0.269)	0.952 (0.246)	0.893 (0.163)	3.972 (0.229)
	Alphas	0.351 (0.104)	0.450 (0.092)	0.528 (0.079)	0.555 (0.080)	0.590 (0.083)	0.632 (0.090)	0.685 (0.097)	0.748 (0.073)	0.817 (0.085)	0.847 (0.136)	0.496 (0.203)		
	Betas	0.501 (0.072)	0.672 (0.069)	0.753 (0.058)	0.846 (0.062)	0.866 (0.064)	0.946 (0.070)	1.011 (0.070)	1.095 (0.046)	1.189 (0.051)	1.440 (0.074)	0.939 (0.128)		
Adverse Beta Herding (Top 20%)	Raw Returns	0.743 (0.194)	0.774 (0.276)	0.826 (0.302)	0.908 (0.337)	0.924 (0.336)	0.898 (0.344)	0.838 (0.381)	0.855 (0.433)	0.783 (0.450)	0.728 (0.629)	-0.016 (0.561)	0.139 (0.379)	6.301 (0.457)
	Alphas	0.769 (0.145)	0.812 (0.192)	0.871 (0.164)	0.961 (0.170)	0.978 (0.183)	0.956 (0.220)	0.901 (0.257)	0.930 (0.196)	0.866 (0.219)	0.837 (0.378)	0.068 (0.417)		
	Betas	0.364 (0.082)	0.542 (0.118)	0.645 (0.107)	0.759 (0.123)	0.776 (0.137)	0.843 (0.162)	0.912 (0.168)	1.088 (0.106)	1.186 (0.124)	1.577 (0.108)	1.213 (0.131)		
No Beta Herding (Middle 60%)	Raw Returns	0.511 (0.159)	0.710 (0.160)	0.834 (0.160)	0.878 (0.168)	0.938 (0.164)	1.057 (0.184)	1.187 (0.190)	1.320 (0.198)	1.475 (0.226)	1.707 (0.304)	1.196 (0.295)	0.997 (0.162)	3.612 (0.153)
	Alphas	0.191 (0.121)	0.290 (0.080)	0.380 (0.069)	0.384 (0.063)	0.446 (0.058)	0.502 (0.058)	0.605 (0.084)	0.726 (0.091)	0.843 (0.108)	0.965 (0.169)	0.773 (0.273)		
	Betas	0.604 (0.079)	0.793 (0.049)	0.859 (0.040)	0.936 (0.041)	0.930 (0.035)	1.049 (0.032)	1.101 (0.051)	1.123 (0.052)	1.195 (0.060)	1.404 (0.103)	0.800 (0.171)		
High Beta Herding (Bottom 20%)	Raw Returns	0.702 (0.196)	0.976 (0.183)	1.137 (0.197)	1.284 (0.237)	1.312 (0.282)	1.384 (0.265)	1.468 (0.283)	1.573 (0.314)	1.743 (0.350)	1.860 (0.352)	1.159 (0.209)	1.314 (0.268)	2.794 (0.136)
	Alphas	0.109 (0.074)	0.351 (0.075)	0.444 (0.058)	0.475 (0.069)	0.384 (0.052)	0.514 (0.054)	0.541 (0.066)	0.559 (0.073)	0.634 (0.086)	0.682 (0.124)	0.573 (0.131)		
	Betas	0.663 (0.049)	0.700 (0.051)	0.775 (0.035)	0.906 (0.047)	1.038 (0.037)	0.973 (0.029)	1.037 (0.036)	1.135 (0.047)	1.241 (0.051)	1.318 (0.070)	0.655 (0.086)		

Table 4 Average returns over 12 months before the portfolio formation conditioning on herding states

The post-formation average monthly return over f months of the high-minus-low standardized-beta portfolio is regressed on the excess market return (EMR or $r_{m,t+1,t+f}$) for the same period, the lagged beta herd measure (BH or H_{t-s}^*), Baker and Wurgler's (2006) sentiment (Sent or S_{t-s}), Bali et al.'s (2017) lottery-like preference factor ($FMAX_{t-s}$), the past return of the high-minus-low standardized-beta portfolio (Lagged $r_{High-Low}$), where s represents the number of lags:

$$r_{HL,t+1,t+f} = \alpha + c_1 r_{m,t+1,t+f} + c_2 H_{t-s}^* + c_3 S_{t-s} + c_4 FMAX_{t-s} + c_5 r_{HL,t-s-f+1,t-s} + \varepsilon_{i,t+1,t+f}$$

where $r_{HL,t+1,t+f}$ and $r_{m,t+1,t+f}$ are the average monthly returns of the high-minus-low standardized-beta portfolios and the market portfolio for $f = 6, 12, 24$ and 36 months, respectively: e.g., $r_{m,t+1,t+f} = \frac{1}{f} \sum_{\tau=1}^f r_{m,t+\tau}$. The lags are allowed to have $s = 0, 6, 12,$ and 24 months. The numbers in brackets represent Newey-West robust standard errors, and bold numbers show significance at the 5% level.

f months	Lags $s=0$							Lags $s=6$						
	Constant	EMR	BH	Sent	FMAX	Lagged $r_{High-Low}$	R ²	Constant	EMR	BH	Sent	FMAX	Lagged $r_{High-Low}$	R ²
6 months	-0.402	0.960					0.508	-0.402	0.960					0.508
	(0.180)	(0.113)						(0.180)	(0.113)					
	-0.245	0.961	-0.036				0.508	-0.173	0.963	-0.052				0.509
	(0.249)	(0.113)	(0.057)					(0.252)	(0.113)	(0.049)				
	-0.149	0.936	-0.039	-0.296	-0.002	-0.078	0.522	-0.101	0.948	-0.054	-0.251	-0.012	-0.078	0.520
	(0.257)	(0.111)	(0.058)	(0.157)	(0.017)	(0.050)		(0.248)	(0.113)	(0.049)	(0.137)	(0.027)	(0.050)	
12 months	-0.368	0.834					0.442	-0.368	0.834					0.442
	(0.171)	(0.125)						(0.171)	(0.125)					
	-0.189	0.838	-0.041				0.444	-0.087	0.845	-0.065				0.450
	(0.214)	(0.124)	(0.046)					(0.225)	(0.124)	(0.042)				
	0.035	0.769	-0.055	-0.287	-0.007	-0.130	0.483	0.090	0.795	-0.071	-0.236	-0.008	-0.134	0.480
	(0.265)	(0.096)	(0.047)	(0.145)	(0.011)	(0.088)		(0.235)	(0.102)	(0.042)	(0.144)	(0.010)	(0.086)	
24 months	-0.330	0.678					0.325	-0.330	0.678					0.325
	(0.148)	(0.148)						(0.148)	(0.148)					
	-0.138	0.691	-0.045				0.335	-0.084	0.694	-0.058				0.342
	(0.182)	(0.145)	(0.032)					(0.197)	(0.144)	(0.033)				
	0.141	0.575	-0.062	-0.128	-0.013	-0.146	0.391	0.241	0.574	-0.079	-0.114	-0.015	-0.169	0.400
	(0.205)	(0.132)	(0.029)	(0.108)	(0.006)	(0.094)		(0.206)	(0.127)	(0.031)	(0.128)	(0.005)	(0.090)	
36 months	-0.218	0.449					0.184	-0.218	0.449					0.184
	(0.122)	(0.152)						(0.122)	(0.152)					
	0.011	0.477	-0.055				0.219	0.037	0.483	-0.062				0.228
	(0.156)	(0.140)	(0.026)					(0.168)	(0.140)	(0.027)				
	0.098	0.433	-0.058	-0.084	-0.014	-0.060	0.248	0.172	0.430	-0.068	-0.092	-0.008	-0.083	0.262
	(0.182)	(0.159)	(0.026)	(0.079)	(0.005)	(0.089)		(0.198)	(0.156)	(0.028)	(0.096)	(0.005)	(0.085)	

<i>f</i> months	Lags s=12							Lags s=24						
	Constant	EMR	BH	Sent	FMAX	Lagged $r_{High-Low}$	R ²	Constant	EMR	BH	Sent	FMAX	Lagged $r_{High-Low}$	R ²
6 months	-0.402	0.960					0.508	-0.402	0.960					0.508
	(0.180)	(0.113)						(0.180)	(0.113)					
	-0.024	0.969	-0.087				0.514	0.051	0.964	-0.104				0.517
	(0.264)	(0.113)	(0.049)					(0.284)	(0.113)	(0.046)				
	0.024	0.963	-0.089	-0.139	-0.033	-0.068	0.522	0.179	0.970	-0.121	-0.182	-0.014	-0.081	0.528
	(0.258)	(0.112)	(0.049)	(0.132)	(0.016)	(0.047)		(0.288)	(0.116)	(0.046)	(0.130)	(0.012)	(0.049)	
12 months	-0.368	0.834					0.442	-0.368	0.834					0.442
	(0.171)	(0.125)						(0.171)	(0.125)					
	0.014	0.846	-0.089				0.458	-0.024	0.844	-0.080				0.455
	(0.235)	(0.124)	(0.044)					(0.259)	(0.124)	(0.041)				
	0.154	0.811	-0.093	-0.150	-0.025	-0.119	0.481	0.193	0.827	-0.101	-0.217	-0.010	-0.129	0.488
	(0.236)	(0.103)	(0.044)	(0.142)	(0.008)	(0.084)		(0.246)	(0.104)	(0.042)	(0.112)	(0.008)	(0.081)	
24 months	-0.330	0.678						-0.330	0.678					0.325
	(0.148)	(0.148)						(0.148)	(0.148)					
	-0.030	0.700	-0.071				0.351	-0.054	0.709	-0.068				0.348
	(0.195)	(0.142)	(0.033)					(0.201)	(0.147)	(0.028)				
	0.290	0.585	-0.089	-0.138	-0.008	-0.179	0.409	0.282	0.584	-0.084	-0.227	-0.002	-0.189	0.430
	(0.212)	(0.125)	(0.031)	(0.129)	(0.006)	(0.096)		(0.227)	(0.129)	(0.033)	(0.088)	(0.008)	(0.095)	
36 months	-0.218	0.449					0.184	-0.218	0.449					0.184
	(0.122)	(0.152)						(0.122)	(0.152)					
	0.042	0.495	-0.065				0.231	-0.049	0.490	-0.045				0.201
	(0.162)	(0.145)	(0.027)					(0.171)	(0.167)	(0.033)				
	0.207	0.435	-0.073	-0.109	-0.006	-0.099	0.273	0.160	0.405	-0.056	-0.125	0.001	-0.119	0.246
	(0.187)	(0.157)	(0.028)	(0.091)	(0.004)	(0.084)		(0.192)	(0.185)	(0.036)	(0.061)	(0.005)	(0.095)	

Table 5 Low-beta anomaly and beta herding

For the sample period from January 1967 to December 2016, every month we form decile portfolios sorted on standardized-betas using non-microcap stocks and NYSE breakpoints. The post-formation return of the high-minus-low standardized-beta portfolio is regressed on lagged beta herding ($H_{m,t-s}^*$), Baker and Wurgler's (2006) sentiment (S_t) and Bali, Cakici, and Whitelaw's (2011) lottery-like preference factor ($FMAX_{t-s}$) in the presence of other explanatory variables $z_{k,t-1}r_{m,t}$ s in addition to the excess market return (EMR or $r_{m,t}$), where $z_{k,t-1}$ the lagged instrumental variable k . Six such instrumental variables are used as in Cederburg and O'Doherty (2016): the fitted market risk premium (\hat{r}_m), the number of IPOs in the prior five years divided by the total number of sample firms (IPO), the cross-sectional standard deviation of firm-level log book-to-market ratios (σ_{BM}), the cross-sectional standard deviation of firm-level book leverage (σ_{LEV}), the cross-sectional average of firm-level idiosyncratic volatility computed from daily returns over the prior 12 months (IVOL), and the standard deviation of daily Treasury-Eurodollar (TED) spread innovations over the prior three months ($\sigma_{\Delta TED}$). These additional explanatory variables are calculated as $z_{k,t+1,t+f}^* = \frac{1}{f} \sum_{\tau=1}^f z_{k,t+\tau-1} r_{m,t+\tau}$ for the time-varying betas over f months following the formation of the beta portfolios:

$$r_{HL,t+1,t+f} = \alpha + c_1 r_{m,t+1,t+f} + c_2 H_{m,t-s}^* + c_3 S_{t-s} + c_4 FMAX_{t-s} + \sum_{k=1}^6 c_k z_{k,t+1,t+f}^* + \varepsilon_{i,t,t+f}$$

The numbers in brackets represent Newey-West robust standard errors, and bold numbers show significance at the 5% level.

A. High-minus-low Standardized-Beta Portfolio

	Constant	EMR	Beta Herding	Sentiment	FMAX	Instrumental variable ($z_{k,t-1}$)						R ²
						\hat{r}_m	IPO	σ_{BM}	σ_{LEV}	IVOL	$\sigma_{\Delta TED}$	
6 months	-0.243 (0.151)	-0.339 (0.801)				-0.065 (0.163)	0.250 (0.795)	0.894 (1.357)	-0.024 (1.042)	0.147 (0.041)	0.312 (0.669)	0.596
	0.087 (0.243)	-0.545 (0.868)	-0.072 (0.052)			-0.090 (0.158)	-0.036 (0.764)	1.138 (1.414)	0.196 (1.022)	0.141 (0.043)	0.211 (0.689)	0.599
	0.088 (0.247)	-0.567 (0.829)	-0.074 (0.053)	-0.111 (0.140)	-0.014 (0.013)	-0.097 (0.154)	-0.052 (0.750)	1.215 (1.352)	0.161 (1.002)	0.138 (0.042)	0.222 (0.678)	0.600
	-0.103 (0.134)	-0.516 (1.148)				-0.178 (0.166)	0.069 (0.773)	1.301 (1.743)	-0.816 (0.807)	0.193 (0.038)	1.146 (0.681)	0.610
12 months	0.046 (0.224)	-0.679 (1.184)	-0.033 (0.041)			-0.190 (0.164)	-0.109 (0.767)	1.533 (1.783)	-0.724 (0.817)	0.189 (0.039)	1.070 (0.708)	0.611
	0.046 (0.231)	-0.685 (1.116)	-0.034 (0.043)	-0.094 (0.122)	-0.007 (0.009)	-0.199 (0.156)	-0.134 (0.748)	1.620 (1.694)	-0.788 (0.798)	0.187 (0.038)	1.057 (0.683)	0.612
	0.044 (0.141)	-1.600 (0.956)				-0.373 (0.215)	-0.265 (0.745)	3.650 (1.725)	-1.879 (0.981)	0.144 (0.052)	1.494 (0.964)	0.518
	0.183 (0.198)	-1.776 (0.999)	-0.031 (0.036)			-0.391 (0.208)	-0.499 (0.729)	3.820 (1.770)	-1.634 (1.054)	0.140 (0.052)	1.320 (1.044)	0.520
24 months	0.174 (0.192)	-1.753 (0.890)	-0.031 (0.038)	-0.126 (0.119)	-0.011 (0.006)	-0.416 (0.195)	-0.520 (0.691)	4.055 (1.623)	-1.878 (1.033)	0.134 (0.050)	1.277 (0.952)	0.531

B. High-minus-low Beta Portfolio

6 months	-0.288 (0.165)	-0.127 (1.058)				-0.093 (0.176)	0.109 (0.888)	1.128 (1.730)	-0.262 (1.233)	0.140 (0.049)	0.044 (0.699)	0.600
	0.015 (0.267)	-0.316 (1.131)	-0.067 (0.054)			-0.115 (0.172)	-0.153 (0.866)	1.352 (1.800)	-0.059 (1.219)	0.135 (0.050)	-0.049 (0.715)	0.602
	0.021 (0.271)	-0.369 (1.041)	-0.069 (0.057)	-0.249 (0.152)	-0.023 (0.015)	-0.128 (0.164)	-0.187 (0.827)	1.526 (1.660)	-0.143 (1.167)	0.129 (0.048)	-0.025 (0.682)	0.608
	-0.113 (0.164)	-0.539 (1.538)				-0.210 (0.213)	0.020 (1.019)	1.938 (2.306)	-1.256 (1.050)	0.181 (0.052)	0.847 (0.828)	0.567
12 months	0.074 (0.274)	-0.744 (1.585)	-0.041 (0.047)			-0.224 (0.210)	-0.205 (1.009)	2.230 (2.360)	-1.141 (1.068)	0.175 (0.052)	0.752 (0.861)	0.569
	0.075 (0.281)	-0.753 (1.456)	-0.043 (0.051)	-0.177 (0.147)	-0.015 (0.011)	-0.242 (0.195)	-0.253 (0.963)	2.391 (2.188)	-1.258 (1.023)	0.171 (0.051)	0.726 (0.811)	0.576
	0.098 (0.174)	-2.474 (1.165)				-0.399 (0.280)	-0.364 (0.976)	5.736 (2.113)	-2.949 (1.280)	0.119 (0.066)	1.664 (1.024)	0.484
	0.424 (0.269)	-2.888 (1.219)	-0.073 (0.047)			-0.443 (0.269)	-0.913 (0.943)	6.135 (2.157)	-2.373 (1.321)	0.110 (0.065)	1.255 (1.108)	0.496
24 months	0.411 (0.255)	-2.857 (1.058)	-0.072 (0.051)	-0.190 (0.132)	-0.014 (0.008)	-0.480 (0.246)	-0.945 (0.871)	6.495 (1.927)	-2.742 (1.237)	0.102 (0.064)	1.193 (0.970)	0.517

Figure 1 Expected excess market return when investors are rational, under- or over-confident about market signal

The picture shows various examples of the effects of investors' confidence levels and signs of signals on betas, expected returns, and the expected excess market return (i.e., the slope of Security Market Line, SML). When there is no signal, the unconditional expected excess market return μ_m is the slope of SML. On the other hand, when investors receive a signal about the market portfolio and form the expected excess market return conditional on the market signal, the slope of the SML is $\mu_m + w_t s_{m,t}$ for rational investors, or $\mu_m + \frac{w_t}{\gamma_t^*} s_{m,t}$ for over- or under-confident investors. The slope changes depending on the signs of the signal as well as the precision of the signal that investors perceive. The thick arrows show how the betas and the expected return of low and high beta stocks are biased by investor under-confidence about negative signal when $\gamma_t^* = 1.4$. In this case, the expected excess market return ($\mu_m + \frac{w_t}{\gamma_t^*} s_{m,t}$) is upwardly biased, and the difference between individual betas and expected excess returns increases.

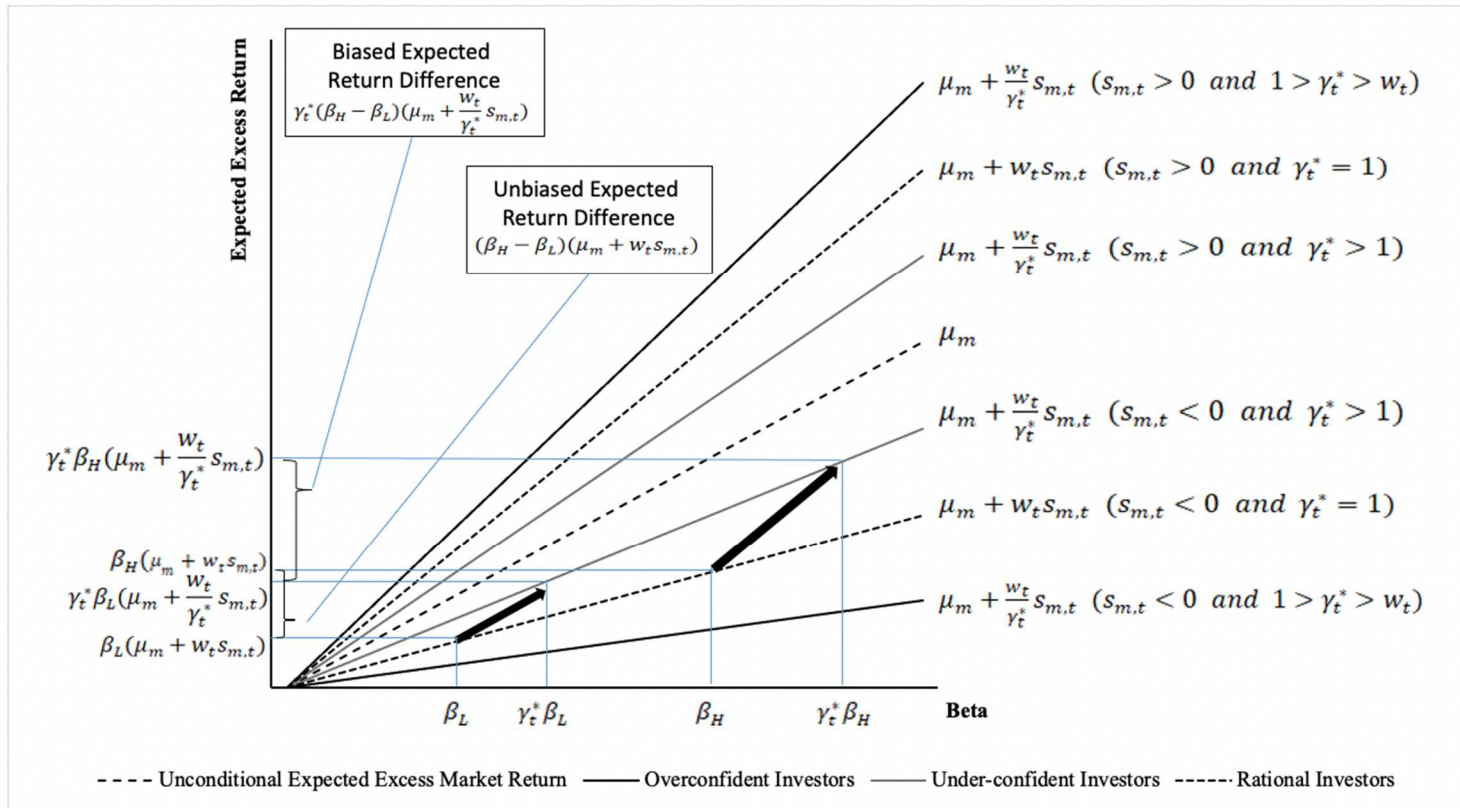


Figure 2 Beta herding in the US market

Every month betas are estimated using rolling windows of the prior 12 months of daily returns (minimum 150 valid daily returns) and update the beta herd measure and its confidence interval as shown in Theorem 1. Current and lagged market returns are used to estimate betas as follows:

$$r_{it} = \alpha_i^{K3} + \beta_{i0}^{K3} r_{mt} + \beta_{i1}^{K3} r_{mt-1} + \beta_{i2}^{K3} [(r_{mt-2} + r_{mt-3} + r_{mt-4})/3] + \varepsilon_{it},$$

Betas and their heteroscedasticity robust standard errors are calculated as $\beta_i^{K3} = \beta_{i0}^{K3} + \beta_{i1}^{K3} + \beta_{i2}^{K3}$. The beta-based herd measure is calculated with the cross-sectional variance of the estimates of betas, and the beta herd measure is calculated with the cross-sectional variance of t statistics of betas that are calculated with the Newey-West heteroscedastic adjusted standard errors. 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 removed from our calculation of the beta herd measure. The beta herd measures are value-weighted.

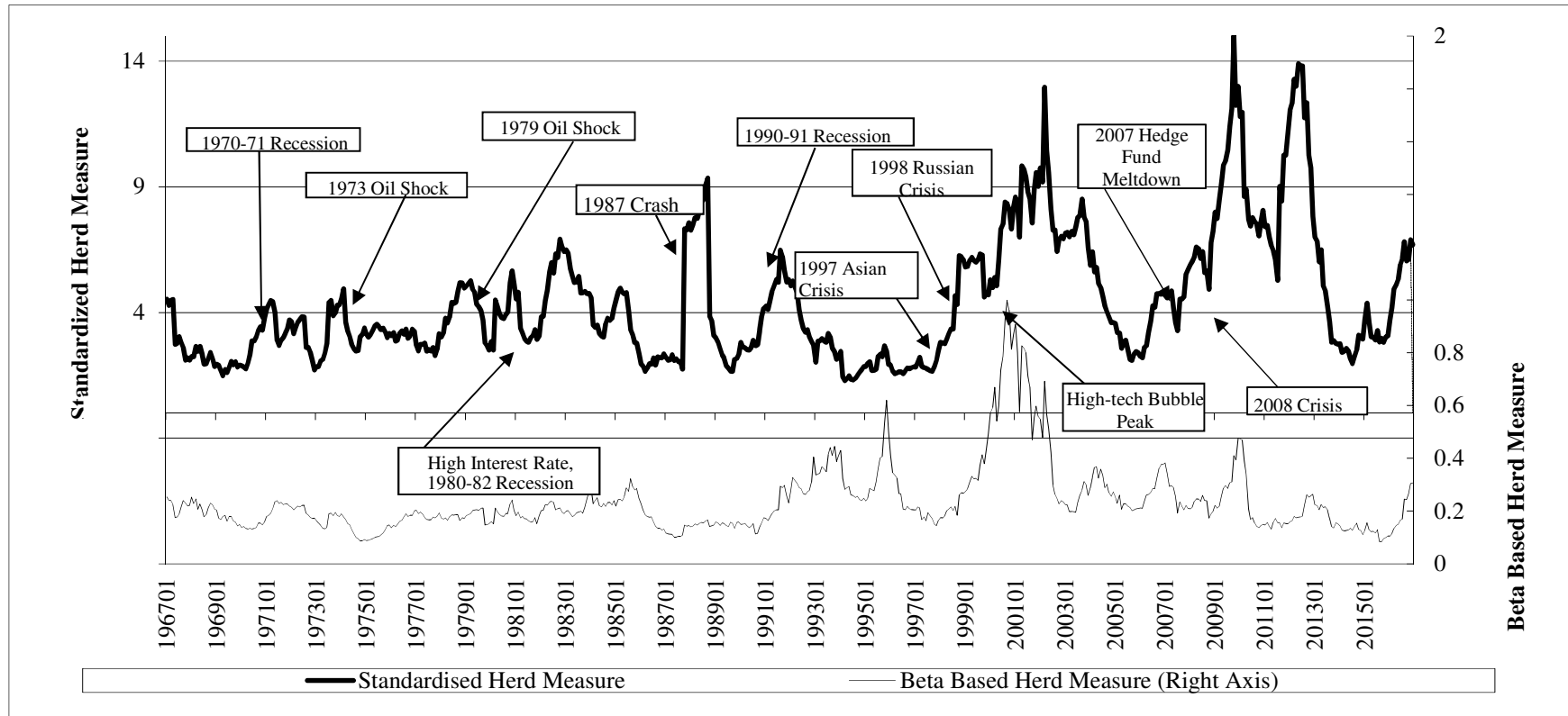


Figure 3 Lead-lag relationship between time-varying beta and beta herding

The lead-lag relationship between the time-variation in beta and beta herding is investigated as follows:

$$V_t^* = c_0^b + c_1^b r_{m,t+1,t+f} + c_2^b H_{m,t-s}^* + \varepsilon_{i,t,t+f} \quad (E1)$$

$$H_{m,t+s}^* = c_0^h + c_1^h r_{m,t+s+1,t+s+f} + c_2^h V_t^* + \varepsilon_{i,t,t+f} \quad (E2)$$

where V_t^* is equal to $\sum_{k=4}^K \hat{c}_k Z_{k,t+1,t+f}^*$, S_t , or $FMAX_t$. $\sum_{k=4}^K \hat{c}_k Z_{k,t+1,t+f}^*$ is estimated in the presence of the excess market return (without the lagged beta herd measure and sentiment), $r_{m,t+1,t+f} = \frac{1}{f} \sum_{\tau=1}^f r_{m,t+\tau}$ is the excess market portfolio for f months, S_t represents the sentiment measure of Baker and Wurgler (2006), and $FMAX$ is the lottery-like preference factor of Bali et al. (2017). The Figure shows the coefficients with the 95% confidence level for various lags, $s = 1, 2, \dots, 36$ when $f = 12$.

