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Herding in Large Cap Stocks during Bull Markets: Evidence from Dow Jones Industrial Stocks

Sung Myun Kang[a] and Chong Soo Pyun[b]

[a]*graduate student at the University of Texas at Arlington, TX, USA.*
[b]*Suzanne Palmer Professor of Finance at the University of Memphis, TN, USA.*

A B S T R A C T

We investigate evidence of investor herding in individual component stocks of the Dow Jones Industrial Index. In the correlation analysis, all stocks show positive correlations between their price and trading volume changes. In the dummy regression, most stocks in their equal- and value-weights show strong herd behavior in the upper values relative to their moving average prices. In log-log regression, we find a diminishing marginal effect in the upper values of their moving average prices. We find that the greater the dispersion of a stock away from its moving average line, the stronger the evidence of true herding in the movement of its price and concomitant change in trading volume.

Keywords: Herding, Dow Jones Industrial Index, Regression, Bull Market

Ⅰ. Introduction

Herding occurs when investors imitate other investors by substituting their own appraisal of a particular stock with what they perceive as a market consensus or the superior knowledge of others. However, investor's cognitive process of mimicking others' judgment is multifaceted and difficult to quantify. The empirical literature has focused on three major types of herding in financial markets: (i) informational herding and cascade, (ii) reputational herding, and (iii) compensation herding (Bikhchandani and Sharma, 2000)

Briefly, in informational herding, individual investors rapidly converge to buy or sell a particular stock with minimal discernible cause while an information cascade is said to occur when investors substitute market signals for their own judgment thus overriding their own information in pricing the stock involved. In reputational herding, both informed and uninformed investors benefit from the herding behavior. This is because the informed investor will act on his superior information while the uninformed investor can choose to either sit on his hands or follow the signal he observes from the action of the informed investor. In each case, the price of the stock changes, and the new herd influenced equilibrium price benefits both types of investors. In compensation herding, portfolio managers (acting as investors' agents) have their compensation at least partially determined based on their performance relative to that of other portfolio managers'. This may lead to herding behavior as portfolio managers try to minimize the performance

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† Corresponding Author - Chong Soo Pyun
FogelmanCollege of Business and Economics, The University of Memphis, Memphis, TN38152 (901) 678-4645; cspyun@memphis.edu

differential between themselves and their peer group of managers by essentially mimicking the investment positions held by their peer group.

In general, the empirical literature on herding is based on two premises: (i) Investor herding behavior can be said to be a divergence from the basic tenets of rational asset pricing models. More specifically, herding tends to misprice the market value intrinsic to the stock involved which ultimately leads to a reduction of efficiency in the stock market; and (ii) This mispricing of the stock is particularly pronounced, and it can be empirically measurable during periods of extreme price or volume volatilities of stock market or individual stocks that are otherwise under stress.

In this paper, we debunk the second premise that herding is especially pronounced and measureable during a period of market under stress by showing that herding in the form of succession in the transitory process is just as well observed during a period of rising and robust stock markets. More specifically, using the price and trading volume data pertaining to individual component companies of the Dow Jones Industrial Average (DJIA) during the bull market following the stock market crash of 2007, we show the prevalence of statistical herding in which investors, seeking to maximize expected profit in a common-value environment have access to independent private signals when observing the behaviors of others. Eventually, through observing evidence of many investors, the private information of an informed investor is submerged, and all investors rationally imitate the prevailing behavior[1].

There are at least four reasons for studying the behaviors of individual component stocks of the DJIA: (i) Many of empirical herd papers in the literature have dealt with portfolios of stocks or stock exchange indices such as ones for the NYSE and FTSE100. We test the inter-temporal herd behavior of individual company stocks during a relatively stress-free, rising market environment; (ii) DJIA stocks represent the 30 largest cap companies[2] in the U. S. across a range of industries except for transportation and utilities. We are neither data mining nor erring on the selection of biased samples for this study. By constructing our sample from 25 of the Dow 30, we are able to study herding behavior in a sample comprising as much as 27 percent of the U. S. stock market by their market capitalization at the end of 2008 (NYSE, 2013).; (iii) All DJI component stocks enjoy a history of successful growth. Thus they are considered as low-risk equity investments and widely held by both institutional and individual investors; (iv) While they are widely held by both individual and institutional investors, institutional investors who are generally regarded as informed traders dominate stocks' daily transactions. Since the informed trades are less susceptible to herding as assumed, the existence of herding in the DJIA stocks has broad implication on investors' portfolio management as well as on the efficiency of U. S. stock markets as a whole.

We report three findings: (i) All 25 DJI component stock s[3] show the contemporaneous movements in tandem with their price and trading volume; (ii) When our logarithmic equations are regressed with dummy variables of extreme values representing 1to 15 percent of upper bands (or lower bands of their respective moving average lines), only the upper value of the most stocks show strong herd behavior whether the stocks are measured in their equal- or value-weights; (iii) In log-log regression, both the equal- and value-weights series also show a non-linear marginal diminishing effect on all upper extreme values of their respective individual stocks. On the balance, the more the individual DJI component stocks moves away from the irrespective moving average price lines, the stronger a herd behavior appears.[4]

The remainder of this study is as follows. Section II presents the analytical framework of this study. Section III discusses a brief literature review while Section IV describes the data and methodology. Section V presents the findings of our three step regressions ‒ correlation, dummy regression, and log-log regression and Section VI further delves into an examination of the significance of marginal diminishing returns and non-linearity with the log-log regressions. The paper concludes with Section VII.

Ⅱ. Analytical Framework

There are two broad approaches for investigating investor group trading behavior. The first is the analysis of investor

[1] See Bikhchandani, *et.al.* (1992) and Ottaviani and Sorensen (2000) for the analytical properties of statistical herding in detail.

[2] Large-cap refers to a company with at least $10 billion market capitalization. As of June 28, 2013, the largest DJI company is Exxon with $401.7 billion and the smallest company McDonalds with $99 billion (NYSE, 2013).

[3] Five DJI stocks ‒ BAC, CVX, HPQ, JNJ, and KO ‒ are eliminated from the study for their unusual corporate actions or aberrant stock transactions during the study period. See Section IV.2,DataDescription.

[4] The findings of our study are confined to the individual component stocks of Dow Industrial Average we analyzed: They may not be applicable to other large cap stocks traded in the U. S. Stock markets.

action using transaction data on stocks which are available only for subset of investors such as insiders, investors in particular network by their working relationship, or by paid subscription. The second approach utilizes easily obtainable information on market prices and considers trading by all investors. This approach can be applied to time-series or cross-sectional contexts (Goodfellow, Bohl and Gebka, 2009).

Using the stock portfolio returns of different industries, Christie and Huang (1995) analyze whether equity return dispersions are significantly lower than the average return during a period of extreme market movements. They use 1 or 5 percent samples in the upper or lower tail of the market returns as their out-of-sample boundary. This is to capture only extreme returns of those portfolios under stress (p. 31). Chang, Chen and Khorama (2000) follow a similar method of analyzing portfolio returns except that they replace their cross-sectional average deviation (CSAD) measures for Christie and Huang's cross-sectional standard deviation (CSSD) measures. In doing so, Chang, *et. al.* identify an important statistical property that prior studies overlooked. Return patterns (either dispersion of returns or volume changes associated with price movements) are an increasing function of the market return. Further, the relationship between return and volume is linear. They show that these relationships can be non-linearly increasing or decreasing since investors exhibiting herding behavior are thought to suppress their own judgments and follow those of the market aggregate in a stock upturn or downturn. It should be noted that both sets of researchers measure their equity returns into portfolio returns.

In this study we expand on the Chang, *et al.*'s analytical concept by implementing three standard statistical tests on price and volume transaction data: analyses of correlation, dummy regression, and log-log regression. Our contributions to the literature in this regard are three. We provide evidence that these three parsimonious statistical tools produce results which are just as analytically meaningful as Christie and Huang's cross-section standard deviation or Chang, *et al.'*s cross-section standard average deviation methods. We can also detect the presence and magnitude of herding which may have been otherwise undetected in the individual large-cap stocks themselves without data-snooping bias or arbitrary out-of-sample data selection for this study. Moreover, our model captures the degree of co-movement of price and volume in relation to attendant herd patterns of individual stocks throughout the entire study period of rising market, not just when specific portfolios of stocks or industries are under stress, which are the focal points of the other two models.

Ⅲ. A Brief Literature Review

Herding behavior is thought to emanate from an investor's cognitive process of mimicking others judgment. On the balance, the literature on herding has accumulated fairly rapidly from the seminal theoretical works by Bikhchandani, Hirshleifer and Welch (1992) and Banerjee (1992).[5] Bikhchandani, et. al. shed light on the nature of information herding in which investors quickly mimic other investors. Information herding often precipitates information cascades because investors substitute market signals for their own judgment thus overriding their own information in pricing the stock involved. Banerjee (1992) presents a theoretical model of information herding in which a succession of learning trials of otherwise rational investors, who substitute market signals for their own judgment, are reflected in the movement of stock prices along with their contemporaneous changes in trading volume. Shefrin and Statman (1994) discuss behavioral finance such as anchoring, mental accounting, gambler's fallacy and herd behavior. They further segment herd behavior into categories such as rational herding, near-rational herding, and an irrational herding. (Davenow and Welch, 1996; Galariotis, Rong and Spyrou, 2012). Venezia, Nashikkar and Shapira (2011) find evidence of herding among both amateur and professional investors and note that the propensity to herd is lower in the professionals.

Scharfstein and Stein (1990) and Hwang and Salmon (2004) analyze reputational herding in a broad sense as they depict portfolio managers, who due to concern for their reputations, face two choices: Do nothing, or choose to follow the behaviors of other managers whom they regard as knowledgeable. In either case, all participants will benefit by the ensuing herd-induced change in equilibrium prices. However, since private information of individual portfolio managers is not visible in the price discovery process, this type of herding can be said to engender inefficiency in the stock market. Nofsinger and Sias (1999), Bikhchandani, et al.,(1992), Ottavani and Sorensen (2000), and Kim and Wei (2002) also shed additional light on the rationality of reputational herding through their identification of stationary, intentional and feedback herding.

With regard to compensation herding, Brennan (1993), Maug and Naik (1996), and Admati and Pfleiderer (1997), among other researchers, show that if a portfolio manager

[5] To be sure, empiricists preceded theoreticians: For instance, Nofsinger and Sias (1999) examine herding behaviors of individual and institutional investors in the NYSE.

as an agent is rewarded based on investment performance as compared to the performance of benchmark peer-portfolio managers, the manager is more likely to follow the investment decision of the benchmark peer-manager, assuming that both managers have imperfect, private information regarding stock returns (Bikhchandani and Sharma, 2000). Dasgupta, Prat and Verardo (2011) demonstrate that persistent institutional trading negatively predicts long-term returns. This is because persistently sold stocks outperform persistently bought stocks at long horizons; however, the negative relationship between returns and institutional trade persistence is focused among smaller stocks and is stronger for stocks with higher institutional ownership. Venezia, et. al. (2011) find evidence that the propensity to herd is lower among professional investors as compared to individual investors. Clement and Tse (2005) classify analysts' earnings forecast as herding or bold and report that bold forecasts give more relevant information to investors than herding forecasts.

Another perspective in the herd literature concerns the effect of capital market liberalization worldwide and country-specific herd studies. Bekaert and Harvey (1997) point out that capital market liberalization often increases the correlation of returns between local markets and the world market with concomitant increases in herd behaviors in the both markets. Chiang and Zheng (2010) show evidence of herding in advanced stock markets in the U. S. and Asia but no evidence of herding in Latin American countries. More recently Lao and Singh (2011) find stock market herding in China and India.

Methodologically, statistical studies dominate the herd literature. Lakonishok, Shleifer and Vishny (1992) use a correlation analysis among cluster patterns of the average price movement for measuring investor herding. In the similar vein, Grinblatt, Titman and Wermers (1995) find statistical herd behaviors among mutual fund managers that bring about momentum investment strategies which produce higher risk-adjusted returns.

Chang, et al. (2000) point out that rational asset pricing models such as Christie and Huang's (1995) CSSD model, indicate that not only is return dispersion an increasing function of market return, it is also non-linearly related to return. With their CSAD model, Chang, et. al. (2000) suggest that during periods of large price movement, market participants have a tendency to herd around the market consensus, and return dispersion also shows a nonlinear relationship.

Blasco, Corredor and Ferreruela (2012), applying causality tests, find that herding intensity depends on past returns and sentiment or subjective assessment, and herding is influenced by both rational and emotional factors. In a fresh perspective of analysis with GMM and Japanese loan data, Nakagawa, Oiwa and Takeda (2012) find inefficient herding behavior by lenders.

Ⅳ. Methodology and Data

A. Methodology

The focus of our study is to investigate whether herd behavior exists throughout the range of equity values or if it is concentrated in the extremely upper and lower value of stock prices as in Christie and Huang (1995) and Chang, et. al. (2000). However, while these previous studies conducted their examination of herding using cross-sectional portfolios of stocks, we analyze herd in individual stocks. Furthermore we use elementary statistical tools, which are quite efficient for the task at hand. First, we use the natural logarithm, which maps multiplication into addition, to mitigate the heteroscedasticity and autocorrelation in the time series of trading volume as well as the trading volume series relative to the stock price time series. In this way, we are able to stabilize the time series data whose stabilities are confirmed by augmented Dickey-Fuller tests. Second, we use the absolute values of individual stocks. The absolute values are obtained by subtracting daily prices of individual stocks from the value of varying moving averages of the individual stocks involved. The four moving averages used are calculated for the following intervals: a10-, a 20-, a 30-, and a 60-day average. Eq. (1) below illustrates the absolute value of a stock obtained from its 20-day moving average:

$$\text{ln(stock volume) vs} \\ \text{Abs(stock price-20day move average line)} \quad (1)$$

We use absolute values not only to delineate the upper and lower zones of the time series for our herd analysis but also to strengthen the predictive power of the log-log regressions used in this study.

Our study is implemented in three phases. In the first, we analyze the correlation between stock price and trading volume. Epps (1977) demonstrates that a correlation exists between the absolute values in price-earnings ratios computed from their time-varying average ratios. In this study we test whether a positive correlation exists between the absolute values of individual stocks computed from their respective 20-day moving average and the natural logarithms of trading volume.

In the second phase, we investigate herd behavior with a modified version of Christie and Huang's (1995) methodology. Instead of their CSSD of returns as their dependent variable, we substitute the natural logarithm of trading volume as the dependent variable. Moreover, we test the statistical properties of the absolute values of stocks which we obtain by subtracting daily prices of individual stocks from the stock's varying moving averages. Herd behaviors are analyzed with the extreme lower and upper values with the natural log trading as the independent variable. Stated here;

$$\ln v_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t \tag{2}$$

To ascertain the diminishing marginal effect in D_t^U or D_t^L, we first delineate the upper value and lower value relative to the 20-day moving average against the absolute value of the difference between the stock price and the 20 days moving average line. Then we evaluate whether the upper value and lower value is in 0 < X < 1 by log-log regression with the absolute value of difference between the stock price and 20-day moving average line as shown in eq. (3) and eq. (4).

$$\ln v_t = \alpha + \beta_1 \ln(Abs(Stock\ price - 20day\ move\ average\ line))_t^L + \epsilon_t \tag{3}$$

$$\ln v_t = \alpha + \beta_1 \ln(Abs(Stock\ price - 20day\ move\ average\ line))_t^U + \epsilon_t \tag{4}$$

Where $D_t^L = 1$, if the market return on day t lies in the extreme lower tail of the independent value distribution

$D_t^L = 0$ otherwise

$D_t^U = 1$, if the market return on day t lies in the extreme upper tail of the independent value distribution, and

$D_t^U = 0$ otherwise.

Based on eq. (2), the coefficients of alpha and lower and upper beta are calculated and analyzed for individual stocks comprising DJIA. The lower and upper betas are 2 percent of each boundary of the lower and upper, and the extreme values ranged from 1 to 15 percent are examined in this study. The dummy variable, beta, signifies the difference between the general routine behaviors of individual stocks and the herd behavior in the individual stocks concerned. Christie and Huang (1995) show that rational asset pricing models predict significantly positive coefficients for β_1 and β_2 and negative estimates of β_1 and β_2 which would be consistent with the presence of herd behavior. They also show that the negative and statistically significant $\beta 1$ and $\beta 2$ coefficients signify herd behavior.

In the third phase, as an alternative to the quadratic regression of Chang et. al. (2000) and the logistic regression of Lee, Lee and Chae (2012), we measure the diminishing marginal effect in the return dispersion series with the log-log regression analysis. In our case, we infer that investor herding exists when beta values of our log-log regression are positive at less than one, that is 0 < X < 1.

We expand the third phase of our investigation by introducing daily returns of the individual stocks in DJIA reported as 10-day, a 20-day, 30-day, a 60-day moving average values and daily stock return. We also repeat our three-phase investigations of the lower value or the upper value of the absolute value against these four new moving averages. Our analysis includes log-log regressions to ascertain that we detect herding behavior when the returns are in fact in the phase of diminishing marginal return[6].

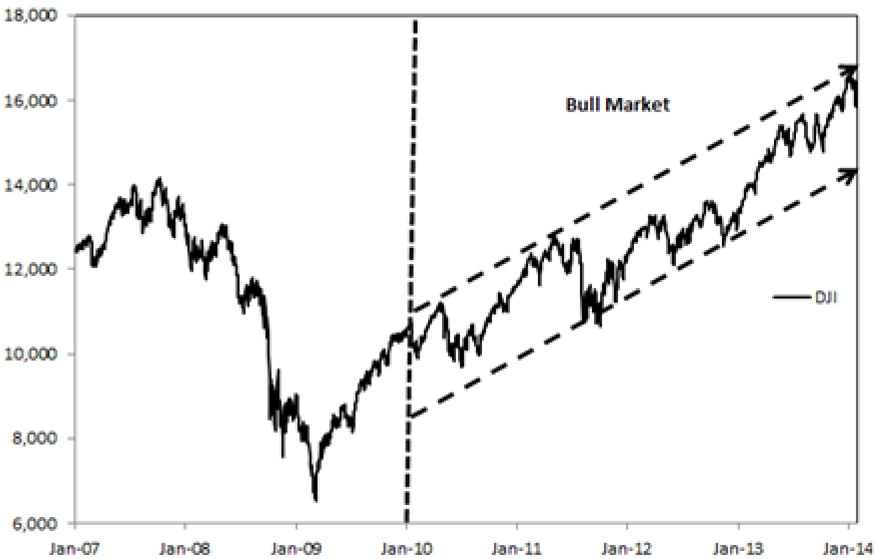
In this study we postulate that herd behavior in the individual firms can be detected by analyzing the movement of the company's stock trading volume against the concomitant movement of the company stock. In order to develop testable hypotheses, we cross pollinate the analytical frameworks of Christie and Huang (1995) and Chang et al.(2000) with those of Lee et al. (2012), which provide the experimental hypotheses for an empirical herd study that deals with the relationship between stock price and trading volume.[7] It should be noted that we use a 20-day moving average of both price and trading volume changes as the basis of calculating abnormal returns of individual stocks involved rather than Christie and Huang's market returns as the basis for calculating equity returns.

More specifically in this study, we test the two hypotheses

[6] Log-log regressions are susceptible to misspecification of transformed variables we used herein. Our findings of herding from the confirmation of diminishing marginal returns in the extreme outliers are by inference that may not be imputable to other large cap stocks listed on the NYSE.

[7] Lee, Lee, and Chae (2012) develop two hypotheses: H1, an auction with a higher participation rate attracts more bids, and H2, there is a diminishing marginal effect of the participation rate when herding is detected.

Figure 1. Dow Jones Industrial Average Monthly Index, 2007-2013



Source: http://www.fnguide.com/

with the standard deviation of the absolute daily stock price with the four moving average lines (of a 10-day, a 20day, a 30-day, a 60-day) and the natural logarithm of firm's trading volume and the absolute stock price as defined:

***H1**: Abs (stock price - 20 day move average line) causes significantly different stock volume.*

***H2**: There is a non-linear diminishing marginal effect of Abs (stock price - 20 day move average line).*

B. Data and Sources

We test herding in individual component companies that make up the DJIA. The component companies are thirty of the largest companies in the U. S. across a range of industries excluding transportation and utility companies. The 30 companies, which are leaders in their respective industries, have a history of successful growth. Taken as a group, these 30 companies are the most widely held stocks among both individual and institutional investors. They are all large-cap stocks ranging from the largest market capitalization of Exxon Mobil's $401 billion to the smallest of McDonalds's $99 billion in June 2013 (NYSE, 2013). We choose these as samples largely to mitigate statistical biases inherent in sampling by cherry-picking or data-snooping.

Our samples consist of 25 of the 30 Dow components companies. Five companies—Bank of America (BAC), Chevron (CVX), Hewett Packard (HPQ), Johnson and Johnson (JNJ), and Coca Cola (KO)—are eliminated because those stocks are involved in their extraordinary high standard deviations and value indications in their daily movements of stock price, trading volume, and total outstanding shares. Our study period covers a daily period from January4, 2010, to December 31, 2013. This period follows the end of the most turbulent time between 2008 and 2009 in the history of American stock markets since the stock market crash of 1929.[8] Figure 1 depicts all price and trading volume data taken from Compustat in Wharton Research Data Services (WRDS).

The use of the absolute values enables us not only to delineate the upper and lower zones of the time series for our herd analysis but also to strengthen the predictive power of the log-log regressions used in this study.

8) The ratio of high and low average of total volume of sample stocks is a low of 5.80 percent for the period from the beginning of 2010 to the end of 2013. The ratio jumps to a 9.46% for the period covering the January 2005 to December 2013. The jump in the ratio is largely due to the 2008-09 financial crisis.

Ⅴ. Empirical Analysis

A. Descriptive Statistics

Table 1 shows the descriptive statistics on the 25 DJIA component stocks in our sample. In terms of price, the highest average price is International Business Machines (IBM) with $166.38 and the lowest average of $11.96 for American Airlines (AA). The average price of the 25 stocks is $51.59. The lowest standard deviation of price is INTC with $.40, and the highest standard deviation goes to Minnesota Mining and Manufacturing (MMM) with $86.45. However, when trading volume is measured in log, Intel (INTC) has the highest standard deviation with 22.6 percent as compared to the lowest average of 15.06 percent for MMM. The average of trading volume of all 25 items is 16.61 percent. INTC has the highest standard deviation of trading volume with 2.60, and Target (T) the lowest of standard deviation with 0.34.

When daily price movement is calculated against the 20-day moving average, Caterpillar (CAT) shows the highest standard deviation with 3.49, while Pfizer's (PFE) 0.43 is the lowest. For the entire sample companies, the average is 1.27. On the balance, IBM has the largest variance when stock price is high while INTC shows the lowest variance in stock price but the highest variance in trading volume. Augmented Dickey-Fuller tests of unit root indicate that both ln (volume) and the 20-day moving average price series are stationary, but daily stock prices are not.

B. Correlation Analysis

The first step to gain insight into herd behaviors is to analyze the movement of stock price vis-à-vis trading volume changes. In this section we test the degree of correlation between price and volume movements. More specifically, we test the correlation of the absolute values for difference between the logarithm of trading volume and stock price and the 20 day moving average. The results are shown in Table 2. All results show that the price and volume changes of the Dow Jones Index (DJI) component stocks are positively significantly correlated. It should be noted that Boeing (BA) shows the highest correlation of .475 and IBM the lowest correlation of .118.

C. Regression with Dummy Variables

In order to analyze herd behavior, the logarithm of trading volume is treated as a dependent variable, and the absolute values for difference between stock price and moving average are designated as independent variables as in eq. (2).

$$\ln v_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^u + \epsilon_t \tag{2}$$

D_t^L will be the closest to the 20-day moving average line, taking into account that it is an extreme value and also a median of extremely high and low value. Therefore, D_t^U is the highest and lowest values computed from the 20-day moving average line.

Table 3 shows the analysis of the relationship between trading volume and stock price when there are the extreme upper and extreme lower values calculated from the 20-day moving average lines. We see that extreme upper and extreme lower show distinct dichotomous results. Looking at how the values on the 11 percent variation column change toward the 5 percent variation column and then how the values on the 5 percent variation column change toward the1 percent variation column, we see that bulk of the extreme upper values increase as the test values move from the 11 percent variation column to the 5 percent variation column. The table also shows that the extreme lower values congregate at 0 from a high negative value, and the alpha values decrease less and less. When the values of 25 individual Dow companies are changed from the 5 percent variation column to the 1 percent variation column, upper betas of 17 stocks increase; lower betas of 12 stocks decrease; and the alphas of 20 stocks decrease. Once again, when the values of 25 Dow individual companies are changed from the 11 percent variation column to the 1 percent column, upper betas of 19 stocks increase; lower betas of 17 stocks decrease; and the alphas of 24 stocks decrease. These findings are consistent with our prior assumption that extreme values dispersed away from the central region show strong value while those near the central region show meager value.

We also find that as the variables move closer to the extreme upper boundary, their differences become more pronounced. In other words, the further one moves from the 20-day moving average line, the larger the difference is between trading volume and stock price. In the case of the extreme lower group, the closer one moves toward the 20-day moving average line, the smaller is the difference of negative value between trading volume and stock price. As we see in their statistical significance, the extreme upper at the 1 percent critical level shows positive and significant differences in every component company except McDonald's (MCD) and Wal-Mart (WMT) while only 6 component

Table 1. Summary Statistics of Dow Jones Industrial Stocks

		Obs	Mean	S.D	Max	Min	Serial Correlation at lag						
							1	2	3	5	20	DF-test	
AA	ln volume	1,006	16.95	0.44	15.53	18.86	0.63	0.50	0.44	0.39	0.28	-6.59	***
	price		11.12	2.91	7.70	18.13	1.00	0.99	0.99	0.98	0.93	-2.251	
	a(20-MA)		0.45	0.44	0.00	3.47	0.86	0.74	0.63	0.45	0.12	-7.833	***
AXP	ln volume	1,006	15.68	0.48	13.86	18.04	0.73	0.63	0.57	0.56	0.48	-4.44	***
	Price		54.50	12.63	36.79	90.73	1.00	1.00	0.99	0.99	0.97	0.873	
	a(20-MA)		1.54	1.16	0.00	7.29	0.80	0.64	0.49	0.25	0.14	-9.351	***
CAT	ln volume	1,006	15.75	0.39	14.61	17.34	0.58	0.46	0.41	0.35	0.29	-6.586	***
	Price		86.70	14.30	50.78	116.20	0.99	0.99	0.98	0.97	0.87	-2.08	
	a(20-MA)		3.12	2.51	0.00	19.65	0.85	0.71	0.58	0.42	0.08	-7.06	***
CSCO	ln volume	1,006	17.66	0.44	16.35	20.14	0.66	0.49	0.43	0.36	0.27	-7.22	***
	Price		20.45	3.11	13.73	27.57	0.99	0.99	0.98	0.96	0.87	-2.013	
	a(20-MA)		0.69	0.57	0.00	3.47	0.86	0.74	0.63	0.46	-0.15	-7.695	***
CVX	ln volume	1,006	15.81	0.38	14.28	17.24	0.68	0.60	0.56	0.52	0.47	-5.029	***
	Price		101.68	16.02	67.31	127.76	1.00	0.99	0.99	0.98	0.94	-1.094	
	a(20-MA)		2.47	1.75	0.00	14.06	0.79	0.61	0.44	0.17	0.14	-9.795	***
DD	ln volume	1,006	15.56	0.41	14.12	17.26	0.63	0.52	0.44	0.37	0.21	-6.349	***
	Price		48.52	7.00	32.19	64.97	0.99	0.99	0.98	0.97	0.90	-1.275	
	a(20-MA)		1.36	1.06	0.00	8.08	0.82	0.68	0.54	0.35	-0.08	-8.174	***
DIS	ln volume	1,006	16.04	0.41	14.84	18.28	0.59	0.45	0.38	0.35	0.24	-6.88	***
	Price		45.36	11.83	29.00	76.40	1.00	1.00	1.00	0.99	0.98	1.114	
	a(20-MA)		1.15	0.90	0.00	6.42	0.81	0.67	0.53	0.29	0.02	-8.375	***
HD	ln volume	1,006	16.11	0.45	14.41	17.71	0.74	0.66	0.62	0.56	0.50	-5.028	***
	Price		48.84	17.52	27.07	82.34	1.00	1.00	1.00	1.00	0.99	0.564	
	a(20-MA)		1.21	0.91	0.00	5.85	0.82	0.68	0.54	0.30	0.02	-9.516	***
HPQ	ln volume	1,006	16.73	0.45	15.42	19.12	0.63	0.44	0.35	0.28	0.12	-8.201	***
	Price		31.01	11.69	11.71	54.52	1.00	1.00	1.00	0.99	0.96	-1.836	
	a(20-MA)		1.28	1.11	0.00	9.24	0.86	0.73	0.61	0.41	-0.13	-7.783	***
IBM	ln volume	1,006	15.36	0.40	14.19	16.92	0.63	0.47	0.40	0.40	0.31	-6.536	***
	Price		173.34	27.58	121.86	215.80	1.00	0.99	0.99	0.99	0.96	-1.608	
	a(20-MA)		3.60	2.89	0.00	21.08	0.80	0.62	0.43	0.21	-0.05	-9.279	***
INTC	ln volume	1,006	17.67	0.44	16.31	19.11	0.68	0.54	0.46	0.45	0.32	-5.833	***
	Price		22.71	2.36	17.67	29.18	0.99	0.98	0.97	0.95	0.81	-2.003	
	a(20-MA)		0.65	0.47	0.00	2.49	0.80	0.64	0.49	0.28	0.04	-9.104	***
JPM	ln volume	1,006	17.22	0.46	15.33	19.19	0.72	0.62	0.55	0.47	0.44	-5.416	***
	Price		42.71	6.66	28.38	58.48	0.99	0.99	0.98	0.97	0.88	-0.834	
	a(20-MA)		1.42	1.07	0.00	7.35	0.80	0.67	0.54	0.35	-0.03	-8.113	***
MCD	ln volume	1,006	15.55	0.37	13.96	17.39	0.57	0.35	0.24	0.19	0.16	-7.964	***
	Price		86.16	11.36	61.45	103.59	1.00	1.00	0.99	0.99	0.97	-1.902	
	a(20-MA)		1.37	0.96	0.00	4.73	0.73	0.58	0.45	0.23	-0.08	-9.592	***
MMM	ln volume	1,006	14.98	0.38	13.77	16.60	0.61	0.50	0.47	0.44	0.32	-5.997	***
	Price		93.29	13.67	70.93	140.25	1.00	0.99	0.99	0.98	0.95	1.548	
	a(20-MA)		1.99	1.55	0.00	11.73	0.80	0.67	0.55	0.38	0.08	-6.936	***
MRK	ln volume	1,006	16.44	0.40	15.26	18.12	0.57	0.37	0.26	0.23	0.04	-8.543	***
	Price		39.46	5.30	29.81	50.18	1.00	0.99	0.99	0.98	0.94	-0.428	
	a(20-MA)		0.84	0.66	0.00	4.62	0.81	0.66	0.53	0.34	0.01	-8.557	***

		Obs	Mean	S.D	Max	Min	Serial Correlation at lag						
							1	2	3	5	20	DF-test	
	ln volume		17.75	0.38	16.47	19.41	0.56	0.40	0.31	0.22	0.15	-7.878	***
MSFT	Price	1,006	28.85	3.40	23.01	38.94	0.99	0.98	0.98	0.96	0.86	-0.982	
	a(20-MA)		0.77	0.60	0.00	3.59	0.81	0.66	0.52	0.34	-0.01	-7.907	***
	ln volume		17.48	0.45	16.20	19.21	0.72	0.62	0.55	0.51	0.33	-5.599	***
PFE	Price	1,006	22.11	4.76	14.14	32.20	1.00	1.00	1.00	0.99	0.98	0.078	
	a(20-MA)		0.47	0.36	0.00	2.51	0.80	0.66	0.52	0.31	0.08	-8.874	***
	ln volume		16.09	0.36	14.88	17.60	0.52	0.35	0.30	0.24	0.12	-8.015	***
PG	Price	1,006	67.66	6.92	58.51	85.41	1.00	0.99	0.99	0.98	0.94	-0.689	
	a(20-MA)		1.10	0.83	0.00	4.93	0.79	0.62	0.48	0.25	-0.01	-9.221	***
	ln volume		17.04	0.35	15.89	18.62	0.49	0.31	0.21	0.15	0.09	-9.39	***
T	Price	1,006	31.32	3.90	24.13	39.00	1.00	0.99	0.99	0.99	0.95	-1.16	
	a(20-MA)		0.56	0.44	0.00	2.30	0.80	0.64	0.50	0.27	-0.12	-8.86	***
	ln volume		14.91	0.48	13.15	16.40	0.74	0.68	0.62	0.57	0.51	-4.96	***
TRV	Price	1,006	64.03	12.64	46.80	90.99	1.00	1.00	1.00	0.99	0.97	0.10	
	a(20-MA)		1.32	1.07	0.00	7.23	0.80	0.68	0.54	0.32	0.02	-8.64	***
	ln volume		15.70	0.44	14.04	17.19	0.66	0.55	0.48	0.41	0.33	-6.35	***
UNH	Price	1,006	49.95	12.64	27.85	75.30	1.00	1.00	0.99	0.99	0.97	-0.25	
	a(20-MA)		1.41	1.09	0.00	7.78	0.80	0.66	0.51	0.29	0.01	-8.65	***
	ln volume		15.18	0.36	13.53	16.39	0.61	0.47	0.43	0.37	0.25	-6.66	***
UTX	Price	1,006	82.27	11.73	63.22	113.80	1.00	0.99	0.99	0.98	0.92	-0.10	
	a(20-MA)		2.01	1.65	0.00	14.39	0.84	0.70	0.58	0.39	0.00	-7.48	***
	ln volume		16.48	0.41	15.03	18.23	0.59	0.44	0.34	0.29	0.19	-7.80	***
VZ	Price	1,006	39.42	7.11	26.49	53.91	1.00	1.00	0.99	0.99	0.97	-0.72	
	a(20-MA)		0.85	0.62	0.00	3.61	0.81	0.67	0.52	0.33	-0.12	-8.75	***
	ln volume		16.06	0.44	14.56	17.63	0.69	0.58	0.53	0.50	0.41	-5.26	***
WMT	Price	1,006	62.46	9.99	48.00	81.21	1.00	1.00	1.00	0.99	0.97	-0.35	
	a(20-MA)		1.13	0.89	0.00	5.28	0.83	0.71	0.59	0.37	0.10	-8.64	***
	ln volume		16.71	0.29	15.46	17.73	0.68	0.57	0.51	0.47	0.37	-5.57	***
EDJI	Price	1,006	56.41	7.44	42.71	72.61	1.00	1.00	0.99	0.99	0.96	-0.15	
	a(20-MA)		0.97	0.69	0.00	6.54	0.76	0.59	0.42	0.23	0.02	-8.65	***
	ln volume		17.17	0.30	15.89	18.18	0.67	0.55	0.48	0.44	0.33	-5.898	***
VDJI	Price	1,006	42.14	5.25	32.86	53.61	1.00	1.00	0.99	0.99	0.96	0.079	
	a(20-MA)		0.69	0.47	0.00	4.36	0.74	0.57	0.38	0.16	-0.03	-9.236	***

Notes: 1) ln volume denotes a log of trading volume and a (20m) an absolute value derived from (stock price - 20 day move average line)
2) The serial correlation is reported for lags of 1-day, 2-day, 3-day, 5-day, and 20-day, respectively.
3) *** DF (Dickey-Fuller) test statistics significant at the 1 percent critical level.

Source: Compustat from Wharton Research Data Service.

companies are significant at the 10 percent level. On balance, our findings strongly suggest that as stock price moves further away from the 20-day moving average, more herd behavior occurs as opposed to the absolute value which moves closer toward the 20-day moving average line where less herding behavior may exist.

With the beta value in dummy analysis, we further analyze whether there is a herd behavior between trading volume and concomitant changes in stock price. This was done by calculating an absolute value representing the difference between the 20-day moving average and stock price as the 20-day moving average line. In our methodology, the control variables are the absolute values as they are by defined and in eq. (3) and eq. (4), respectively. If or value move inversely from the 20-day moving average line as the critical values are changed from the 15 percent level to the

Table 2. Correlation for Dow Jones Industry Stocks

Ticker or Index	Correlation	Ticker or Index	Correlation	Ticker or Index	Correlation	Ticker or Index	Correlation
AA	0.431 ***	HD	0.049 ***	MRK	0.325 ***	UTX	0.273 ***
AXP	0.195 ***	HPQ	0.405 ***	MSFT	0.343 ***	VZ	0.126 ***
CAT	0.380 ***	IBM	0.145 ***	PFE	0.143 ***	WMT	0.058 ***
CSCO	0.3705 ***	INTC	0.3370 ***	PG	0.161 ***	EDJI	0.253 ***
CVX	0.236 ***	JPM	0.431 ***	T	0.253 ***	VDJI	0.248 ***
DD	0.4033 ***	MCD	0.155 ***	TRV	0.105 ***		
DIS	0.268 ***	MMM	0.283 ***	UNH	0.068 ***		

Notes: This table shows the Pearson correlation coefficient between a log of the firm's trading volume and the absolute value of the firm's stock price which is calculated from the daily deviation from its 20-day moving averages EDJI=Equally weighted Dow Jones Industrial index; VDJI=Value weighted Dow Jones Industrial index.

***Significant at the one percent critical level.

Table 3. Regressed Extreme Absolute-Values of Dow Jones Industrial Stocks

	1%Extreme Value			5%Extreme Value			11%Extreme Value		
	Alpha	BetaL	BetaU	Alpha	BetaL	BetaU	Alpha	BetaL	BetaU
AA	16.96	-0.22	0.94	17.01	-0.19	0.90	17.12	-0.30	0.78
	(1,197.82)***	(-3.96)***	(2.17)**	(1,047.98)***	(-6.44)***	(2.09)**	(857.94)***	(-11.54)***	(1.90)*
AXP	15.68	-0.10	1.19	15.70	-0.12	1.18	15.72	-0.12	1.04
	(1,031.27)***	(-1.12)	(2.51)**	(972.84)***	(-2.88)***	(2.49)**	(868.14)***	(-3.85)***	(3.11)***
CAT	15.40	-0.13	1.11	15.42	-0.17	1.09	15.44	-0.20	1.04
	(1,245.82)***	(-2.10)**	(2.84)***	(1,162.28)***	(-5.33)***	(2.80)***	(1,007.49)***	(-8.10)***	(2.72)***
CSCO	17.66	-0.11	1.52	17.67	-0.11	1.19	17.70	-0.16	1.08
	(1,264.42)***	(-1.48)	(3.48)***	(1,185.99)***	(-2.92)***	(3.86)***	(1,070.83)***	(-5.68)***	(5.65)***
CVX	15.81	-0.03	1.14	15.81	-0.04	1.14	15.84	-0.09	1.11
	(1,289.98)***	(-0.49)	(2.99)***	(1,207.91)***	(-1.08)	(2.98)***	(1,069.53)***	(-3.65)***	(2.93)***
DD	15.63	-0.08	1.15	15.66	-0.16	1.12	15.71	-0.19	1.07
	(1,116.48)***	(-1.21)	(3.05)***	(1,059.27)***	(-4.46)***	(3.02)***	(922.19)***	(-7.07)***	(2.95)***
DIS	16.03	0.03	2.25	16.06	-0.14	2.22	16.09	-0.15	2.19
	(1,243.00)***	(0.34)	(5.57)***	(1,162.30)***	(-4.07)***	(5.56)***	(1,029.65)***	(-5.84)***	(5.53)***
HD	16.10	0.08	1.35	16.10	0.02	1.11	16.10	0.01	1.11
	(1,115.64)***	(0.88)	(2.99)***	(1,050.39)***	(0.47)	(3.48)***	(917.96)***	(0.32)	(3.48)***
HPQ	16.73	-0.12	1.94	16.77	-0.17	1.91	16.84	-0.22	1.84
	(1,152.56)***	(-1.85)*	(4.33)***	(1,056.13)***	(-4.98)***	(4.31)***	(863.59)***	(-8.04)***	(4.22)***
IBM	15.37	-0.07	0.74	15.37	-0.01	1.06	15.38	-0.03	1.05
	(1,210.77)***	(-1.12)	(1.86)*	(1,103.77)***	(-0.42)	(3.82)***	(965.93)***	(-1.34)	(3.78)***
INTC	17.68	-0.14	0.96	17.69	-0.12	0.95	17.71	-0.16	0.65
	(1,274.83)***	(-1.21)	(2.20)**	(1,217.58)***	(-2.64)***	(2.19)**	(1,147.29)***	(-4.87)***	(3.67)***
JPM	17.35	-0.09	1.06	17.37	-0.17	1.04	17.40	-0.18	0.94
	(1,139.87)***	(-1.10)	(2.59)***	(1,080.80)***	(-4.05)***	(2.56)**	(1,059.92)***	(-4.69)***	(4.12)***
MCD	15.55	-0.05	0.47	15.55	-0.03	0.45	15.54	0.01	0.33
	(1,312.02)***	(-0.73)	(1.28)	(1,258.25)***	(-0.75)	(2.08)**	(1,181.99)***	(0.33)	(1.97)**
MMM	14.98	-0.03	1.28	14.99	-0.08	1.27	15.01	-0.08	1.15
	(1,219.44)***	(-0.42)	(3.35)***	(1,140.93)***	(-2.53)**	(3.33)***	(980.02)***	(-3.11)***	(4.29)***
MRK	16.45	-0.15	1.01	16.46	-0.10	1.00	16.50	-0.15	0.89
	(1,283.73)***	(-2.46)**	(2.53)**	(1,198.45)***	(-2.97)***	(2.51)**	(1,045.97)***	(-5.87)***	(3.23)***
MSFT	17.75	-0.12	1.24	17.77	-0.14	1.22	17.80	-0.16	1.19
	(1,467.52)***	(-1.79)*	(3.29)***	(1,377.71)***	(-4.31)***	(3.26)***	(1,252.19)***	(-6.45)***	(3.22)***
PFE	17.48	0.03	1.13	17.49	-0.07	1.12	17.51	-0.08	1.10
	(1,221.95)***	(0.34)	(2.54)**	(1,137.70)***	(-1.86)*	(2.52)**	(1,001.25)***	(-2.66)***	(2.48)**
PG	16.09	0.11	0.60	16.09	-0.01	0.41	16.10	-0.02	0.31
	(1,394.19)***	(1.85)*	(1.66)*	(1,308.33)***	(-0.35)	(1.60)	(1,187.11)***	(-0.91)	(1.72)*

	1%Extreme Value			5%Extreme Value			11%Extreme Value		
	Alpha	BetaL	BetaU	Alpha	BetaL	BetaU	Alpha	BetaL	BetaU
T	17.04	-0.03	0.61	17.05	-0.080	0.67	17.06	-0.07	0.68
	(1,512.45)***	(-0.45)	(1.73)*	(1,425.80)***	(-2.56)**	(2.69)***	(1,304.99)***	(-3.08)***	(3.88)***
TRV	14.91	0.06	1.20	14.90	0.05	0.87	14.91	0.00	0.65
	(962.84)***	(0.69)	(2.49)**	(887.08)***	(1.19)	(2.53)**	(770.51)***	(0.02)	(3.01)***
UNH	15.70	-0.018	0.93	15.69	0.07	0.94	15.69	0.03	0.80
	(1,101.78)***	(-0.22)	(2.09)**	(1,020.17)***	(1.79)*	(2.12)**	(889.76)***	(1.04)	(2.56)**
UTX	15.18	-0.07	0.97	15.19	-0.06	1.04	15.23	-0.10	1.00
	(1,312.21)***	(-1.28)	(2.71)***	(1,191.15)***	(-2.22)**	(4.12)***	(1,003.90)***	(-4.62)***	(4.02)***
VZ	16.48	0.02	0.06	16.48	0.01	0.19	16.49	-0.06	0.11
	(1,257.69***	(0.15)	(0.14)	(1,190.57)***	(0.30)	(0.65)	(1,071.23)***	(-2.01)**	(0.46)
WMT	16.06	-0.01	0.26	16.05	0.06	0.59	16.04	0.04	0.59
	(1,132.84)***	(-0.17)	(0.59)	(1,062.33)***	(1.61)	(1.89)*	(956.74)***	(1.49)	(1.91)*
EDJI	16.71	-0.03	1.02	16.72	-0.04	1.02	16.73	-0.06	0.94
	(1,815.68)***	(-0.70)	(3.56)***	(1,695.15)***	(-1.75)*	(3.55)***	(1,471.59)***	(-3.19)***	(4.70)***
VDJI	17.17	0.01	1.02	17.17	-0.05	1.01	17.18	-0.04	0.95
	(1,777.38)***	(0.12)	(3.36)***	(1,676.64)***	(-1.74)*	(3.34)***	(1,440.55)***	(-2.07)**	(4.45)***

Notes: This table shows the Pearson correlation coefficient between a log of the firm's trading volume and the absolute value of the firm's stock price which is calculated from the daily deviation from its 20-day moving averages EDJI=Equally weighted Dow Jones Industrial index; VDJI=Value weighted Dow Jones Industrial index.

***Significant at the one percent critical level.

1 percent level, it means that those dummy values become progressively different from the relevant alpha values.

Table 3 provides initial insight into the degree of statistical relationship between stock price and trading volume that suggests herding in many of the 25 Dow component companies. However, the significance of the table can be depicted in Figure 2, which graphically plots the travel patterns of the changes in the number of Dow component companies as the statistical critical values increase.

Figure 2 depicts the simple average value of and , where the alpha is analyzed by dummy regressions for the 25 sample Dow companies shown in Table 3. The figure illustrates that as the alpha and thevalue travel from the 15 percent level toward the 1 percent level, the coefficient value decreases significantly. Inversely, the value shows that the coefficient value continues to increase while the alpha value continues to descend.

This outcome means that thevalue exhibits a strong variation from alpha. As changes from the 15 percent level to the 1 percent level, it is in the top range (see Figure 2.A). Additionally, the more the stock price goes further away from the 20-day moving average, the greater the increase in the trading volume. These findings strongly suggest a strong investor herding. Our findings with are that as the variation in the absolute values is changed from a 15 percent to a 1 percent level, the lower beta dummy variable approaches to 0 as shown in Table 3 (see Figure 2.B). An inference that can be drawn here is that the closer the variable to its 20-day moving average line, the less evidence that there exists herd behavior in the extreme lower group.

Two tentative conclusions can be drawn from Table 3 and Figure 2: (i) Nearly all 25 Dow sample stocks show that their individual statistical significances of alpha and beta values increase as their testing variations increases from a 15 percent level to a 5 percent level and then from a 5 percent level to a 1 percent level; (ii) While we find evidence suggestive of herd behavior with a strong value, our findings with value do not clearly indicate herd behaviors until we have transformed the statistics from Table 3 into Figure 2. However, these two findings are tentative because by our own specifications the values of betas related toand are mutually exclusive in our sample selections (see eq. (3) and eq. (4)). We must consider that the statistical relationship we found in the betas may have been spurious. These may be attributable to the arbitrary selection of the 20-day moving average from which the absolute values used in the study are obtained.

We rectify the possible spurious relationship that may have been caused by the arbitrary selection of the 20-day moving averages in this manner. First, Table 3 uses the Dow sample data based on their equally-weighted. We convert the equal-weighted data to their respective value-weighted data. Then, we recalculate daily returns of the 25 Dow sample stocks with the absolute values calculated from a 10-day, a 20-day, a 30-day, and a 60-day moving average

Figure 2. A: Beta Values of Extreme Upper and Lower Band Stocks of Dow Jones Industrial Stocks with Dummy Variables Ranging from 15% to 1% of Their Moving Average Lines

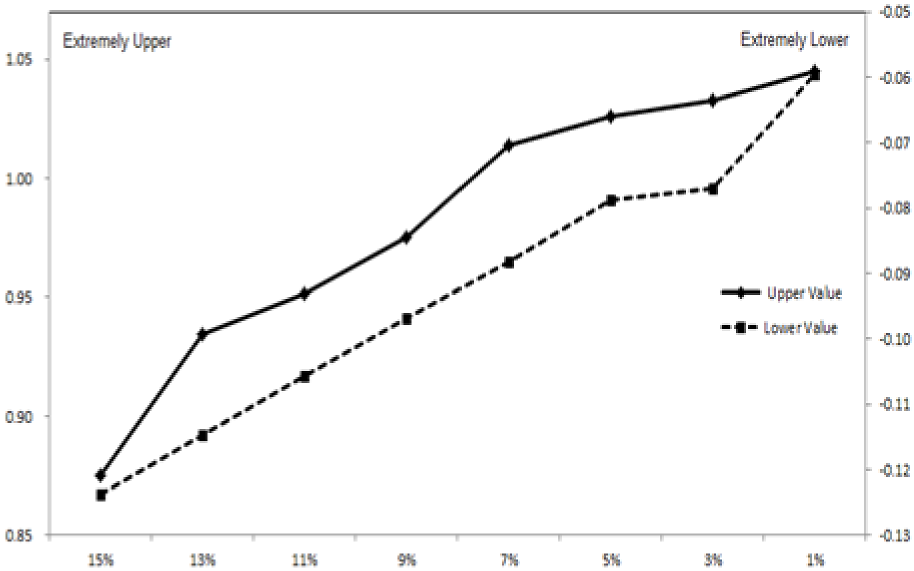
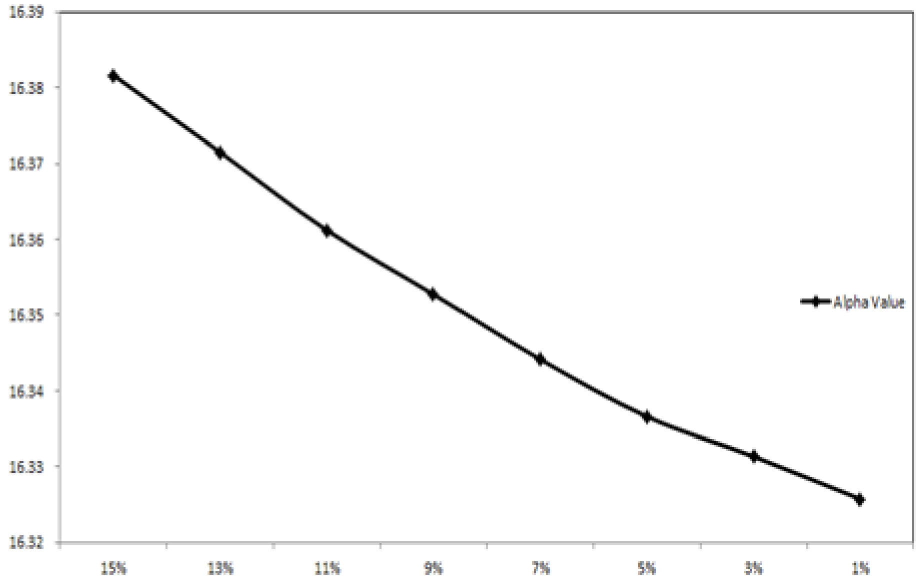


Figure 2. B: Alpha Values of the Absolute Value of Dow Jones Industrial Stocks by Dummy Variables Ranging from a 15 Percent to 1 Percent Variation from Their Moving Average Lines



using eq. (3) and eq. (4). Here we are essentially repeating what we analyzed in Table 3 with the value-weighted stock index data in terms of the absolute values derived from the four new moving average lines. And we evaluate how the statistical variables of , , and alpha values change when they are evaluated with variations of the absolute values ranging from a 15 percent variation to a 1 percent variation from the four different moving average lines. The results are presented in Tables 4, 5, and 6, respectively.

Table 4 shows the results of. They are essentially the

Table 4. Upper Beta Value Trends with Dummy Variables

		15%	13%	11%	9%	7%	5%	3%	1%
10-day MA	EW	0.9820	0.9801	0.9895	0.9912	1.0037	1.0109	1.0182	1.0231
			(-0.190)	(0.959)	(0.170)	(1.260)	(0.720)	(0.720)	(0.483)
	VW	0.9683	0.9759	0.9839	0.9915	1.0014	1.0061	1.0138	1.0147
			(0.784)	(0.812)	(0.779)	(0.999)	(0.465)	(0.762)	(0.096)
20-day MA	EW	0.9258	0.9399	0.9443	0.9460	0.9529	1.0153	1.0200	1.0210
			(1.516)	(0.468)	(0.184)	(0.726)	(6.547)	(0.466)	(0.099)
	VW	0.9310	0.9382	0.9454	0.9464	0.9519	1.0089	1.0139	1.0157
			(0.775)	(0.773)	(0.098)	(0.590)	(5.989)	(0.493)	(0.178)
30-day MA	EW	0.9497	0.9550	0.9563	0.9613	0.9614	0.9667	0.9645	1.0219
			(0.560)	(0.135)	(0.516)	(0.018)	(0.547)	(-0.225)	(5.944)
	VW	0.9461	0.9490	0.9494	0.9555	0.9568	0.9571	0.9606	1.0150
			(0.301)	(0.048)	(0.641)	(0.136)	(0.032)	(0.368)	(5.660)
60-day MA	EW	0.8393	0.9578	0.9564	0.9590	0.9588	0.9635	0.9666	0.9673
			(14.120)	(-0.147)	(0.266)	(-0.015)	(0.492)	(0.314)	(0.075)
	VW	0.9509	0.9529	0.9534	0.9549	0.9560	0.9580	0.9562	0.9592
			(0.210)	(0.053)	(0.159)	(0.119)	(0.208)	(-0.185)	(0.305)
Daily Return	EW	0.8892	0.9135	0.9328	0.9508	0.9605	0.9822	0.9994	1.0173
			(2.729)	(2.112)	(1.938)	(1.014)	(2.259)	(1.750)	(1.791)
	VW	0.8772	0.9066	0.9236	0.9402	0.9637	0.9765	0.9878	1.008
			(3.355)	(1.865)	(1.805)	(2.501)	(1.328)	(1.151)	(2.049)

Notes: 1) Above value is the beta value of a regression analysis using the dummy variables ranging from a 15% to a 1% extreme value of their moving average lines.
2) Moving averages of 10-day , 20-day, 30-day, 60-day are analyzed with absolute-value of their moving average lines while the daily return is analyzed by absolute-value of increase or decrease on the t-day of the moving average.
3) The number in parenthesis indicates a change from a prior value.

same as we find in Figure 2. That is, the beta values continuously increase as their variation level changes from a15 percent variation toward a 1 percent variation. One exception is a decrease in the significance of the values of the statistical variable when the significance is evaluated at the 1 percent critical level for the absolute values derived from the 30-day and 60-day moving average lines. It should be noted that our new results with the 10-day and 20-day moving average are similar to the results we see in Table 3; that is, on the balance, herd behaviors do exist. In view of our findings with the 30-day and 60-day moving average thresholds in Table 4, we can draw an inference that the life of herd behavior may be relatively short. This is because when the absolute values are evaluated with the 10-day or 20-day moving averages, daily return rate increases or decreases, both of which are accompanied by trading volume changes in either of the two moving averages threshold. It should be pointed out that when the absolute price of stock moves further away from the 10-day to 20-day moving average lines, changes in daily returns are much more pronounced for the 10-day moving average regime. Additionally, return rates move close to zero on the last day with diminishing changes in price and trading volume.

Table 5 presents the results of the lower bound beta value. In the preceding analysis, we find that the absolute price moves closer to the moving average line as we change from a 15 percent variation level to a 1 percent variation level and daily return rate close to 0. However, in Table 5, we find that the movements of absolute price against their 10-day moving average show no unidirectional trend line: Not only the value of the absolute price disperses from zero, but also the significance of the test variables decrease as the variables are evaluated from a 15 percent variation level to a 1 percent level.

Moreover, when we analyze the standard deviations, we find that return volatility increases rapidly as we change among the four variation levels of 13 percent, 9 percent, 5 percent, and the 1 percent, respectively. (The test statistics for each critical level are 4.45 for the 13 percent, 10.94 for the 9 percent, 25.82 for the 5 percent, and 98.74 for the 1 percent, respectively.) We find that as we move the variation test levels upward, trading volume changes

Table 5. Lower Beta Value Trends with Dummy Variables

		15%	13%	11%	9%	7%	5%	3%	1%
10-day MA	EW	-0.0624	-0.0732	-0.0647	-0.0749	-0.06	-0.0523	-0.0322	0.0189
			(-17.292)	(11.601)	(-15.783)	(19.827)	(12.811)	(38.43)	(158.549)
	VW	-0.0743	-0.0699	-0.0647	-0.0603	-0.0454	-0.045	-0.0155	-0.0262
			(5.914)	(7.489)	(6.755)	(24.679)	(0.939)	(65.675)	(-69.308)
20-day MA	EW	-0.0714	-0.0549	-0.0588	-0.0666	-0.0588	-0.0427	-0.0235	-0.0333
			(23.006)	(-6.981)	(-13.309)	(11.737)	(27.291)	(45.128)	(-42.183)
	VW	-0.0565	-0.0502	-0.0406	-0.0491	-0.0417	-0.048	-0.0188	0.0073
			(11.065)	(19.108)	(-20.889)	(15.139)	(-15.142)	(60.736)	(138.503)
30-day MA	EW	-0.0373	-0.0299	-0.032	-0.0209	-0.0253	0.0004	-0.0259	-0.017
			(19.624)	(-6.726)	(34.476)	(-20.628)	(101.499)	(-6,953.29)	(34.325)
	VW	-0.0345	-0.0341	-0.0406	-0.0223	-0.0218	-0.0265	0.0021	-0.019
			(0.909)	(-18.883)	(45.058)	(2.121)	(-21.354)	(107.891)	(-1,009.10)
60-day MA	EW	-0.0291	-0.0367	-0.0489	-0.0488	-0.0613	-0.0362	-0.0015	0.0311
			(-26.017)	(-33.069)	(0.139)	(-25.696)	(40.954)	(95.814)	(2,150.17)
	VW	-0.0343	-0.0318	-0.0368	-0.0332	-0.0347	-0.026	-0.0782	-0.0865
			(7.25)	(-15.587)	(9.718)	(-4.464)	(25.085)	(-201.008)	(-10.695)
Daily Return	EW	-0.1832	-0.162	-0.1457	-0.1317	-0.1343	-0.1164	-0.1084	-0.0676
			(11.579)	(10.006)	(9.656)	(-2.033)	(13.39)	(6.803)	(37.619)
	VW	-0.1944	-0.1663	-0.1538	-0.1434	-0.1191	-0.1199	-0.1476	-0.1374
			(14.454)	(7.515)	(6.805)	(16.898)	(-0.617)	(-23.153)	(6.932)

Notes: 1) Above shows the beta value of a regression analysis using the dummy variables ranging from a 15% to a 1% extreme value of their moving average lines.
2) Moving averages of 10-day, 20-day, 30-day, 60-day are analyzed with absolute-value of their moving average lines while daily return is analyzed by absolute-value of increase or decrease on the t-day of the moving average.
3) The number in parenthesis indicates a change from a prior value.

inversely in relation to price changes and that as the absolute prices come closer to their respective moving average lines, we find little testable herd behaviors in the extreme lower bound group.

A detailed analysis of the alpha properties is shown on Table 6. Note that the alpha continues to decrease as its evaluations move from a 15 percent variation level to a 1 percent level. These results are analogous to Figure 2.A regarding and . As in Table 4, the equal-weight beta values of a 60-day moving average line increase somewhat from a 5 percent variation level to a 9 percent level for the value-weight series. This means that the absolute prices calculated from a high value moving average line, such as a 60-day moving average line, do not capture statistical properties that mimic investor herding. Since most return rates with an approach 0 at the all variation test levels, our statistical absolute prices have no effect on the alpha values in our model specifications.

From Table 4, we already know that has the opposite directional movement against betas at all level of returns ranging from a 15 percent variation level to a 1 percent level. This means that a decrease in the alpha may be attributable to the attendant changes in the values. Stated differently, beta dummies represent the extreme upper absolute prices. Thus, when they are evaluated with the variation levels ranging from a 15 percent to a 1percent as they are shown on the top columns of Table 4, we find diminishing alpha values. Since Table 6 shows no contradictory evidence, we affirm the tentative findings of Table 4 that herd behavior exists.

Restating the dummy variable regression results, the closer an absolute price comes to the moving average line and the closer the return rate clusters around zero, there are increases in trading volume even though their statistical significances of the coefficient diminish. On the other hand, the return rates, trading volumes, and their coefficients increase when the absolute prices are further away from their moving average lines. This is true whether the return rates show increase or decrease. Since the statistical significance of the coefficients associated withincrease positively, we postulate that the extreme upper groups exhibit herd behavior.

Table 6. Constant Alpha Value Trends with Dummy Variables

		15%	13%	11%	9%	7%	5%	3%	1%
10-day MA	EW	16.7485	16.7503	16.7409	16.7392	16.7268	16.7195	16.7122	16.7073
			(0.011)	(-0.056)	(-0.010)	(-0.075)	(-0.043)	(-0.044)	(-0.029)
	VW	17.2144	17.2068	17.1989	17.1912	17.1813	17.1766	17.1690	17.1680
			(-0.044)	(-0.046)	(-0.045)	(-0.058)	(-0.027)	(-0.045)	(-0.006)
20-day MA	EW	16.7481	16.7340	16.7296	16.7279	16.721	16.7151	16.7104	16.7094
			(-0.084)	(-0.026)	(-0.010)	(-0.041)	(-0.035)	(-0.028)	(-0.006)
	VW	17.1958	17.1885	17.1813	17.1804	17.1748	17.1738	17.1688	17.1670
			(-0.042)	(-0.042)	(-0.005)	(-0.032)	(-0.006)	(-0.029)	(-0.011)
30-day MA	EW	16.7242	16.7189	16.7176	16.7126	16.7125	16.7072	16.7094	16.7086
			(-0.032)	(-0.008)	(-0.030)	(-0.001)	(-0.031)	(0.013)	(-0.005)
	VW	17.1806	17.1778	17.1773	17.1712	17.1699	17.1696	17.1661	17.1677
			(-0.017)	(-0.003)	(-0.035)	(-0.008)	(-0.002)	(-0.021)	(0.009)
60-day MA	EW	16.7148	16.7161	16.7175	16.7149	16.7151	16.7104	16.7073	16.7066
			(0.008)	(0.008)	(-0.015)	(0.001)	(-0.028)	(-0.018)	(-0.004)
	VW	17.1758	17.1739	17.1733	17.1718	17.1707	17.1687	17.1705	17.1676
			(-0.012)	(-0.003)	(-0.009)	(-0.007)	(-0.012)	(0.010)	(-0.017)
Daily Return	EW	16.8412	16.8169	16.7977	16.7796	16.7699	16.7482	16.7311	16.7132
			(-0.144)	(-0.115)	(-0.108)	(-0.057)	(-0.129)	(-0.103)	(-0.107)
	VW	17.3055	17.2761	17.2592	17.2425	17.219	17.2062	17.1949	17.1747
			(-0.170)	(-0.098)	(-0.097)	(-0.136)	(-0.074)	(-0.065)	(-0.118)

Notes: 1) The above values are the beta value of a regression analysis with the dummy variables ranging from a15% to a 1%.
2) Moving averages of 10-day, 20-day, 30-day, 60-day are analyzed with absolute-value of their moving average lines while the daily return is analyzed by an absolute-value of increase on the last day of the moving average.
3) The number in parenthesis indicates a change from a prior value.

Ⅵ. Log-log regressions for Herding in Outlier Groups

We now test for the existence of a diminishing marginal effect on the center of the upper group value or the lower group value respectively. Table 7 shows the results for the log-log regressions for the 25 Dow sample stocks. The upper and lower groups are delineated by a 20-day moving average, and daily return rates are calculated from the middle of the 20-day moving average line involved. We first calculate statistical absolute prices and then apply log-log regressions with diminishing returns that yield negative numbers. If a beta value is $0 < X < 1$, and p-value is statistically significant, we posit that a diminishing marginal effect exists.

From Table 7, we see that there are significant differences between the upper and lower group values with the log-log tests. For the upper group values, all individual stock prices show between 0 and 1 at the one percent critical level. For the lower group value, however, the stock prices of six stocks--DuPont (DD), IBM, INTC, PFE, Proctor & Gamble (PG), and United Health Group (UNH)--fall between 0 and 1. Their coefficient values also show a significant statistical difference for stocks in the upper group.

When the 25 individual sample stocks are evaluated for their Adj. R-sq, the stock prices all show high values in the upper group. Additionally, when the results of dummy regressions and diminishing marginal effect in return dispersion are analyzed together, we find a positive relationship between changes in stock price and trading volume even when the absolute prices are farther away from the 20-day moving average line. They tend to decrease rather than increase during market environments where there are extreme price movements in stock prices.

We replicate the log-log regressions on the test variables for Table 4, Table 5, and Table 6 to investigate whether there are marginal diminishing effects in return dispersion as reported by Chang et al. (2000).Table 8 shows the replication results obtained with the transformation of the 25 Dow sample stocks from equal-weight into their value-weight. We then obtain an individual company's daily returns computed with their daily price against their respective four moving averages: a 10-day, a 20-day, a

Table 7. Diminishing Marginal Effect for Dow Jones Industry Stocks

	Model A Lower			Model B Upper			Test statistics	
	Alpha	BetaLN	AdjR_sq	Alpha	BetaLN	AdjR_sq	F1	F2
AA	17.08	0.09	0.07	17.28	0.15	0.18	38.33	104.56
	(496.91)***	(6.19)***		(538.80)***	(10.23)***			
AXP	15.66	0.04	0.01	15.76	0.07	0.02	4.18	12.63
	(704.82)***	(2.05)**		(630.25)***	(3.55)***			
CAT	15.69	0.06	0.02	15.80	0.12	0.11	14.17	58.11
	(961.52)***	(3.76)***		(902.19)***	(7.62)***			
CSCO	17.62	0.02	0.00	17.89	0.12	0.10	1.24	51.23
	(628.89)***	(1.12)		(566.64)***	(7.16)***			
CVX	15.77	0.01	0.00	15.85	0.07	0.03	0.79	17.12
	(973.07)***	(0.89)		(893.65)***	(4.14)***			
DD	15.48	-0.02	0.00	15.71	0.10	0.06	0.97	30.34
	(781.15)***	(-0.98)		(704.28)***	(5.51)***			
DIS	15.98	0.00	0.00	16.16	0.07	0.03	0.00	17.76
	(747.91)***	(0.06)		(667.71)***	(4.21)***			
HD	16.02	-0.04	0.01	16.19	0.03	0.00	4.69	2.61
	(658.11)***	(-2.17)**		(627.34)***	(1.62)			
HPQ	16.67	0.06	0.03	16.97	0.14	0.13	16.80	64.54
	(858.11)***	(4.10)***		(656.63)***	(8.03)***			
IBM	15.30	-0.01	0.00	15.42	0.06	0.03	0.94	13.24
	(953.22)***	(-0.97)		(784.93)***	(3.64)***			
INTC	17.63	0.01	0.00	17.86	0.08	0.06	0.30	30.07
	(572.31)***	(0.55)		(580.54)***	(5.48)			
JPM	17.20	0.03	0.01	17.35	0.14	0.10	3.90	52.42
	(791.01)***	(1.97)**		(698.70)***	(7.24)***			
MCD	15.51	0.01	0.00	15.63	0.07	0.04	0.19	22.38
	(810.76)***	(0.44)		(794.28)***	(4.73)***			
MMM	14.95	0.04	0.01	15.06	0.08	0.05	6.24	25.09
	(889.51)***	(2.50)**		(785.67)***	(5.01)***			
MRK	16.39	0.02	0.00	16.63	0.08	0.05	2.35	25.20
	(726.40)***	(1.53)		(608.93)***	(5.02)***			
MSFT	17.64	-0.02	0.00	17.94	0.08	0.05	1.91	26.41
	(731.00)***	(-1.38)		(672.34)***	(5.14)***			
PFE	17.39	-0.02	0.00	17.65	0.07	0.02	1.60	12.18
	(462.21)***	(-1.27)		(459.48)***	(3.49)***			
PG	16.01	-0.02	0.00	16.25	0.09	0.08	1.49	38.86
	(847.16)***	(-1.22)		(766.44)***	(6.23)***			
T	17.04	0.03	0.01	17.17	0.05	0.02	4.47	12.59
	(665.53)***	(2.11)**		(623.64)***	(3.55)***			
TRV	14.87	0	0.00	14.99	0.06	0.02	0.01	9.20
	(607.52)***	(-0.08)		(552.06)***	(3.03)***			
UNH	15.62	-0.043	0.01	15.80	0.05	0.01	5.72	7.89
	(725.03)***	(-2.39)**		(653.68)***	(2.81)***			
UTX	15.14	0.00	0.00	15.24	0.06	0.03	0.12	18.20
	(1,002.94)***	(0.35)		(855.48)***	(4.27)***			

	Model A Lower			Model B Upper			Test statistics	
	Alpha	BetaLN	AdjR_sq	Alpha	BetaLN	AdjR_sq	F1	F2
VZ	16.46	0.00	0.00	16.57	0.05	0.02	0.08	12.59
	(609.95)***	(0.28)		(649.95)***	(3.55)***			
WMT	16.00	-0.03	0.00	16.16	0.07	0.02	2.38	12.62
	(670.04)***	(-1.54)		(618.44)***	(3.55)***			
EDJI	16.68	0.00	0.00	16.79	0.04	0.03	0.08	13.65
	(1,020.95)***	(-0.28)		(849.88)***	(3.69)***			
VDJI	17.16	0.02	0.00	17.27	0.05	0.03	1.70	15.36
	(805.10)***	(1.30)		(728.79)***	(3.92)***			

Notes: 1) Models A and B specifications: Model A:

Model B: ; 2) The standard for up and low is to calculate existing a(p-20m) to new 20-day moving average line, and based on that line, the bottom is low and upper is up. Heteroscedasticity consistent t-statistics are reported in parentheses. 3) *** The coefficient is significant at the 1% level. ** The coefficient is significant at the 5% level. * The coefficient is significant at the 10% level

Table 8. Diminishing Marginal Effect for Equal- and Value-Weight

		Model A Lower			Model B Upper			Test statistics	
		Alpha	Beta LN	AdjR_sq	Alpha	Beta LN	AdjR_sq	F1	F2
10-day MA	EW	16.74	0.03	0.01	16.78	0.04	0.03	5.91	13.99
		(828.29)***	(2.43)**		(775.65)***	(3.74)***			
	VW	17.22	0.03	0.01	17.27	0.05	0.04	6.98	18.11
		(688.28)***	(2.64)***		(652.45)***	(4.26)***			
20-day MA	EW	16.68	0.00	0.00	16.79	0.04	0.03	0.08	13.65
		(1,020.95)***	(-0.28)		(849.88)***	(3.69)***			
	VW	17.16	0.02	0.00	17.27	0.05	0.03	1.70	15.36
		(805.10)***	(1.30)		(728.79)***	(3.92)***			
30-day MA	EW	16.70	0.01	0.00	16.76	0.04	0.02	1.55	8.83
		(1,141.66)***	(1.24)		(913.87)***	(2.97)***			
	VW	17.17	0.01	0.00	17.27	0.07	0.04	1.56	22.39
		(956.51)***	(1.25)		(765.35)***	(4.73)***			
60-day MA	EW	16.70	-0.01	0.00	16.74	0.04	0.02	0.35	12.81
		(1,205.37)***	(-0.59)		(1,041.77)***	(3.58)***			
	VW	17.18	0.02	0.01	17.23	0.05	0.02	4.12	13.33
		(1,063.51)***	(2.03)**		(877.17)***	(3.65)***			
Daily Return	EW	16.72	0.035	0.01	16.85	0.08	0.13	8.42	61.36
		(861.77)***	(2.90)***		(932.66)***	(7.83)***			
	VW	17.16	0.02	0.00	17.31	0.07	0.09	3.27	41.09
		(842.49)***	(1.81)*		(869.10)***	(6.41)***			

Notes: 1) This table is based on the following regression models:
Model A:
Model B:
2) The standard for up and low is to calculate existing a(p-20m) to new 20-day moving average line, and based on that line, the bottom is low and upper is up. Heteroscedasticity consistent t-statistics are reported in parentheses.
3) *** The coefficient is significant at the 1% level. ** The coefficient is significant at the 5% level. * The coefficient is significant at the 10% level.

30-day, and a 60-day moving averages. All negative numbers and daily returns are measured by their absolute values.

Note that Model B's upper group shows all differences that are statistically significant with all beta coefficient values from 0 to 1. In the case of Model A's lower group, however, it shows statistical significance for both equal-weight and value-weight measured by a 10-day moving average line and daily return in value-weight. For the most part, the Model A's lower group does not reveal materially significant results. Moreover, the equal-weight values with a 60-day moving average show a negative value supporting our conclusions regarding Model A's lower group.

Additionally, our analysis of Adj. R-sq on the two groups indicates that Model B's upper has a higher explanatory power. When we analyze the results of the dummy variable regressions and the diminish marginal effect test together, several salient results from Model B's upper group emerge: (i)There is a distinct pattern of return rates diminishing as the absolute prices move further away from their respective moving average lines; (ii) stock prices show a high beta coefficient value associated with contemporaneously changing trading volume; and (iii) there is a tendency that the dispersion of returns decreases rather than increases when the stock prices move from one extreme to another.

Ⅶ. Conclusions

We have tested the existence of herd behavior for a sample of 25 DJIA component stocks by analyzing the relationship between their absolute stock value and contemporaneously changing trading volumes. Three basic statistical analyses are performed – correlation, dummy regression and log-log regression analyses. For robustness of our test results, we have eliminated from our samples those raw data that indicate abnormal and are subject to data-snooping biases. The augmented Dickey-Fuller unit root test ascertains the stationarity of the time series data.

First, we have found a positive correlation among all individual stock prices, be they equally-weight or value-weighted series. These preliminary findings regarding herding are consistent with the findings reported in the literature.

As compared to Christie and Huang's (1995) dummy variable regression which focuses on return dispersions, we analyze changes in returns with respect to their contemporaneous change in trading volumes. We follow their methodology in separating the absolute values into to the extreme upper or extreme lower values' deviations. We find a positive and significant relation in the extreme upper values; that is, the coefficient value becomes bigger as the variation levels of absolute price are changed from a 15 percent to a one percent 1 percent extreme value. On the other hand, a negative relation is found at the extremely lower value; that is, the coefficient value decreased as we move the extreme variation levels from a 15 percent to a one percent level. These findings, which are consistent with those by Christie and Huang (1995), suggest the existence of a strong herd behavior in the extreme upper values while there is little evidence that herding exists in the extreme lower values.

The two key questions are made in our analysis: How near do the absolute prices change from the 20-day moving average line of actual stock prices and how close are their concurrent changes in daily returns clustered around zero. We find that as the variation levels of absolute values change from a 15 percent level to 1percent level, the negative coefficient between price and trading volume decreases as does their statistical significance. With regard to the alpha, we find that as the variation values change from a 15 percent to a 1 percent level, the alpha value decreases continuously, and the extremely upper value increases. We interpret these findings to reflect indirectly the effects of herd behavior since we expanded Christie and Huang's (1995) dummy regression with the inclusion of trading volume in our analysis.

Another key test in our analysis is to ascertain that not only does our dummy independent variable have a significant positive correlation in relation to the dependent variable at the extreme upper value, but also whether the correlations satisfy the condition of a decrease in dispersion levels. This test is to rule out the two conditions which have been shown to have no statistical relationship in herd behavior. For this reason, Chang *et. al.*(2000) tested the significance of herd behavior through quadratic models, while Lee *et. al.*(2012) tested through logistic regression. In the present study, we implement the same test by a log-log regression because we postulate that while stock prices may follow a random walk, the extreme upper values in our specifications do not. We demonstrate that the coefficients of all individual stock prices and returns show diminishing marginal effects between 0 to 1 in the extreme upper values. In comparison to the extreme lower value, the extreme upper value shows a strong coefficient and high Adj. R-sq. In short, herding behavior is detected in every one of the 25 individual sample stock prices in our study. In particular, we find a strong evidence of true herding behavior as stock prices move to their upper extreme value during a bull market.

Integrating our results with those of the recent events which took place in the U. S. housing, mortgage, and banking industries, herding behaviors may have been the precipitating event for the extreme volatility of the U. S. stock market during the financial crisis of 2008 and 2009. Operationally, housing bubbles, which were inflated partially by herding behavior of the housing industry itself, may have given rise to another significant herding in the U. S. stock markets. Our study, which covers the three-year period immediately following the 2008-09 stock market crash, sheds new light on the herding concentrated in a rising stock market which can be isolated and measured by the elementary technical analyses.

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