# Introduction and Literature Review

It is well established that over the recent decades a significant progress has been achieved in explaining the behaviour of financial markets. Probably one of the most influential concepts in the mainstream finance literature is that of market efficiency that was formulated by Fama ([1970](#ref-fama1970efficient)) among others. However, market efficiency rests on a series of assumptions that are mostly related to the existence of costly and asymmetric information, agency costs, market frictions such as transaction costs or limits to arbitrage and non-rational economic behaviour. Rational behaviour is a very popular concept among economic agents that is in the epic-enter of many economic models. Since the pioneer work of economist John Keynes who made the notion of ‘animal spirits’ acceptable in economics in 1936, literature of financial economics is still treating animal spirits across financial markets with scepticism in spite of many notable attempts ([Kahneman 2003](#ref-kahneman2003maps); [Shiller 2005](#ref-shiller2005behavioral); [Dai, Weder, and Zhang 2020](#ref-dai2020animal)) and the award of the Noble Prize in Economics for systematic attempts to explore the psychological biases in economic decision-making ([Kahneman 2003](#ref-kahneman2003maps)).

As previously stated, market efficiency is achieved when markets are perfect while deviations from perfect markets can be attributed to various causes that might be related to developments in the macroeconomic environment or market frictions such as transaction costs and limits to arbitrage. Behavioural biases and other deviations from rationality such as herding or other positive feedback behaviour classify as potential drivers of market inefficiency as well ([Aggarwal 2014](#ref-aggarwal2014animal)). Some of these forces against market efficiency can be mitigated, but they cannot be eliminated. Thus, while there are many self-correcting forces that move markets towards efficiency, there are also many obstacles and costs that these equilibrating forces must overcome.

Financial markets that are dominated by agents’ actions have been a perfect setting to study human behavior and in particular the occurrence of various biases since the seminal study of Tversky and Kahneman ([1974](#ref-tversky1974judgment)). Literature on the behavioral effects on decision making has flourished in recent decades (see [Aggarwal 2014](#ref-aggarwal2014animal) for a detailed review). Behavioural economics that lie in the intersection of psychology and economics attempt to shed more light on these biases and how they affect decisions made by agents acting under cognitive and emotional constraints ([Mullainathan and Thaler 2000](#ref-mullainathan2000behavioral)). Human behavior that is by nature prone to heuristics, emotional biases and framing effects ([Aggarwal 2014](#ref-aggarwal2014animal)) might result in sub-optimal decisions that in turn cause market inefficiencies and market failures.

Under this context, market participants and financial economists provide increasingly convincing evidence that imitative behaviour is widespread in financial markets ([Devenow and Welch 1996](#ref-devenow1996rational)). This correlated trading behaviour of investors at large scale could pose significant threats to financial stability since they might increase volatility and create headaches for policymakers and supervisory authorities ([Riza Demirer, Lee, and Lien 2015](#ref-demirer2015commodity)).

Therefore, the concept of herding behavior started to gain the attention of researchers and academics early in the 1990s, when the studies of Banerjee ([1992](#ref-banerjee1992simple)) and Bikhchandani, Hirshleifer, and Welch ([1992](#ref-bikhchandani1992theory)) appeared. Literature on herding is voluminous but still remains inconclusive. Herding behaviour can be distinguished between unintentional and intentional. In the former case investors respond to a common set of information that refers to market developments and in the latter case investors discard their own beliefs and decide to follow the decisions of other leading to intentional herding ([Bikchandani and Sharma 2000](#ref-bikchandani2000herd)). Spyrou ([2013](#ref-spyrou2013herding)) and Komalasari et al. ([2022](#ref-komalasari2022herding)) provide some excellent reviews of the relevant studies. Herding studies have expanded across the behavior of individual investors across all financial markets namely stock markets (see inter alia [Rıza Demirer and Kutan 2006](#ref-demirer2006does); [Chiang and Zheng 2010](#ref-chiang2010empirical); [Ukpong, Tan, and Yarovaya 2021](#ref-ukpong2021determinants)), bond markets (see inter alia [Galariotis, Krokida, and Spyrou 2016](#ref-galariotis2016herd)), commodities’ markets ([Riza Demirer, Lee, and Lien 2015](#ref-demirer2015commodity); [Babalos and Stavroyiannis 2015](#ref-babalos2015herding); [Babalos, Stavroyiannis, and Gupta 2015](#ref-babalos2015commodity); [Júnior et al. 2020](#ref-junior2020analyzing); [Youssef 2022](#ref-youssef2022oil)), real estate markets (see inter alia [Philippas et al. 2013](#ref-philippas2013herding); [Lesame et al. 2024](#ref-lesame2024herding)) using returns data. Another strand of literature focus on herding behaviour of institutional investors such as money managers ([Jiang and Verardo 2018](#ref-jiang2018does)), financial analysts ([Leece and White 2017](#ref-leece2017effects)) and FX market forecasters ([Tsuchiya 2015](#ref-tsuchiya2015herding)) employing mostly information from transactions data. Most recently, herding behavior of investors in cryptocurrency markets has received the attention of literature (see inter alia [Bouri, Gupta, and Roubaud 2019](#ref-bouri2019herding)).

Herding has been in the epicentre of a heated discussion that seeks robust empirical evidence in an attempt to confirm that correlated actions of investors at a large scale could induce market instability and volatility. Likewise, the above argument could work the other way around that is herding is more intense during market turmoil or increased volatility. Welch ([2000](#ref-welch2000herding)) points out: “Herding in financial markets, in particular, is often presumed to be pervasive, even though the extant empirical evidence is surprisingly sparse”. Studies on herding examine the behaviour of investors towards market as a whole or at a sector level. Researchers have been concerned with herding activity across sectors in the US or in an international context with contradictory results (see inter alia [Christie and Huang 1995](#ref-christie1995following); [Choi and Sias 2009](#ref-choi2009institutional); [Litimi, BenSaı̈da, and Bouraoui 2016](#ref-litimi2016herding)). Herding behaviour might vary across sectors probably because of the specific style of the industry, the economic conditions that might affect each sector or the trading patterns of investors in certain industries. Henker, Henker, and Mitsios ([2006](#ref-henker2006investors)) find that herding is more prevalent in industries such as materials, consumer staples and financials. Gębka and Wohar ([2013](#ref-gkebka2013international)) employing data for 32 countries find that herding is more intense in sectors such as basic materials, consumer services, and oil and gas and this behaviour might be the result of a group of investors that follow each other in and out of markets, overconfidence, or excessive flight to quality. They also stressed that testing herding towards market could underestimate the real effect of herding behaviour and research should try to shed light on the behaviour of investors at sector level. In the Malaysian market, Dehghani and Sapian ([2014](#ref-dehghani2014sectoral)) find that herding behaviour is only constrained to technology sector. Nine Asian markets were investigated by Zheng, Li, and Chiang ([2017](#ref-zheng2017herding)) for herding at sector level. They provided evidence in favour of herding in the Technology and Financial industries, but weaker in the Utility industry. Moreover, herding in certain industries was more intense during bear markets and low trading volumes. Returning to US, BenSaı̈da ([2017](#ref-bensaida2017herding)) confirmed the presence of herding behaviour for 10 out of 12 sectors of US stock market during periods of financial crises and bubbles. Ukpong, Tan, and Yarovaya ([2021](#ref-ukpong2021determinants)) document weak evidence of herding especially in the Financials, Real Estate, Telecoms and Utilities sectors for US market.

Therefore, the study of herding behaviour across financial markets has become increasingly important in understanding the dynamics of investor decision-making and market stability. Herding, whether intentional or unintentional, reflects the tendency of investors to follow the crowd rather than act on independent information or analysis. This behaviour can exacerbate market volatility and pose challenges for regulators and policy-makers aiming to maintain financial stability.

In summary the paper makes the following contributions to the literature. First, we provide new evidence on the presence of herding behaviour across different industry sectors in the US stock market. We concede that the study of industry herding is not novel, however, we offer a comprehensive perspective of its evolution going back to the great depression. We argue that there is value in this. Second, this comprehensive perspective includes the examination of the determinants of herding behaviour across different sectors, focusing on the intersection of herding behaviour and market crisis periods. Inspired by Nath and Brooks ([2020](#ref-nath2020investor)), we investigate the relationship between herding behaviour and political cycles and approval ratings. This is a new area in the literature that we attempt to add to. It exposes risk-aversion as one of the key determinants of herding behaviour. The paper is structured as follows. Section 2 presents the data and methodology. Section 3 presents the results and Section 4 concludes.

# Data and Methodology

## Data

Our analysis utilises Kenneth French’s 49 industry portfolio returns.[[1]](#footnote-21) Through his website Kenneth French provides a variety of financial market related data for research purposes, which include the famous Fama/French factors data. These data have two main advantages for researchers. First, the industry portfolio data varies in detail from 5 to 49 industry data-sets. Second, the data cover long periods of time, typically to pre World War II. Specifically, the daily data covers the period 1 July 1926 to 29 July 2022. The significant length and breadth of this data is essential for our analysis.

We create 5 industry groups from the 49 industries in order to calculate the cross sectional dispersions as outlined in the methodology. In the data, stocks are assigned from the NYSE, AMEX, NASDAQ to an industry portfolio using a four-digit Centre for Research in Security Prices Standard Industry Classification Codes (CSRP-SIC).[[2]](#footnote-22) Essentially, the CSRP-SICs determine the level of industry aggregation in the data. Therefore, in [Table 8](#tbl-grouping) we group the industries using the CSRP-SICs.[[3]](#footnote-23) Lastly, [Figure 16](#fig-cons) to [Figure 20](#fig-mines), and [Table 10](#tbl-desc) show the described industry data.

In addition, we focus on herding behaviour in periods of financial crisis. Therefore, we use Wikipedia to identify 5 crises periods.[[4]](#footnote-24) That is, the Great Depression, Dot-com Bubble, Great Financial Crisis and the recent Covid-Crisis. The crises periods are shown in [Table 9](#tbl-crises_description).

Lastly, in order to understand the effect of political cycles on industry herding we estimate the relationship between the time-varying herding coefficient and US presidential terms as outlined in [Equation 11](#eq-political) below.[[5]](#footnote-25) The US presidential terms are shown in [Table 11](#tbl-terms). In order to match with the industry herding coefficients, the terms are converted to a daily frequency. We then estimate the relationship between presidential approval ratings (general and economic) and industry herding coefficients. The approval ratings unlike the presidential term data focuses on the performance of specific presidents and not just party terms. This analysis, therefore, adds to presidential term results which focused on party affiliation and industry herding. The approval ratings are shown in [Figure 23](#fig-approval).[[6]](#footnote-26) The presidential approval ratings (PAR) are compiled from the Gallup Poll by the American Presidency Project. The respondents answer the same question since 1941, “Do you approve or disapprove of the way (enter President name) is handling his job as President?”. Then the percentage of respondents to the affirmative (or approval) forms the popularity or public approval rating. The presidential economic approval ratings (PEAR) data are collected by several organisations[[7]](#footnote-27) overtime based on the question, “Do you approve or disprove of the way (name of the president) is handling the economy?”.[[8]](#footnote-28) The PAR data are available from 1941 to 2022 at a monthly frequency. Whilst the PEAR data is from 1981 to 2022, also at a monthly frequency. We converted these to a daily frequency to match the industry herding data.[[9]](#footnote-29)

## Testing for industry herding

Following Christie and Huang ([1995](#ref-christie1995following)) and Chang, Cheng, and Khorana ([2000](#ref-chang2000examination)) we calculate the cross-sectional absolute standard deviations () for each industry group. The is calculated for all markets as follows:

where observed returns from individual industry at time , is the average of the or the market return. In this case, is the group industry return which is an average of the individual industry returns. The return dispersion measures capture the directional similarity industry returns at a given point in time with respect to the aggregate market or group return. Herding tests, in turn, are based on the pattern of return dispersions during periods of large price movements.

The rationale behind the testing methodology is that, if herding is present, the correlated trades by investors will lead to greater directional similarity in industry returns, thus leading to lower dispersion in returns. This can be measured by the sign of the coefficients of the relationship between the return dispersion and and (or market return measures) in these equations for the general market herding:

where is the herding coefficient. The expectation is that and if herding is present. , therefore, is a non-linear term which captures the herding effect. This non-linear effect implies no herding when , anti-herding when and, obviously, herding when . We estimate with heteroskedastic and autocorrelation consistent (HAC) standard errors (See [Newey and West 1987](#ref-newey1987simple)).[[10]](#footnote-33) Furthermore, for all testing equations, we estimate changes in herding behaviour over time using a rolling-window approach with a 250 day.[[11]](#footnote-34)

## Industry herding in periods of financial crisis

Herding is known to be more pronounced in times of market crisis. To test for this we use a dummy variable approach to test whether herding is more pronounced during periods of financial crisis. [Equation 2](#eq-csad2) is adjusted to include the , which is an crisis period indicator, as follows:

where is a dummy variable which takes the value of 1 during periods of financial crisis and 0 otherwise. That is, to isolate the herding effect () only to periods of market crisis. Therefore, in [Equation 3](#eq-csad3) herding is present if and is significant.

## Industry herding and fundamental information

Herding can be considered either a rational response to public information by investors, or an accumulation of irrational behaviour by investors due to, for example, fear of under performance or fear of missing out on a market run (see [Bikhchandani and Sharma 2000](#ref-Bikhchandani2001)). In order to test for the rationality of herding, we test whether herding is related to fundamental information. We use the following equations to test for the relationship between herding and fundamental information, and herding and non-fundamental information. First we isolate the non-fundamental component of herding as follows:

where is the risk-free rate, is the high-minus-low portfolio and is the small-minus-big portfolio. The , and are all from the Fama-French 3 factor model (see [Fama and French 1993](#ref-fama1993common)) and are shown in [Figure 21](#fig-famafrench).

The non-fundamental component of herding is then:

It stands to reason that the fundamental component of herding is then:

where is the fundamental component of herding.

We then test the relationship between and and herding as follows:

where is the herding coefficient. Again, the expectation is that and if herding is present.

Extending the analysis further, we test if the rational and irrational components of herding are more pronounced during periods of financial crisis. We use the following equations to test for the relationship between herding and fundamental information, and herding and non-fundamental information during periods of financial crisis:

where, again, to isolate the herding effect () to periods of market crisis. is a dummy variable which takes the value of 1 during periods of financial crisis and 0 otherwise. Therefore, both in [Equation 9](#eq-nonfundacrisis) and [Equation 10](#eq-fundacrisis) herding is present if and is significant.

## Industry herding and political cycles

Inspired by the resent findings that risk aversion is a determinant of herding ([Nath and Brooks 2020](#ref-nath2020investor)), we construct a somewhat novel test to ask whether herding is related to political cycles. After taking market volatility into account, we estimate the following equations:

where is dummy variable with value 1 when herding is present and 0 otherwise. is a dummy variable which takes the value of 1 for the Democratic party, and 0 for the Republican party.[[12]](#footnote-47) is the Republican party estimate. is the market volatility from a model of the overall market returns (CSRP) of the industry portfolios as described above, and is shown in [Figure 22](#fig-volatility).

A natural question which follows is if the political cycle is a determinant herding, how is this affected by the rational or irrational herding. A similar analysis is conducted using herding related to fundamental and non-fundamental information in the following manner:

where and are dummy variables with value 1 when non-fundamental and fundamental herding is present and 0 otherwise.

To further understand the relationship between industry herding and political cycles, we turn our attention to the effect of the performance of specific US presidents on industry herding using the following equation:

where is the industry herding coefficient when it is negative (that is, when herding is present), is the presidential approval rating and the presidential economic approval rating (), and is the error term. The expectation is that , that is, industry herding is negatively related to approval ratings. This is in line with Pástor and Veronesi ([2020](#ref-pastor2020political)) who suggests that herding is high when uncertainty in high (which occurs when presidential ratings are low). [Equation 14](#eq-approval) and [Equation 15](#eq-approval_econ) was estimated with OLS and HAC standard errors.

# Results

## Descriptive analysis

[Table 10](#tbl-desc) presents the descriptive statistics namely median, standard deviation, minimum and maximum, IQR and total number of observations of the employed variables for the whole US market and for every industry separately during normal times and during the pre-defined crisis periods. [Table 10](#tbl-desc) is built on the daily industry data in [Figure 16](#fig-cons) to [Figure 20](#fig-mines), the industry grouping scheme in [Table 8](#tbl-grouping), and the crises periods in [Table 9](#tbl-crises_description). With over 25000 observations in the sample, these form the basis of the empirical analysis. The reader will note the low to zero returns in some industries in the earlier crisis periods influenced by the high volatility of returns in the market. These also explain some of the low estimates in the forthcoming results.

## Evidence of industry herding in the US

[Table 1](#tbl-ols) reports the ordinary least squares results of [Equation 2](#eq-csad2) employing the US industry returns both at aggregate level and at an industry level. [Table 1](#tbl-ols) is divided into three separate panels: the top panel presents estimated coefficients of [Equation 2](#eq-csad2) employing all days for the whole period of analysis while the middle panel presents the estimation results only for the top market returns and the bottom panel the relevant estimates during the down markets. Herding is detected examining the statistical significance and the sign of coefficient that can be found at the last column. When herding is present, assumes negative sign and appears statistically significant. A quick look of the results in [Table 1](#tbl-ols) reveals no herding behaviour when we use all day returns but significant herding effects for the whole sample and for separate sectors such as Consumables, Health and Other only during up markets. For example, in the middle panel and at the last column for Consumables we see a herding coefficient of -0.00016 that is highly significant. If we turn our attention to the bottom panel we document weak evidence of herding effects in the Manufacturing sector, an estimated value of coefficient -0.00006 that is statistically significant at 1%.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 1: Industry herding ols results   | Industry |  |  |  | | --- | --- | --- | --- | | Full market | | | | | All industries | 0.002275\*\*\* | 0.008697\*\*\* | -0.00004 | | Business services | 0.000218\*\*\* | 0.000520\*\*\* | 0.000018 | | Consumables | 0.000556\*\*\* | 0.002527\*\*\* | -0.00004 | | Health | 0.000091\*\*\* | 0.000195\*\*\* | 0.000017\* | | Manufacturing | 0.000438\*\*\* | 0.001421\*\*\* | 0.000051 | | Other | 0.000773\*\*\* | 0.003137\*\*\* | -0.00002 | | Top market (5% market returns) | | | | | All industries | -0.00846\*\*\* | 0.016707\*\*\* | -0.00062\*\*\* | | Business services | -0.00046 | 0.001034\*\*\* | -0.00001 | | Consumables | -0.00235\*\*\* | 0.004754\*\*\* | -0.00016\*\*\* | | Health | -0.00024 | 0.000420\*\*\* | 0.000009\*\*\* | | Manufacturing | -0.00104 | 0.002387\*\*\* | 0.000006 | | Other | -0.00355\* | 0.005988\*\*\* | -0.00022\*\*\* | | Bottom market (5% market returns) | | | | | All industries | 0.005373 | 0.005694\* | 0.000160 | | Business services | -0.00000 | 0.000627\*\*\* | -0.00000 | | Consumables | 0.001845\* | 0.001434\*\* | 0.000025 | | Health | 0.000151 | 0.000125 | 0.000015 | | Manufacturing | -0.00069 | 0.002054\*\*\* | -0.00006\* | | Other | 0.001566 | 0.002194\* | 0.000058 | | Note: \*\*\* = p value < 0.01, \*\* = 0.01 < p value < 0.05, \* = 0.05 < p value < 0.1. The regressions are based on | | | | |

|  |
| --- |
| Figure 1: Industry herding rolling regressions with 250 day window. Note: The perforated lines represents a 5% level of significance. |

Following previous studies that highlight the dynamic nature of herding effect ([Babalos, Stavroyiannis, and Gupta 2015](#ref-babalos2015commodity); [Klein 2013](#ref-klein2013time); [Mohamad and Stavroyiannis 2022](#ref-mohamad2022birds)) we have estimated [Equation 2](#eq-csad2) using a rolling window estimation period of 250 days for the whole period of analysis. [Figure 1](#fig-rol_gen) presents the graphical illustration of the results. In particular, we can see the time evolution of the t-statistic of the estimated coefficients with the t statistic of being at the epi-center of our focus. Contrary to previous findings using the static approach, the rolling window analysis reveals substantial anti-herding effects for the whole market (all industries) and for a number of industries, with periods of herding being present only during the crisis periods. The results are in line with the findings of previous studies that document the dynamic nature of herding effects, that herding is closely related to crisis periods. We focus on this point in the next section.

## US industry herding in periods of financial crises

[Table 2](#tbl-ols_crisis) reports the ordinary least squares results of [Equation 2](#eq-csad2) employing the US industry returns both at aggregate level and at an industry level during the pre-defined four crises periods: the Great Depression, Dot-com Bubble, Great Financial Crisis and the covid crisis. The estimation of the crisis periods is according to [Equation 3](#eq-csad3). As stated earlier, herding during crisis periods is verified by means of the negative sign of the estimated coefficient . The results point to the existence of significant herding effects for all industries employed during the four crisis periods. In particular, during the Great Depression herding is present when we employ all industries while across industries we document herding in three out of five industries namely Business services, Consumables and Other display strong herding effects. Health industry displays weak evidence of positive or anti-herding behaviour. Therefore, herding persists for all industries during the other four crisis periods.

[Figure 2](#fig-rol_crisis_gd) to [Figure 5](#fig-rol_crisis_cv) plot the results of the rolling window estimation of 250 days for [Equation 3](#eq-csad3) during the above mentioned crisis periods. These plots confirm the herding effects observed in the static results above, that herding was mainly present during crisis periods.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 2: Industry herding in crisis periods   | Industry |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | | Great Depression | | | | | | | All industries | 0.003473\*\*\* | 0.010209\*\*\* | 0.004698\* | -0.00047\*\*\* | 0.001102\*\* | | Business services | 0.000284\*\*\* | 0.000842\*\*\* | 0.000298\*\* | -0.00002\*\*\* | 0.000063\* | | Consumables | 0.000963\*\*\* | 0.003193\*\*\* | 0.001179\* | -0.00012\*\*\* | 0.000260\* | | Health | 0.000210\*\*\* | 0.000215\*\*\* | -0.00011 | 0.000009\* | 0.000101 | | Manufacturing | 0.000669\*\*\* | 0.001643\*\*\* | 0.000732\* | 0.000005 | 0.000226\*\* | | Other | 0.001164\*\*\* | 0.003108\*\*\* | 0.001943\*\* | -0.00012\*\*\* | 0.000367\*\*\* | | Dot-com Bubble | | | | | | | All industries | 0.001954\*\*\* | 0.026974\*\*\* | 0.008227\*\*\* | -0.00504\*\*\* | 0.000011 | | Business services | 0.000234\*\*\* | 0.001227\*\*\* | 0.000427\*\*\* | -0.00006\*\*\* | 0.000027\* | | Consumables | 0.000465\*\*\* | 0.007138\*\*\* | 0.002468\*\*\* | -0.00156\*\*\* | -0.00003 | | Health | 0.000084\*\*\* | 0.000730\*\*\* | 0.000169\*\*\* | -0.00006\*\* | 0.000018\* | | Manufacturing | 0.000357\*\*\* | 0.005130\*\*\* | 0.001362\*\*\* | -0.00095\*\*\* | 0.000058 | | Other | 0.000618\*\* | 0.010531\*\*\* | 0.003021\*\*\* | -0.00212\*\*\* | -0.00000 | | Financial Crisis | | | | | | | All industries | 0.003058\*\*\* | 0.038814\*\*\* | 0.005898\*\*\* | -0.00315\*\*\* | 0.000096 | | Business services | 0.000257\*\*\* | 0.002592\*\*\* | 0.000382\*\*\* | -0.00018\*\*\* | 0.000024\* | | Consumables | 0.000695\*\*\* | 0.011446\*\*\* | 0.001898\*\*\* | -0.00118\*\*\* | -0.00000 | | Health | 0.000090\*\*\* | 0.001248\*\*\* | 0.000165\*\*\* | -0.00014\*\*\* | 0.000018\* | | Manufacturing | 0.000587\*\*\* | 0.006586\*\*\* | 0.000941\*\*\* | -0.00042\*\*\* | 0.000077\* | | Other | 0.001125\*\*\* | 0.014239\*\*\* | 0.002010\*\*\* | -0.00108\*\*\* | 0.000025 | | Covid Crisis | | | | | | | All industries | 0.003019\*\*\* | 0.059462\*\*\* | 0.005799\*\*\* | -0.00412\*\*\* | 0.000050 | | Business services | 0.000270\*\*\* | 0.004796\*\*\* | 0.000324\*\*\* | -0.00037\*\*\* | 0.000032\*\* | | Consumables | 0.000730\*\*\* | 0.015527\*\*\* | 0.001811\*\*\* | -0.00112\*\*\* | -0.00001 | | Health | 0.000132\*\*\* | 0.001162\*\*\* | 0.000104\*\* | 0.000064 | 0.000014\*\*\* | | Manufacturing | 0.000576\*\*\* | 0.011363\*\*\* | 0.000899\*\*\* | -0.00079\*\*\* | 0.000080\*\* | | Other | 0.001074\*\*\* | 0.020953\*\*\* | 0.002058\*\*\* | -0.00137\*\*\* | 0.000016 | | Note: \*\*\* = p value < 0.01, \*\* = 0.01 < p value < 0.05, \* = 0.05 < p value < 0.1. The regressions are based on | | | | | | |

|  |
| --- |
| Figure 2: Industry herding during the Great Depression using a 250-day rolling window. Note: The perforated lines represents a 5% level of significance. |

|  |
| --- |
| Figure 3: Industry herding during the Dot-com Bubble using a 250-day rolling window. Note: The perforated lines represents a 5% level of significance. |

|  |
| --- |
| Figure 4: Industry herding during the Financial Crisis using a 250-day rolling window. Note: The perforated lines represents a 5% level of significance. |

|  |
| --- |
| Figure 5: Industry herding during the Covid Crisis using a 250-day rolling window. Note: The perforated lines represents a 5% level of significance. |

## The role of fundamental information in US industry herding

### In normal times

Following relevant literature that attempts to isolate intentional from spurious herding ([Holmes, Kallinterakis, and Ferreira 2013](#ref-holmes2013herding) for institutional investors; [Galariotis, Rong, and Spyrou 2015](#ref-galariotis2015herding) for stock market investors) we estimate [Equation 7](#eq-nonfundaherd) and [Equation 8](#eq-fundaherd) for the non-fundamental related and fundamental related Cross Sectional Absolute Deviation during non-crisis period. [Table 3](#tbl-ols_fund) presents the results of the estimated coefficients that capture the existence of intentional and spurious herding through the coefficient that is presented in the last column of [Table 3](#tbl-ols_fund). It is worth mentioning that herding on fundamentals is evident for the whole market and for three out of five industries namely Consumables, Manufacturing and Other. However, if we turn our attention to intentional herding, we observe no significant herding behavior across no industry or the market whatsoever. [Figure 6](#fig-rol_fundamental) and [Figure 7](#fig-rol_nonfundamental) plot the time evolution of coefficients of interest along with the t-statistic using a 250-day rolling window analysis for fundamental and non-fundamental herding during non-crisis period.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 3: Industry herding on fundamental information   | Industry |  |  |  | | --- | --- | --- | --- | | Fundamental | | | | | All industries | 0.007491\*\*\* | 0.001009\*\*\* | -0.00005\*\* | | Business services | 0.000649\*\*\* | 0.000033\*\*\* | -0.00000 | | Consumables | 0.001987\*\*\* | 0.000280\*\*\* | -0.00001\* | | Health | 0.000262\*\*\* | 0.000011\*\*\* | -0.00000 | | Manufacturing | 0.001468\*\*\* | 0.000217\*\*\* | -0.00001\*\*\* | | Other | 0.002707\*\*\* | 0.000448\*\*\* | -0.00002\*\* | | Non Fundamental | | | | | All industries | -0.00521\*\*\* | 0.007687\*\*\* | 0.000006 | | Business services | -0.00043\*\*\* | 0.000486\*\*\* | 0.000020 | | Consumables | -0.00143\*\*\* | 0.002246\*\*\* | -0.00002 | | Health | -0.00017\*\*\* | 0.000183\*\*\* | 0.000017\* | | Manufacturing | -0.00103\*\*\* | 0.001204\*\*\* | 0.000062\* | | Other | -0.00193\*\*\* | 0.002688\*\*\* | 0.000002 | | Note: \*\*\* = p value < 0.01, \*\* = 0.01 < p value < 0.05, \* = 0.05 < p value < 0.1. The regressions are based on and | | | | |

|  |
| --- |
| Figure 6: Industry herding on fundamental information using a 250-day rolling window. Note: The perforated lines represents a 5% level of significance. |

|  |
| --- |
| Figure 7: Industry herding on non-fundamental information using a 250-day rolling window. Note: The perforated lines represents a 5% level of significance. |

### During crisis periods

[Table 4](#tbl-ols_crisis_fund) presents the results of herding on fundamental and non-fundamental information for US industries during the four crisis periods. The coefficient of interest is which in cases of negative and statistically significant reflects herding behaviour. Observing the results of [Table 4](#tbl-ols_crisis_fund) some interesting findings emerge. Firstly, during the Great Depression investors appear to herd both on fundamental and non-fundamental information at market level.

For industries, we document a unintentional herding across all industries during the Great Depression where intentional herding is evident only for Business Services, Consumable and Other. Secondly, a striking result refers to the behaviour of investors in US industries during Dot-com bubble. According to the estimated results, investors appear to herd only intentionally since the coefficient of interest appears negative and strongly statistically significant across all industries and the market as a whole. Moving more recently to the Global Financial Crisis (GFC), our results highlight substantial evidence of spurious and intentional herding for all industries and for the market as a whole.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 4: Industry herding on fundamental information in crisis periods   | Industry |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | | Great Depression: Fundamental | | | | | | | All industries | 0.007674\*\*\* | 0.001991\*\*\* | 0.000364\* | -0.00013\*\*\* | -0.00000 | | Business services | 0.000661\*\*\* | 0.000142\*\*\* | -0.00001 | -0.00001\*\*\* | 0.000001 | | Consumables | 0.002037\*\*\* | 0.000499\*\*\* | 0.000111\*\* | -0.00002\*\* | -0.00000 | | Health | 0.000270\*\*\* | 0.000041\*\*\* | -0.00000\* | -0.00000\*\*\* | 0.000000 | | Manufacturing | 0.001508\*\*\* | 0.000363\*\*\* | 0.000098\*\*\* | -0.00002\*\*\* | -0.00000 | | Other | 0.002759\*\*\* | 0.000721\*\*\* | 0.000273\*\*\* | -0.00004\*\*\* | -0.00001\* | | Great Depression: Non Fundamental | | | | | | | All industries | -0.00420\*\*\* | 0.008217\*\*\* | 0.004333\* | -0.00034\*\*\* | 0.001111\*\* | | Business services | -0.00037\*\*\* | 0.000699\*\*\* | 0.000309\*\* | -0.00001\*\* | 0.000062\* | | Consumables | -0.00107\*\*\* | 0.002694\*\*\* | 0.001068\* | -0.00010\*\*\* | 0.000265\* | | Health | -0.00005 | 0.000173\*\*\* | -0.00011 | 0.000010\*\* | 0.000100 | | Manufacturing | -0.00083\*\*\* | 0.001279\*\*\* | 0.000634\* | 0.000028 | 0.000228\*\* | | Other | -0.00159\*\*\* | 0.002387\*\*\* | 0.001669\* | -0.00008\*\*\* | 0.000385\*\*\* | | Dot-com Bubble: Fundamental | | | | | | | All industries | 0.007504\*\*\* | -0.00018 | 0.001083\*\*\* | -0.00002 | -0.00006\*\* | | Business services | 0.000647\*\*\* | -0.00001 | 0.000042\*\*\* | -0.00000 | -0.00000 | | Consumables | 0.001992\*\*\* | -0.00007 | 0.000296\*\*\* | -0.00000 | -0.00001\* | | Health | 0.000262\*\*\* | -0.00001 | 0.000014\*\*\* | -0.00000 | -0.00000 | | Manufacturing | 0.001474\*\*\* | -0.00005 | 0.000225\*\*\* | 0.000025 | -0.00001\*\*\* | | Other | 0.002714\*\*\* | 0.000008 | 0.000469\*\*\* | -0.00001 | -0.00002\*\*\* | | Dot-com Bubble: Non Fundamental | | | | | | | All industries | -0.00555\*\*\* | 0.027159\*\*\* | 0.007144\*\*\* | -0.00502\*\*\* | 0.000074 | | Business services | -0.00041\*\*\* | 0.001245\*\*\* | 0.000384\*\*\* | -0.00006\*\* | 0.000029\* | | Consumables | -0.00152\*\*\* | 0.007208\*\*\* | 0.002171\*\*\* | -0.00156\*\*\* | -0.00001 | | Health | -0.00017\*\*\* | 0.000743\*\*\* | 0.000155\*\*\* | -0.00006\*\* | 0.000018\*\* | | Manufacturing | -0.00111\*\*\* | 0.005187\*\*\* | 0.001136\*\*\* | -0.00098\*\*\* | 0.000070\* | | Other | -0.00209\*\*\* | 0.010523\*\*\* | 0.002551\*\*\* | -0.00211\*\*\* | 0.000019 | | Financial Crisis: Fundamental | | | | | | | All industries | 0.007500\*\*\* | 0.001734\*\*\* | 0.000963\*\*\* | -0.00017\*\* | -0.00005\* | | Business services | 0.000650\*\*\* | 0.000109\*\* | 0.000028\*\* | -0.00001 | -0.00000 | | Consumables | 0.001988\*\*\* | 0.000552\*\*\* | 0.000269\*\*\* | -0.00006\*\* | -0.00001\* | | Health | 0.000262\*\*\* | 0.000057\*\*\* | 0.000010\*\*\* | -0.00000\*\* | -0.00000 | | Manufacturing | 0.001470\*\*\* | 0.000320\*\*\* | 0.000211\*\*\* | -0.00002\*\* | -0.00001\*\*\* | | Other | 0.002708\*\*\* | 0.000614\*\*\* | 0.000440\*\*\* | -0.00005\*\*\* | -0.00002\*\* | | Financial Crisis: Non Fundamental | | | | | | | All industries | -0.00444\*\*\* | 0.037080\*\*\* | 0.004935\*\*\* | -0.00297\*\*\* | 0.000146 | | Business services | -0.00039\*\*\* | 0.002483\*\*\* | 0.000354\*\*\* | -0.00017\*\*\* | 0.000025\* | | Consumables | -0.00129\*\*\* | 0.010894\*\*\* | 0.001628\*\*\* | -0.00111\*\*\* | 0.000008 | | Health | -0.00017\*\*\* | 0.001190\*\*\* | 0.000154\*\*\* | -0.00013\*\*\* | 0.000018\* | | Manufacturing | -0.00088\*\*\* | 0.006265\*\*\* | 0.000730\*\*\* | -0.00039\*\*\* | 0.000088\*\* | | Other | -0.00158\*\*\* | 0.013624\*\*\* | 0.001570\*\*\* | -0.00102\*\*\* | 0.000049 | | Covid Crisis: Fundamental | | | | | | | All industries | 0.007522\*\*\* | 0.003193\*\*\* | 0.000876\*\*\* | -0.00033\*\*\* | -0.00003\* | | Business services | 0.000652\*\*\* | 0.000218\*\*\* | 0.000023\* | -0.00002\*\*\* | -0.00000 | | Consumables | 0.001992\*\*\* | 0.000927\*\*\* | 0.000250\*\*\* | -0.00010\*\*\* | -0.00000\* | | Health | 0.000263\*\*\* | 0.000072\*\*\* | 0.000008\*\*\* | -0.00000\*\* | -0.00000 | | Manufacturing | 0.001472\*\*\* | 0.000685\*\*\* | 0.000197\*\*\* | -0.00007\*\*\* | -0.00000\*\*\* | | Other | 0.002718\*\*\* | 0.001116\*\*\* | 0.000405\*\*\* | -0.00010\*\*\* | -0.00002\*\* | | Covid Crisis: Non Fundamental | | | | | | | All industries | -0.00450\*\*\* | 0.056269\*\*\* | 0.004923\*\*\* | -0.00378\*\*\* | 0.000088 | | Business services | -0.00038\*\*\* | 0.004577\*\*\* | 0.000301\*\*\* | -0.00035\*\*\* | 0.000032\*\* | | Consumables | -0.00126\*\*\* | 0.014599\*\*\* | 0.001561\*\*\* | -0.00102\*\*\* | -0.00000 | | Health | -0.00013\*\*\* | 0.001090\*\*\* | 0.000096\* | 0.000070\* | 0.000014\*\*\* | | Manufacturing | -0.00089\*\*\* | 0.010678\*\*\* | 0.000702\*\*\* | -0.00072\*\*\* | 0.000089\*\* | | Other | -0.00164\*\*\* | 0.019837\*\*\* | 0.001652\*\*\* | -0.00127\*\*\* | 0.000036 | | Note: \*\*\* = p value < 0.01, \*\* = 0.01 < p value < 0.05, \* = 0.05 < p value < 0.1. The regressions are based on and | | | | | | |

The only exception is the Business sector that displays no spurious herding during GFC. Our results are partly consistent with those reported by Galariotis, Rong, and Spyrou ([2015](#ref-galariotis2015herding)) who documented only non-fundamental herding during sub-prime crisis for the whole market. However, we must be cautious with the comparison since the defined crisis periods might vary. Spurious and intentional herding of investors is also present during covid crisis period except for the Health industry that under the non-fundamental formulation we document an anti-herding behaviour ([Nath and Brooks 2020](#ref-nath2020investor)). [Figure 8](#fig-rol_fundamental_gd) to [Figure 11](#fig-rol_fundamental_cv) plot the time evolution of the estimated coefficients of [Equation 8](#eq-fundaherd) during the four crisis periods while [Figure 12](#fig-rol_nonfundamental_gd) to [Figure 14](#fig-rol_nonfundamental_fc) present the behaviour of the rolling window estimated coefficients for the non-fundamental herding equation.

|  |
| --- |
| Figure 8: Industry herding on fundamental information during the Great depression using a 250-day rolling window. Note: The perforated lines represents a 5% level of significance. |

|  |
| --- |
| Figure 9: Industry herding on fundamental information during the Dot-com bubble using a 250-day rolling window. Note: The perforated lines represents a 5% level of significance. |

|  |
| --- |
| Figure 10: Industry herding on fundamental information during the Financial crisis using a 250-day rolling window. Note: The perforated lines represents a 5% level of significance. |

|  |
| --- |
| Figure 11: Industry herding on fundamental information during the Covid crisis using a 250-day rolling window. Note: The perforated lines represents a 5% level of significance. |

|  |
| --- |
| Figure 12: Industry herding on non-fundamental information during the Great depression using a 250-day rolling window. Note: The perforated lines represents a 5% level of significance. |

|  |
| --- |
| Figure 13: Industry herding on non-fundamental information during the Dot-com bubble using a 250-day rolling window. Note: The perforated lines represents a 5% level of significance. |

|  |
| --- |
| Figure 14: Industry herding on non-fundamental information during the Financial crisis using a 250-day rolling window. Note: The perforated lines represents a 5% level of significance. |

|  |
| --- |
| Figure 15: Industry herding on non-fundamental information during the Covid crisis using a 250-day rolling window. Note: The perforated lines represents a 5% level of significance. |

## Industry herding and political cycles

Lastly, [Table 5](#tbl-political) presents the results of the estimated [Equation 11](#eq-political), [Equation 12](#eq-politicalnonfund) and [Equation 13](#eq-politicalfund) in an attempt to answer the question whether herding behaviour across US industries is related to political cycles. The coefficient of interest assumes a positive and a statistically significant value when we measure overall herding for All Industries and three other industries namely Consumables, Health and Other. This finding reflects a tendency of herding to be stronger when Democrats are in power while herding seems to diminish when Democrats are in power only for Business services. These linear probability model results are further affirmed by the probit results in [Table 12](#tbl-probit).

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 5: Herding and political cycles.   | Industry |  |  |  | | --- | --- | --- | --- | | General Herding | | | | | All industries | 0.1328\*\*\* | 0.1253\*\*\* | 0.0216 | | Business services | 0.4883\*\*\* | -0.135\*\*\* | -0.108\*\*\* | | Consumables | 0.3158\*\*\* | 0.1460\*\*\* | 0.0070 | | Health | 0.2164\*\*\* | 0.1774\*\*\* | 0.0752\*\* | | Manufacturing | 0.3855\*\*\* | 0.0139 | 0.0043 | | Other | 0.2070\*\*\* | 0.1464\*\*\* | 0.0091 | | Fundamental Herding | | | | | All industries | 0.8082\*\*\* | 0.0733 | -0.121\*\*\* | | Business services | 0.7485\*\*\* | 0.0564 | -0.118\*\*\* | | Consumables | 0.7240\*\*\* | 0.1167\*\*\* | -0.100\*\*\* | | Health | 0.7156\*\*\* | 0.0527 | -0.046 | | Manufacturing | 0.7012\*\*\* | 0.0753\* | -0.070\* | | Other | 0.7315\*\*\* | 0.1267\*\*\* | -0.108\*\*\* | | Non-Fundamental Herding | | | | | All industries | 0.1588\*\*\* | 0.0013 | 0.0283 | | Business services | 0.3150\*\*\* | -0.115\*\*\* | -0.045\* | | Consumables | 0.1580\*\*\* | 0.0020 | 0.1112\*\*\* | | Health | 0.0924\* | 0.0853\*\* | 0.0913\*\* | | Manufacturing | 0.3074\*\*\* | -0.127\*\*\* | 0.0336 | | Other | 0.1825\*\*\* | -0.058\* | 0.0541\* | | Note: \*\*\* = p value < 0.01, \*\* = 0.01 < p value < 0.05, \* = 0.05 < p value < 0.1. The regressions are based on , and | | | | |

As an attempt to isolate overall to herding due to fundamentals and non-fundamentals we find that in the former case herding becomes stronger during Democratic administration for three out of five industries and for fundamental herding while in the latter case herding tends to be smaller when democratic party is in power for Business services, Manufacturing and Other. Pástor and Veronesi ([2020](#ref-pastor2020political)) state convincingly: ’when risk aversion is high, as during economic crises, voters are more likely to elect a Democratic president because they demand more social insurance. When risk aversion is low, voters are more likely to elect a Republican because they want to take more business risk. Therefore, risk aversion is higher under Democrats.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 6: Herding and PAR   | Industry |  |  | | --- | --- | --- | | General Herding | | | | All industries | -9.99545 | 5.670591 | | Business services | -2.09215\*\* | 2.016127 | | Consumables | -6.21527 | 4.476214 | | Health | 3.724126 | -2.00933 | | Manufacturing | -4.02430 | 3.696601 | | Other | -4.03812 | -9.50704 | | Fundamental Herding | | | | All industries | -0.00019 | -1.08895 | | Business services | -9.44031 | -1.03996 | | Consumables | -6.75705\* | -2.90099 | | Health | -1.06597\*\* | 5.650244 | | Manufacturing | -1.69978 | -4.37575\* | | Other | -7.90795\*\* | -9.00466 | | Non-fundamental Herding | | | | All industries | -6.55803 | -2.47335 | | Business services | -3.76468\*\*\* | 4.243582\*\* | | Consumables | -0.00013 | 1.273648 | | Health | 2.315849 | -2.61553 | | Manufacturing | -8.44433 | 8.504663 | | Other | -5.44288 | -7.09065 | | Note: \*\*\* = p value < 0.01, \*\* = 0.01 < p value < 0.05, \* = 0.05 < p value < 0.1. The regressions are based on . PAR is the presidential approval rating as described in the data section above. was estimated using OLS with robust standard errors. | | | |

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 7: Herding and PEAR.   | Industry |  |  | | --- | --- | --- | | General Herding | | | | All industries | -6.60522 | -7.37137 | | Business services | -1.90968 | 9.750426 | | Consumables | 1.997194 | -1.63086 | | Health | -4.13266 | -1.20378 | | Manufacturing | -7.71036 | 8.948093 | | Other | 4.538253 | -2.49227 | | Fundamental Herding | | | | All industries | -0.00050\*\* | 5.852570 | | Business services | -2.71407\*\* | 3.082719\* | | Consumables | -0.00013\*\* | 1.268313 | | Health | -1.25927\*\* | 1.162627 | | Manufacturing | -3.14887\* | -5.24704 | | Other | -0.00014\*\* | 1.346976 | | Non-fundamental Herding | | | | All industries | 0.000279 | -1.21615 | | Business services | -8.08935 | -3.25287 | | Consumables | 3.641498 | -2.67763 | | Health | -2.63164 | 1.673378 | | Manufacturing | -7.72694 | 4.807278 | | Other | -2.23635 | -2.30217\* | | Note: \*\*\* = p value < 0.01, \*\* = 0.01 < p value < 0.05, \* = 0.05 < p value < 0.1. The regressions are based on . PEAR is the presidential economic approval rating as described in the data section above. was estimated using OLS with robust standard errors. | | | |

Extending the analysis to the presidential approval ratings, [Table 6](#tbl-par) and [Table 7](#tbl-pear) show that in terms of the general herding behaviour no statistically significant relationship is found with the presidential approval ratings. However, when we isolate the industry herding due to fundamentals and non-fundamentals we find that the former is positively related to the presidential approval ratings for Business services and negatively related to manufacturing, and other for the economic approval ratings. That is, it seems the approval ratings are mainly significant only in ‘production’ industries. This results are consistent with the party term results above, suggesting that risk-aversion is a driving factor of herding behaviour in these industries.

# Conclusion

The study investigates herding behaviour in the US market across different periods and industries using static and rolling-window models. The results suggest that herding behaviour is more pronounced during crisis periods, that is, in general and in industries. The findings are consistent with the literature that suggests that herding behaviour was more pronounced during periods of high uncertainty and risk aversion. The results also suggest that herding behaviour was not particular pronounced in one industry versus another. A departure from the thinking that fast moving industries such as business services which may be considered more sensitive to market conditions, would have more prevalent herding behaviour. This suggests that investors tend to herd to broader market conditions that industry specific market conditions.

A novel aspect of the study is the investigation of the relationship between herding behaviour and presidential approval ratings. The results suggest that the presidential approval ratings are not significantly related to herding behaviour in general, but it seems the approval ratings are mainly significant only in ‘production’ industries. This results are consistent with the party term results above which showed that herding was more pronounced during Democratic administration. The results suggest, similar to Nath and Brooks ([2020](#ref-nath2020investor)), that risk-aversion is a driving factor of herding behaviour in these industries.

The results have important implications for policy-makers, and regulators who are interested in understanding the dynamics of herding behaviour in the US market. For example, in order to mitigate the effects of herding behaviour, regulators and policy-makers can improve market transparency, risk management requirements, and investor educational initiatives, amongst others. These initiatives are still relevant given that the results indicate similar herding behaviour in the recent Covid-crisis compared to previous market crises.

The study focuses on the US market, and the results may not be generalizable to other markets. However, the study provides valuable insights into the dynamics of herding behaviour in the US market and highlights the importance of considering market conditions and sector-specific dynamics in understanding investor behaviour, and its implications for market stability and efficiency.

# References

Aggarwal, Raj. 2014. “Animal Spirits in Financial Economics: A Review of Deviations from Economic Rationality.” *International Review of Financial Analysis* 32: 179–87.

Babalos, Vassilios, and Stavros Stavroyiannis. 2015. “Herding, Anti-Herding Behaviour in Metal Commodities Futures: A Novel Portfolio-Based Approach.” *Applied Economics* 47 (46): 4952–66.

Babalos, Vassilios, Stavros Stavroyiannis, and Rangan Gupta. 2015. “Do Commodity Investors Herd? Evidence from a Time-Varying Stochastic Volatility Model.” *Resources Policy* 46: 281–87.

Banerjee, Abhijit V. 1992. “A Simple Model of Herd Behavior.” *The Quarterly Journal of Economics* 107 (3): 797–817.

BenSaı̈da, Ahmed. 2017. “Herding Effect on Idiosyncratic Volatility in US Industries.” *Finance Research Letters* 23: 121–32.

Bikchandani, Sushil, and Sunil Sharma. 2000. “Herd Behavior in Financial Markets: A Review.” 48. IMF Working Papers.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch. 1992. “A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades.” *Journal of Political Economy* 100 (5): 992–1026.

Bikhchandani, Sushil, and Sunil Sharma. 2000. “Herd Behavior in Financial Markets.” *IMF Staff Papers* 47 (3): 279–310.

Bouri, Elie, Rangan Gupta, and David Roubaud. 2019. “Herding Behaviour in Cryptocurrencies.” *Finance Research Letters* 29: 216–21.

Chang, Eric C, Joseph W Cheng, and Ajay Khorana. 2000. “An Examination of Herd Behavior in Equity Markets: An International Perspective.” *Journal of Banking & Finance* 24 (10): 1651–79.

Chiang, Thomas C, and Dazhi Zheng. 2010. “An Empirical Analysis of Herd Behavior in Global Stock Markets.” *Journal of Banking & Finance* 34 (8): 1911–21.

Choi, Nicole, and Richard W Sias. 2009. “Institutional Industry Herding.” *Journal of Financial Economics* 94 (3): 469–91.

Christie, William G, and Roger D Huang. 1995. “Following the Pied Piper: Do Individual Returns Herd Around the Market?” *Financial Analysts Journal* 51 (4): 31–37.

Dai, Wei, Mark Weder, and Bo Zhang. 2020. “Animal Spirits, Financial Markets, and Aggregate Instability.” *Journal of Money, Credit and Banking* 52 (8): 2053–83.

Dehghani, Pegah, and Ros Zam Zam Sapian. 2014. “Sectoral Herding Behavior in the Aftermarket of Malaysian IPOs.” *Venture Capital* 16 (3): 227–46.

Demirer, Riza, Hsiang-Tai Lee, and Donald D Lien. 2015. “Commodity Financialization and Herd Behavior in Commodity Futures Markets.” *International Review of Financial Analysis* 39.

Demirer, Rıza, and Ali M Kutan. 2006. “Does Herding Behavior Exist in Chinese Stock Markets?” *Journal of International Financial Markets, Institutions and Money* 16 (2): 123–42.

Devenow, Andrea, and Ivo Welch. 1996. “Rational Herding in Financial Economics.” *European Economic Review* 40 (3-5): 603–15.

Fama, Eugene F. 1970. “Efficient Capital Markets.” *Journal of Finance* 25 (2): 383–417.

Fama, Eugene F, and Kenneth R French. 1993. “Common Risk Factors in the Returns on Stocks and Bonds.” *Journal of Financial Economics* 33 (1): 3–56.

Galariotis, Emilios C, Styliani-Iris Krokida, and Spyros I Spyrou. 2016. “Herd Behavior and Equity Market Liquidity: Evidence from Major Markets.” *International Review of Financial Analysis* 48: 140–49.

Galariotis, Emilios C, Wu Rong, and Spyros I Spyrou. 2015. “Herding on Fundamental Information: A Comparative Study.” *Journal of Banking & Finance* 50: 589–98.

Gębka, Bartosz, and Mark E Wohar. 2013. “International Herding: Does It Differ Across Sectors?” *Journal of International Financial Markets, Institutions and Money* 23: 55–84.

Henker, Julia, Thomas Henker, and Anna Mitsios. 2006. “Do Investors Herd Intraday in Australian Equities?” *International Journal of Managerial Finance* 2 (3): 196–219.

Holmes, Phil, Vasileios Kallinterakis, and MP Leite Ferreira. 2013. “Herding in a Concentrated Market: A Question of Intent.” *European Financial Management* 19 (3): 497–520.

Jiang, Hao, and Michela Verardo. 2018. “Does Herding Behavior Reveal Skill? An Analysis of Mutual Fund Performance.” *The Journal of Finance* 73 (5): 2229–69.

Júnior, Gerson de Souza Raimundo, Rafael Baptista Palazzi, Marcelo Cabus Klotzle, and Antonio Carlos Figueiredo Pinto. 2020. “Analyzing Herding Behavior in Commodities Markets–an Empirical Approach.” *Finance Research Letters* 35: 101285.

Kahneman, Daniel. 2003. “Maps of Bounded Rationality: Psychology for Behavioral Economics.” *American Economic Review* 93 (5): 1449–75.

Klein, Arne C. 2013. “Time-Variations in Herding Behavior: Evidence from a Markov Switching SUR Model.” *Journal of International Financial Markets, Institutions and Money* 26: 291–304.

Komalasari, Puput Tri, Marwan Asri, Bernardinus M Purwanto, and Bowo Setiyono. 2022. “Herding Behaviour in the Capital Market: What Do We Know and What Is Next?” *Management Review Quarterly* 72 (3): 745–87.

Leece, Ryan D, and Todd P White. 2017. “The Effects of Firms’ Information Environment on Analysts’ Herding Behavior.” *Review of Quantitative Finance and Accounting* 48: 503–25.

Lesame, Keagile, Geoffrey Ngene, Rangan Gupta, and Elie Bouri. 2024. “Herding in International REITs Markets Around the COVID-19 Pandemic.” *Research in International Business and Finance* 67: 102147.

Litimi, Houda, Ahmed BenSaı̈da, and Omar Bouraoui. 2016. “Herding and Excessive Risk in the American Stock Market: A Sectoral Analysis.” *Research in International Business and Finance* 38: 6–21.

Mohamad, Azhar, and Stavros Stavroyiannis. 2022. “Do Birds of a Feather Flock Together? Evidence from Time-Varying Herding Behaviour of Bitcoin and Foreign Exchange Majors During Covid-19.” *Journal of International Financial Markets, Institutions and Money* 80: 101646.

Mullainathan, Sendhil, and Richard H Thaler. 2000. “Behavioral Economics.” National Bureau of Economic Research Cambridge, Mass., USA.

Nath, Harmindar B, and Robert D Brooks. 2020. “Investor-Herding and Risk-Profiles: A State-Space Model-Based Assessment.” *Pacific-Basin Finance Journal* 62: 101383.

Newey, Whitney K, and Kenneth D West. 1987. “A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix.” *Econometrica: Journal of the Econometric Society*, 703–8.

Pástor, L’uboš, and Pietro Veronesi. 2020. “Political Cycles and Stock Returns.” *Journal of Political Economy* 128 (11): 4011–45.

Philippas, Nikolaos, Fotini Economou, Vassilios Babalos, and Alexandros Kostakis. 2013. “Herding Behavior in REITs: Novel Tests and the Role of Financial Crisis.” *International Review of Financial Analysis* 29: 166–74.

Shiller, Robert J. 2005. “Behavioral Economics and Institutional Innovation.” *Southern Economic Journal* 72 (2): 269–83.

Spyrou, Spyros. 2013. “Herding in Financial Markets: A Review of the Literature.” *Review of Behavioral Finance* 5 (2): 175–94.

Tsuchiya, Yoichi. 2015. “Herding Behavior and Loss Functions of Exchange Rate Forecasters over Interventions and Financial Crises.” *International Review of Economics & Finance* 39: 266–76.

Tversky, Amos, and Daniel Kahneman. 1974. “Judgment Under Uncertainty: Heuristics and Biases: Biases in Judgments Reveal Some Heuristics of Thinking Under Uncertainty.” *Science* 185 (4157): 1124–31.

Ukpong, Idibekeabasi, Handy Tan, and Larisa Yarovaya. 2021. “Determinants of Industry Herding in the US Stock Market.” *Finance Research Letters* 43: 101953.

Welch, Ivo. 2000. “Herding Among Security Analysts.” *Journal of Financial Economics* 58 (3): 369–96.

Youssef, Mouna. 2022. “Do Oil Prices and Financial Indicators Drive the Herding Behavior in Commodity Markets?” *Journal of Behavioral Finance* 23 (1): 58–72.

Zheng, Dazhi, Huimin Li, and Thomas C Chiang. 2017. “Herding Within Industries: Evidence from Asian Stock Markets.” *International Review of Economics & Finance* 51: 487–509.

# Appendix

## Industry data

|  |
| --- |
| Figure 16: Consumables returns |

|  |
| --- |
| Figure 17: Health returns |

|  |
| --- |
| Figure 18: Manufacturing returns |

|  |
| --- |
| Figure 19: Business services returns |

|  |
| --- |
| Figure 20: Other returns |

## Industry groupings

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 8: Industry grouping using CRSP SICs   | Consumables | Health | Manufacturing | Other | Business services | | --- | --- | --- | --- | --- | | Agriculture | Health Care | Chemicals | Entertainment | Electronic Equipment | | Food Products | Medical Equipment | Rubber and Plastic Products | Textiles | Automobiles and Trucks | | Candy and Soda | Drugs | Machinery | Construction Materials | Communication | | Beer and Liquor |  | Aircraft | Construction | Computers | | Tobacco Products |  | Shipbuilding and Railroad Equipment | Steel Works | Software | | Recreation |  | Defense | Fabricated Products | Electronic Equipment | | Printing and Publishing |  | Coal | Non-Metallic and Industrial Metal Mining | Measuring and Control Equipment | | Consumer Goods |  | Utilities | Precious Metals |  | | Apparel |  | Business Supplies | Petroleum and Natural Gas |  | | Personal Services |  |  | Business Services |  | | Wholesale |  |  | Shipping Containers |  | | Retail |  |  | Transportation |  | | Restaurants, Hotels, Motels |  |  | Banking |  | |  |  |  | Insurance |  | |  |  |  | Real Estate |  | |  |  |  | Trading |  | |  |  |  | Other |  | |  |  |  | Automobiles and Trucks |  | |

## Crises periods

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 9: Crises periods. Source: Wikipedia (2023)   | Crisis | Start | End | | --- | --- | --- | | Great Depression | 1929-01-01 | 1939-12-31 | | Dot-com Bubble | 1997-01-01 | 2003-12-31 | | Financial Crisis | 2007-01-01 | 2009-12-31 | | Covid Crisis | 2020-01-01 | 2021-12-31 | |

## Descriptive statistics

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 10: Descriptive statistics   | Crisis | Variables | Median | SD | Min | Max | IQR | Obs | | --- | --- | --- | --- | --- | --- | --- | --- | | All industries | | | | | | | | | Full Sample | CSAD | 0.00 | 0.02 | 0.00 | 0.29 | 0.00 | 25,292 | | Full Sample | Market Return | 0.13 | 1.08 | -13.70 | 18.98 | 0.83 | 25,292 | | Covid Crisis | CSAD | 0.08 | 0.03 | 0.04 | 0.29 | 0.03 | 504 | | Covid Crisis | Market Return | 0.14 | 2.00 | -11.75 | 10.16 | 1.87 | 504 | | Dot-com Bubble | CSAD | 0.02 | 0.01 | 0.01 | 0.08 | 0.01 | 1,760 | | Dot-com Bubble | Market Return | 0.15 | 0.85 | -5.33 | 3.90 | 0.92 | 1,760 | | Financial Crisis | CSAD | 0.05 | 0.03 | 0.02 | 0.21 | 0.03 | 755 | | Financial Crisis | Market Return | 0.17 | 1.93 | -9.32 | 9.98 | 1.70 | 755 | | Great Depression | CSAD | 0.02 | 0.01 | 0.01 | 0.12 | 0.01 | 3,279 | | Great Depression | Market Return | 0.12 | 1.85 | -13.70 | 18.98 | 1.56 | 3,279 | | Business services | | | | | | | | | Full Sample | CSAD | 0.00 | 0.00 | 0.00 | 0.03 | 0.00 | 25,292 | | Full Sample | Market Return | 0.12 | 1.24 | -12.88 | 16.01 | 1.08 | 25,292 | | Covid Crisis | CSAD | 0.01 | 0.00 | 0.00 | 0.03 | 0.00 | 504 | | Covid Crisis | Market Return | 0.24 | 1.99 | -12.06 | 10.56 | 1.91 | 504 | | Dot-com Bubble | CSAD | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 1,760 | | Dot-com Bubble | Market Return | 0.22 | 1.52 | -9.40 | 8.81 | 1.60 | 1,760 | | Financial Crisis | CSAD | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | 755 | | Financial Crisis | Market Return | 0.18 | 1.94 | -8.89 | 9.69 | 1.78 | 755 | | Great Depression | CSAD | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | 3,279 | | Great Depression | Market Return | 0.05 | 1.87 | -12.88 | 16.01 | 1.65 | 3,279 | | Consumables | | | | | | | | | Full Sample | CSAD | 0.00 | 0.00 | 0.00 | 0.10 | 0.00 | 25,292 | | Full Sample | Market Return | 0.11 | 1.03 | -13.05 | 21.52 | 0.82 | 25,292 | | Covid Crisis | CSAD | 0.02 | 0.01 | 0.01 | 0.10 | 0.01 | 504 | | Covid Crisis | Market Return | 0.18 | 1.86 | -11.91 | 9.34 | 1.71 | 504 | | Dot-com Bubble | CSAD | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | 1,760 | | Dot-com Bubble | Market Return | 0.12 | 0.77 | -5.02 | 3.27 | 0.84 | 1,760 | | Financial Crisis | CSAD | 0.01 | 0.01 | 0.00 | 0.06 | 0.01 | 755 | | Financial Crisis | Market Return | 0.13 | 1.65 | -7.80 | 7.98 | 1.49 | 755 | | Great Depression | CSAD | 0.00 | 0.00 | 0.00 | 0.04 | 0.00 | 3,279 | | Great Depression | Market Return | 0.10 | 1.85 | -13.05 | 21.52 | 1.62 | 3,279 | | Health | | | | | | | | | Full Sample | CSAD | 0.00 | 0.00 | 0.00 | 0.06 | 0.00 | 25,292 | | Full Sample | Market Return | 0.10 | 1.21 | -14.25 | 33.53 | 1.06 | 25,292 | | Covid Crisis | CSAD | 0.00 | 0.00 | 0.00 | 0.06 | 0.00 | 504 | | Covid Crisis | Market Return | 0.18 | 2.11 | -13.00 | 15.48 | 2.10 | 504 | | Dot-com Bubble | CSAD | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 1,760 | | Dot-com Bubble | Market Return | 0.19 | 1.16 | -8.45 | 5.91 | 1.21 | 1,760 | | Financial Crisis | CSAD | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 755 | | Financial Crisis | Market Return | 0.14 | 1.50 | -6.89 | 8.29 | 1.43 | 755 | | Great Depression | CSAD | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | 3,279 | | Great Depression | Market Return | -0.02 | 2.07 | -14.25 | 33.53 | 1.66 | 3,279 | | Manufacturing | | | | | | | | | Full Sample | CSAD | 0.00 | 0.00 | 0.00 | 0.08 | 0.00 | 25,292 | | Full Sample | Market Return | 0.11 | 1.25 | -15.86 | 20.71 | 0.96 | 25,292 | | Covid Crisis | CSAD | 0.01 | 0.01 | 0.00 | 0.08 | 0.01 | 504 | | Covid Crisis | Market Return | 0.12 | 2.06 | -10.92 | 8.30 | 1.98 | 504 | | Dot-com Bubble | CSAD | 0.00 | 0.00 | 0.00 | 0.03 | 0.00 | 1,760 | | Dot-com Bubble | Market Return | 0.13 | 0.84 | -4.44 | 4.04 | 0.96 | 1,760 | | Financial Crisis | CSAD | 0.01 | 0.01 | 0.00 | 0.05 | 0.01 | 755 | | Financial Crisis | Market Return | 0.14 | 2.21 | -10.64 | 12.02 | 1.93 | 755 | | Great Depression | CSAD | 0.00 | 0.00 | 0.00 | 0.08 | 0.00 | 3,279 | | Great Depression | Market Return | 0.10 | 2.33 | -15.86 | 20.71 | 1.96 | 3,279 | | Other | | | | | | | | | Full Sample | CSAD | 0.00 | 0.01 | 0.00 | 0.13 | 0.00 | 25,292 | | Full Sample | Market Return | 0.12 | 1.15 | -14.56 | 20.35 | 0.88 | 25,292 | | Covid Crisis | CSAD | 0.03 | 0.02 | 0.01 | 0.12 | 0.01 | 504 | | Covid Crisis | Market Return | 0.12 | 2.19 | -12.79 | 11.20 | 2.07 | 504 | | Dot-com Bubble | CSAD | 0.01 | 0.00 | 0.00 | 0.03 | 0.00 | 1,760 | | Dot-com Bubble | Market Return | 0.13 | 0.84 | -5.18 | 4.41 | 0.93 | 1,760 | | Financial Crisis | CSAD | 0.02 | 0.01 | 0.01 | 0.13 | 0.01 | 755 | | Financial Crisis | Market Return | 0.15 | 2.20 | -10.76 | 10.58 | 1.97 | 755 | | Great Depression | CSAD | 0.01 | 0.00 | 0.00 | 0.03 | 0.00 | 3,279 | | Great Depression | Market Return | 0.11 | 1.99 | -14.56 | 20.35 | 1.71 | 3,279 | |

## Fama-French factors

|  |
| --- |
| Figure 21: Fama-French Factors |

## Presidential terms

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 11: Presidential terms   | Party | Start | End | | --- | --- | --- | | Republican | 1921 | 1922 | | Republican | 1923 | 1928 | | Republican | 1929 | 1932 | | Democrat | 1933 | 1944 | | Democrat | 1945 | 1952 | | Republican | 1953 | 1960 | | Democrat | 1961 | 1962 | | Democrat | 1963 | 1968 | | Republican | 1969 | 1973 | | Republican | 1974 | 1976 | | Democrat | 1977 | 1980 | | Republican | 1981 | 1988 | | Republican | 1989 | 1992 | | Democrat | 1993 | 2000 | | Republican | 2001 | 2008 | | Democrat | 2009 | 2016 | | Republican | 2017 | 2020 | | Democrat | 2021 | 2022 | |

## Market volatility

|  |
| --- |
| Figure 22: Market volatility |

## Probit estimation

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 12: Probit estimation (Marginal Effects)   | Industry |  |  | | --- | --- | --- | | General Herding | | | | All industries | 0.1254\*\*\* | 0.0223\*\*\* | | Business services | -0.136\*\*\* | -0.126\*\*\* | | Consumables | 0.1460\*\*\* | 0.0071 | | Health | 0.1768\*\*\* | 0.0733\*\*\* | | Manufacturing | 0.0139\* | 0.0044 | | Other | 0.1464\*\*\* | 0.0095 | | Fundamental Herding | | | | All industries | 0.0737\*\*\* | -0.107\*\*\* | | Business services | 0.0564\*\*\* | -0.112\*\*\* | | Consumables | 0.1167\*\*\* | -0.092\*\*\* | | Health | 0.0529\*\*\* | -0.043\*\*\* | | Manufacturing | 0.0756\*\*\* | -0.066\*\*\* | | Other | 0.1273\*\*\* | -0.099\*\*\* | | Non-Fundamental Herding | | | | All industries | 0.0008 | 0.0265\*\*\* | | Business services | -0.116\*\*\* | -0.048\*\*\* | | Consumables | 0.0019 | 0.1001\*\*\* | | Health | 0.0828\*\*\* | 0.0798\*\*\* | | Manufacturing | -0.127\*\*\* | 0.0318\*\*\* | | Other | -0.058\*\*\* | 0.0496\*\*\* | | Note: \*\*\* = p value < 0.01, \*\* = 0.01 < p value < 0.05, \* = 0.05 < p value < 0.1. The marginal effects are based on probit estimations of , and | | | |

## Presidential approval ratings

|  |
| --- |
| Figure 23: Presidential approval ratings (Daily). |

[1] TRUE TRUE TRUE FALSE TRUE TRUE TRUE

[1] TRUE

1. [↑](#footnote-ref-21)
2. At the end of June each year [↑](#footnote-ref-22)
3. These are also available from [↑](#footnote-ref-23)
4. [↑](#footnote-ref-24)
5. The US presidential terms can be found at [↑](#footnote-ref-25)
6. The data can be accessed from: [↑](#footnote-ref-26)
7. These include ABC News, American Research Group, CNN, and Fox News, amongst others. [↑](#footnote-ref-27)
8. The PEAR data can be accessed at [↑](#footnote-ref-28)
9. Essentially repeating the monthly value for all the days of that specific month [↑](#footnote-ref-29)
10. We utilise the Newey-West estimator for all estimations in this paper. [↑](#footnote-ref-33)
11. This is a commonly used window in the literature. We do this throughout the herding analysis [↑](#footnote-ref-34)
12. [Equation 11](#eq-political), [Equation 12](#eq-politicalnonfund) and [Equation 13](#eq-politicalfund) were estimated as linear probability and probit models. The estimates of the linear probability model are the similar to the probit marginal effects. For simplicity we use the linear probability model estimates. The probit marginal effects are shown in [Table 12](#tbl-probit). [↑](#footnote-ref-47)