Wrangling the Herd: A Cross-Cultural and Cross-Industry Approach to Herding Market Behavior

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Honors thesis submitted in partial fulfillment of the requirements for Graduation with Distinction in Economics in Trinity College of Duke University.

Duke University
Durham, North Carolina
2019

Acknowledgements

We would like to thank our faculty advisor, Professor Connel Fullenkamp, for his guidance and mentorship throughout the process. His willingness to spend time talking through the challenges of our thesis was invaluable in developing our final product. We would also like to thank Professor Kent Kimbrough, who offered us consistent, constructive feedback throughout the early stages of the process. We will look back upon this entire venture with fond memories, as one of the formative experiences during our time here at Duke.

Abstract

The traditional efficient market hypothesis serves as the foundation of modern economic theory, governing the investigation of financial markets. While this premise assumes all investors are rational and all information is immediately incorporated into markets, this paper explores herding behavior – a central tenet of behavioral finance that explains the apparent inefficiencies of financial markets. Utilizing return data from the past 10 years from eight exchanges around the world, segmented into 10 industry classes as well as a broad market index, we compare levels of herd behavior using return dispersion proxies. We find significant evidence of herding in nearly all exchanges and all industries included in the study and the degree of this herd behavior varies across industries in different countries. Overall, we find support for the behavioral finance principle of herding and conclude that certain cultural or non-cultural factors affect this activity differently in various countries and industries.

JEL Codes: G4, G14, G15

Keywords: Efficient market hypothesis, behavioral finance, herding, cross-countries, cross-industries

I. Introduction

The efficient market hypothesis (EMH) proposes that at any given time in a liquid market, all available information is reflected in asset prices. However, there have been certain events, as well as recurring anomalies, in which experts claim EMH has been violated. These events include, but are not limited to, the bursting of the dot-com bubble in the late-1990's and the bursting of the economic bubble in Japan in the 1980's (Vail, 2017). Some of the anomalies, which will be discussed in further detail below, include the January Effect, the Size Effect, and the Neglected Firms Effect. While there is not unanimous agreement upon whether these occurrences truly represent outright contradictions of EMH, it is becoming more widely accepted among economists that the current models, which assume perfect investor rationality, cannot explain all events that occur in markets. Many economists cannot reconcile the clear difference between certain assets' trading values and their fundamental economic values, which according to EMH should be exactly the same. Thus, behavioral finance was established to fill this void by integrating cognitive reasoning and principles of psychology and neuroscience into conventional economic and financial theory. While not all violations of EMH stem solely from cognitive issues, mental errors appear to play at least some part in the majority of these EMH failures.

The recent emergence of behavioral finance is an indirect byproduct of the breakdown of the Bretton Woods regulation system that began in the early-1970's. The breakdown was gradual, thus true global financial deregulation, denoted by the removal of restrictions on international capital flows and exchange rate movements, was not reached until the late-1980's. The deregulation was the first domino to fall, in a chain that would change the way modern economics is viewed and studied. When failures in the global financial system began to emerge in the 1990's, it became increasingly clear that EMH might not be the optimal model of financial market theory it was previously thought to be (Quiggin, 2009). The slew of global financial crises, coupled with the cyclical formation and bursting of asset bubbles worldwide, directly contradicted the core assumptions of EMH. If market prices included all public information, asset price bubbles would not exist, and in turn would never burst (Shiller, 2015). The bursting of the dot-com bubble and the Japanese "bubble economy" crash both serve as case studies in which investors do not behave rationally and asset prices do not reflect all available public information.

Overall, behavioral finance exists to provide reasoning behind why market activity strays from what is suggested by EMH. As an area of study, behavioral finance is founded on four main pillars: mental accounting, herd behavior, anchoring, and self-rating (Behavioral Finance, 2018). Each of these concepts leads individuals astray from "perfect" investor rationality in its own way.

Herd behavior, which will be the focus of this paper, can be described as the tendency for individuals to mimic the actions and behavior of the majority or herd. Similar to that of high self-rating, this concept has roots in general social psychology, but its implications in the scope of behavioral finance may be the most dangerous of the four main concepts in terms of leading investors astray from perfectly rational behavior. Herd behavior is driven by the herd instinct, which leads individuals to follow popular trends without giving any significant thought of their own. The herd instinct is closely related to one of behavioral finance's many biases, the empathy gap bias, which hinders an individual's ability to make rational decisions under circumstances of high emotion, such as anxiety, excitement, or anger. Experts often identify herd behavior as the driver behind massive sell-offs and rallies. The dot-com bubble in the late-1990's is a perfect example of herd behavior in action, as it was attributed to be a main driver behind both the massive run up and sell-off. (Herd Instinct, 2018). The run up and sell-off are both generally explained as and accepted to be the result of individual investors casting aside their personal views and acting in accordance with the majority of the crowd. This type of coordinated and systematic buying and selling of securities was unprecedented, leaving many uncertain when trying to explain the colossal market collapse adhering strictly to traditional economic theory (Delong & Magin 2006). In the context of financial markets, herd behavior is generally a product of either greed or fear. Investors hate missing out on opportunities for positive returns, but loss aversion tells us that they hate experiencing negative returns even more, especially when these losses could have been avoided (Heshmat, 2018). While this behavior could also be explained by a heuristic, many suggest that loss aversion is a main driver behind herd-like behavior in markets.

Herding behavior in financial markets takes two specific forms (within intentional and spurious herding as discussed later): information-based herding, and reputation-based herding. Information-based herding occurs when everyone reacts in the same manner to announced information. While on the surface this may sound like rational investor behavior, in line with EMH, a deeper look reveals otherwise (Duff, 2017). The underlying cause of information-based herding is a phenomenon called information cascades. Information cascades occur when individuals make decisions based on observations of others, ignoring their own personal information. These cascades are triggered by the initial individuals reacting to some piece of public information (Çelen & Kariv, 2004). On the surface, it may appear as if all investors are reacting the same way to a piece of information, when in reality the majority are blindly following the initial reactors, all serving as links in a large chain reaction that is the information cascade. When these cascades reach the point of no more novel information and all investments are pure imitation, it is considered to be information-based herding (Jane, 2018). While it is difficult to empirically parse out information-based herding from rational investor reactions to news, one can infer that not all investors possess the necessary expertise on financial markets to reach the same conclusions as market professionals.

Reputation-based herding is a product of investors being influenced by a respected investor or large trading house that formulates a certain view or stance on a given asset (Roider & Voskort, 2016). When renowned investors such as Carl Icahn, Bill Ackman, or Warren Buffett announce they are taking a new position in a certain stock, there is consistently an upward shift in the stock price (Erickson, 2018). Overall, everyday investors trust the knowledge and expertise of these illustrious investors much more than they trust their own, and are subsequently willing to blindly follow these big names. While this might seem rational in the literal sense, it violates the traditional definition of "rational behavior" as defined by traditional economic theory, namely the idea that individuals act independently of one another according to their own personal views.

Herding behavior has been a major area of interest for economists since the introduction of behavioral finance paradigms. Thus, existing research has uncovered many significant nuances of herding and the relationship between the degree of herding and various market conditions. Previous studies have distinguished between fundamental and non-fundamental herding and have established that herd behavior is more prevalent in emerging markets, during extreme market conditions (periods in which market returns reside on the tails of the distribution), and asymmetric in up and down markets. Additionally, studies have been conducted to investigate herding in nearly all major markets around the world. Our work seeks to fill a gap in the existing literature by comparing the degree of herding in various industries within major markets as well as comparing herding in individual industries across markets globally.

Within a single market, we expect industries that are more volatile and typically have higher betas to exhibit a higher degree of herding behavior. Intuitively, volatile industries, as well as those that move more than the market index, tend to be more complex and less understood by the majority of investors. These unsophisticated investors will generally deploy capital in these industries based on other, more sophisticated investors' actions or by other news sources, thus acting as a herd. Additionally, we don't expect the degree of herding activity to be consistent in industries across countries, but rather we expect various cultural aspects, such as power distance, masculinity, and individualism, to influence which industries exhibit more or less herding in different markets. These factors have a huge impact on how individual and institutional investors implement their strategies and view other investors and should therefore lead to varying degrees of herd mentality in the markets.

We employ a more macro-focused herding approach to empirically evaluate aggregate market data, isolate intentional herding components, and achieve an accurate measure of the biases caused by herd behavior across industries and markets. Several existing studies have used these methodologies to investigate the presence of herd mentality in individual markets around the world, as discussed herein. In the following paper, we will first establish a baseline of herding knowledge through a comprehensive review of existing literature. Then, we will provide a more detailed theoretical framework that is generally accepted in the field, upon which our study will expand. Finally, this paper will detail relevant empirical data sources, methodology, and results of the study that creates evidence for relationships between the degree of herding and industry within and across global markets.

II. Literature Review

The literature on herd behavior can be classified into two different schools of thought (Dang & Lin, 2016). One school of thought is held by researchers who use investor-specific data to detect herd mentality through correlations in trading patterns among specific groups of investors. Others typically utilize aggregate market data to reveal convergence to market consensus due to individual investor behavior. Essentially, some papers solely use more micro-focused data to analyze trends within and between specific investor groups and others supplement this with aggregated macroeconomic data to draw conclusions about herding in the larger market. Additionally, one can generally decompose "herd behavior" into general spurious and intentional components, with information- and reputation-based herding serving as subcategories within these patterns. Spurious or fundamental herding occurs when investors solely employ macroeconomic information to guide investment decisions because they don't know enough about individual firms. This aspect of herding is often thought of as the rational component, especially for less sophisticated investors, when costs of obtaining firm-specific information outweigh the benefits when compared to gains resulting from mimicking other investment strategies (Chiang & Zheng, 2009). Intentional or non-fundamental herding represents the irrational component because investors suppress their private information and turn to others' strategies due to preferences for conformity (Dang & Lin, 2016).

The herding study on the Vietnamese market performed by Dang & Lin (2016) will serve as a good starting point on which to expand for this paper. Dang & Lin (2016) explain that the main theoretical causes of herding include information externalities and cascades, reputation-based herding, and compensation structure. In this study, they use two different methods of return dispersion to separate and quantify herding into spurious and intentional behaviors based on other major studies conducted in the field. The cross-sectional standard deviation (CSSD) and cross-sectional absolute deviation (CSAD), as seen in equations [1] and [2] below, both avoid positive and negative deviations cancelling each other out. As market returns increase, lower or negative CSSD or CSAD values serve as proxies for herd signals in the market because under EMH, the dispersion amongst different returns should increase as market returns increase due to stocks' varying betas. A low CSSD or CSAD measure would directly oppose this notion, signaling lower return dispersions as market returns increase and thus providing evidence of herding.

$$CSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2} \quad [1]$$

$$CSAD = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \quad [2]$$

where R_{it} represents the actual stock return of firm i at time t, R_{mt} is the actual cross-sectional average of all the N stock returns in the market portfolio at time t (Dang & Lin, 2016)

Dang & Lin (2016) formalized several time-series regressions involving CSSD and CSAD, utilizing dummy variables as well as quadratic forms, to capture market extremes and the relationship between return dispersions and market return. We plan on expanding upon these regressions and incorporating additional regressors that capture industry differences as well as cultural factors present in different countries. The main regression of the paper that we will use as a stepping-stone can be seen below in equation [3]. This equation is the simplest of herding proxies. The Dang & Lin (2016) study constructed market portfolios as regressors based on a variety of characteristics depending on what they were looking to test, such as daily price limits or stock volatility.

$$CSAD_t = \gamma_0 + \gamma_1\left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \varepsilon_t \quad [3]$$

where $|R_{m,t}|$ and $R^2_{m,t}$ represent the absolute return and the squared return of an equally weighted market portfolio, which was selected based on a variety of characteristics.

Additionally, the Dang & Lin (2016) paper references an empirical study conducted by Christie & Huang (1995) that we can improve upon. This study posits that individuals are more likely to suppress their own beliefs in favor of market consensus and form herds during periods of unusual market movements. When markets move in an unpredictable and irregular manner, investors doubt their own beliefs or information and simply employ a strategy that mimics other investors whom they trust or have revered reputations in the finance world. Individuals turn to these investing techniques in an attempt to find stability in a abnormal market. They employ a time series regression, shown in equation [4] below, to model equity return dispersions in times of market stress, defined as the lower and upper tails of the return distribution curve.

$$S_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t \quad [4]$$

where S_t represents the dispersion of equity returns at time t (CSAD), D^L_t indicates a lower market extreme (if market return lies in extreme lower tail of distribution on day t), D^U_t indicates an upper market extreme (if market return lies in the upper tail of distribution on day t), and α denotes the average dispersion of the sample excluding the extreme upper and lower tails of the distribution. This regression was tested using both a 1% cutoff for the extreme market tails and a 5% cutoff (Christie & Huang, 1995).

While traditional rational asset pricing models would predict positive betas in this regression, indicating an increase in equity return dispersion as market return increases due to differences in stocks' beta values, the presence of negative betas is consistent with herding inefficiencies (Christie & Huang, 1995). We can build upon this study's industry segments to test the significance of different herding activity across industry sectors within markets and between different countries.

The Chang, Cheng & Khorana (2000) study set out to explore and examine investment behavior in international markets of varying levels of development including the US, Hong Kong, Japan, South Korea, and Taiwan. They aimed to expand upon the work done by Christie & Huang (1995), which utilized CSSD as a proxy of the average propinquity of individual asset returns to the true market average to ultimately determine the presence of herd behavior. Chang, Cheng & Khorana (2000) employed a more powerful approach, utilizing a non-linear regression specification to examine the correlation between equity return dispersions (as measured by CSSD or CSAD) and the overall market return. They also looked to broaden the scope of the study to both developing and developed financial markets. They predicted how factors such as importance of institutional vs. individual investors, quality and quantity of information disclosure, and sophistication of derivatives markets would potentially affect levels of herd behavior. We hope to expand the geographical scope of the study, including data from a more diversified set of international markets, specifically Europe and China.

Furthermore, studies conducted by Tan et al. (2007) and Yao et al. (2013) specifically focus on herding behavior in the Chinese stock market. These studies examine how the reliance on collective, rather than private, information causes prices to deviate from their fundamental value in the Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZES) (Tan et al., 2007). According to Amadeo (2018), the SHSE is China's largest exchange, composed of large, predominantly state-owned companies that fuel China's core economic expansion. The SZES is smaller and trades smaller, more entrepreneurial, privately-owned companies whose growth is important for China's economic reform. Most SHSE investors are pension funds and big banks, while individuals typically invest in stocks listed on the SZES exchange (Amadeo, 2018). These exchanges each offer class A stocks, which can only be traded by individual domestic investors, and class B stocks, which were solely available to foreign investors until February 2001, when they were offered to the Chinese public as well (Yao et al., 2013). Typically, A-share investors have lacked investment knowledge and experience, while B-shares have been dominated by sophisticated institutional investors (Yao et al., 2013). Thus, one would expect a greater degree of herding among class-A stocks than class-B stocks.

Tan et al. (2007) combined the empirical herding approaches introduced by Christie and Huang (1995) and Chang et al. (2000) to detect herding over the entire market return distribution using a non-linear model that relates market return and dispersion. This study focused on data from 1994 to 2003 and only included stocks that were dual-listed as both class A and B. After regressing CSAD on absolute market return and market return squared, Tan et al. (2007) found that dispersion was consistently higher in class-B shares than in class-A, but there was evidence of statistically significant herding in all four markets (classes A and B in SHSE and SZES). Additionally, this study found that the degree of herding activity was not significantly influenced by the Asian financial crisis of 1997 and that there was a higher degree of herd behavior when trading volume was high (Tan et al., 2007). This suggests the potential existence of a positive correlation, or furthermore the possibility of an underlying causal relationship, between market turnover and herding. A further look into these findings could fill an important gap in the existing literature with regard to the relationship between the liquidity of and herding tendencies within a given asset or asset class.

Yao et al. (2013) expanded upon and updated the Tan et al. (2007) work, instead focusing on the period leading up to the global financial crisis, between 1999 and 2008. Additionally, this more recent study improved the explanatory power of the herding regression by changing the squared market return term to the difference between market return and its arithmetic mean squared (Yao et al., 2013). This modification reduced a large portion of multicollinearity between the regressors and thus reduced the standard errors of the regression. Overall, this study also found statistically significant evidence of herding in A and B stocks in the SHSE and SZES and found a greater degree of herding in the largest and smallest stocks, under conditions of declining markets, and found very strong evidence of herding in B markets (Yao et al., 2013). This paper will expand upon existing herding knowledge by incorporating industry buckets and comparing these results across markets within Chinese exchanges as well as cross-culturally to other global markets.

In order to capture varying culture effects across different Asian countries, this paper will also investigate herding in the Indian stock market. Lao and Singh (2011) provide insightful background on the market and compare herding activity in India and the aforementioned Chinese exchanges. Lao and Singh (2011) explain that their large geographical areas and labor forces, supportive government policies, and emergence of middle classes can foster great economic growth. However, this could be coupled with high degrees of herding due to generally less sophisticated investors and cultures that emphasize acquiescing with rather than criticizing the collective.

Additionally, Lao and Singh (2011) ran separate regressions for extreme market conditions, increasing and decreasing markets, and high and low volume trading states. Ultimately, the study found evidence of herding in both markets with a greater degree of herding in China. The degree of Indian market herding increased in extreme market conditions (more so in up than down markets), was greatest in mid-cap stocks, and was independent of trading volume (Lao & Singh, 2011). A similar study conducted by Prosad et al. (2012) attempted to replicate the results for a more recent time period. While this study found little to no evidence of herding, presumably due to the increase in information dissemination and transparency in Indian markets, it comparatively found greater evidence of herding for up markets (Prosad et al., 2012). We hope to expand upon the existing literature on the Indian market and examine how certain cultural factors affect its degree of herding behavior differently than other Asian and global markets.

Lindhe (2012) applied the approach of Chiang and Zheng (2010) to analyze market behavior of four Nordic European market participants (Denmark, Finland, Norway, Sweden). Using Thomson Reuters Datastream, Lindhe (2012) utilized industry indices that captured at least 75% of the total market capitalization of each industry using daily market data spanning from 2001 to 2012. The findings revealed significant evidence of local market-wide herding in Finland during both up and down markets. No evidence was found for local market-wide herding in Denmark, Norway, or Sweden. Evidence, however, suggested that all four countries herded around the European market and that Finland and Sweden herded around the US market. The study indicated the possibility that level of herding across borders was influenced by geographic proximity.

Filip et al. (2015) examined market behavior in five Central and Eastern European countries. They looked at market data in Romania, Poland, Bulgaria, Czech Republic, and Hungary to determine whether herding behavior was present, to explore differences in behavior pre- and post-crises compared to behavior during crises, and to uncover any differences in herding behavior during up markets versus down markets. The authors used a slightly modified version of Chang et al.'s (2000) CSAD approach, adding a regressor to account for the non-linear relationship between stock return and market return. They also introduced a new variable and a lag term to correct for multicollinearity and increase the overall power of their regression.

They found evidence of herding behavior in Romania, Bulgaria, Czech Republic, and Hungary. They also found that herding behavior manifested itself more in down markets than in up markets, while finding no significant difference between herding behavior before and after a given crisis compared to during a crisis.

Chiang (2013) examined market behavior in 10 countries in the Pacific-Basin (PB) region, both developed and emerging, as well as in the US. The developed PB countries included Australia, Hong Kong, Japan, and Singapore, while the emerging PB countries included China, Indonesia, Malaysia, South Korea, Thailand, and Taiwan. He implemented a modified version of Chang, Cheng, and Khorona's (2000) CSAD approach, using the Kalman-filter-based model to account for the time-varying nature of the data. The Kalman-filter-based model uses a series of observations measured over time and formulates estimates of variables that explain underlying relationships within time series data. It does so by creating a joint probability distribution over the variables in each of the specified time frames. Through this approach, Chiang (2013) found evidence of herding in all 10 PB countries, however did not find any evidence of herding in the US. He also found that increased stock returns were correlated with increased herding behavior. Using the VIX as a proxy for volatility, he also found evidence that increases in volatility were correlated with reductions in herding behavior.

BenSaida (2017) examined market behavior in the United States at a sector level, during four different periods of market turmoil. Using a modified CSAD model, with added regressors for trading volume and investor sentiment, he attempted to find evidence of relationships between herding and trading volume and market sentiment. The four periods investigated were the months surrounding black Monday, the dot-com bubble, the market downturn in 2002, and global financial crisis in 2008. The results ultimately showed evidence that the US market only herded during down markets. Trading volume was not found to have any relationship with market herding, however Bensaida (2017) found that market sentiment was correlated with herding behavior in 4 out of the 12 industries.

III. Theoretical Framework

As a relatively new and emerging discipline, behavioral finance is still debated among economic scholars. Specifically, some researchers tend to doubt the existence of herding in financial markets in favor of the classic efficient market hypothesis. While we acknowledge the compelling literature on the benefits and validity of the efficient market hypothesis, there is also a breadth and depth of literature on behavioral finance axioms, such as market herding behavior.

In general, herding is an information inefficiency in markets and thus violates the efficient market hypothesis. Herding can come in the form of investors irrationally ignoring their own analysis and information to conform to market consensus or to maintain their reputation (Lao & Singh, 2011). While herding is an abstract concept and difficult to definitively measure empirically, two proxies of herding behavior have emerged as the standards in the field. CSAD and CSSD are employed in nearly all existing herding literature and they are measures of stock dispersion around the market return. Dang & Lin (2016) summarize several important existing studies that use these proxies and essentially if regressions of various market return variables on CSAD or CSSD have statistically significant negative coefficients for these variables, researchers can reasonably explain this as evidence of herding. This is due to the differentials between individual stock beta values; if the market return increases, individual stock returns are expected to become increasingly dispersed. Thus, dispersion (as measured by CSAD or CSSD) that is decreasing in market return can be attributed to herding behavior in markets as people suppress or don't have access to private information and financial analysis (Dang & Lin, 2016).

In order to study more specific aspects of herding, such as herding response to general market trends and timing, researchers have modified a simple market return regression that utilizes CSAD or CSSD as the dependent variable and market returns as the independent variables. Several studies, such as BenSaida (2017), have incorporated a quadratic market return term in order to capture non-linear changes in herding behavior and a market return term to account for differences in up- and down-markets. Others, such as Yao et al. (2013) have incorporated lag terms to test if past herding behavior affects that of the future.

Overall, we have selected CSAD as the proxy of herding for the regression in this study in order to eliminate outliers in our cross-cultural data sets. In our review of the relevant existing literature, we discovered that CSAD is the standard proxy for herding in studies in this field. Additionally, our available data set allows us to easily calculate CSAD measures across time and these measures allow for the development of robust models. We will further discuss our specific regression and empirical methodology herein, but there are many possibilities to revise this regression based on existing theoretical framework. While we expect the signs of market return coefficients to be negative to indicate herding, we will build on existing assumptions to uncover the magnitude, sign, and statistical significance of various cultural dimensions discussed in the empirical specification section.

IV. Data

The aforementioned studies, as well as several other notable studies in the field, utilize a variety of financial data sources. Among the most popular and seemingly the most accessible is *Datastream International* from the Thomas Reuters Datastream website. The Thomas Reuters Datastream provides over 10 million economic time series data points for 162 markets and is accessible through Ford Library at Duke University's Fuqua School of Business. This dataset has been proven to be the most effective in testing for market herding behavior and has essentially become the standard of researchers in the field. The majority of herding studies utilized some subset of *Datastream International*, thus data from this source has been exploited in studies using both CSAD and CSSD methods and a myriad of regressions to test for herding effects.

Datastream provides its users with a variety of industry indices for many markets around the world from many different sources. We have chosen to utilize the Standard & Poors (S&P) and Financial Times Stock Exchange (FTSE) market indices for the 10 industries specified by the Global Industry Classification Standard (GICS) - Energy, Materials, Industrials, Consumer Staples, Healthcare, Financials, Information Technology, Telecommunications, Utilities, and Real Estate (DST Systems, 2016). We have obtained daily return data for each of these industry indices in the US, China (both the Shanghai and Shenzhen exchanges), Japan, India, Denmark, Germany, and Poland. After collecting the cross-cultural industry data, we rebased each industry market index to 0 in order to standardize all return data regardless of currency and industry scale and make daily increases and decreases in the returns more explicit. We then converted our data to from daily returns to monthly returns. Thus, our cleaned data set comprises standardized monthly returns for these 10 industries in each country as well as a Broad Market index from October 2008 to October 2018.

Figure 1 - Correlations between Broad Market indices of sample countries

	Poland	US	Germany	Denmark	Japan	India	Shenzhen	Shanghai
Poland	1.000							
US	0.628	1.000						
Germany	0.706	0.931	1.000					
Denmark	0.436	0.890	0.910	1.000				
Japan	0.636	0.944	0.961	0.916	1.000			
India	0.589	0.973	0.906	0.897	0.911	1.000		
Shenzhen	0.268	0.617	0.726	0.824	0.736	0.667	1.000	
Shanghai	0.345	0.659	0.758	0.819	0.768	0.713	0.978	1.000

The Broad Market correlations help to provide a general sense of how different countries' markets move with each other and to develop initial intuition about which countries herd around each other. Interestingly, the United States market was highly correlated with markets in Germany, Denmark, Japan, and India and its correlations with Poland and both Chinese markets were much weaker. As expected, the Shanghai and Shenzhen exchanges were very highly correlated and all of the Asian exchanges generally had high correlations. No two exchanges were negatively correlated, but the weakest positive correlations occurred between Poland and the Chinese exchanges. In order to provide more insight into these markets, we have addressed each country in turn, providing Broad Market summary statistics and general market descriptions and trends herein.

In order to build upon existing literature, we segmented Chinese market data into equities listed on the Shanghai exchange and those listed on the Shenzhen exchange, as seen in figures 12 and 13 in the appendix. In the Shanghai market, the Healthcare industry consistently outperformed all other industry sector indices and Energy underperformed other industries. Indices across the market spiked in mid-2015 and overall, the Shanghai industry returns were less volatile than those of the Shenzhen exchange. In the more capricious Shenzhen market, Healthcare has also prevailed in the recent past as the highest returning industry, while Utilities have consistently returned less than other industries. This exchange also saw a large positive spike in mid-2015 due to the devaluation of China's currency at this time, making Chinese goods relatively cheaper in the global market.

Figure 2 - Shanghai Broad Market summary statistics

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Shanghai	118	.0068	.0802	-.3133	.2169

Figure 3 - Shenzhen Broad Market summary statistics

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Shenzhen	118	.0075	.0879	-.3567	.3144

Unfortunately, Datastream did not have data for the Indian industries before September 2011, but the data from then onward show a general upward trend for most industries, as seen in figure 14 in the appendix. Consumer Staples consistently outperformed other industries in the market, whereas Telecommunications was the worst performing industry on the National Stock Exchange (NSE), essentially remaining static over the 7-year period. All other industries have exhibited consistent growth during this time with no major spikes, but the growth rate increased after new financial regulations were instituted in late-2016.

Figure 4 - India Broad Market summary statistics

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
India	84	.0103	.0450	-.1142	.1679

In comparison to the industry returns of other countries, Japan's returns over the past 10 years have been confined to a much smaller range, as seen in figure 15 in the appendix. The Telecommunications industry was the best performing industry, while Utilities has consistently been the worst performing industry, representing the only industry that had returns that decreased since 2008. Furthermore, in early-2013, all industries except for Utilities saw an increase in growth rates that has spurred consistent growth until today.

Figure 5 - Japan Broad Market summary statistics

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Japan	118	.0084	.0480	-.1102	.1612

In the US, over the 10-year time period from October 2008 until October 2018, equities showed an upward trend, as seen in figure 16 in the appendix. The worst performing industry was Energy, increasing a meager 28% over the past decade. The best performing industry was Information Technology, increasing 340% over the same time period. We used the S&P 500 composite as the Broad Market index for the US. The only industry other than Information Technology to beat the Broad Market index over the past decade was Healthcare. Information Technology has shown a regression towards the rest of the industry indices over the past two months, losing 1,000 basis points since September 15th, 2018.

Figure 6 - US Broad Market summary statistics

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
United States	118	.0109	.0401	-.1095	.1402

In Denmark, over the past 10 years only two of the main industry indices managed to beat the 309% Broad Market index return, as seen in figure 17 in the appendix. The Information Technology sector soared past the others, returning over 800%, while the Healthcare sector reported a healthy 480% growth over the same period. The Energy and Utilities sectors reported the worst growth figures, with Energy losing 70% of its value, and Utilities growing a meager 60%. The other six industry indices reported gains between 70% and 210%

Figure 7 - Denmark Broad Market summary statistics

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Denmark	118	.0103	.0442	-.1349	.1271

Similar to the Denmark equity market, only three industry indices managed to outperform the Broad Market index in Poland over the past 10 years, as seen in figure 18 in the appendix. Consumer Staples, Materials, and Energy all experienced gains in excess of the 43% gain brought in by the Broad Market index, with returns of 229%, 107%, and 90% respectively. Of the remaining seven industry indices, only Financials managed to muster a positive return, with Industrials, Healthcare, Information Technology, Telecommunications, Utilities, and Real Estate all experiencing negative returns over the time period. Telecommunications was the worst performing industry index, losing 80% since 2008.

Figure 8 - Poland Broad Market summary statistics

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Poland	118	.0048	.0485	-.1064	.1888

The German industry indices, as seen in figure 19 in the appendix, experienced generally more positive results than Poland over the past 10 years, with only two industry indices experiencing negative returns. Utilities and Energy had the worst performances by far of the 10 industry indices, reporting a 69% and 76% loss, respectively. Only two of the remaining eight indices failed to beat the Broad Market index, those being Financials and Telecommunications, which still managed to record positive returns. Information Technology and Real Estate had the highest reported gains since 2008, gaining 239% and 211% respectively. The Broad Market index return a modest 63% over the 10-year period.

Figure 9 - Germany Broad Market summary statistics

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Germany	118	.0065	.0499	-.1659	.1476

Future investigations can try to incorporate as many countries into this dataset as possible. They can cross-reference Hofstede's database with robust data that can be pulled from Datastream to broaden the global dataset. This will allow studies to capture more variation between countries and cultures and ultimately improve the explanatory power of the regression.

V. Empirical Specification

The empirical methodology of this paper essentially rests on the measurement and relationship of two abstract concepts – herding and culture. Given recent literature, our methodology will quantify the degree of herding in a market as well as different cultural dimensions in order to assess whether or not culture impacts financial herding and if this effect is more pronounced in certain industries.

In order to empirically measure differences in herding between industries within and across markets, our methodology will build upon widely accepted regressions from existing literature. We decided to regress CSAD on various market return variables, as well as regressors that encapsulate different industries and the culture aspects of different markets.

In terms of quantifying different cultural aspects, two main methodologies dominate the existing literature - Geert Hofstede's cultural insight model and the Global Leadership and Organizational Behavior Effectiveness (GLOBE) model. Hofstede defines culture as "the collective programming of the mind distinguishing the members of one group or category of people from others" and posited that a culture is formed and reinforced through outside influences, ecological factors, societal norms, and institutions (Hofstede, 1980). In order to assess and compare cultures, Hofstede's model divided a nation's culture into six dimensions: power distance index (PDI), individualism versus collectivism (IDV), masculinity versus femininity (MAS), uncertainty avoidance index (UAI), long-term orientation versus short-term normative orientation (LTO), and indulgence versus restraint (IND), according to Hofstede Insights. The values for each of these dimensions have essentially no interpretive meaning when taken alone, but can provide great insight into cultural differences when compared to values from other countries.

According to Hofstede's Insights, the power distance index illuminates how a society handles or accepts inequalities and hierarchy, while IDV is increasing in individualism (i.e. if one expects to solely care for oneself and one's family). A more "masculine" culture values achievement, heroism, materialism, and competition more than cooperation, modesty, and quality of life, as valued in a more "feminine" culture. The UAI dimension reflects people's comfort with ambiguity about the future and relatively higher values indicate societies that are more rigid in behavior, unaccepting of "unorthodox behavior and ideas." Lower scores in the LTO dimension reflect a society's preference for tradition, whereas higher values reflect willingness to encourage modern techniques to prepare for the future. Finally, more indulgent societies will allow more gratification of human drives related to enjoying life and more restrained societies will suppress or regulate this gratification social norms. Each cultural dimension is scored from 0 to 100 and have proved useful in a myriad of contexts, including international negotiation, management, marketing, and communication.

In response to Hofstede's six-dimensional model, another notable cultural model has gained traction in the field. GLOBE researchers have sought to quantify cultural aspects in 62 different societies spread across the world through two groundbreaking studies. The 2004 study aggregated survey-based information from over 17,000 middle managers in over 950 organizations. This study was the largest of its kind to that point, looking to provide color on how leadership and culture varied by society. In 2014, GLOBE shifted their focus to CEO's and other Top Management Team members of a variety of companies across a broad geographic scope. Researchers looked to uncover whether a given society's culture influences leadership behaviors, as well as whether leadership success depends on leadership matching societal expectations. Data was collected from over 1,000 CEOs and over 5,000 senior executives to ultimately allow researchers to quantify cultural factors across 24 nations. The GLOBE study specifies nine dimensions upon which a cultural may be quantified: uncertainty avoidance, future orientation, power distance, institutional collectivism, humane orientation, performance orientation, in-group collectivism, gender egalitarianism, and assertiveness.

The GLOBE studies look more to distinguish between values and practice, while the Hofstede study serves more as an analytical model of nations on both societal and organizational levels. According to Earley (2006), the GLOBE method exemplifies a hybrid research design, in which both gestalt and reduced perspectives are employed to examine a cultural system as intact as well as analyze its constituent parts. On the other hand, Hofstede's approach would be more similar to a unitary form study in which researchers understand a cultural group on its own terms intermixed with aspects of the gestalt approach (Earley, 2006). While both methods have their own flaws, the Hofstede approach seemed more suitable for this paper due to the general acceptance of this model in many papers and the accessibility of the country comparison data in each cultural dimension. Given the relatively short time frame of our investigation, when compared to gradual cultural changes, we initially believed the current Hofstede cultural measures would be sufficient in estimating the cultural dimensions of each country over the course of our time-series regression.

Given the best practices seen throughout the herding literature, as well as the Hofstede six-dimension cultural model, we refined our regression, as seen in equation [5] below:

$$CSAD_{i,t} = \beta_0 + \beta_1 R_{m,i,t} + \beta_2 \left| R_{m,i,t} \right| + \beta_3 R^2_{m,i,t} + \sum_{c=1}^{7} \beta_c D_c + \sum_{I=11}^{10} \beta_I D_I + \sum_{j=1}^{6} \beta_{j,i,t} CULT_{j,t} + \varepsilon_{i,t} \quad [5]$$

where $R_{m,i,t}$ represents a general market return for a given month, $|R_{m,i,t}|$ represents the absolute value of this market return, $R^2_{m,i,t}$ represents this market return squared, D_c is a dummy variable used to represent each of the eight countries in our sample, D_I is a dummy variable used to represent each of the 11 industries in our sample, and $CULT_{j,t}$ represents each of the six dimensions of Hofstede's cultural measures, as scored from 0 to 100.

In this equation, CSAD is used as a proxy to indicate the degree of market herding and is inversely correlated with the degree of herd behavior. Under EMH, stock return dispersion is expected to increase with market return. Thus, a lower measure of CSAD would be indicative of a higher degree of herding. The absolute value market return and the squared market return terms account for the linear relationship between return dispersion and mean return while capturing possible non-linearities (i.e. differences between up and down markets). The market return variable incorporates the general positive or negative sign of the market return, allowing for differential effects of up- and down-markets to impact CSAD. We expect β1, β2, and β3 to be negative, reflecting a general divergence from EMH and tendency of investors to herd and this tendency to be greater in up markets than down markets. Ideally, we would have liked to include a regressor representing the trading volume in an exchange at a given time, but a lack of data available prevented us from incorporating this at this juncture.

Each of the series of dummy variables, D_c and D_I, will allow us to analyze differences across countries and industries, respectively. The sum of cultural variables $CULT_j$, would have afforded us the opportunity to capture the cultural nuances of a given country as specified by Hofstede's six cultural dimensions. Each variable represented the given country's score from 0 to 100 in one of these cultural dimensions - PDI, IDV, MAS, UAI, LTO, and IND. We planned on comparing the magnitude, sign, and significance of the coefficients of these cultural variables across industry and country to determine the role each of them plays in affecting the degree of herding behavior.

In our continued efforts to refine our regression, we incorporated interaction terms between market return variables and cultural and/or country variables in order to capture the idiosyncratic effects each culture and industry has on herding. Moreover, when incorporating Hofstede's cultural dimensions into our analysis, we encountered several problems. Most notably, these aspects of a country's culture were highly correlated with country dummy variables, leading to multicollinearity in our regression. Given our small sample of countries, the variability of the values of the five cultural dimensions across the seven countries in this study was too minimal to produce any statistically significant results. Furthermore, we did not have access to time series data of Hofstede's cultural measures, but assuming that a country's culture is generally not very capricious and these measures wouldn't change much over time, the dimensions could be captured using a fixed effects panel series regression. Thus, we decided to pursue our investigation without implementing Hofstede's cultural dimensions, but future research with a larger sample size of countries could explore this avenue for information on more specific influences on cross-cultural herding. Finally, we decided to eliminate the squared returns term from our regression – this term introduced multicollinearity problems with absolute returns and had consistently produced statistically insignificant results.

VI. Results

Cross-Country Herding Findings

When starting to investigate the presence of herding in a variety of global markets, we wanted to first detect any herding proxy in the collated markets. A panel regression of CSAD on returns, squared returns, and absolute returns while grouping variables by country revealed a slightly negative return coefficient that was statistically significant at the 1% level. Thus, one can reasonably conclude that there is some degree of herding in the markets we chose to include in this study.

Then, we continued to research the degree of herding on a country and industry level, while increasing the granularity of our analyses. We ran a fixed-effects panel regression of CSAD on returns, absolute returns, squared returns, and country dummy variables while grouping variables by industry, as seen in equation [6] below. several countries showed a statistically significant degree of herding.

$$CSAD_{i,t} = \beta_0 + \beta_1 R_{m,i,t} + \beta_2 \left| R_{m,i,t} \right| + \beta_3 R_{m,i,t}^2 + \sum_{c=1}^{7} \beta_c D_c + \varepsilon_{i,t} \quad [6]$$

where $R_{m,i,t}$ represents the market return in a given country for a given month, $|R_{m,i,t}|$ represents the absolute value of this market return, $R^2_{m,i,t}$ represents this market return squared, and D_c is a dummy variable used to represent each of the eight countries in our sample.

However, the squared market return term proved to be statistically insignificant to a great degree, so we removed it from the regression and subsequently found several countries that showed a statistically significant degree of herding, as seen in the table below. As previously mentioned, a lower or negative measure of CSAD indicates the presence of herding behavior in a market, thus regressors with negative coefficients reflect market herding.

Figure 10 - Cross-Country Stata Output

Regressor	Coefficient	Standard Error	t-value	P > l t l
Return	-0.0084889	0.0029241	-2.9	0.004
Absolute Return	0.1817686	0.0042493	42.78	0.000
Germany	-0.0104461	0.0008090	-12.91	0.000
India	-0.0045735	0.0008836	-5.18	0.000
Japan	-0.0169625	0.0008093	-20.96	0.000
Poland	-0.00490029	0.0008145	-6.02	0.000
Shanghai	0.0025135	0.0008174	3.07	0.002
Shenzhen	0.002602	0.0008352	3.12	0.002
USA	-0.0191318	0.0008109	-23.59	0.000
Denmark	0.0377344	0.0006224	60.62	0.000

All return and country coefficients proved to be statistically significant at the 1% level; however, coefficients representing the market dispersion effects in Denmark and both the Shanghai and Shenzhen exchanges were positive. This indicates that these markets, when evaluated as composites, fail to show herding behavior as approximated by the returns on CSAD. But markets in Germany, India, Japan, Poland, and the United States all demonstrated varying degrees of statistically significant herding behavior. Surprisingly, the magnitude of herding in the US was the greatest, followed by Japan and then Germany. We therefore hypothesized that these markets can see fewer contrarian investors or even a greater percentage of less savvy or sophisticated investors. Alternatively, this pattern of activity could be due to any number of factors, including sheer volume of trading, access to financial markets, and the degree of news dissemination in these countries, when compared to others.

Moreover, we were able to parse out interesting patterns when segmenting this study's country sample in different ways. We first grouped the country variables into a Western group and a non-Western group and ran a regression. In general, Western countries exhibited a greater degree of herding than non-Western countries, as indicated by negative return coefficients that were larger in magnitude. Additionally, we found that a country's income level was directly correlated with its level of herding and that countries with lower levels of income, on average, actually exhibited positive return coefficients, which indicate a lack of herding in the market.

We also found that countries that have more defined and ubiquitous financial laws and bank regulation, measured by the number of regulations and intensity of restrictions, displayed a greater degree of herding in the markets. These results could be related to the inherent cultures that develop in countries with each of these characteristics or other such factors as market and information accessibility and sophistication of average investors. This could also be a case of reverse causality, where the culture already exists in a given country, and naturally leads to a less regulated financial system.

Next, we grouped the country variables into low, medium, and high smartphone penetration groups. We defined low smartphone penetration as a value below 33%, medium as a value between 34-66%, and high as a value over 67%. We discovered that smartphone penetration in a given country had a weak, but positive correlation with degree of herding as measured by CSAD. We expected this relationship to be stronger, our line of thinking being that herding behavior is proliferated by easier access to centralized news sources, in this case smartphones. Thus, we figured higher smartphone penetration values would be correlated with a greater degree of herding, given that more people would be consuming the same news about markets, and therefore would be more likely to make similar investment decisions. We also acknowledged that smartphone penetration might not be the best proxy for mobile news consumption, and might be a more direct proxy for individual wealth, which in itself could have an interesting relationship with herding. Nevertheless, Denmark was a clear outlier, having a smartphone penetration of just over 80%, the highest of the seven countries, but showing the lowest degree of herding. India fell more in line with expectations, having a smartphone penetration rate of 27.4% and being one of the lesser exhibitors of herding market behavior (Pariona, 2017).

The last grouping we explored was separating the seven countries based on the foundation of their legal system to see if we could uncover any sort of underlying relationship. All seven countries are governed by legal systems, that at their core are considered to be either civil law systems, commonly referred to as French or Roman law systems, and common law systems, often referred to as English law systems. All seven countries besides for the US employ some variation of civil law, so this grouping was ultimately not useful given our data set. A deeper dive into this subject would be interesting in a future study that included a broader data set that included more nations of each legal origin.

Cross-Industry Herding Findings

In order to further our analysis, we ran a similar regression, but compared industries rather than countries and instead grouped the data by country, as seen in equation [7] below.

$$CSAD_{i,t} = \beta_0 + \beta_1 R_{m,i,t} + \beta_2 \left| R_{m,i,t} \right| + \sum_{I=1}^{10} \beta_I D_I + \varepsilon_{i,t} \quad [7]$$

where $R_{m,i,t}$ represents the average return in a given industry across countries for a given month, $|R_{m,i,t}|$ represents the absolute value of this average return, and D_I is a dummy variable used to represent each of the 11 industries in our sample.

Similar to our country regression, negative coefficients of the regressors will indicate herding behavior in a given industry because this would cause a lower or negative measure of return dispersion. The results of this regression, displayed in figure 11, proved fruitful for our analysis.

Figure 11 - Cross-Industry Stata Output

Regressor	Coefficient	Standard Error	t-value	P > l t l
Return	-0.0084889	0.0002941	-2.9	0.004
Absolute Return	0.1817686	0.0042493	42.78	0.000
Consumer Staples	-0.0000295	0.0009431	-0.03	0.975
Energy	-0.0039795	0.0009595	-4.15	0.000
Financials	-0.0024736	0.0009449	-2.62	0.009
Healthcare	-0.0004734	0.0009432	-0.5	0.616
Industrials	-0.0010353	0.0009434	-1.1	0.273
Materials	-0.0025214	0.0009828	-2.57	0.010
Real Estate	-0.0023168	0.0009447	-2.45	0.014
Info Technology	-0.0017173	0.0009582	-1.79	0.073
Telecommunications	-0.0022349	0.0009461	-2.36	0.018
Utilities	-0.0018319	0.0009718	-1.89	0.059
Broad Market	0.0327404	0.0006900	47.45	0.000

We found significant evidence of herding in most of the industries included in our study. The Energy, Financials, and Materials industries were statistically significant at the 1% level, while Real Estate and Telecommunications were statistically significant at the 5% level. The two additional industries that showed significance of herding at the 10% significance were Information Technology and Utilities. Energy exhibited the greatest evidence of herding, with a coefficient of -.004, while Consumer Staples showed the least evidence of herding with a coefficient that was only slightly negative. At first, these results were surprising – we had anticipated to find the greatest degree of herding in Information Technology or Consumer Staples industries as companies in these sectors are very esoteric and prevalent in the news, respectively. However, within the past decade the Energy sector has been a hot topic and the average investor does not have a great source of knowledge in this industry, so it makes sense that investors investing in Energy stocks herded the most. Since information about Consumer Staples companies is so ubiquitous, investors could have access to lots of data and make more informed, individual investment decisions in this sector, thus leading to a lesser degree of herding than other industries. Financials displayed the second highest degree of herding, which is not extremely surprising given the news coverage that publicly traded financial institutions have received world-wide in recent years. Herding is commonly attributed to individuals reacting the same way to the same information distributed in the news. Along a similar line of thought, it is not surprising that Information Technology and Telecommunications exhibited evidence of herding given how high profile and widely covered many Information Technology and Telecommunications companies have been in the past few years.

Country / Industry Interaction Herding Findings

In order to make our study more robust and investigate our main question regarding cross-cultural market herding throughout different industries, we produced a panel series regression that incorporates several interaction terms between country / industry dummy variables and return variables. This regression can be seen in equation [8] below:

$$CSAD_{i,t} = \beta_0 + \beta_1 R_{m,t} + \beta_2 \left|R_{m,t}\right| + \sum_{c=1}^{7} \beta_c D_c + \sum_{I=1}^{10} \beta_I D_I + \sum_{c=1}^{7} \beta_c R_{c,t} D_c + \sum_{I=1}^{10} \beta_I R_{I,t} D_I + \varepsilon_{i,t} \quad [8]$$

where $R_{m,i,t}$ represents a general market return for a given month, $|R_{m,i,t}|$ represents the absolute value of this market return, D_c is a dummy variable used to represent each of the eight countries in our sample, D_I is a dummy variable used to represent each of the 11 industries in our sample, $R_{c,t}$ represents the monthly market returns within a specific country, and $R_{I,t}$ represents the monthly returns within a specific industry.

After running this regression, we found that most beta coefficients were negative, indicating a lower CSAD measure as returns increase and thus indicating herding in the market, as seen in figure 12 below.

Figure 12 - Country / Industry Interaction Stata Output

Regressor	Coefficient	Standard Error	t-value	P > l t l
Absolute Return	0.1829759	0.0042908	42.46	0.000
Return	0.0151149	0.0009546	0.012	0.903
Consumer Staples	0.0001162	0.0009637	-4.04	0.000
Energy	-0.0038897	0.0009507	-2.52	0.012
Financials	-0.0023974	0.0009516	-0.34	0.733
Healthcare	-0.0003244	0.0009497	-1.07	0.284
Industrials	-0.0010182	0.0009894	-2.54	0.011
Materials	-0.0025145	0.0009505	-2.35	0.019
Real Estate	-0.0022303	0.0009683	-1.58	0.114
Information Technology	-0.0015294	0.0009502	-2.24	0.025
Telecommunications	-0.0021283	0.0009754	-1.81	0.071
Utilities	-0.0017618	0.0128265	1.09	0.274
Consumer*Return	-0.0176595	0.0166814	-1.06	0.290
Energy*Return	-0.0179574	0.0142567	-1.26	0.208
Financials*Return	-0.0109700	0.0143375	-0.77	0.444
Healthcare*Return	-0.0144328	0.0159258	-0.91	0.365
Industrials*Return	-0.0012786	0.0154747	-0.08	0.934
Materials*Return	-0.0057211	0.0152539	-0.38	0.708
Real Estate*Return	-0.0097992	0.0143623	-0.68	0.495
Info Technology*Return	-0.0212676	0.0153236	-1.39	0.165
Telecommunications*Return	0.0078854	0.0140977	0.56	0.576
Utilities*Return	-0.0099437	0.0154042	-0.65	0.519
Germany	-0.0103589	0.0008129	-12.74	0.000
India	-0.0044351	0.0008882	-4.99	0.000
Japan	-0.0168864	0.0008149	-20.72	0.000
Poland	-0.0048636	0.0008172	-5.95	0.000

Shanghai	0.0027117	0.0008206	3.3	0.001
Shenzhen	0.0028718	0.0008387	3.42	0.001
USA	-0.0190956	0.0008204	-23.28	0.000
Germany*Return	-0.011256	0.0115765	-0.97	0.331
India*Return	-0.0156364	0.0126899	-1.23	0.218
Japan*Return	-0.0101374	0.0122476	-0.83	0.408
Poland*Return	0.0144459	0.0116255	1.24	0.214
Shanghai*Return	-0.0286807	0.0202836	-2.82	0.005
Shenzhen*Return	-0.0397549	0.0102712	-3.87	0.000
USA*Return	-0.0051817	0.0132594	-0.39	0.696
Denmark	0.0391544	0.0008852	44.23	0.000

These coefficients varied a great deal in magnitude, but most of them proved to not be statistically significant. All of the country dummy coefficients were significant at the 1% level and highlighted the presence of herding behavior in all countries except the Denmark and the China exchanges. This was helpful because it reinforced the findings from our initial regression that solely included country dummy variables and return metrics. The industry variable coefficients told a similar story - while most of them were negative, not all were statistically significant. The Energy sector had the most statistically significant indication of herding, holding up at the 1% significance level. Additionally, the Financials, Materials, Real Estate, Telecommunications, and Utilities industries all had negative coefficients that were significant at the 5% level with Financials indicating the greatest degree of herding.

The interaction terms in this regression equation are key to the analysis of the findings of our study. The coefficients of the interaction terms represent additional effects of returns in specific countries and industries on our CSAD measure of market dispersion. Additionally, using these interactions, we were able to parse out and compare the specific herding behavior between different industries in different countries. All of the coefficients of the interactions between industries and returns indicated additional herding behavior based on their negative signs (other than the slightly positive coefficient for the Telecommunications term). This relationship was greatest in magnitude in the interaction between return and the Information Technology, Energy, and Consumer Staples industries, as we initially suspected in our hypotheses. However, none of these coefficients proved statistically significant even at the 10% level, so further investigation is required to validate the conclusions drawn from these interaction terms.

We saw a similar pattern when evaluating the coefficients of the interactions between countries and returns. However, the relationships between returns and both the Shanghai and Shenzhen exchanges (interaction terms involving Shanghai and Shenzhen) were statistically significant at the 1% level and had negative coefficients. These negative coefficients are much larger than the positive coefficients of the country dummy variables terms (absolute differences of .026 and .037 for the Shanghai and Shenzhen exchanges, respectively). Therefore, the net effect of these interaction terms indicates a significant level of herding in the Shanghai and Shenzhen markets that exceeds that of many other countries in this study. Using the regression solely involving country dummies (equation [6] shown above), we had concluded a lack of herding in these two markets, which contradicted our hypotheses. However, this more robust regression provides evidence of the presence of herding in these markets and indicates that the degree of herding is greater than that of the other countries in the sample. Overall, the inclusion of interaction terms in our regression provided valuable insights, but there are several avenues of future research that can improve on the study even further and boost the statistical validity of many of the metrics.

Contributions & Implications

Our study contributes valuable insights to the existing and rapidly growing literature on herd behavior in financial markets. Herd behavior is becoming an increasingly important building block in the effort to try to understand global financial anomalies, and more broadly, the overall narrative that is behavioral finance. In this study, we set out to fill a gap that we discovered in the literature by implementing both a cross-cultural (cross-country) and cross-industry approach to market herding. While several other studies utilized similar methods to investigate herding, they focused their work on specific market conditions (up vs down markets, for example) or herd behavior within a single market. We used these studies to help inform our interdisciplinary approach and discovered evidence of herding in multiple countries and industries throughout the course of our study. The evidence found elevates the investigation of herding behavior in financial markets to a new level and provides for a new foundation upon which future research can be built.

Ultimately, our results stand to help explain certain occurrences in financial markets, such as the dot-com bubble of 2001, which cannot be explained by traditional economic theory. We found evidence of herding in all of the countries and most of the industries in our sample and, importantly, the degree of this herding behavior varied between countries and industries. Herd mentality in the markets is not a “one size fits all” theory; the insights we provide into how herding varies in different markets and market sectors can better inform models and change the context in which we investigate the phenomenon of herding in the future. While we do not provide the absolute explanation for herding variations, we believe we contribute sufficiently, bringing future researchers one step closer to being able to explain such events in scientific terms.

There are several important implications that can be drawn from the methodology and conclusions of this study. It is clear that given our data set and herding proxies, there is clear evidence present in many global exchanges and industry classes that consistently oppose EMH. Over the past decades there have been a multitude of studies, whether they be lab studies or financial crises that serve as case studies, that build a strong case against EMH. The "perfectly rational individual," a multitude of which EMH assumes every economy is composed, is beginning to seem further and further from reality. Investors are assumed to make decisions based on their own individual judgements, the opposite of which is true when herding is present. While this paper does not disprove EMH, it does contribute evidence to the growing case against traditional economic theory.

Given the findings from this paper, and the numerous events and papers over the past few decades, it appears as though there are three courses of action moving forward. The first is to maintain our current economic models and theories. However, these seem outdated and the accompanying assumptions of EMH have been called into question by many scholars. Additionally, actions and policies based on these assertions have allowed several financial crises to cripple financial systems and economies worldwide.

The second course of action is to engineer forms of policy aimed at guiding individuals' behaviors towards that of "rational individuals," and keep a close watch on large financial institutions capable of forming the bubbles that ultimately burst and cause financial crises. There are a few potential issues with this plan. The first is that in order to curb herding behavior, and other "irrational" behaviors, it is necessary to first understand it, which on a holistic level we do not. Individuals seem to be increasingly irrational, consistently making decisions that go against what is defined as and widely considered to be rational. Even if we are able to develop a deep and robust understanding of human decision making and subsequently implement policies that look to steer individuals towards "rationality," they would likely be difficult to enforce. Law enforcement agencies have enough difficulty as it is policing the financial giants of the world. Expanding the scope to all individuals and tasking these agencies with enforcing even more rules does not appear to be the most effective course of action.

The third option is to revise, or potentially overhaul, the core model of markets, integrating new data and the growing understanding of human behavior. EMH was originally proposed in 1912 by Bachelier, and in the past century there have been numerous breakthroughs in nearly every field of science. Behavioral finance is on the frontier of bridging fundamental economics with modern psychology. It continues to grow and gain traction as a field, filling in valuable gaps in knowledge that previously stumped many academics. Behavioral finance provides the possibility to integrate the wealth of knowledge gathered over the years on human behavior with the concrete and established principles of economics and finance. By increasing our overall understanding of how individuals behave, we will be able to change our perspective on economics and markets and ultimately give EMH the makeover it appears it may soon need. It is becoming clear that humans are not fully "rational" by the current definition. With this in mind, we should either modify the definition or modify the model, but refuting the growing mound of evidence against EMH threatens to grow the existing collection of problems, rather than look to begin solving them.

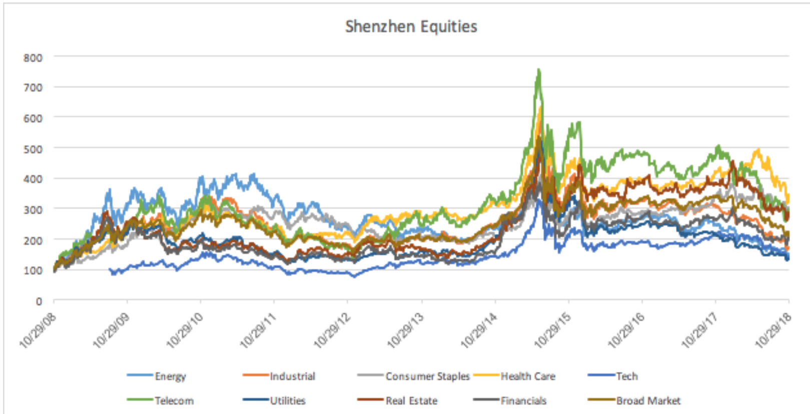
Future Research

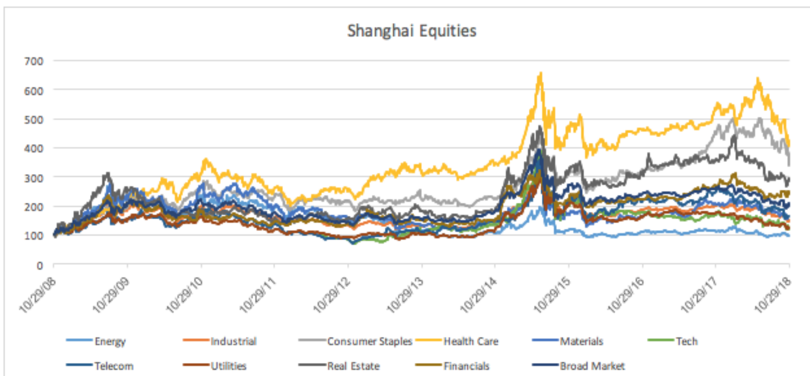
There is much still to be done in the lines of behavioral finance, psychology, and economics before we can be confident that we understand humans and the decisions we make in the marketplace. With regard to herding specifically, there are still many factors to be considered that might explain how and why some markets herd more than others. One line that could be explored further is how consumption of news correlates with and ultimately causes individuals to herd. We attempted to uncover such a relationship by looking at smartphone penetration, but this analysis was likely far too vague. A further study might analyze the number of views on articles and videos that mention certain companies and monitor how their stock price changes in the time following such news releases.

There are multiple other avenues that could also be explored. There are few studies that examine the correlation that market turnover, as proxied by trading volume, has with the degree of herding behavior in markets. A deeper dive into this relationship has the potential to uncover new knowledge on the subject. An investigation into the ratio of investments held by individuals as opposed to 401k's and pension funds could uncover another factor that impacts degree of herding. On a similar line of reasoning, a future study that explored the presence of hedge funds and their equity holdings and how that played into degree of herding would have the potential to uncover another important factor.

Investigating and understand herding is a single, yet important building block in the grand scheme of advancing behavioral finance as a whole. Every study and paper contributes to the newfound science and inches us closer to fully understanding why individuals act the way they do under various circumstances. We have only begun to scratch the surface, and there is undoubtedly many more advancements to come in the following years.

VII. Appendix





Figures 12 and 13 - Shanghai and Shenzhen equity returns segmented by industry.

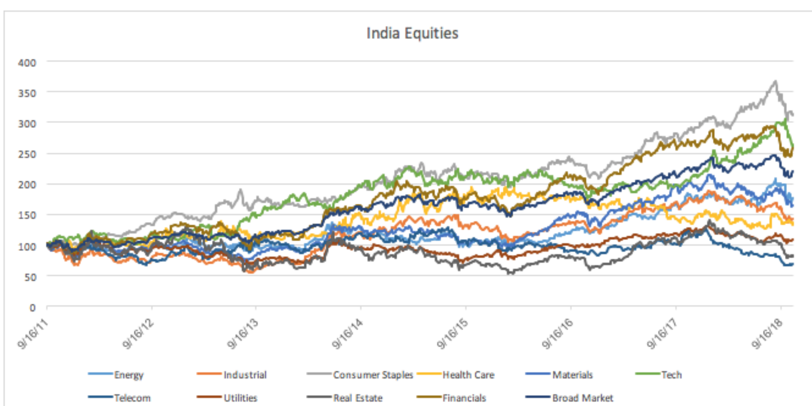


Figure 14 - India equity returns segmented by industry.

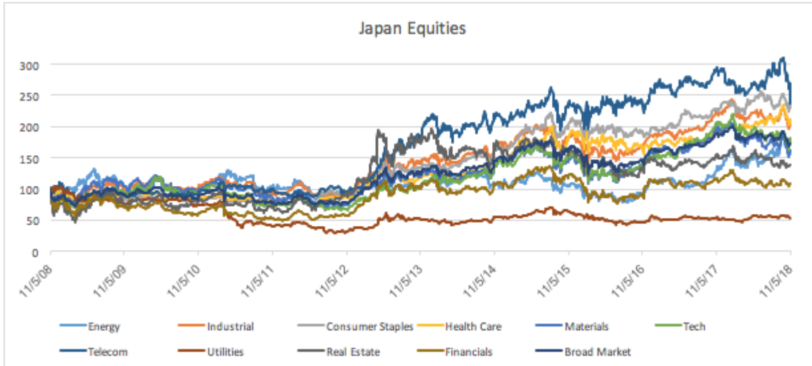


Figure 15 - Japan equity returns segmented by industry.

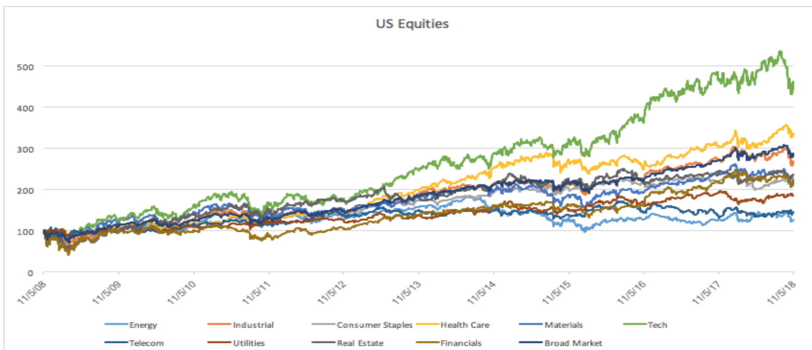


Figure 16 - US equity returns segmented by industry.

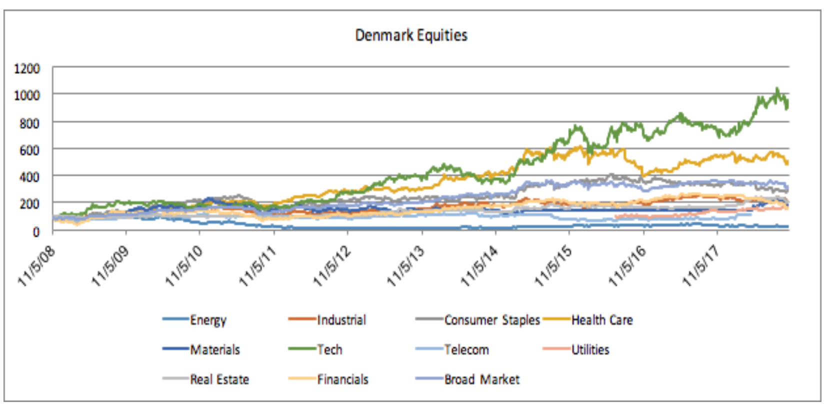


Figure 17 - Denmark equity returns segmented by industry.

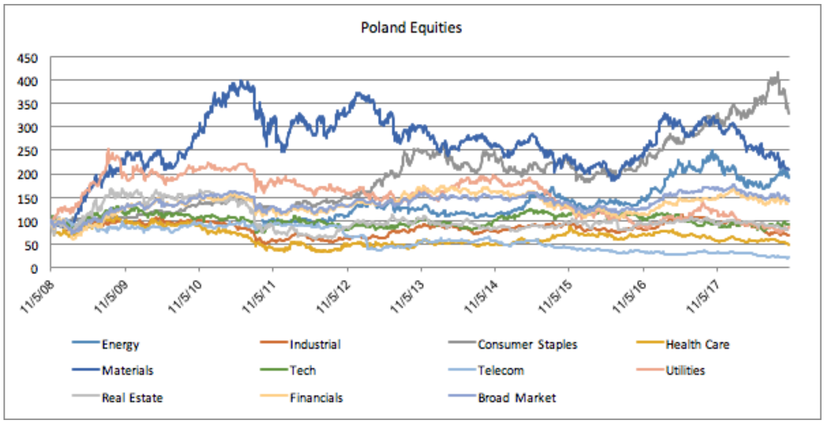


Figure 18 - Poland equity returns segmented by industry.

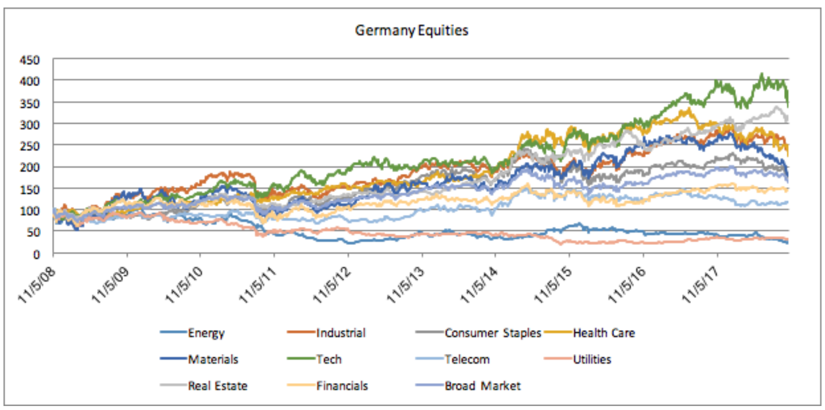


Figure 19 - Germany equity returns segmented by industry.

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