TWO ESSAYS ON HERDING

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ABSTRACT

TWO ESSAYS ON HERDING

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This thesis examines the herding behavior within the banking and the mutual fund industries. It highlights the existence of herding, its potential reasons, and its effects on the industry dynamics.

A review of the herding behavior literature is provided in the first chapter. In the second chapter, we analyze herding in lending decisions. Using loan data from 30 commercial banks, the presence of herding in cash credit lending decisions is investigated first, followed by the effects of herding on bank performance and loan quality. We further examine whether the worldwide liquidity increase that accompanied credit growth in the 2000s and the regulator's policy responses have an impact on banks' collective lending decisions. We show that herding has a considerable negative impact on bank profitability from 2002Q4 to 2012Q2, and there is insufficient evidence to support a link between loan herding and credit risk. We document that a significant portion of the variance in herding behavior is explained by the increase in global liquidity and corresponding macroprudential policy applications during the 2000s. In the third chapter, we investigate industry herding by mutual funds in Turkey and its effects on industry valuations. Using monthly portfolio holdings of 37 stock-weighted mutual funds traded in BIST, we employ herding measures of Lakonishok et al. (1992, hereafter LSV) and Sias (2004). We find significant industry herding with the LSV measure and no overall industry herding with the Sias measure. We also document that industry herding is not one of the factors that destabilizes industry return.

Keywords: loan herding, mutual fund herding, macroprudential policies, industry values, global liquidity

ÖZ

SÜRÜ DAVRANIŞI ÜZERİNE İKİ ÇALIŞMA

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Bu tezde bankacılık ve yatırım fonu sektörlerindeki sürü davranışı incelenmektedir. Sürü davranışının varlığı, potansiyel sebepleri ve sektör dinamikleri üzerindeki etkileri vurgulanmaktadır.

Tezin ilk bölümünde sürü davranışı ile ilgili literatür araştırması derlenmiştir. İkinci bölümde, bankaların kredi verme kararlarındaki sürü davranışı analiz edilmektedir. 30 ticari bankanın kredi verileri kullanılarak, önce nakdi kredi verme kararlarındaki sürü davranışı sorgulanmış, ardından sürü davranışının banka performansı ve kredi kalitesi üzerindeki etkileri incelenmiştir. Ayrıca, 2000'lerde kredi büyümesine eşlik eden global düzeydeki likidite artışı ile düzenleyici otoritenin politika karşılıklarının, bankaların kolektif kredi verme kararları üzerindeki etkileri incelenmiştir. Bulgularımız, sürü davranışının 2002Ç4'ten 2012Ç2'ye kadar olan dönemde, banka kârlılığı üzerinde önemli bir ölçüde olumsuz etkiye neden olduğunu ve kredi verme kararlarındaki sürü davranışı ile kredi riski arasında bir ilişkiden bahsedebilmek için ise yeterli kanıta sahip olmadığımızı göstermiştir. Buna ek olarak, sürü davranışındaki değişkenliğin 2000'li yıllarda küresel likiditedeki artış ve buna karşılık uygulamaya alınan makro ihtiyati politika uygulamaları ile önemli ölçüde açıklanabildiği gösterilmiştir. Üçüncü bölümde, Türkiye'de işlem gören yatırım fonlarının belirli endüstri alanlarında sürü davranışı gösterip göstermedikleri ve sürü davranışının sektör değerlemelerinde önemli bir etkisinin olup olmadığı ortaya konulmaktadır. BİST'te işlem gören 37 hisse senedi ağırlıklı yatırım fonunun aylık portföy varlıklarının bulunduğu örneklem kullanılarak Lakonishok vd. (1992, bundan sonra LSV olarak anılacaktır) ile Sias (2004)'ın önerdiği sürü davranışı ölçüm yöntemleri uygulanmıştır. Analizler sonucunda LSV yöntemi ile istatistiksel açıdan anlamlı bir endüstri özelinde sürü davranışı bulunurken, Sias yöntemi ile endüstri özelinde bir sürü davranışı bulunamamıştır. Ayrıca, endüstri özelindeki sürü davranışının, endüstri getirisini istikrarsızlaştıran bir faktör olduğunu gösteren herhangi bir kanıt bulunamamıştır.

Anahtar Kelimeler: kredilerde sürü davranışı, yatırım fonlarında sürü davranışı, makro ihtiyati politikalar, endüstri değerleri, küresel likidite

To my dad, mum, and the brown-eyed girl

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LIST OF ABBREVIATIONS

AMEX	American Stock Exchange (today, known as NYSE American)
B/M	Book-to-Market
BIST	Borsa İstanbul
BRSA	Banking Regulation and Supervision Agency
CAPM	Capital Asset Pricing Model
CBRT	Central Bank of the Republic of Turkey
CFO	Chief Financial Officer
CFTC	Commodity Futures Trading Commission
CIR	Cost-to-Income Ratio
CR	Current Ratio
CRn	n-firm Concentration Ratio
CRSP	Center of Research in Security Prices
CSAD	Cross-Sectional Absolute Deviation
DB	Defined Benefit
EA	Equity-to-Assets
EPS	Earnings per Share
FDI	Foreign Direct Investments
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
HHI	Herfindahl-Hirschman Index
I/B/E/S	Institutional Brokers' Estimate System
IMF	International Money Fund
KAP	Kamuyu Aydınlatma Platformu (Public Disclosure Platform)
LTRS	Large Trader Reporting System
NASDAQ	National Association of Securities Dealers Automated Quotations

NII	Non-Interest Income
NPL	Non-Performing Loans
NYSE	New York Stock Exchange
PE	Price-to-Earnings
ROA	Return on Assets
ROE	Return on Equity
SCP	Structure-Conduct-Performance Hypothesis
SSIA	State Street Investment Analytics
TEJ	Taiwan Economic Journal

CHAPTER 1

LITERATURE REVIEW

1.1 Theoretical Background

The tendency of financial organizations to adopt similar strategies in risk-taking, asset holding, and investment decisions is known as herding behavior in financial markets and financial institutions. Many studies have looked into the theoretical grounds behind herding. Haiss (2010) divides reasoning into two categories: rational and behavioral. According to the rational view, investment decisions are distorted due to a lack of accurate information, the compensation and reputation structure of principal agents, and externalities. The behavioral perspective focuses on decision makers' tendency to use "heuristics" to reduce information acquisition and processing costs, as well as internal and/or external variables that limit their rationality, such as investor psychology.

1.1.1 Rational View

Many studies have suggested a variety of causes for rational herding behavior (Devenow and Welch, 1996; Haiss, 2010; Hirshleifer and Hong Teoh, 2003; Liu, 2014). Information cascades, reputation/compensation structures, and payoff externalities are the most well-known of these.

1.1.1.1 Information Cascades

According to the “informational cascades” view of Banerjee (1992) and Bikhchandani et al. (1992), people follow the information of others rather than their own, when they believe their knowledge is less accurate than that of others. According to Barron and Valev (2000), wealth disparities have a major impact on investment decisions. As the number of investors purchasing available information grows, so does the quality of inference drawn from their investment decisions. As a result, low-wealth investors will prefer to wait rather than purchase knowledge, and as a result, there will be a division between agents: leaders, and followers. In support of the “leader-follower” setting, Bikhchandani and Sharma (2000) construct an information cascade using the Bayesian rule and conclude that an information cascade to invest will begin only if the number of predecessors who invest is two or more times the number of predecessors who do not invest. There may be investors who invest in their private information at first, as well as those who invest in the acts of others. When the cascade begins, however, an individual investor's actions no longer represent private information. Welch (1992) describes a situation in which an issuer sells a new security via an underwriter. When an underwriter's distribution channels are limited, it takes time for the underwriter to reach interested investors. As a result, later investors will be able to track the performance of the offering or compare it to earlier offerings done by the same underwriter. Hence, later investors can infer information from previous investors. Investors can only witness the behaviors of previous investors from early sales, but not the signals possessed by earlier investors. As a result, an investor who has witnessed previous sales demand will make a purchase decision based on previous sales rather than his private information. When one individual investor finds it profitable to disregard private information in favor of inferred information from previous sales, all subsequent investors will be faced with the same investment decision and will behave accordingly. As a result, the offering may fail if a group of early investors believes it is overpriced. Similarly, if a group of early investors believes the offering is underpriced, they can create an endless demand for it.

1.1.1.2 Reputation/Compensation

Scharfstein and Stein (1990) investigate the "reputational herding" hypothesis, which suggests that managers are hesitant to make decisions based on their information and beliefs for fear of harming their reputation in the labor market. They assume two types of managers in their model: "smart" managers receive reliable signals about an investment's value, whereas "dumb" managers receive noisy signals. The labor market adjusts its beliefs based on two factors: 1) whether the management makes a profitable investment, and 2) whether the manager's actions are similar or distinct from those of other managers. Due to the unpredictable components of the investment, smart managers may be unfortunate and receive misleading signals. As a result, even if the absolute profitability of the investment decision remains unchanged, managers who herd rather than bet against the market will be viewed more favorably in the labor market. Therefore, an unproductive decision may not be detrimental to one's reputation if others make the same mistake. This is also known as the “sharing-the-blame” effect. Borio et al. (2001) point out that misperceptions of risk's evolution through time, as well as inaccurate responses to it, have an impact on lending and investment decisions, as well as amplify economic fluctuations. They claim that herding may lead to misperception of sustainable asset values and risks, as well as lending booms and busts that amplify the financial cycle. Rajan (1994) proposes a model in which low-quality managers might trade bad loans in exchange for short-term profits. When the economy is bad, all bankers struggle. When enough bankers write down their loans, low-quality managers can follow suit and write down their problematic loans without being detected. Consequently, when the first bank allocates loan loss reserves, those previously reluctant to recognize bad loans may follow the leader. According to Rajan (2006), managers' performance in comparison to their peers is important either because it is directly linked to their compensation or because the flow of funds is shaped on that basis. As a result, despite the knowledge that managers are being evaluated against others, superior performance is also induced, leading to a variety of perverse behaviors. One of these behaviors is herding with other investment managers when making investment decisions, because herding protects managers from performing worse than their peers.

1.1.1.3 Payoff Externalities

Market runs are the subject of the "payoff externalities" hypothesis. This is referred to by Hirshleifer and Hong Teoh (2003) as behavior convergence or divergence because an individual's action affects the payoffs to others who also take the action. Diamond and Dybvig (1983), as well as Bernardo and Welch (2004), model a run in which investors fear a liquidity shock. When investors are hit by a potential liquidity shock at random, their actions to reach liquidity, such as selling shares or withdrawing deposits, may be followed by other investors who are concerned about the future position of their assets. Hirshleifer and Hong Teoh (2003) present a different perspective that can be evaluated within the scope of the payoff externalities hypothesis. They argue that when a struggling company tries to renegotiate its debt, one creditor's refusal may cause others to be skeptical. Due to the rejection, the expected return to the others will be reduced, which can result in multiple equilibria involving runs on the bank or the company, or widespread bank runs as a result of random shocks to withdrawals. Payoff externalities, according to Devenow and Welch (1996), are to blame for the huge reduction in the number of stock exchanges during the 19th and 20th centuries. There were almost 250 stock exchanges in the US in the 19th century. The number was less than one-tenth of 250 in 1996. They argue that when intelligent traders impose fixed costs or an externality on uninformed traders, both informed and uninformed investors profit from trading in a more liquid market, they argue. As a result of this externality, most investors are forced to trade in only one market. Payoff externalities, according to Devenow and Welch (1996), may impact investors' decisions about which stocks to be more informed about. Investors believe it is only reasonable to obtain information if other investors do as well. As a result, investors might be said to herd on information acquisition. Traders have a restricted time frame to trade in Brennan's (1990) model, and the true value of an asset is sometimes revealed exogenously. The private information is reflected in the asset price with a one-period lag, but only if it is acquired by a required minimum number of investors. Therefore, the expected utility of acquiring information is contingent on the expected gains of others.

Chen et al. (2010) focus on mutual fund runs caused by payoff externalities in the mutual fund market. They state that when the expectation that investors will react to certain actions (e.g., redeeming fund assets) by other investors increases, a multiplier effect is expected to emerge. The likelihood of such reactions increases for funds with bad past performance and illiquid underlying assets. Qian and Tanyeri (2017) examine fire sales by mutual funds with a similar motivation. They state that, unlike banks, mutual funds are shielded against runs since they allocate proceeds from asset sales on a pro-rata basis. However, they are still vulnerable to adverse information about the quality of the management or the value of underlying assets. Fund runs may be motivated as a result of the early reaction of investors to an upcoming fire sale, a loss of confidence in the quality of management, or a willingness to minimize damage in the event of a fire sale.

In addition to these most well-known herding hypotheses, Liu (2014) presents the "regulatory arbitrage" hypothesis. This hypothesis is exemplified by Acharya and Yorulmazer's (2007) study. They indicate that when the number of bank failures is high, the regulator finds out that bailing out bankrupt banks is the best option. When the number of failed banks is small, however, remaining banks are forced to buy the failed banks, increasing the risk that the surviving banks would fail as well. As a result, banks prefer to herd since they can survive or fail together without having to take on the risk of acquiring failed banks.

1.1.2 Behavioral View

According to Hirshleifer and Hong Teoh (2003), we are influenced by others in many aspects of our lives, including our financial decisions. Although such influence can be completely rational, investors frequently respond irrationally because of beliefs, herd instincts, or a contagious emotional reaction to unpleasant acts and occurrences. Theoretical studies on social learning and behavioral convergence look at how some seemingly illogical propensities might emerge in totally rational settings and become the core cause of herding behavior. Hirshleifer and Hong Teoh (2003) summarize these propensities as follows: (1) individual and firm convergence on erroneous actions based on insufficient investigation and supporting information, (2) the tendency for social outcomes to be sensitive to seemingly minor shocks, and (3) the tendency for individuals or firms to delay actions for periods and then suddenly rush to act simultaneously without regard for external factors.

Behavioral herding patterns (e.g., overconfidence, groupthink, heuristic simplification) are mostly disguised in the financial markets under phenomena like bubbles, contagion, investor sentiment, and noise traders. These patterns emerge because of non-information-based decision activities. Lin et al. (2013) indicate that non-informational herding may have two alternative effects on subsequent trading noise. If non-informational herding acts as "noise trading", it may drive the prices away from the fundamental values. On the other hand, non-information-based herding may decrease trading noise. The absence of non-information-based herding is an indicator that investors herd as liquidity providers. Hirshleifer et al. (1994) present a model in which an investor follows the same stock as the others in the hopes of receiving the information signal first. Due to the link between the expected payoff and the time of information, it will be more appealing to research the stocks reviewed by other investors if the investor is convinced that he/she would obtain the information earlier than the others. As a result of their overconfidence, they continue to invest in the same stocks. The "institutional memory" problem is hypothesized by

Berger and Udell (2004). They underline that bank loan officers' ability to spot potential loan problems may decline over time. As loan officers' abilities deteriorate, credit standards loosen as officers become less able to distinguish between good and bad borrowers. As a result, banks may face substantial difficulties in making lending decisions. Berger and Udell (2004) indicate that the institutional memory problem may be exacerbated by herding behavior.

1.2 Empirical Literature

Most empirical research in the literature, according to Bikhchandani and Sharma (2000), do not look at specific herd behaviors. Instead, the strategy is to use statistical approaches to see if decision-makers in different financial markets behave similarly, regardless of the underlying causes for such conduct. The studies by Wermers (1999) and Graham (1999) can be counted as exceptions. Wermers (1999) shows that stock price adjustments caused by mutual fund herds are permanent, proving that mutual fund herds speed up the price adjustment process while not causing instability. As a result, his findings support herding theories based on private information but not those based on reputational concerns. The paper by Graham (1999) provides evidence for the reputational herding category. He demonstrates how analysts with a good reputation herd to defend their status and compensation.

One of the key works that attempts to assess the influence of herding on stock prices is LSV (1992). The work is especially important since it produces the LSV measure, which is commonly used as a herding metric in the literature. The herding measure is defined by LSV (1992) as the average tendency of a group of money managers to buy (sell) specific stocks at the same time. They use the following example to demonstrate their herding measure: Assume that in a particular period, half of money managers' stock holdings increase, and the other half drop when averaged across stocks and money managers. Consider that in the first case, half of the money managers increase their holdings of most individual stocks and the other half decrease. There is no herding at the individual stock level in this setting.

Alternatively, suppose that 70% of money managers increase their holdings in several stocks while 30% decrease their holdings. In other stocks, 70% of money managers decrease their holdings while 30% increase their holdings. In this case, money managers complete their trading activity on the same side of the market for most stocks. As a result, it can be concluded that there is herding at the stock level. LSV (1992) use the investing behavior of 769 US tax-exempt stock funds managed by 341 money managers to test herding behavior. The majority of the funds in the portfolio are pension funds. The data set is composed of end-of-quarter holdings of those funds for the period between 1985 and 1989. The tests of LSV (1992) can be divided into three: They examine the degree of correlation between money managers' buying and selling actions for a given stock to assess herding. They test positive-feedback trading by looking at the relationship between money managers' demand for a stock and its previous performance. Finally, they test the relationship between institutional excess demand and stock price changes. According to the evidence, money managers appear to herd relatively little in their large-stock deals. For small stocks, the level of herding is a little higher, but still far from dramatic. There is some evidence for positive-feedback strategies in small stocks, but not in the large stocks that compose the preferred holdings of institutions. Finally, the relationship between institutional excess demand for a stock and price change is rather weak, contradicting the notion that swings in institutional excess demand cause price changes in individual stocks.

Christie and Huang (1995) investigate equity returns to see if it is possible to reveal herd behavior. Their measure of herding is dispersion, which is defined as the cross-sectional standard deviation of returns. Dispersion measures how close an individual return is to the mean. The goal of their research is to see if herd behavior is present when herds are most likely to form. Herd behavior would most likely occur during periods of market stress, because individuals prefer to hide their own beliefs during periods of extraordinary market movements. They employ daily and monthly return data from NYSE and AMEX firms. The daily data covers the period from July 1962 to 1988, and the monthly data covers the period from December 1925 to December 1988. They estimate dispersion within various industry-based portfolios with the assumption that if individual security returns herd around their industry average during a stressful market era, a significant reduction in dispersion should be observed. When dispersions are evaluated using the average industry return, they discover that significant increases in dispersions occur during market stress. Their findings also reveal that during up markets, dispersion increases more substantially than during down markets. They estimate the dispersion of predicted returns generated by a rational asset pricing model to see if this asymmetry is due to herding. They show that the actual and predicted dispersions are nearly comparable, implying that the rise in dispersion during down markets is due to rational pricing rather than herding.

Herding and feedback trading, according to Nofsinger and Sias (1999), may be the cause of a variety of phenomena, including excess volatility, momentum, and stock price reversals. They concentrate on institutional herding, defining it as more (or less) important than individual herding if there is a positive (or negative) link between changes in institutional ownership and returns over the same period. According to their view, a positive relationship between institutional ownership and returns arises if institutional investors engage in intra-year positive feedback trading, and/or the herding behavior of institutional investors has a greater impact on prices than that of individual investors. Therefore, they investigate four aspects. First, they look at the cross-sectional link between changes in institutional ownership and stock returns to determine the relative importance of herding by institutional and individual investors. Second, they look at post-herding returns to see if there are any regular patterns in the pricing of post-herding asset prices. Third, they look for a link between institutional ownership changes, lag returns, and stock return momentum. Finally, they attempt to distinguish the price impact of herding from positive feedback trading using data categorized by trader type. The data set consists of monthly stock returns, annual market capitalizations, and the annual fractions of shares held by institutional investors for NYSE firms and covers the period between 1977 and 1996. The findings reveal that annual changes in institutional ownership and returns have a substantial relationship. The findings imply that institutional investors engage in more feedback trading than individual investors, or that institutional investors' herding behavior has a greater impact on prices than that of individual investors. There isn't any proof that return reversals occurred after the herding phase. Instead, they find that securities that are purchased by institutional investors outperform those they sell. Furthermore, analysis results show that institutional investors engage in positive feedback trading. The analysis to differentiate the price impact of feedback trading from that of herding indicates that changes in institutional ownership have an impact on stock returns or that institutional investors are short-term positive feedback traders.

Chang et al. (2000) extend the work of Christie and Huang (1995) in three dimensions. First, they propose a new measure for herding behavior (i.e., CSAD). They use a non-linear regression to look at the relationship between the extent of equity return dispersion and the overall market return. The return dispersion will decrease in the presence of severe herding, increasing the market return. Second, they examine herding behavior in developed and emerging economies. The selected countries for the study are the US, Hong Kong, Japan, South Korea, and Taiwan. Third, they test the changes in herding behavior after the liberalization of Asian financial markets. They use data from 1963 to 1995 for the aforementioned economies, including daily stock prices, equally-weighted market indices, and year-end market capitalization. The empirical findings show that during moments of extreme price fluctuations, equity return dispersions in the United States, Hong Kong, and Japan tend to rise rather than fall, indicating that herding behavior is not present. However, smaller equity return dispersions, indicating herding behavior, are documented for South Korea and Taiwan. According to Chang et al. (2000), the differences in return dispersion between developed and emerging economies could be due to insufficient information disclosure in emerging markets. According to the results of market capitalization-based portfolio tests, herding behavior is unrelated to whether the traded stocks are large-capitalization or small-capitalization stocks.

Hwang and Salmon (2004) develop a new method for calculating herding based on price deviations from equilibrium beliefs expressed in CAPM (Capital Asset Pricing Model) prices. They claim that by using this strategy, they can adjust in response to fundamental news rather than herding due to market sentiment. As a result, they will be able to see the herding component in observed asset returns. Their method is similar to Christie and Huang's (1995), in that it makes use of the information contained in the market's cross-sectional movements. Hwang and

Salmon (2004) provide a new aspect of their technique as the focal point: instead of returns, they focus on the cross-sectional variability of factor sensitivities. As a result, idiosyncratic components do not affect their measure. Rather than herding by individuals or small investor groups, the measure examines market-wide herding when there is a convergence of market perceptions around particular assets or asset classes. Hwang and Salmon (2004) examine the US and South Korean stock markets using daily data from 1993 to 2002. The period includes the Asian crisis of 1997 and the Russian crisis of 1998. The findings reveal that significant and persistent herding is evident regardless of market conditions. Macro factors are almost useless when it comes to explaining herding patterns. Furthermore, the evidence suggests that herding is possible while the market is rising as well as failing. The Asian and Russian crises have been identified as herding behavior turning points. During market stress, investors, contrary to common belief, tend to focus on fundamentals rather than overall market movements. In the sense that herding begins to vanish during crisis moments, the findings are similar to Christie and Huang (1995). Hwang and Salmon (2004), on the other hand, discover herding when the market is quiet and investors are confident in the market's direction, which Christie and Huang (1995) do not.

Sias (2004) investigates the correlation of institutional traders' trades across time. Institutional investors can follow their prior trades and/or the trades of other institutional traders in the adjacent periods, according to Sias' (2004) novel methodology. Sias (2004) claims that true herding should be counted as that which is caused by following other traders because following their trades could be the result of following a trading strategy. Sias (2004) uses two sources of data for his analyses: returns, shares outstanding, and company capitalization for NYSE, AMEX, and NASDAQ equities are gathered from the Center of Research in Security Prices (CRSP). Each stock's institutional investor ownership data comes from CDA-Spectrum and is obtained from 13F filings. The institutional ownership data is collected quarterly and spans the years from March 1983 to December 1997. Sias (2004) essentially conducts cross-sectional regressions throughout this period and calculates correlation coefficients using these regressions. Furthermore, Sias' (2004) methodology allows for the separation of correlation coefficients due to following one's own transactions versus following others' trades in the same stock. The findings reveal that institutions in adjacent periods follow both their own and each other's lag trades into and out of the same stocks. Furthermore, analyses reveal that the tendency of institutions to follow their lag trades is unrelated to their net flows (i.e., habit investing) or investment net flows in their existing portfolios. Although little evidence for momentum trading has been discovered, it does not account for a significant portion of herding. Furthermore, the findings of Sias (2004) show that institutional herding is not a factor driving security prices away from their fundamental values.

Demirer and Kutan (2006) examine the existence of herding behavior in Chinese stock markets. The study is based on the methodology presented by Christie and Huang (1995), Chang et al. (2000), and Gleason et al. (2004). When herding is prevalent, the main idea underlying this methodology is that security returns will not diverge much from the total market return. This argument is based on the idea that investors ignore their own beliefs and make investments based on the market's collective behavior. Therefore, according to this methodology, herd behavior is most likely to occur during extreme market movements, because investors tend to follow the market consensus during such times. As a result, during times of market stress, the behavior of the dispersion measure is examined. The data set includes daily individual firm-level returns and sector returns from the Shanghai and Shenzhen Stock Exchanges over the 1999–2002 period. There is no evidence of herd formation in the empirical results, implying that market participants in Chinese stock markets make rational investment decisions. This outcome is presented by the authors as evidence for rational asset pricing models. Furthermore, the findings show that traders in the Shanghai market are as well-informed as those in the Shenzhen market, indicating a smooth flow of information between markets. Therefore, it is concluded that segmentation in stock markets is not a valid barrier to the efficient flow of information.

Chiang and Zheng (2010) examine herding behavior in global stock markets. They divide the 18 selected economies for the study into three categories: advanced markets (Australia, France, Germany, Hong Kong, Japan, the United Kingdom, and the United States); Latin American markets (Argentina, Brazil, Chile, and Mexico);

and Asian markets (China, Indonesia, Malaysia, Singapore, South Korea, Taiwan, and Thailand). The study employed daily data from 1989 to 2009, and it consisted of industry and market price indices. As for the herding measure, they use a modified version of Chang et al.'s (2000) CSAD. Apart from using a larger global data set, Chiang and Zheng (2010) claim that their study is unique in that it attempts to determine the significance of the US market in examining local market herding behavior. They also evaluate investing behavior related to the regions by dividing the sample into regions. They also investigate how the financial crisis has affected herding behavior. Herding conduct is more common in nations categorized as advanced markets and Asian markets, according to the empirical findings. In Latin American markets, there is little evidence of herding. It is also demonstrated that, in the majority of cases, investors in local markets herd around the US market. The findings on the effect of crisis periods on herding behavior support the common intuition that herding is more visible during times of crisis. They specifically observe herding in the Mexican and Argentine stock markets during the Mexican and Argentine crises of 1994 and 1999, respectively.

Gebka and Wohar (2013) investigate whether international herding exists and how it affects stock prices. They try to identify whether herding is a worldwide phenomenon, and how it differs from herding inside the country's borders, for different industrial sectors, and over time. The exact cause of international herding is investigated in depth: is it the result of global information cascades that affect all countries in a similar way (market-wide herding), or is it the result of coordinated actions of a small group of investors moving in and out of specific countries (localized herding)? They use daily closing values of indices from 32 nations, at both the national and sector levels, as well as the global stock market index. They employ cross-country deviations in index returns (CSAD) as the herding measure, which is proposed by Christie and Huang (1995) and Chang et al. (2000). The results indicate that when the focus is on the behavior of national indices, there is no evidence for international herding. When national indices are disaggregated and individual economic sectors are examined separately, however, some irrational price behavior is observed, particularly in basic materials, consumer services, and oil and gas stocks. The deviations from the fundamental level of cross-country return dispersion are observed mostly in upmarkets rather than in downmarkets. The findings of the study on the nature of irrational price behavior at an industrial level reveal that, despite having similar fundamentals, asset prices in different countries become extremely distinct. This could be a sign of localized herding: when a group of investors engage in joint actions in a set of countries for their target market, they may cause excessive dispersion in returns internationally. Other reasons include investor overconfidence and an excessive flight to fundamentals during times of uncertainty.

There is a common belief that institutional investors trade together. One generally held belief regarding institutional investors is that they have short trading horizons and, as a result, frequently trade the same equities at the same time without regard for fundamentals (Wermers, 1999). The following are the most prominent theories for understanding institutional herding, according to Wermers (1999): (1) Due to reputational concerns, managers may disregard their private information and trade with the crowd; (2) managers may have correlated private information, most likely because they are analyzing the same indicators; (3) managers may obtain information from better-informed managers' previous trades and trade in the same direction; and (4) managers may avoid stocks with certain characteristics, such as low liquidity. There is significant empirical literature focused on mutual funds and hedge funds that examines the herding behavior of institutional investors and money managers.

Grinblatt et al. (1995) investigate the extent to which mutual funds buy stocks based on their prior performance and herding behavior. They define herding behavior as the degree to which people buy or sell the same stock at a certain period. They look at the quarterly holdings of 155 mutual funds from 1975 to 1984. They also look at the impact of herding and momentum strategies on the funds' overall performance. According to their view, if irrationality or agency problems cause these trading strategies, then mutual funds applying these strategies will tend to push the prices of stocks that they purchase above their intrinsic values, which leads to lower future performance. Alternatively, if these strategies arise because informed portfolio managers pick the same underpriced stocks, then funds performing these strategies will realize high future performance. According to the evidence, mutual funds tend to buy stocks based on their prior performance and engage in herding behavior.

Although the average level of herding and investing using momentum strategies are statistically significant, it is not dramatically large. Furthermore, individual funds' tendency to buy past winners and engage in herding behavior has been proven to be highly correlated with fund performance across the given period. The funds following momentum strategies show significant excess performance, but the same is not valid for contrarian funds. Finally, the evidence for the link between herding behavior and the performance of the fund is so weak that it largely disappears after controlling for the fund's tendency to buy past winners.

Wermers (1999) investigates whether mutual funds herd in their transactions and whether this herding has an impact on stock prices in terms of stabilization or destabilization. According to Wermers (1999), we should expect a stock price increase followed by a decrease if funds buy stocks in a destabilizing manner. However, if they buy stocks in a stabilizing manner, we should expect a price increase without a subsequent decrease. Wermers (1999) investigates the long-term return patterns of herd trades to determine if herding has stabilizing or destabilizing consequences. Furthermore, the link between herding and the use of feedback trading strategies is analyzed by the tendency of funds to herd into past winners versus past losers. The dataset is from CDA Investment Technologies and provides portfolio holdings for all mutual funds based in the United States that existed between 1974 and 1994. The herding tendency is analyzed by the measure proposed by LSV (1992). The funds' herding in transactions is determined to be relatively low. When buying versus selling stocks, there is also an equilibrium in herding behavior. However, looking at subgroups, it's clear that herding is more prevalent among growth funds than among income funds. This result is consistent with the fact that growth funds are less knowledgeable about the future earnings of their stock holdings than income funds. Furthermore, there is a significantly larger amount of herding in small stocks, particularly on the sell side. According to the results of the subgroup analysis, mutual funds exhibit higher levels of herding in stocks with extreme prior-quarter returns than in other stocks, indicating that growth-oriented funds rely heavily on positive-feedback strategies as a source of herding. The relationship between fund herding and both contemporaneous and future stock returns is also examined. The findings suggest that stocks purchased by herds have higher contemporaneous and future returns than stocks sold by herds.

Walter and Weber (2006) analyze the trading activity of German mutual funds to examine potential herding behavior among German mutual fund managers. They claim that this research addresses two major issues. First, they want to know if German mutual fund managers engage in herding and positive feedback trading and if correlated trading has a stabilizing or destabilizing effect on stock prices. Second, they want to add to the literature by identifying previously unknown mechanisms that cause herding behavior. As a result, new stock subsamples based on their inclusion in or exclusion from a benchmark index, as well as accounting standards of stocks, have been developed. In addition, subsamples are analyzed in terms of their location, historic tracking error, relative net flows, and size. The dataset is a hand-collected one and is composed of the portfolio holdings of 60 mutual funds specializing in German stocks. The investigated period is between 1997 and 2002. The herding tendency is analyzed by the measure proposed by LSV (1992). The overall level of herding they find is 5.1%, which is slightly higher than the values published in earlier studies for other mature capital markets. The level of buy-side herding is found to be higher in the bull market. Likewise, the level of sell-side herding is observed to be higher in the bear market. The investigation into benchmark effects reveals that a significant portion of the herding detected in the German market is associated with spurious herding due to the changes in benchmark index composition. The analysis of the effect of accounting standards shows that a higher level of herding is measured for stocks that apply international standards for accounting. In addition, when stocks are classified according to their past and contemporaneous returns, it is observed that fund managers tend to follow short-term positive feedback strategies. The analysis of the subsamples shows that despite high geographic concentration having an increasing effect on herding, fund size seems to have no influence. Furthermore, the findings show that herding is more closely connected with low tracking error and that funds that attract more flow tend to herd more. Furthermore, the results provide no evidence for the destabilizing influence of herding behavior on stock prices.

Choi and Sias (2009) investigate the herding of institutional investors into specific industries in the United States. They first reveal if institutional investors follow each other (i.e., engage in herding) in the form of investing in the same sectors, then examine reasons that may lead to institutional industry herding, using the method of Sias (2004). The return, market capitalization, and industry classification codes are all collected from the CRSP database. Compustat data is used to generate the book values. The institutional ownership data comes from quarterly 13f filing reports and spans 92 quarters between 1983 and 2005. The evidence suggests that there is institutional herding for the sample period and that the herding has an industry component. The first step in determining the causes of industry herding is to reveal whether the herding is caused by underlying investors' flows. The findings of the analysis show that institutional industry herding is caused by managers' deliberate choices rather than the transactions of the existing investors. It is also studied if institutional investors' preference for high lag returns, as indicated in Barberis and Shleifer's (2003) style investing model, encourages industry herding. It is shown that despite institutional investors' tendencies to buy past winners and sell past losers, such momentum trading is not a significant factor to explain the industry herding. The reputational herding is also tested by looking at industry herding by investor type. The tested hypotheses are: (1) institutional investors that are concerned about their reputation tend to follow similarly classified institutions rather than differently classified institutions, and (2) compared to other institutional investors, mutual funds and independent advisors care more about their reputations, which makes them more likely to herd. It is discovered that the evidence for reputational herding is conflicting. The majority of investor groups—four out of five—tend to follow institutional investors who are similarly categorized. There isn't much proof, though, that mutual funds and independent advisors herd like other institutional investors do. Choi and Sias (2009) also investigate the link between institutional industry herding, volatility, and industry size. The following hypotheses are tested: (1) if industry herding is predominantly triggered by linked signals, herding intensity is expected to be stronger in larger and less volatile industries; and (2) if industry herding is observed as a result of informational cascades, herding intensity is expected to be stronger in smaller and less volatile industries. The results of these hypothesis tests show that industries with higher herding intensity are smaller and more volatile than others. Choi and Sias (2009) further investigate whether institutional industry herding is more intense when institutions have easier access to details of other institutions' trades. It is revealed that easy access to the trades of other institutions boosts institutional herding. Last but not least, Choi and Sias (2009) explore whether institutional industry herding leads to a divergence between prices and underlying values. The findings show a positive correlation between institutional industry demand and industry returns over the herding period, suggesting that institutional industry herding occasionally pushes prices away from their underlying values.

Following Choi and Sias (2009), Celiker et al. (2015) investigate mutual funds' industry herding. They use the LSV (1992) and Sias (2004) methodologies to analyze a large dataset of US fund holdings gathered from Thomson-Reuters Mutual Fund Holdings. Their study spans the years 1980 to 2013, excluding international and non-equity funds. Their findings begin with the proof of the existence of industry herding. The analyses show that the mutual funds in the sample engaged in industry herding from 1980 to 2013. Following this core conclusion, they investigate several potential causes of industry herding. They first look at whether investment flows influence industry herding. Even after isolating the effect of fund flows, the evidence for this hypothesis suggests that there remains significant industry herding. Second, they examine whether individual stock herding causes industry herding. This argument is based on the fact that some sectors are dominated by a few stocks, making herding into these stocks appear to be industry herding. Their findings show that while individual stock herding accounts for a considerable amount of herding, industry herding also accounts for a significant portion. Third, they investigate whether style investing plays a role in industry herding. Style investing may create industry herding since many industries are composed of firms with same market capitalization (size) and book-to-market (B/M) ratios. As a result, funds with strategies (i.e., investment styles) that invest in companies with comparable market capitalization and book-to-market ratios may be perceived as herding into specific industries. Furthermore, industry-related information may include size and B/M components. As a result, managers can use this information to invest in alternative stocks within the same industry that have a similar size and B/M. The results show that style investing does not contribute to industry herding. Additional research on the impact of trading periods and investor sentiment on industry herding reveals a marginally greater level of industry herding throughout the internet bubble and bust phase. Additionally, there is inconclusive evidence of increased sell herding after periods of high investor sentiment. They also find that industry conditions are effective for industry herding. According to the evidence, industries with high past returns and high volatility face higher levels of buy herding in the following period. They conducted a test to see whether mutual fund industry herding affects industry returns, and the results show a strong positive contemporaneous relationship between herding and returns. On the other hand, industry herding doesn't seem to shift industry values away from their fundamentals. Celiker et al. (2015) also report on the industry momentum. They assert that industry momentum earnings in the first half of the year following the construction of winning and losing industry portfolios are positively correlated with herding during the formation period. Furthermore, the outperformance of winners in high-herding industries is solely responsible for the return difference between those industries with low and high herding rates. Finally, they find that herding has no impact on price stability but shortens the underreaction period to positive news.

Boyson (2010) studies hedge fund managers' herding tendency over the course of their careers and concentrates on three topics. First, Boyson (2010) looks at fund managers' incentives and reputational concerns, highlighting two implicit incentives in the hedge fund industry: avoiding termination and increasing capital inflows. Then Boyson (2010) examines how managers respond in the face of these implicit incentives, such as whether more experienced managers engage in more herding. Finally, Boyson (2010) looks into how herding behavior affects risk-adjusted performance. The data set is provided by Credit Suisse/Tremont. It comprises 2,345 hedge funds that exist between 1994 and 2004. Three different methods are used to measure herding: tracking error deviation, beta deviation, which is also employed by Chevalier and Ellison (1997), and a total risk measure. The findings reveal that a manager's termination is linked to the level of experience and tendency for herding. Managers with more experience are more likely to lose their jobs if they don't follow the herd than managers with less experience. Furthermore, senior managers who do not follow the herd are not more successful in attracting higher financial inflows than less experienced managers. These two findings together suggest that senior managers should avoid diverging from the herd if they want to advance in their careers. The results of the fixed-effects regression demonstrate that manager experience and herding have a significantly positive connection. The investigation into the impact of herding on fund performance indicates that despite risk-adjusted performance decreasing as a manager’s experience level increases, this decreasing performance cannot be directly linked to the propensity for more experienced managers to herd more.

Koch (2017) provides a different perspective on herding among mutual fund managers. To measure herding behavior, most research in the literature traditionally focuses on funds that buy the same stocks. Koch (2017), on the other hand, contributes to the argument by assessing a manager's tendency to move the entire portfolio in the same direction as peers. This tendency is quantified using a sort of vector correlation between a manager's portfolio weight changes and those of peers. The relationship between this measurement and subsequent fund performance is then assessed. The analogy behind it is provided as follows: if managers herd, due to correlated information, they should outperform. If they are herding for non-informational reasons, their transactions will diverge prices from fundamentals, causing them to underperform. Another question tried to be answered in the paper is the reason for herding. The most mentioned reason in the literature is career concerns. According to Koch (2017), managers who are concerned about their careers would rather follow the herd and reduce their chances of getting dismissed, even if this raises the likelihood of underperformance. Managers who trade in a contrarian fashion profit from increased performance, but they run the risk of being perceived as the unskilled kind by the market. Koch (2017) emphasizes the importance of trade time and observability when conducting these empirical tests. According to a central prediction of the career concerns theory, managers with career concerns will ignore their private information and instead choose to focus on similar public signals. Therefore, the form of the signal may dictate the relevant timing for measuring trade correlations. Managers who follow this signal will engage in contemporaneously correlated trading if the signal is in the form of analyst recommendation revisions. If, on the other hand, the signal is prior peer trading, the trade will be cross-autocorrelated with peers. In this study, Koch (2017) refers to contemporaneous correlation as herding and cross-autocorrelated trading as the following. The data set includes quarterly mutual fund holdings data obtained from Thompson Reuters and stock and mutual fund data from CRSP for the 1990-2006 period. The results of the examination that focuses on the relationship between herd behavior and subsequent fund performance show that herding managers underperform other funds with more independent or contrarian portfolio weight changes. The tests on the reason for herding show that managers that trade with peers but away from peers' holdings are not likely to be herding because of career concerns. Furthermore, it has been discovered that herding managers that trade against their peers' holdings perform poorly. It is also found that herding tendencies are stronger among inexperienced managers with poor prior performance.

Boyd et al. (2015) study herding and positive feedback strategies in futures markets for managed money traders (i.e., hedge funds). They concentrate on three points: First, the reasons for herding among managed money trades are explored, as well as the impact of market structure on herding. Second, the determinants of herding are assessed through an examination of multiple information measures, market structure and design, and pricing impact. Third, whether herding in futures markets contributes to destabilization via positive (or negative) feedback strategies is investigated. For the period between 2004 and 2009, a complete time series of daily data from the CFTC's Large Trader Reporting System (LTRS) is acquired for 30 futures markets that account for more than 90% of total US futures trading volume. Herding among money management traders is analyzed using the LSV (1992) measure. According to Boyd et al. (2015), herding in futures markets is similar to but slightly higher than, herding in equity markets. It is suggested that the reason for this difference can be attributed to common trading strategies and common performance benchmarking. Boyd et al. (2015) show that the herding among these traders is due to the lack of information, which increases the tendency to follow contrarian-based trading strategies. Another important finding is that as the number of traders in the market grows, herding diminishes. With the greater participation of traders in the market, the opportunity to profit from simple mimicking behavior is drawn away. As a result, herding and trading volume might be concluded to be inversely related. Based on past daily results, there is some evidence of positive feedback trading among managed money traders. Significant positive feedback trading, on the other hand, appears to be related more to the number of traders than to net buying imbalances among traders. This shows that positive feedback traders trade with fewer negative feedback traders who take larger positions.

Managerial-level herding may also be observed by investigating pension funds. Using a unique data set for the Chilean market, Raddatz and Schmukler (2013) study herding behavior among pension funds. The Chilean market is important because Chile is the first country to embrace a new mandatory, privately-managed, defined-contribution pension fund model by replacing the public, defined-benefit pension system in 1981. Many developed and emerging countries (such as Argentina, Colombia, Hungary, Lithuania, Mexico, Peru, Slovakia, Sweden, Poland, and the United Kingdom) modify their pension fund regimes as a result of it. Three important topics are discussed in particular. First, does institutional investors' herding behavior varies by traded asset type? Herding in corporate bonds, financial institution bonds, government bonds, mortgage bonds, and equity is investigated in the study. Second, can herding be explained by managers that use similar trading strategies, such as momentum? Third, do managers herd to avoid penalties or reduce risks such as a reduction in their salary? The dataset, received from the Chilean Superintendency of Pensions, contains detailed portfolios of Chilean pension funds in all sorts of securities and asset classes for 10 years period from 1996 to 2005. LSV (1992) method is used to determine the degree of herding. The findings reveal that there is evidence that pension funds herd, and the degree of herding varies across asset classes. In particular, herding is more pronounced in corporate bonds and financial institution bonds. It is shown that herding is more common, especially for assets for which there is less information. Among the same types of funds, herding is determined to be the most intense. The reasons for that might be either the willingness of fund administrators to retain pensioners or the avoidance of market or regulatory punishment. There is no evidence that links herding and momentum strategies.

Blake et al. (2017) examine herding in the UK pension fund market. They bring up a well-known point in the literature that institutional investors keep a closer eye on each other's trades than individual investors. Furthermore, institutional signals are often more correlated than those obtained by individuals. Institutional investors are more prone to herd than individual investors as a result of this discrepancy. Blake et al. (2017) refer to the study by LSV (1992) and indicate that the finding by LSV (1992) that there is "no major evidence" of herding in pension funds is subject to an essential qualification: while the level of herding in individual stocks and industries is low, there are times when money managers simultaneously move into and out of the stock market. However, it is not possible to investigate this sort of herding since LSV's (1992) dataset is made up completely of all-equity funds. Herding may also be more common among some subgroups than it is overall due to the nature of the pension fund sector, but their dataset does not allow them to identify this tendency. Therefore, the main purpose of this research is to explore the above-mentioned challenges to improve our understanding of pension fund investment behavior. The analysis' attention can be divided into two categories. First, it is investigated if UK pension funds herd in asset classes as opposed to particular stocks. Second, it is investigated if herding is more prevalent in subgroups. The dataset consists of monthly observations on 189 UK DB pension funds from 1987 to 2012 and is obtained from State Street Investment Analytics (SSIA). The herding method proposed by Sias (2004) is employed. The empirical findings can be divided into three categories. First, there is compelling evidence of herding in the asset allocations of pension funds. It is found that cross-sectional variance in funds' net asset demands in one month and those in the previous month have a positive correlation, suggesting that pension funds herd in the very near term. Second, pension funds are seen to herd into subgroups. Public-sector funds tend to follow other public-sector funds more frequently than private-sector funds, and private-sector funds tend to follow other private-sector funds less frequently. Pension funds are discovered to behave similarly to other funds of a similar size. The findings also show that herding behavior is caused by short-term mechanical portfolio rebalancing rather than superior information. In accordance with traditional asset-liability management, pension funds either rebalance to target their long-term asset composition or rebalance to address variances in portfolio weights brought on by short-term valuation fluctuations. Third, there is no proof of a long-term price impact in the investigation conducted to determine whether pension fund herding influences asset prices and offers short-term liquidity to financial markets. The results corroborate earlier findings that pension funds adjust their holdings mechanically by demonstrating that trades by pension funds are typically uninformed and consequently unrelated to changes in expected returns. Therefore, it may be concluded that the investment behavior of pension funds does not act as a market stabilizer. The investigation of the performance of pension funds reveals that returns among pension funds are largely similar, which is a sign of widespread herding behavior in the UK pension fund industry. The top performers are private and large and less likely to herd less. The worst performers are small and have higher bond weightings than equities, which is unlikely. The research also reveals that funds prefer to herd around the typical fund that produces the average return for the peer group.

Rather than looking at the joint actions of money managers and individual investors in specific financial markets and instruments, one section of the literature looks at herd behavior among investment analysts and newsletters. According to Bikhchandani and Sharma (2000), there is an available environment for herd behavior in a situation where recommendations from other newsletters can be easily observed. They also mention that there is an unresolved issue of to what extent herding by analysts in recommending certain investments is followed by investors herding into those investments.

Graham (1999) explores the concept of herding using a stock analyst model based on Scharfstein and Stein's (1990) work. There are two types of analysts in the model: smart and dumb. The type of analysts is not observable. The difference between the types of analysts is due to the information they receive. Smart analysts receive informative signals regarding the stock market’s expected return, whereas dumb analysts receive uninformative signals. Smart analysts' signals are positively cross-correlated, implying that smart analysts following their private information may behave similarly. Therefore, in some cases, the analysts who herd can look smart. The analysts use Bayes’ rule to determine their optimal actions. The other critical factors in the decision-making process are the prior public information and the precision of the private information. According to Graham's (1999) model the likelihood of herding:

i. increases with the analyst's initial reputation – analysts with high reputation tend to her to protect their current status and payoff.
ii. decreases with the analyst's ability – low-ability analysts have great incentive to herd to hide their identity.
iii. increases with the strength of prior public information that is in line with the market leader's action – when the prior public information is held strongly and supported by the actions of the market leader, the followers rarely act in the opposite direction.
iv. increases with the level of correlation across informative signals.

The data covers the period between 1980 and 1992 and includes 5,293 recommendations made by 237 newsletters. Because it is plainly observable and well-respected by industry participants, Value Line's advice is obtained as the market leader. The question to be answered is whether a newsletter's portfolio weight advice changes in the same way as Value Line's. The empirical results show that herding decreases with the precision of private information. In addition, it is found that herding after Value Line increases with newsletter reputation, when a proxy for private information is highly correlated across analysts, and when prior information is strong.

Hong et al. (2000) investigate the relationship between herding and security analyst career concerns. According to Hong et al. (2000), security analysts are typically employed by brokerage firms, and an analyst's salary is based on his long-term forecasting skills. Security analysts' decisions attract public scrutiny. As a result, analysts who outperform their counterparts are noticed in the press and given future employment opportunities by competing brokerage houses. Therefore, what an analyst offers becomes a great deal for his future career. In this study, Hong et al. (2000) express the importance of perceived forecasting ability on analysts' career concerns by estimating the link between the likelihood that an analyst will be terminated from his job and his past forecast accuracy. They gain from the forecast's boldness (i.e., forecasts that depart significantly from the consensus) to perform this estimation. Hong et al. (2000) investigate how earnings forecasts change between inexperienced and experienced security analysts to account for experience as a factor that may alter forecast behavior. For the years 1983 through 1986, the dataset contains earnings forecasts from 8,421 analysts representing 4,527 US companies. The findings suggest that the worst-performing security analysts are the ones who are most likely to be terminated and least likely to be promoted. This is especially true for inexperienced analysts. Therefore, controlling for forecast accuracy, it is found that inexperienced analysts are more likely to be terminated and less likely to be promoted when they make relatively bold forecasts than their experienced peers. Furthermore, there is little evidence that being bold and bad leads to worse future career opportunities; however, being bold and good does not significantly improve an analyst’s future career opportunities. According to Hong et al. (2000), existing theories suggest that as younger analysts face more career concerns, they should take fewer risks in their forecasts. The findings suggest that inexperienced analysts herd more than more experienced analysts, forecasting closer to the consensus than their more experienced counterparts.

Welch (2000) investigates whether security analysts' purchase recommendations for individual equities are influenced by herding. Welch (2000) points out the complexities of the elements that influence security analysts' purchasing recommendations. According to Welch (2000), the prevailing consensus and the most recent revisions by other analysts, in addition to prior analysts' choices, are important influence factors on the next recommendation. The dataset used in the study is from the Zacks Historical Recommendation Database. The dataset consists of about 50 thousand recommendations issued by 226 brokers over the period 1989–1994. The empirical findings reveal that the two most recent decisions have a positive impact on the next analyst's revision. Moreover, the influence is stronger when the recent revisions are more recent and when they are proven to be more accurate predictors of ex-post security returns. Welch (2000) suggests that this influence can be related to analysts’ expectancy to exploit fundamental and short-lived information in these revisions. Welch (2000) also discovers that analysts' decisions are influenced by the prevailing consensus. However, this influence is not significantly stronger when it is revealed that the consensus is correct depending on the subsequent price movements. This finding shows that fundamental knowledge is less likely to cause herding toward consensus, which is consistent with models arguing that analysts herd based on little or no information.

Lamont (2002) investigates the role of reputation in economic forecasting. According to the evidence in the literature, forecasters are not compensated based on their mean squared error. Instead, they try to improve their reputation, deceive investors about their quality, and use their forecasts in ways that have nothing to do with minimizing mean squared error. Because reputation is awarded in the marketplace, there is an incentive for forecasters to try to manipulate their forecasts relative to those of competitors. Furthermore, as a forecaster's reputation grows over time, the degree to which forecasts are manipulated will change over time. The dataset includes macroeconomic forecasts obtained from Business Week’s annual year-end outlook issue from 1971 through 1992. The results of the test to see if forecast dispersion is connected to the forecaster's age and reputation demonstrate that as forecasters get older and more established, they make more extreme predictions. As a result of this trend, forecast accuracy decreases over time as experience grows. This could indicate that forecasters who are younger and less experienced tend to follow the herd and make predictions based on the consensus. However, when they are experienced and have a reputation, they are less concerned about their reputation, thus leaving the herd at the expense of forecast accuracy.

Using a new methodology, Zitzewitz (2001) measures herding and exaggeration among equity analysts. In the study, herding is defined as the practice of underweighting one’s private information and issuing an opinion or forecast that is closer to the existing consensus. Likewise, exaggeration is defined as overweighting one’s private information and forecasting further away from the consensus. The methodology, according to Zitzewitz (2001), has two major advantages over the dispersion of forecast method, which is widely employed in previous empirical studies on herding. First, it allows one to extract the absolute amount of herding or exaggeration relative to unbiased forecasting, whereas the forecast dispersion method only allows one to define where there is more or less herding relatively. Second, the method controls for the amount of independent private information embodied in forecasts. The I/B/E/S Detail History dataset is used to measure herding and exaggeration. Quarterly earnings projections made up to 6 months previous to earnings announcement for the period 1993 to 1999 are taken from this dataset. According to the analysis results, equity analysts overestimate their differences with the consensus by a ratio of 2.4. This means that when forecasters combine their private and public information to generate an estimate, they overweight their private information and issue forecasts that are 2.4 times away from the consensus. In addition, exaggeration does not vary significantly with forecast, firm, and analyst characteristics, but rather varies with the past exaggeration of an analyst.

Clement and Tse (2005) attempt to determine the causes and effects of analyst herding, as well as equip market players with intuition to assist them to analyze the information in analysts' earnings estimates better. They divide forecasts into two categories: bold and herding forecasts. Forecasts are labeled "bold" if they are higher or lower than the analyst's previous forecast as well as the consensus forecast immediately before the analyst's forecast. All other forecasts are known as herding forecasts. They are attempting to respond to three research questions. The first question is whether there are any analyst characteristics other than experience that are associated with forecasting boldness. As a result, in addition to the analyst's experience, this study expands on Hong et al. (2000) by assessing the relative importance of characteristics such as the analyst's prior accuracy, brokerage size, forecast frequency, and the number of firms and industries the analyst follows. The second research question is whether bold forecasts are, on average, more accurate than herding forecasts. According to Clement and Tse (2005), previous studies have never answered this question. The third research question is based on Trueman's (1994) view that analysts' revisions do not reflect all of the private information possessed by analysts. Therefore, this incomplete forecast revision results in a correlation between the analyst's forecast revision and the same analyst's earnings forecast revision. Trueman (1994) also indicates that small forecast revisions are more likely to be incomplete than extreme forecast revisions. Therefore, Clement and Tse (2005) examine the association between forecast revisions and forecast errors for analysts providing herding and bold forecasts. The results show that the likelihood that an analyst's forecast revision is bold increases with forecast horizon, brokerage size, forecast frequency, and general experience and decreases with days passed since the prior forecast and the number of industries the analyst follows. Even after controlling for other analyst characteristics, bold forecasts are proven to be more accurate than herding forecasts. Furthermore, the relationship between herding forecast revisions and analyst forecast error is found to be stronger than the relationship between bold forecast revisions and analyst forecast error. This outcome supports Trueman's (1994) claim that bold forecast revisions more accurately reflect the analyst's private information than herding forecast revisions.

According to Bernhardt et al. (2006), clustered forecasts may not indicate that analysts engage in herding behavior. The root cause may be other than herding behavior. First, previous forecasts may offer insightful data that followers can utilize to enhance their own predictions (Welch, 2000). Second, analysts rely on well-known information sources like a company's CFO. It will be obvious to see how the same information influences their estimates if a CFO shares the same information with all the analysts. Third, market-wide unanticipated earnings shocks may cause most projections to be overly low or high concerning the results. Fourth, there may be discrepancies between analyst earnings forecasts and what econometricians see (Keane and Runkle, 1998). Fifth, analysts may be systematically optimistic or pessimistic, causing forecasts to exceed or fall short of the consensus (Richardson et al., 2004). By considering the aforementioned issues, Bernhardt et al. (2006) in this work develop tests to identify herding in the earnings projections provided by professional analysts. They describe anti-herding as a forecast that deviates from the analysts' expectations and define herding as an analyst's choice to bias his or her own forecast toward the analysts ' expectations of preceding analysts. They assess the frequency of these variances in their tests. Given all available information, an unbiased analyst's estimates are provided to be equivalent to the median of their posterior earnings. Because of this, the analyst's estimate, both unconditionally and conditionally, based on the available information set, including the analysts' expectations, should exceed realized earnings to be undershot. Instead, if an analyst produces biased forecasts, the forecast will fall somewhere between the analysts' expectations and own best earnings estimate. They calculate two conditional probabilities as a result: (1) the conditional probability that a forecast outweighs realized earnings given that it outweighs the analysts' expectations; and (2) the conditional probability that a forecast underperforms earnings given that it underperforms the current consensus. The data comes from the I/B/E/S Detail tapes and includes individual analyst quarterly earnings forecasts from 1989 through 2001. The empirical results provide strong evidence against herding. It is discovered that analysts consistently make anti-herding forecasts that are biased in the direction of their personal information and outperform the analysts' expectations. Almost 60% of the time, their forecasts overshoot actual earnings per share (EPS).

When it comes to stock recommendations, Jegadeesh and Kim (2010) investigate whether sell-side analysts herd. Their model allows them to test for herding based on market price reactions around recommendation revisions. In addition, the model allows for incorporating a key distinction between earnings forecasts and recommendations. When analysts revise their forecasts, Jegadeesh and Kim (2010) argue that they also include the information in the consensus forecasts, even though the information is not fresh to the market. However, analysts make investment recommendations based on prevailing market prices. They do not modify their suggestions based on old information because market prices reflect all available information. They also imply that when analysts forecast earnings, they are aware that actual earnings will be reported on specified dates, revealing the accuracy of their predictions. Analysts submit their thoughts for twelve months in the case of recommendations; however, they commonly change their minds within that time. Therefore, it is hard to define the accuracy of their recommendations. As a result, analysts' motivations to herd for earnings forecasts and recommendations may differ. Jegadeesh and Kim (2010) also try to draw inferences about whether the market acknowledges analysts' tendencies to herd when they revise their recommendations. The data for stock recommendations and earnings announcements are obtained from I/B/E/S, and the data for stock returns and index returns are obtained from the daily CRSP. The sample period selected for the study is between 1993 and 2005. The findings reveal that when experts' recommendations diverge from the consensus, the market reacts more strongly than when the updated recommendations are closer to the consensus recommendation for that stock. It suggests that analysts' herding tendencies have a role in recommendation modifications. It's also been discovered that analysts herd more while issuing downgrades than upgrades. This result shows that analysts are reluctant to behave differently than the herd when they convey negative information. Another outcome is that analysts from brokerage firms with a higher reputation likely to herd more than those from firms with a lower reputation. Further, analysts following stocks with a small dispersion in opinion and analysts who issue infrequent recommendation revisions are more likely to herd.

Jain and Gupta (1987) analyze the herding behavior among US banks in international lending decisions. In the paper, herding in lending decisions is defined as a bank's attitude of considering only other banks' loan portfolio allocation decisions while making its own loan portfolio allocation decision. They then examine the premise that there are causal relationships between international lending decisions made by US banks of various sizes, and that giant money center banks are followed by other banks. To test the hypothesis, they adopt a Granger (1969) causality model. They employ a data set generated from US bank net loan figures and calculated from end-of-period exposures. They look at a set of banks that submitted reports between 1977 and 1982, and they divide them into three groups based on their size: the top nine, the next fifteen, and the rest. The findings imply that US banks' international lending decisions are not influenced by herding. Furthermore, there is no clear size distinction for the leader-follower relationship. The results show that regional banks follow both the top nine and the next fifteen banks.

According to Uchida and Nakagawa (2007), one of the most significant reasons for the Japanese banking crisis in the early 1990s is the non-performing loan problem. Furthermore, one of the elements that led to the accumulation of bad loans is believed to be Japanese banks' irrational herd behavior during the bubble period in the late 1980s. According to the proponents of this behavioral explanation, Japanese banks could have made better lending decisions, and thus they were responsible for the non-performing loan problem. Uchida and Nakagawa (2007) pose three questions to determine if the irrational herding theory is true or not: (1) Have Japanese banks shown herding behavior in the past? (2) If so, is it a reasonable or irrational form of herding? (3) Was the irrationality (or rationality) evident only during the bubble period, or was it a long-standing trait of Japanese banks? To highlight the answers to these questions, the LSV (1992) measure is applied to a dataset of loans obtained from banks' balance sheets, which are available in the Nikkei Needs Company Data File and issued for different industries in Japan from 1975 through 2000. The results show that there is evidence for the existence of herd behavior among Japanese banks during the sample period. Herding is observed around the second oil crisis in the late 1970s, during the bubble period in the late 1980s, and during the stagnation period that came after. Furthermore, the results indicate that irrational bank behavior might have been exceptionally visible during the bubble period and might have contributed to the non-performing loan problem. For comparison purposes, the analysis is also conducted with regional banks, which operate regionally on a smaller scale than city banks. It is observed that regional banks have been more frequently showing irrational herd behavior than city banks.

Previous research, according to Nakagawa et al. (2012), are insufficient to demonstrate how bank herding affects the real economy. As a result, they explore the impact of bank herd behavior on the real economy in this study by focusing on loan data (obtained from Financial Journal Monthly) of Japanese banks and other financial institutions from 1975 to 1999. According to Nakagawa et al. (2012), Japanese financial institutions are good research targets for studying herding because lending practices during the asset-price bubble in the 1980s and until the bubble's collapse in the 1990s may have resulted in an inadequate level of monitoring of borrowers' financial conditions. This lack of lending supervision is claimed to have contributed to the rise in non-performing loans at the time, as well as providing a foundation for loan herding. They follow a two-step approach. First, they examine whether Japanese financial institutions in the domestic loan market exhibit herd behavior based on the methodology suggested by Nakagawa (2008). Second, they investigate how herd behavior in the loan market affects the Japanese economy. The empirical results provide evidence of inefficient herd (i.e., loans resulting from the herd behavior are not based on the profitability of the borrowing firms) behavior across different types of financial institutions, which is not explained by economic variables during the asset-price bubble in the late 1980s. Loans resulting from inefficient herding are found to be negatively connected with GDP and land prices in the years following. On the other hand, ordinary loans, which are independent of inefficient herding, are found to be positively correlated with those macroeconomic variables. As a result, the findings point to the harmful impact of Japanese financial institutions' herding behavior on the Japanese economy.

Herding among banks, according to Liu (2014), should be given special attention since, in comparison to other industries; the banking sector's industry-specific characteristics encourage banks to herd more. In addition, herding among banks may create or help several potential problems, such as deterioration of lending standards, misallocation of resources, and increased systematic risk to worsen, given the important role of banks in the economy. Liu (2014) investigates banks' herding tendency in their domestic lending decisions in this paper. She examines the level of deviation from the banking sector's average lending decision by looking at collective changes in the weights of five loan categories (i.e., commercial real estate loans, residential real estate loans, consumer and industrial loans, individual loans, and all remaining loans). The data is taken from the Federal Reserve's Call Reports and comprises a hand-collected set of quarterly bank loan information for US banks from 1976 to 2010. The paper's economic and market data come from the US Bureau of Economic Analysis, the Federal Reserve Board of Governors' Release, and Bloomberg. The herding measures used in the study are the traditional herding measure of LSV (1992) and a more recent measure by Frey et al. (2014) (i.e., the FHW measure). The empirical results provide evidence of herding in the entire sample period. Furthermore, regression results show that herding measures are positively related to the unemployment rate, inflation, and risk premium interest spreads, indicating that banks herd more when economic conditions and the health of the banking industry are not favorable. On the other hand, herding is negatively correlated with the bank’s deposit ratio, the ratio of liquid assets to total assets, profitability, and loan quality. Herding is also positively related to off-balance-sheet activities, for which the reason may be the opportunity for banks to earn more fees by investing fewer resources to obtain information. When the banks are compared according to their sizes, it is observed that large banks tend to herd more in most quarters of the sample.

Lu et al. (2014) examine herding behavior in the lending decisions of Chinese banks. They claim that, as a result of the government's goal of speeding up market liberalization for foreign investors, the Chinese banking system has steadily evolved away from planned-economy management and toward a market-oriented business model. However, this transition has left some items incomplete. Chinese banks suffer from operating efficiency issues (e.g., non-performing loans, low capital adequacy ratios, low rates of return on capital, and low differentiation of business types) and supervision insufficiency issues (e.g. oligopoly and regulatory intervention), which may lead to herding behavior in lending decisions. As a result, Lu et al. (2014) analyze whether bank herding exists by looking at how lending patterns influence subsequent bank lending behavior. Second, if herding exists for Chinese banks, is herding behavior observed for banks that hold higher percentages of risky assets than those that hold a lower portion of risky assets? Third, what is the motivation for herding?: Reputational herding or characteristic herding. In reputational herding, banks of the same kind follow each other in lending to comparable sectors to protect their reputation from the risk of lending to an industry that collapses within a short period. In characteristic herding, banks prefer to lend to industries with the same characteristics, which differ across bank classes. Finally, the last investigation subject is whether such herd behavior leads to banks' better understanding of their borrowers and improving resource allocation or causes inefficient fund allocation and non-performing loans. The study's data comes from the Taiwan Economic Journal's (TEJ) risk module for Chinese banks in lending, the Infotimes database, and the China Banking Regulatory Commission, and covers transaction data on business lending by Chinese state-owned commercial banks, joint-equity banks, and city banks from 2006 to 2011. To calculate herding, Sias (2004)'s approach is followed. The empirical results show that there is evidence of loan herding for joint-equity banks and city banks. The reasons for herding are presented as magnitudes of financial indices, habit-lending, reputational herding, and characteristic herding. It is observed that loan herding occurs in banks with a higher proportion of risky assets, a higher proportion of non-performing loans, a lower capitalization, and a lower ROE (Return on Equity). The habit-lending is observed because banks are easily attracted by industries that are supported by the government in the scope of the economic plan. Both reputational and characteristic herding are supported by city banks because they tend to herd in the same types of industries with their more local and small loan bases to avoid credit risk. Finally, loan herding is found to harm the macroeconomic and financial parameters such as the industrial GDP growth rate, stock prices, PE (price-to-earnings) ratios, and the overall proportion of FDI (foreign direct investments) and non-performing loans in the following year.

This study examines institutional actors' decision-making processes with an emphasis on herding behavior in the banking and mutual fund industries. This study explores an emerging economy, differentiating itself from other studies that have looked at various economic environments in developing economies. The second chapter looks at herding behavior in loan decisions beginning from the early 2000s. During that period, Turkish economic management experiences a transformation as a result of local and global crises and global fund inflows. One of the novel aspects of this work is how it combines the herding literature with the effects of regulation to examine how regulatory activities affect herding behavior and its logic in a situation when financial stability is at risk. The third chapter of the study focuses on mutual funds that invest in stocks (i.e., equity-intensive or stock-weighted mutual funds). It tests previously noted characteristics that may cause industrial herding behavior in a small-scale market with distinct dynamics from developed ones. This study contributes to the body of literature by seeking to show whether the viability of those earlier arguments depends on market features by studying those arguments in a market that is more prone to information asymmetry and hence ideal for the establishment of herding behavior.

CHAPTER 2

LOAN HERDING

2.1 Introduction

The term "herding" appears in the finance literature in various research areas. As a result, a broad meaning for this phrase might include the inclination of financial institutions to pursue similar risk-taking, asset-holding, and investment strategies.

The initial research on herding mostly focuses on equity funds and a substantial percentage of current work is still being developed for this domain. The main motivations of the previous works are to investigate the effect of herding on asset prices such as price volatility and excess returns (LSV, 1992; Nofsinger and Sias 1999), the timing of the herding behavior (Demirer and Kutan, 2006), the relationship between the trading strategies of the institutional investors and herding (Grinblatt et al., 1995; Wermers, 1999), and the incentives, informational and reputational concerns that lead money managers to engage in herding (Boyson, 2010; Koch, 2017).

The primary focus of herding studies within the banking domain is herding in bank loans. "Loan herding" is defined as the tendency of banks to follow the lending decisions of other banks. The motivations that lead banks to follow other banks in their lending decisions are grouped into three: information-based, reputation-based, and bank characteristics-based hypotheses.

The information-based hypotheses indicate that the noise regarding the borrowers' intrinsic value directs the lending decision, thus causing the herd. When the level of noise regarding the borrower's financial situation is high, banks neglect their own information and make their decisions with the herd (i.e., informational cascades). Unlikely, when the borrower's intrinsic value is publicly available and transparent, banks can make rational decisions, and their loans may focus on the same industries and loan types (i.e., investigative herding). According to the reputation-based hypothesis, a bank may increase or decrease its loan level in an industry or loan type simply because other same-type banks are increasing or decreasing their loans in the same industry or loan type. Hence, they consider the potential reputational costs of not being in the herd. The characteristic herding hypothesis emphasizes that certain types of banks may prefer to lend to industries with specific characteristics. They band together in the same herd while granting loans in the same industry since they share similar perceptions and evaluation standards with other same-type banks.

There are three main approaches dealing with the various facets of the loan herding phenomenon. The first approach examines the economic, regulative, and bank-specific factors that lead banks to herd (Liu, 2014; Tran et al., 2017). The second approach investigates the effects of loan herding on macroeconomic and real sector variables (Nakagawa, 2008; Nakagawa and Uchida, 2011; Uchida and Nakagawa, 2007). The third approach looks into the effects of loan herding on banking efficiency and performance (Fang et al., 2019; Lu et al., 2013).

The Turkish commercial banking industry is of particular importance in this study. There are three motivations why this chapter was written. The first and primary motivation is to investigate if herding behavior had an impact on bank decision-making during the early 2000s, when the Turkish banking industry was undergoing significant change. It's crucial to emphasize whether this herding behavior has any impact on bank profitability and loan quality as well. Third, whether it is possible to connect the rationality of herding behavior with the changes in economic management and new regulatory applications. The presence of herding in cash credit lending decisions is researched first, followed by the consequences of herding on the bank's performance and loan quality, using loan data from 30 commercial banks. Using LSV (1992) and Sias (2004) herding measures, we study herding behavior for two periods between 2002:Q4 and 2017:Q4. For both periods, we find significantly positive LSV herding. However, we only find significant herding for the first period when we use the Sias herding measure, especially for the contribution of banks following other banks' lending decisions. Our findings indicate that herding has a significantly harmful effect on bank profitability during the 2002Q4–2012Q2 period. However, we do not find similar evidence for the 2012Q3–2017Q4 period. Our results indicate that there is not enough evidence to confirm a potential relationship between loan herding and credit risk. Following Fang et al.'s (2021) argument that herding has a more visible negative effect on profitability during turbulent periods, we wanted to see if herding becomes a significant factor in bank profitability and loan quality during crisis periods. However, we cannot confirm a reinforced effect of herding on bank profitability and loan quality during crisis periods. Finally, we look into whether the global liquidity increase that accompanied credit growth in the 2000s, as well as the regulator's policy applications, has an impact on banks' collective lending decisions. We document that increase in global liquidity and corresponding macroprudential applications explain a significant portion of the variance in herding behavior.

The remainder of the chapter is organized as follows: Section 2 discusses the data, section 3 provides the model and herding measure specifications, section 4 presents the analysis results, and section 5 is composed of our concluding remarks.

2.2 Data

The data set is composed of cash loans and financial ratios. The herding measures are calculated using loan data, and the financial ratios are employed as regressors in the analysis section.

2.2.1 Loan data

The quarterly amounts of the commercial banks' "non-specialized loans" sub-category of the "cash loans" are used from December 2002 to December 2017. The loan data are collected from the banks' financial statements in The Banks Association of Turkey data system and controlled manually against errors using the banks' quarterly reports. The Banking Regulation and Supervision Agency (BRSA) modified the rules for a collection of information that must be released to the public via a communiqué as of June 2012. As a result of the modification, loan categories under the "non-specialized" section were changed: some of the previously reported categories were eliminated, and the composition of "other loans" was changed. As a result, the data set had to be split into two pieces to ensure that the relevant loan types were traced within the appropriate time frames. Some loan categories were left out of the final collection due to missing data points and a small number of active banks. Table 2.1 shows the final set of included and excluded loan categories, and Table 2.2 shows the number of active banks in each loan category for the relevant period. Table 2.3 shows the fraction of non-specialized loans in total loans for the sample periods.

Table 2.1 Composition of final loan data

Period 1: 2002Q4 – 2012Q2			Period 2: 2012Q3-2017Q4		
Loan Category	Category #	Included/Excluded	Loan Category	Category #	Included/Excluded
Discount and Surrender Bills	1	Included	Business Loans	1	Included
Export Loans	2	Included	Export Loans	2	Included
Import Loans	-	Excluded	Import Loans	-	Excluded
Loans to Financial Institutions	3	Included	Loans to Financial Institutions	3	Included
Overseas Loans	4	Included	Consumer Loans	4	Included
Consumer Loans	5	Included	Credit Card Loans	5	Included
Credit Card Loans	6	Included	Other Loans	6	Included
Precious Metal Loans	-	Excluded			
Other Loans	7	Included			

This table shows the final set of included and excluded loan categories. The categories are determined based on “cash loans” under the “non-specialized loans” section. The data set is divided into two periods (Period1: 2002Q4-2012Q2 and Period2:2012Q3-2017Q4), because the change in the information disclosure standards made by BRSA as of June 2012.

Table 2.2 Number of active banks according to period and loan category
Panel A. Period 1: 2002Q4 – 2012Q2

Period	Category #1	Category #2	Category #3	Category #4	Category #5	Category #6	Category #7
2012:Q2	26	25	24	20	27	20	27
2012:Q1	25	25	24	20	27	19	27
2011:Q4	26	24	24	20	27	19	27
2011:Q3	25	24	24	20	27	19	27
2011:Q2	26	24	24	20	27	19	27
2011:Q1	25	25	23	21	27	20	27
2010:Q4	26	26	24	22	28	21	28
2010:Q3	26	25	23	22	27	21	28
2010:Q2	24	26	22	21	27	21	28
2010:Q1	26	26	24	20	27	21	28
2009:Q4	24	26	23	20	27	21	28
2009:Q3	24	26	24	22	27	21	28
2009:Q2	23	26	23	21	27	21	27
2009:Q1	23	26	24	21	27	21	27
2008:Q4	24	26	23	20	26	21	27
2008:Q3	23	26	21	19	26	21	28
2008:Q2	25	26	21	19	26	21	28
2008:Q1	23	27	23	21	27	21	28
2007:Q4	23	27	23	21	27	21	28
2007:Q3	24	26	21	20	27	20	27
2007:Q2	26	26	19	22	27	21	28
2007:Q1	25	25	21	20	27	21	26
2006:Q4	24	26	19	19	26	21	27
2006:Q3	25	27	18	19	27	22	28
2006:Q2	24	26	18	19	27	22	28
2006:Q1	23	25	19	21	27	22	28
2005:Q4	25	25	17	21	27	22	28
2005:Q3	25	26	16	19	27	22	28
2005:Q2	24	25	16	18	27	22	28
2005:Q1	23	24	17	17	27	22	28
2004:Q4	25	26	18	18	26	22	28
2004:Q3	25	27	17	17	27	22	29
2004:Q2	23	26	17	17	27	22	28
2004:Q1	23	25	16	17	26	21	27
2003:Q4	25	27	16	17	26	22	27
2003:Q3	22	25	18	17	25	23	27
2003:Q2	21	26	17	17	25	22	27
2003:Q1	22	27	15	14	25	21	26
2002:Q4	21	28	14	15	24	22	28

Table 2.2 Number of active banks according to period and loan category (cont'd)
Panel B. Period 2: 2012Q3-2017Q4

Period	Category #1	Category #2	Category #3	Category #4	Category #5	Category #6
2017:Q4	16	25	26	24	21	27
2017:Q3	16	25	26	24	21	27
2017:Q2	16	25	25	24	21	27
2017:Q1	16	25	25	24	21	27
2016:Q4	16	25	25	24	21	27
2016:Q3	16	25	25	24	21	27
2016:Q2	16	26	24	24	21	27
2016:Q1	16	26	26	24	21	27
2015:Q4	16	26	25	24	21	27
2015:Q3	16	26	26	24	22	26
2015:Q2	16	26	26	24	21	27
2015:Q1	16	26	24	25	21	27
2014:Q4	16	25	24	26	21	25
2014:Q3	15	25	24	26	22	27
2014:Q2	16	25	24	26	21	27
2014:Q1	15	25	24	25	21	26
2013:Q4	17	26	24	25	20	25
2013:Q3	17	26	24	26	21	26
2013:Q2	17	26	24	26	21	27
2013:Q1	17	25	24	27	22	27
2012:Q4	18	25	25	28	20	27
2012:Q3	17	24	25	27	20	25

This table shows the active banks in each loan category (i.e. having existing loan balance) highlighted in Table 2.1. Panel A shows the number of active banks in Period 1 (2002Q4-2012Q2) and Panel B shows the number of active banks in Period 2 (2012Q3-2017Q4).

Table 2.3 Fraction of non-specialized loans in total loans according to period
Panel A. Period 1: 2002Q4 – 2012Q2

Period	Total Loans (MTL)	Non-Specialized Loans (MTL)	Percentage
2012:Q2	681.31	616.17	90.44%
2012:Q1	648.25	586.21	90.43%
2011:Q4	636.72	576.69	90.57%
2011:Q3	620.65	564.63	90.97%
2011:Q2	580.09	527.17	90.88%
2011:Q1	526.40	478.37	90.88%
2010:Q4	489.92	443.87	90.60%
2010:Q3	443.04	402.60	90.87%
2010:Q2	424.29	384.05	90.52%
2010:Q1	388.22	347.19	89.43%
2009:Q4	364.54	322.56	88.49%
2009:Q3	351.30	310.54	88.40%
2009:Q2	346.68	307.31	88.64%
2009:Q1	348.42	311.23	89.33%
2008:Q4	351.93	315.05	89.52%
2008:Q3	342.78	314.03	91.61%
2008:Q2	324.50	297.55	91.69%
2008:Q1	303.28	278.71	91.90%
2007:Q4	269.03	247.97	92.17%
2007:Q3	245.85	226.37	92.08%
2007:Q2	232.91	213.44	91.64%
2007:Q1	218.43	199.96	91.55%
2006:Q4	208.17	188.26	90.43%
2006:Q3	194.57	178.53	91.76%
2006:Q2	190.16	175.30	92.18%
2006:Q1	159.59	146.29	91.67%
2005:Q4	145.34	131.64	90.57%
2005:Q3	128.97	116.12	90.03%
2005:Q2	117.93	104.03	88.22%
2005:Q1	104.28	91.16	87.42%
2004:Q4	95.98	83.40	86.90%
2004:Q3	89.88	77.54	86.27%
2004:Q2	84.09	71.37	84.88%
2004:Q1	68.70	57.27	83.37%
2003:Q4	63.38	52.14	82.27%
2003:Q3	55.45	44.36	80.01%
2003:Q2	51.93	40.22	77.44%
2003:Q1	53.40	41.06	76.89%
2002:Q4	50.31	37.67	74.88%

Table 2.3 Fraction of non-specialized loans in total loans according to period (cont'd)
Panel B. Period 2 : 2012Q3 – 2017Q4

Period	Total Loans (MTL)	Non-Specialized Loans (MTL)	Percentage
2017:Q4	1,929.40	1,716.31	88.96%
2017:Q3	1,837.75	1,646.73	89.61%
2017:Q2	1,777.68	1,593.89	89.66%
2017:Q1	1,701.03	1,520.97	89.41%
2016:Q4	1,607.35	1,438.41	89.49%
2016:Q3	1,493.50	1,330.03	89.05%
2016:Q2	1,453.64	1,303.03	89.64%
2016:Q1	1,402.01	1,254.94	89.51%
2015:Q4	1,377.70	1,245.63	90.41%
2015:Q3	1,378.45	1,252.91	90.89%
2015:Q2	1,295.64	1,179.64	91.05%
2015:Q1	1,227.85	1,118.56	91.10%
2014:Q4	1,146.20	1,027.62	89.65%
2014:Q3	1,095.39	999.83	91.28%
2014:Q2	1,032.32	941.90	91.24%
2014:Q1	996.15	908.94	91.25%
2013:Q4	963.34	879.81	91.33%
2013:Q3	911.95	834.09	91.46%
2013:Q2	848.10	772.51	91.09%
2013:Q1	768.53	696.19	90.59%
2012:Q4	733.52	658.79	89.81%
2012:Q3	698.79	627.32	89.77%

This table shows the fraction of non-specialized loans in total loans for the selected period. Panel A shows the percentages in Period 1 (2002Q4-2012Q2) and Panel B shows the percentages in Period 2 (2012Q3-2017Q4).

2.2.2 Data for ratios and macroeconomic variables

The data on banks' financial ratios are from the statistical reports and data repository of The Banks Association of Turkey. The ratios are either directly obtained from the statistical reports or calculated using the data from the data repository (please see Table 2.4 for the financial ratios). The macroeconomic data comes from the Refinitiv Eikon and Turkish Statistical Institute's data repository. These are the real GDP growth, inflation, and unemployment rates. We also use a dummy variable to flag subprime (2007Q3-2008Q4) and European sovereign debt (2009Q4-2012Q4) crises. The dummy variable gets "1" for a crisis period and "0" otherwise.

2.3 Model specification

2.3.1 Background

Looking through the literature, it is clear that many studies have been conducted to investigate the elements that influence bank profitability and loan quality. These factors are generally observed under three categories: bank-specific, industry-specific, and macroeconomic factors. Herding in lending decisions is one of these factors that has mostly gone unnoticed. Considering the institutional, technological, and regulatory growth phases that the Turkish banking sector has gone through since the turn of the century, it provides a solid foundation for examining the elements that influence bank profitability and loan quality. Furthermore, researching the influence of herding in lending decisions is an attractive context for two reasons: first, because such studies are relatively rare, and second because it provides an opportunity to highlight an alternative element that contributes to bank profitability and loan quality.

2.3.1.1 Bank profitability determinants

In this study, bank profitability is represented by the return on assets (ROA) ratio. This ratio assesses the bank management's capacity to generate profit from its assets.

The literature treats profitability factors as bank-specific, industry-specific, and macroeconomic variables, as previously stated. We focus on macroeconomic and bank-specific variables in this particular study. When we research through the literature, we observe that several works (Athanasoglou et al., 2008; Petria et al., 2015; Staikouras and Wood, 2011) employ either the same or similar variables to proxy for certain characteristics of profitability. We generally follow Athanasoglou et al.'s (2008) bank-specific profitability factors in this study, but we also incorporate some additional proxies from the literature that are believed to have explanatory value:

<u>Capital</u>: Athanasoglou et al. (2008) use capital as a determinant of profitability since it is seen as a safety net in the event of an adverse shock. It refers to the bank's own cash available to support its operations, as well as an indication of the bank's positive expectations for future performance. The "Equity to Assets" ratio is utilized as a proxy for the capital in this study.

<u>Credit risk</u>: Credit risk is expected to have a negative relationship with bank profitability. As a result, it needs to be continuously monitored through screening and monitoring actions to increase profitability. The ratio of non-performing loans (gross) to total loans (hereinafter NPL) is utilized as a proxy for credit risk in this study.

<u>Inefficiency:</u> Because the cost of a bank's operations is supposed to be negatively related to its profitability, it is a measure of the efficiency of the bank's management. The cost-to-income ratio, which is the difference between non-interest income and non-interest expense, is used as a proxy for inefficiency.

Size: It is expected that the growing size has a positive relationship with profitability. The relationship between size and profitability, however, becomes non-linear at a certain point. As a result, banks may target an optimal size to maximize profitability. In this study, the natural logarithm of the assets is used to measure size.

Liquidity: Petria et al. (2015) assert that a bank with sufficient liquidity will be able to fulfill its obligations even during tumultuous times. Therefore, a sound liquidity level may reduce financing costs and enhance profitability. They also argue that liquid assets are less beneficial in terms of return-generating prospects as a counter-argument. Liquidity is represented in this study by the current ratio.

Off-balance sheet activities: According to Petria et al. (2015), a bank's profitability is not solely determined by balance sheet items. The net gains are also influenced by off-balance sheet operations. As a result, the non-interest income to total assets ratio in this study serves as a proxy for these off-balance sheet gains.

2.3.1.2 Loan quality determinants

Louzis et al. (2012) investigate the bank-specific, macroeconomic, and debt-related factors that drive non-performing loans. To highlight the bank-specific factors they refer to the paper by Berger and Deyoung (1997). In this paper, Berger and Deyoung (1997) express three main hypotheses:

(1) Bad management hypothesis: Low cost-efficiency stemming from bad management is positively linked to increases in future non-performing loans.
(2) Skimping hypothesis: Banks that allocate fewer resources to assure improved loan quality are more cost-effective, but they will face an increase in non-performing loans in the long run.
(3) Moral hazard hypothesis: Managers of banks with low capital tend to enhance the riskiness of their loan portfolios to create moral hazard incentives, which lead to an increase in non-performing loans.

Another element driving loan quality, according to Louzis et al. (2012), is banks' diversification prospects. Because diversification reduces credit risk, they predict a negative relationship between diversification and non-performing loans. They also highlight a second management-related hypothesis (the bad management II hypothesis), which states that when performance is employed as an indicator of management quality, an increase in future non-performing loans is adversely related to management quality.

Credit policy and ownership structure are also mentioned as contributing reasons to the growth of non-performing loans. The management of a bank may overstate current earnings at the expense of potential future problem loans in order to convince the market that the bank is viable. This strategy is evaluated by Louzis et al. (2012) under the "procyclical credit policy" hypothesis. Finally, they refer to the relationship between ownership concentration and risk-taking behavior as the "tight control hypothesis." They argue that more ownership concentration leads to more cautious risk-taking, which is associated with a lower rate of non-performing loans.

The loan quality is examined in this study using the non-performing loans to total loans ratio (NPL). The hypotheses and proxies by Louzis et al. (2012) are mostly applied in the identification of loan quality factors. The following is the hypothesis-proxy match, with expected signals in parenthesis:

(1) Bad management: Cost-to-income ratio (+)
(2) Bad management II: Return on equity (ROE) (-)
(3) Skimping: Cost-to-income ratio (-)
(4) Moral hazard: Equity to total assets ratio (-)
(5) Diversification: Non-interest income to total income ratio (-) and size (-)
(6) Procyclical credit policy: ROE (+)

Table 2.4 lists both dependent variables and explanatory variables for profitability and loan quality.

Table 2.4 Bank-specific variable definitions

Variable	Definition
Return on Assets (ROA)	$= \frac{Net\ Income}{Total\ Assets}$
Return on Equity (ROE)	$= \frac{Net\ Income}{Equity}$
Non-performing Loans Ratio (NPL)	$= \frac{Non-performing\ Loans\ (Gross)}{Total\ Loans}$
Equity to Assets Ratio (EA)	$= \frac{Equity}{Total\ Assets}$
Size	$= \ln\ (Total\ Assets)$
Cost-to-Income Ratio (CIR)	$= \frac{Non-interest\ Expenses}{Non-interest\ Income}$
Current Ratio (CR)	$= \frac{Liquid\ Assets}{Short-term\ Liabilities}$
Non-interest Income to Total Assets (NII)	$= \frac{Non-interest\ Income}{Total\ Assets}$
Non-interest Income Ratio (NIR)	$= \frac{Non-interest\ Income}{Total\ Income}$

This table presents the bank-specific variable definitions used either as dependent or explanatory variable in the econometric models. The variables are selected based on the literature on bank profitability and loan quality.

2.3.2 Herding measure

2.3.2.1 LSV herding measure

The LSV measure, developed by LSV (1992), is a generally acknowledged herding intensity evaluation technique that was originally used to investigate herding by all-equity pension funds. When we use the LSV approach in the loan/lending domain, the method's essential assumption is that when there is no herding, a lending decision is randomly distributed with an equal distribution across all loan categories.

For a certain loan category j at time t, the LSV measure is,

$$LSV_{j,t} = |p_{j,t} - p_t| - E|p_{j,t} - p_t|$$
$$= \left|\frac{X_{j,t}}{N_{j,t}} - \frac{\sum_{j=1}^{n} X_{j,t}}{\sum_{j=1}^{n} N_{j,t}}\right| - E\left[\left|\frac{\widetilde{X_{j,t}}}{N_{j,t}} - p_t\right|; \tilde{X}_{j,t} \sim B(p_t, N_{j,t})\right] \quad (1)$$

where $p_{j,t}$ is the proportion of banks that increase outstanding loans for category j in quarter t. Therefore, $X_{j,t}$ stands for the banks that increase outstanding loans in category j, and $N_{j,t}$ is the number of active banks in category j at quarter t. p_t is the cross-sectional average of the total number of banks that increase their loans in quarter t. n is the number of loan categories. As a result, p_t can be considered as a proxy for the overall lending trend during quarter t. The first term in equation (1) will be close to zero if each bank increases (or decreases) its loans in the outstanding category j in quarter t. The observed value of $p_{j,t}$ will deviate from p_t, if banks act together and increase or decrease loans for a specific loan category.

Under the null hypothesis of no herding, the adjustment factor $E|p_{j,t} - p_t|$, is employed to account for the distribution of banks' lending decisions and normalizes the measure to zero (Liu, 2014). The adjustment factor can be written as,

$$AF_{jt} = E\left[\left|\frac{\widetilde{X_{j,t}}}{N_{j,t}} - p_t\right|; \tilde{X}_{j,t} \sim B(p_t, N_{j,t})\right] = \sum_{k=0}^{N_{jt}} \binom{N_{jt}}{k} p_t^k (1-p_t)^{N_{jt}-k} \left|\frac{X_{jt}}{N_{jt}} - p_t\right| \quad (2)$$

which is the outcome of a binomial distribution with loan increase (with probability p_t) or decrease (with probability $1 - p_t$) as two possible outcomes in a $N_{j,t}$ active banks space.

2.3.2.2 Sias herding measure

The LSV measure focuses on the imbalance between the number of actions (banks increasing or decreasing their loans in a specific category) in the same direction, and the expected number of actions in the same direction for the period in question. Sias (2004), on the other hand, proposes a different measure in which herding is computed using the cross-sectional correlation between the activities of consecutive periods. Furthermore, the impacts of one's own activities and those of other parties on the herding measure can be distinguished. Sias (2004) originally focus on institutional herding on stocks. Thus, we need to adapt Sias' (2004) approach to the loan environment. We start by defining the ratio of banks increasing their loans in a certain loan category to the total number of banks actively trading that loan category:

$$p_{k,t} = \frac{I_{k,t}}{\left(I_{k,t} + D_{k,t}\right)} \tag{3}$$

where $I_{k,t}$ ($D_{k,t}$) is the number of banks that increases (or decreases) the outstanding loans in category k at quarter t. Following the definition of this ratio, we can present the Sias measure as follows:

$$\rho\left(p_{k,t}, p_{k,t-1}\right) = \left[\frac{1}{(K-1)\sigma(p_{k,t})\sigma(p_{k,t-1})}\right]\sum_{k=1}^{K}(p_{k,t} - p_t)(p_{k,t-1} - p_{t-1}) \tag{4}$$

where $\rho\left(p_{k,t}, p_{k,t-1}\right)$ is the cross-sectional correlation between the ratios of banks increasing loans to all active traders in the subsequent quarters. K is the number of loan categories, $\sigma(p_{k,t})$ is the standard deviation of the number of banks that are increasing their loans to all active traders ratio across loan categories for quarter t, and $p_{k,t}$ is the ratio of the number of banks that increase loans to the number of active banks in loan category k during quarter t. If a bank increases (or decreases) the amount of lending in a loan category k following its own or other banks' previous quarter lending decisions, the term $\rho\left(p_{k,t}, p_{k,t-1}\right)$ will be positive. Sias (2004) separates the cross-sectional correlation into two components to distinguish between the components of herding caused by following own and other banks' lending actions:

$$\begin{aligned}\rho\left(p_{k,t}, p_{k,t-1}\right) &= \left[\frac{1}{(K)\sigma\left(p_{k,t}\right)\sigma\left(p_{k,t-1}\right)}\right] \times \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}}\frac{(D_{n,k,t} - p_t)(D_{n,k,t-1} - p_{t-1})}{N_{k,t}N_{k,t-1}}\right] \\ &+ \left[\frac{1}{(K)\sigma\left(p_{k,t}\right)\sigma\left(p_{k,t-1}\right)}\right] \times \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}}\sum_{m=1,m\neq n}^{N_{k,t-1}}\frac{(D_{n,k,t} - p_t)(D_{m,k,t-1} - p_{t-1})}{N_{k,t}N_{k,t-1}}\right]\end{aligned} \tag{5}$$

The portion of the cross-sectional correlation due to banks following their own lending decisions in the previous quarter is the first term on the right-hand side of equation (5), while the second term is the portion of correlation due to banks following other banks' lending decisions in the previous quarter. $D_{n,k,t}$ is a dummy variable that equals 1 (0) if the bank n increases (decreases) the amount of loans in category k during quarter t. In the analysis we focus on the second component of the Sias measure (i.e., the contribution of following the lending decisions of other banks), because banks may spread their lending decisions out over time as a result of their strategy (Choi and Sias, 2009). Therefore, following own previous quarter lending decision may not mean a herding behavior.

2.3.2.3 Existence of herding

Table 2.5 illustrates the results of one–sample t-test that we perform to examine the existence of herding using the LSV and Sias measures. To show the contribution of following own and other banks' lending decisions, the Sias herding measure is broken into two parts. According to Panel A, the LSV measure results are significantly positive at the 1% significance level for both periods. "Beta," "Own," and "Other" in Panel B, respectively, denote overall cross-sectional correlation, contribution to cross-sectional correlation as a result of tracking own lending decisions, and contribution to cross-sectional correlation as a result of tracking other banks' lending decisions in the subsequent quarters. In Period 1, Beta, Own and Other metrics are significant at 1% significance level and in Period 2, Beta and Own metrics are significant at 10% and 1% significance levels, respectively. The contribution from following the lending decisions of other banks is not statistically significant. The results show that when the herding measure is LSV, we measure herding in both periods. However, when the herding measure is Sias, we only find herding in Period 1.

Table 2.5 Evidence of herding – LSV and Sias measures

	Period 1			Period 2		
Panel A. LSV herding measure						
Mean	0.051***			0.028***		
t-Stat	(7.881)			(3.718)		
Median	0.046			0.017		
Panel B. Sias herding measure						
	Beta	Own	Other	Beta	Own	Other
Mean	0.382***	0.047***	0.335***	0.183*	0.165***	0.018
t-Stat	(7.048)	(7.090)	(6.364)	(2.074)	(7.162)	(0.195)
Median	0.378	0.049	0.394	0.173	0.131	-0.087

This table presents evidence for the existence of herding in lending decisions. Periods 1 and 2 stand for 2002Q4 -2012Q2 and 2012Q3 -2017Q4, respectively. The results of the LSV herding and Sias herding measures are presented in Panel A and B, respectively. In Panel B, "Beta" represents overall Sias herding. "Own" shows the contribution of following own lending decision for a bank to the overall herding. "Other" shows the contribution of following another bank's lending decision to the overall herding. T-statistics are presented in parenthesis and *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively.

2.3.3 Econometric methodology

2.3.3.1 Panel data estimation

The process of selecting a competent econometric technique is a step-by-step process. The first stage in most circumstances is to explain the requirements of the hypotheses to be investigated concerning the data available. When we look at the recent panel data studies on the factors affecting non-performing loans and bank profitability, we observe dynamic modelling approaches to account for the time persistence of these structures (Athanasoglou et al., 2008; Louzis et al., 2012). The most used technique for ensuring a dynamic panel model specification is to include the dependent variable's first lag as a regressor on the right-hand side. However, Nickell (1981) states that the estimates of the lagged dependent variable become biased and inconsistent, as a result of the correlation between the fixed effects and the lagged dependent variable. Furthermore, the bias becomes more severe when the panel's temporal dimension (i.e., T) decreases, and Judson and Owen (1999) claim that even with a T of 30, a considerable amount of the bias may persist. In terms of the relationship between panel T and the biasedness of estimates, Roodman (2009) claims that the dynamic panel bias decreases as the panel's temporal dimension grows. This statement allows a fixed-effects estimator to execute correctly. Flannery and Hankins (2013) give additional evidence for the inverse relationship between panel T and estimate bias. Their simulation results show that when independent variable coefficients are estimated with fixed effects models, they are as accurate as those estimated with more advanced estimators. Fixed effects models, on the other hand, produce poor coefficient estimates for the lagged dependent variable.

We create dynamic models to account for time persistence in the dependent variable, based on recent literature in panel data studies studying factors that affect non-performing loans and bank profitability (Athanasoglou et al., 2008; Castro, 2013; Louzis et al., 2012). The following is the general form of our dynamic panel data specification:

$$y_{it} = \alpha y_{it-1} + \sum_{i=1}^{n} \beta_i X_{t-i} + \varepsilon_{it}$$

$$\varepsilon_{it} = v_i + u_{it} \tag{6}$$

where the subscripts i and t denote the cross-sectional and time dimensions respectively. y_{it} is the dependent variable and y_{it-1} is the lagged dependent variable that is implemented as a regressor to account for the time persistence of the dependent variable. X_{t-i} denotes the lags of the regressors other than the lagged dependent variable (n is the number of lags). ε_{it} is the error term and is composed of the unobserved individual effects v_i and the idiosyncratic portion u_{it}.

We estimate our models using system GMM developed by Arellano and Bover (1995) and Blundell and Bond (1998) with robust standard errors. In system GMM, two simultaneous equations are estimated: one for levels and one for first differences. As previously stated, the lagged dependent variable is inherently linked with the error term, resulting in estimate bias. However, the second-order lag of the dependent variable is expected to be correlated with the lagged dependent variable and uncorrelated with the error term. This shows that lags of the dependent variable of order two or more fulfill the moment criteria to be suitable instruments for the lagged dependent variable. The second source of the bias is the potential endogeneity of the regressors and their correlation with the error term. In the case of strict exogeneity, all previous and future values of the regressors are uncorrelated with the error term, so they can be instrumented by themselves. In the case of weak exogeneity or predetermined explanatory variables, only current and lagged values of the explanatory variables satisfy the moment conditions and are valid instruments. When we examine the literature, we find that the majority of studies treat macroeconomic variables as strictly exogenous (Athanasoglou et al., 2008; Danışman, 2018; Louzis et al., 2012). For bank-specific variables, however, strict exogeneity is presumed to be overly restrictive, and bank-specific variables are instead regarded as forward-looking, making them more ideal candidates for being predetermined variables (Louzis et al., 2012).

We should examine how the literature treats the factors most similar to herding because “herding intensity” is not a commonly utilized explanatory variable in bank profitability and loan quality research. From here, we can conclude that the herding variable is analogous to the often-used “bank concentration” variables. The bank concentration is proxied by the Herfindahl-Hirschman index (HHI) and deemed external in terms of structure by Athanasoglou et al. (2008). Similarly, Berger et al. (2004) use HHI and n-firm concentration ratio (CRn) to quantify concentration while evaluating the structure-conduct-performance hypothesis (SCP) and conclude that these proxies can be used as external indicators of market power and intensity. As a result, the herding variable is treated as strictly exogenous.

We apply one-step estimator. The two-step estimator is accepted to be asymptotically more efficient than the one-step estimator, and the homoscedasticity of errors assumption is relaxed with two-step estimator. However, efficiency gains due to using two-step estimator are not at significant levels (Arellano and Bond, 1991; Blundell et al., 2000; Blundell and Bond, 1998). The findings of Monte Carlo experiments conducted by Judson and Owen (1999) reveal that one-step estimators outperform two-step estimators, supporting this claim. The Hansen specification test is used to determine the validity of instruments (Hansen, 1982). The null hypothesis for the Hansen test is "Overidentifying restrictions are valid". We also see if the error terms are connected in the second order (m_2 test). The null hypothesis for this test is "No second-order autocorrelation", and rejection of the null hypothesis means inconsistent GMM estimates.

2.3.3.2 Model specification

We start with a baseline model that contains the lags of the macroeconomic regressors as well as the lagged dependent variable. As a result, equation (6) has the following form:

$$y_{it} = \alpha y_{it-1} + \sum_{j=1}^{2} \beta_{1j} \Delta GDP_{t-j} + \sum_{j=1}^{2} \beta_{2j} \Delta UNEM_{t-j} + \sum_{j=1}^{2} \beta_{3j} INFL_{t-j} + \varepsilon_{it} \tag{7}$$

where y_{it} denotes either bank profitability or loan quality/credit risk measures depending on the model, ΔGDP_t is the real GDP growth rate, $\Delta UNEM_t$ is the change in the unemployment rate and $INFL_t$ is the inflation rate. We determine the lag order for macroeconomic variables following the relevant literature (Louzis et al., 2012) and taking into account the relationship between the number of instruments and the number of cross-sectional units (N)[1]. Then, we add each explanatory variable to the baseline model one by one to check if they have any explanatory power. As a result, we enhance the baseline model in the following way:

$$y_{it} = \alpha y_{it-1} + \sum_{j=1}^{2} \beta_{1j} \Delta GDP_{t-j} + \sum_{j=1}^{2} \beta_{2j} \Delta UNEM_{t-j} + \sum_{j=1}^{2} \beta_{3j} INFL_{t-j} + \sum_{j=1}^{4} \beta_{4j} X_{it-j} + \varepsilon_{it} \tag{8}$$

where X_{it} denotes the bank-specific and herding variables. We utilize four-lags of the bank-specific variables, as recommended by Berger and Deyoung (1997) and Louzis

[1] According to Roodman (2009), having too many instruments (i.e., instrument proliferation) may lead endogenous variables to overfit, and overidentifying restrictions and error correlation tests to be downwardly biased.

et al. (2012), to capture the fluctuations of regressors in the previous year. Because there is a time delay between the financial managers' actions and their reflection in the accounting data, we assume that the existing level of the bank-specific regressors does not affect the existing level of the dependent variables, as also proposed by Louzis et al. (2012). A restricted GMM procedure[2] is implemented in which we include only a limited number of lagged regressors as instruments. Furthermore, as previously noted, bank-specific and herding factors are added one at a time to guarantee that a minimal number of new instruments are required. The goal is to keep the number of Instruments to a minimum in comparison to the number of cross-sectional units. Collapsing, as proposed by Holtz-Eakin et al. (1988), is another procedure we follow to ensure that the number of instruments does not exceed the number of cross-sectional groups. We also use orthogonal deviations, as advised by Roodman (2009), because we have an unbalanced panel and lose observations due to differencing processes.

In addition to developing models using macro and micro-level variables, we are also interested in the cumulative long-term impact of these variables on the dependent variable. As a result, the long-run coefficients[3] are calculated as follows:

$$\beta_4^L = \frac{\sum_{j=1}^{4} \beta_{4j}}{(1-a)} \tag{9}$$

where superscript L denotes "long-run". According to Louzis et al. (2012), we account for the covariance between the estimated coefficients of the lags when estimating the long-run coefficient variance (i.e., β_{4j}), which gives an accurate and robust statistical interpretation for the cumulative effect of the lagged regressors. When we employ long-run standard errors, we also account for multicollinearity-related frictions such as the insignificance of the individual lags. As a result, we test our hypotheses based on the long-run coefficients as follows:

$H_0: \beta_4^L = 0$

[2] According to Judson and Owen (1999), employing a restricted GMM procedure does not worsen the performance of the estimation.

[3] In calculating long-run coefficients, we follow Louzis vd. (2012, Merkl and Stolz (2013), and Castro (2013). Depending on the lag order, the equation can be modified. The "delta method" can be used to calculate the coefficients' standard errors.

H_a: $\beta_4^L < or > 0$ depending on the hypothesis.

The effect of regressors on the dependent variable may be moderated by specific periods, such as crises (Fang et al., 2021). We investigate if the impact of herding intensity on bank profitability/loan quality varies depending on whether the referred period is within a generally recognized crisis period or not. As a result, we use interaction terms to describe the relationship between herding intensity and crises. Brambor et al. (2006) indicate that it is necessary to include all constitutive terms when specifying a multiplicative interaction term to prevent a misspecified model. As a result, the following is the econometric specification, which includes the interaction term:

$$y_{it} = \alpha y_{it-1} + \sum_{j=1}^{2} \beta_{1j} \Delta GDP_{t-j} + \sum_{j=1}^{2} \beta_{2j} \Delta UNEM_{t-j} + \sum_{j=1}^{2} \beta_{3j} INFL_{t-j} + \beta_4 CRISIS_t + \sum_{j=1}^{4} \beta_{5j} HERD_{t-j} + \sum_{j=1}^{4} \beta_{6j} CRISIS_t \times HERD_{t-j} + \varepsilon_{it} \tag{10}$$

where “HERD” and “CRISIS” denote herding intensity and crisis period (i.e., equals 1 if the current period is within the crisis period), respectively. As mentioned by Brambor et al. (2006), Shehzad et al. (2010), and Louzis et al. (2012) statistical inference for the multiplicative interaction terms should not be based on simple t-statistics of the constitutive terms. Therefore, we take the derivative of equation (10) with respect to the crisis term and asses its impact on the dependent variable over a range of herding intensity, as indicated by Aiken et al. (1991). As a result, we state the following for the long-run marginal effect of herding on the dependent variable conditional on crisis:

$$\beta_4^L + \beta_6^L HERD = \frac{\beta_4}{(1-\alpha)} + \left(\frac{\sum_{j=1}^{n} \beta_{6j}}{(1-\alpha)}\right) \times HERD \tag{11}$$

To determine the statistical significance of the long-run marginal effect of herding intensity on the dependent variable conditional on the crisis term, we test the following null and alternative hypotheses:

H_0: $\beta_4^L + \beta_6^L HERD = 0$

$H_a: \beta_4^L + \beta_6^L HERD > 0.$

Based on the standard errors produced from Stuart and Ord's (1998) variance approximation, we create confidence intervals to assess if the null hypothesis is rejected.

2.4 Results

2.4.1 Preliminary analyses

Tables 2.6 and 2.7 show the pairwise correlations for the first and second periods, respectively. Although there are significant correlations among variables for the first period, they are not strong enough to consider a potential multicollinearity problem[4]. The correlations that demand attention in the second period are those between capital (i.e., EA) and size variables (i.e. Size), as well as off-balance sheet activities (i.e. NII) and diversification (i.e. NIR).

[4] We believe that correlation coefficients of less than 0.7 in absolute terms do not cause a problem of multicollinearity. In the modeling phase, we additionally assess correlation coefficients for the variables utilized in the first difference forms. We do not report those coefficients in the correlation results because we do not see any cases that violate the preceding requirement.

Table 2.6 Correlation results for the first period

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $Size$	1						
(2) CIR	0.001	1					
(3) CR	-0.297***	0.006	1				
(4) NIR	-0.104***	0.03	0.032	1			
(5) EA	-0.525***	0.073**	0.314***	0.036	1		
(6) $INFL$	-0.130***	0.015	0.116***	0.206***	0.051*	1	
(7) LSV	-0.060*	0.023	0.115***	0.102***	0.035	0.451***	1
(8) NII	-0.139***	0.005	0.023	0.477***	0.265***	0.197***	0.045
(9) NPL	-0.169***	0.036	0.079**	-0.071**	0.321***	0.112***	0.054*
(10) ΔGDP	-0.037	0.027	-0.003	0.050*	-0.007	-0.171***	0.196***
(11) ROA	0.125***	-0.038	0.014	0.152***	0.021	0.058*	0.041
(12) ROE	0.298***	-0.013	-0.03	0.071**	-0.108***	0.154***	0.096***
(13) $Sias$	-0.036	0.064**	0.008	0.005	-0.008	-0.032	-0.089***
(14) $UNEM$	0.001	-0.028	-0.028	-0.074**	0.086***	-0.138***	-0.191***

Table 2.6 Correlation results for the first period (cont'd)

Variables	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) $Size$							
(2) CIR							
(3) CR							
(4) NIR							
(5) EA							
(6) $INFL$							
(7) LSV							
(8) NII	1						
(9) NPL	-0.026	1					
(10) ΔGDP	0.082***	0.047	1				
(11) ROA	0.351***	-0.060*	-0.008	1			
(12) ROE	0.239***	-0.054*	-0.004	0.766***	1		
(13) $Sias$	0.001	0.031	0.117***	-0.029	-0.009	1	
(14) $UNEM$	-0.004	0.012	-0.204***	0.035	-0.006	-0.176***	1

This table presents the correlation results for the variables used in the models built for Period 1 (2002Q4 -2012Q2). *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 2.7 Correlation results for the second period

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) $Size$	1						
(2) CIR	-0.014	1					
(3) CR	-0.185***	0.001	1				
(4) NIR	0.175***	-0.002	0.067*	1			
(5) EA	-0.666***	-0.004	0.135***	0.037	1		
(6) $INFL$	0.082*	-0.029	0.100**	-0.029	-0.088**	1	
(7) LSV	0.001	-0.011	0.015	-0.016	-0.013	-0.052	1
(8) NII	0.072*	-0.002	0.048	0.828***	0.116***	-0.041	-0.056
(9) NPL	-0.338***	-0.002	-0.004	0.024	0.550***	0.04	-0.009
(10) ΔGDP	-0.008	-0.001	0.014	0.016	0.003	0.123***	0.132***
(11) ROA	0.069*	-0.014	-0.557***	0.039	0.246***	-0.015	-0.023
(12) ROE	0.447***	-0.01	-0.458***	0.05	-0.124***	0.019	-0.036
(13) $Sias$	0.011	-0.033	-0.005	0.016	-0.015	0.203***	0.051
(14) $UNEM$	0.084**	-0.016	0.016	0.024	-0.085**	0.304***	-0.053

Table 2.7 Correlation results for the second period (cont'd)

Variables	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) $Size$							
(2) CIR							
(3) CR							
(4) NIR							
(5) EA							
(6) $INFL$							
(7) LSV							
(8) NII	1						
(9) NPL	0.078*	1					
(10) ΔGDP	0.017	0.014	1				
(11) ROA	0.074*	0.327***	0.002	1			
(12) ROE	0.068*	-0.007	0.009	0.821***	1		
(13) $Sias$	-0.009	-0.01	-0.046	-0.008	-0.011	1	
(14) $UNEM$	0.049	0.031	0.132***	-0.035	-0.014	-0.092**	1

This table presents the correlation results for the variables used in the models built for Period 2 (2012Q3 -2017Q4). *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively.

We use the Fisher-type unit roots test since it outperforms the others and does not require a balanced panel (Athanasoglou et al., 2008; Maddala and Wu, 1999). Because we have a relatively large panel of data, we use the modified inverse chi-squared test statistic to analyze unit root results, as suggested by Choi (2001). Tables 2.8 and 2.9 show the results of the unit roots tests for the first and second periods, respectively. The null hypothesis "All panels contain unit roots" is rejected at the 1% level for all variables except the size variable (rejected at 5%) in the first period. The null hypothesis is rejected at the 1% level for all variables except loan quality/credit risk and inflation in the second period. For the loan quality models, we use a first difference transformation (i.e. since NPL is the dependent variable in these models), and we do not exclude the inflation variable from our models because we are less likely to get spurious results given that the dependent variables are stationary (Athanasoglou et al., 2008).

Table 2.8 Fisher-type panel unit root test results

Variable	Test-statistic
$Size$	2.226**
CIR	24.224***
CR	26.203***
NIR	20.040***
EA	12.709***
NII	27.516***
NPL	22.278***
ROA	13.075***
ROE	13.398***
LSV	117.033***
$Sias$	38.697***
ΔGDP	44.315***
$INFL$	103.261***
$UNEM$	5.472***

This table presents the Fisher-type panel unit root test results. The null hypothesis of the test is "H0: all panels contain unit roots. The selected test statistic is "modified inverse chi-squared". *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 2.9 Fisher-type panel unit root test results

Variable	Test-statistic
$Size$	7.089***
CIR	17.359***
CR	14.355***
NIR	2.940***
EA	11.665***
NII	36.927***
NPL	1.519*
ROA	4.808***
ROE	4.756***
LSV	29.799***
$Sias$	14.642***
ΔGDP	96.099***
$INFL$	-3.743
$UNEM$	2.355***
$Size$	25.205***
CIR	32.913***

This table presents the Fisher-type panel unit root test results. The null hypothesis of the test is "H0: all panels contain unit roots. The selected test statistic is "modified inverse chi-squared". *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively.

2.4.2 Model results

Due to a change in the loan classification principles as of June 2012, we divide the data set into two according to period start and end dates; the first and second parts cover the periods 2002Q4-2012Q2 and 2012Q3-2017Q4, respectively. As a result, the results of one-step system GMM models for these periods are shown in separate tables. We also include Hansen J statistics and m 2 test results at the bottom of each table. We validate our hypothesis based on the significance of long-run coefficients, as stated in the model specification. Individual lag and long-run coefficient estimations for the first and second periods are shown in Tables 2.10 and 2.11, respectively, for models with bank profitability as the dependent variable. Panel

A shows the results of individual coefficient estimations, whereas Panel B shows the results of long-run coefficient estimations in each table.

Tables 2.10 and 2.11 both begin with baseline models that solely include macroeconomic variables and lagged dependent variable as regressors. When we look at the results presented in Panel B of Table 2.10, only the coefficient of the inflation variable is statistically significant with a positive sign. The positive relationship between inflation and profitability implies that managers of the banks in Turkey can accurately forecast inflation and adjust the interest rates accordingly to achieve higher profits in the first period. This conclusion is consistent with Athanasoglou et al.'s (2008) findings for Greek banks and Tan and Floros (2012)' findings for Chinese banks. A similar conclusion may be drawn for the second period, as Panel B of Table 2.11 shows a significantly positive inflation coefficient. For the second period, however, the total long-run effect of inflation is stronger. It is observed that most of the models in Tables 2.10 and 2.11 show that adding bank-specific and herding factors into the model does not affect on the long-run impact of inflation on bank profitability. As a result, the inflation variable estimation findings are fairly consistent across different models.

For the first period, the coefficient of the LSV herding measure is notably negative. This conclusion is in line with Fang et al.'s (2021) findings. They show that irrational loan herding has a considerably negative impact on bank performance, particularly during the financial crisis. They state that this is due to increased competition, which can lead to irrational herding during a crisis. For the first period, the coefficient of the Sias herding measure is not significant. This finding indicates that following other banks in lending decisions for adjacent quarters has no impact on the profitability in the first period. The coefficient of LSV herding is not significant for the second period, indicating that the cross-sectional average for deviation from the expected lending amount in the quarters of the second period does not affect profitability. The coefficient of the Sias herding measure is significantly positive. This result would have shown a positive impact of following other banks in consecutive periods on profitability if the "following other banks" portion of the Sias measure had been significantly positive. However, from Table 2.5, we recall that the mean of the "following other banks" portion is not significantly different from zero.

As a result, using the Sias measure, it is not valid to mention a positive relationship between herding and profitability for the second period.

According to Athanasoglou et al. (2008), capital is perceived as a buffer against adverse shocks and an indicator of good performance. Tables 2.10 and 2.11 show that the capital variable's coefficient is not statistically significant for the first period, but it is significantly positive for the second, as implied by Athanasoglou et al. (2008). Because poor asset quality is one of the reasons for bank failures, the expected sign for the link between credit risk and bank profitability is negative (Athanasoglou et al., 2008). The credit risk variable's long-run coefficient estimation in Table 2.10 for the first period is not statistically significant. The predicted coefficient for the second period, on the other hand, is significantly positive, which contradicts previously published results in the literature (Athanasoglou et al., 2008). Because it is a measure of managerial inefficiency, costs associated with a bank's operations are predicted to be negatively related to the bank's performance. For both periods, the coefficient estimations for the "cost-to-income ratio" are not statistically significant. As a result, cost efficiency is not a major determinant of profitability. Growing size has been connected to increasing profitability in the literature. However, some studies argue that a bank's size should be optimized to maximize profits (Athanasoglou et al., 2008). For both periods, our estimation results for the coefficient of size variable are not statistically significant. This finding is consistent with Athanasoglou et al.'s (2008) findings, which suggest that one possible explanation is that small-sized banks aim to grow faster at the expense of profitability. The liquidity level of a bank is crucial since it indicates the bank's ability to meet obligations even during difficult times. According to Petria et al. (2015), a negative relationship with profitability is also feasible because liquid assets are less profitable in terms of return generation. The liquidity variable's coefficient estimations do not yield a significant result for the first period, but the results support the claim that there is a positive association between profitability and liquidity in the second period. Off-balance sheet activities, just like loans, add to profitability, particularly when banks exploit them as a diversion from the limited profitability environment imposed by strict regulatory requirements. Off-balance sheet activities do not have a significant impact on profitability in both periods, according to the coefficient estimates in Tables 2.10 and 2.11.

Table 2.10 GMM estimation results for bank profitability models in the first period

Dep. Variable: ROA	(1)		(2)		(3)		(4)
Panel A: Estimation of individual lag coefficients							
Constant	-0.002		0.001		0.001		0.002
	(-1.021)		(1.041)		(0.436)		(0.787)
ROA_{t-1}	0.805***		0.766***		0.769***		0.759***
	(59.378)		(28.895)		(27.588)		(21.021)
ΔGDP_{t-1}	0.020		0.020		0.003		0.013
	(1.281)		(1.175)		(0.127)		(0.849)
ΔGDP_{t-2}	-0.043*		-0.046**		-0.051**		-0.046**
	(-2.026)		(-2.273)		(-2.282)		(-2.133)
$INFL_{t-1}$	0.065***		0.088***		0.064***		0.059***
	(3.824)		(3.979)		(3.565)		(4.798)
$INFL_{t-2}$	-0.005		-0.024*		-0.031*		-0.027**
	(-0.453)		(-1.713)		(-1.996)		(-2.073)
$\Delta UNEM_{t-1}$	-0.041		-0.021		-0.037		-0.044
	(-1.423)		(-0.680)		(-1.285)		(-1.524)
$\Delta UNEM_{t-2}$	-0.004		0.011		0.007		0.003
	(-0.180)		(0.632)		(0.328)		(0.144)
		LSV_{t-1}	-0.017	$Sias_{t-1}$	-0.001	EA_{it-1}	0.025*
			(-1.488)		(-0.569)		(1.859)
		LSV_{t-2}	0.001	$Sias_{t-2}$	0.001	EA_{it-2}	-0.020
			(0.039)		(0.675)		(-1.013)
		LSV_{t-3}	-0.031***	$Sias_{t-3}$	0.001*	EA_{it-3}	-0.002
			(-2.834)		(1.707)		(-0.121)
		LSV_{t-4}	-0.013	$Sias_{t-4}$	0.001	EA_{it-4}	-0.003
			(-1.460)		(1.165)		(-0.270)

Table 2.10 GMM estimation results for bank profitability models in the first period (cont'd)

Dep. Variable: ROA	(1)		(2)		(3)		(4)
Panel B: Estimation of long-run coefficients							
ΔGDP	-0.119		-0.108		-0.211		-0.136
	(-0.790)		(-0.830)		(-1.370)		(-1.090)
$INFL$	0.310***		0.274**		0.145*		0.129*
	(2.970)		(2.720)		(1.800)		1.790
$\Delta UNEM$	-0.232		-0.042		-0.130		-0.171
	(-1.590)		(-0.310)		(-1.090)		(-1.250)
		LSV	-0.257**	$Sias$	0.010	EA	0.001
			(-2.170)		(1.250)		(0.010)
Observations	957		928		928		928
# of banks	29		29		29		29
# of instruments	10		14		14		21
Hansen J	3.631		3.834		3.819		13.89
Hansen p-value	0.163		0.147		0.148		0.126
m_2	-1.114		-0.584		-0.531		-0.471
m_2 p-value	0.265		0.559		0.595		0.638

Table 2.10 GMM estimation results for bank profitability models in the first period (cont'd)

Dep. Variable: ROA	(5)		(6)		(7)		(8)		(9)
Panel A: Estimation of individual lag coefficients									
Constant	0.002		0.001		0.007		0.001		0.000
	(1.128)		(0.800)		(0.893)		(0.391)		(0.272)
ROA_{t-1}	0.776***		0.778***		0.776***		0.770***		0.769***
	(26.363)		(28.598)		(25.926)		(25.207)		(20.479)
ΔGDP_{t-1}	0.009		0.011		0.009		0.011		0.017
	(0.616)		(0.729)		(0.629)		(0.731)		(1.003)
ΔGDP_{t-2}	-0.054**		-0.048**		-0.049**		-0.049**		-0.033
	(-2.468)		(-2.176)		(-2.326)		(-2.259)		(-1.602)
$INFL_{t-1}$	0.063***		0.062***		0.057***		0.065***		0.060***
	(4.041)		(3.854)		(3.532)		(3.738)		(3.756)
$INFL_{t-2}$	-0.036**		-0.028**		-0.031**		-0.030**		-0.015
	(-2.640)		(-2.083)		(-2.263)		(-2.197)		(-1.144)
$\Delta UNEM_{t-1}$	-0.035		-0.037		-0.038		-0.040		-0.038
	(-1.175)		(-1.264)		(-1.357)		(-1.379)		(-1.215)
$\Delta UNEM_{t-2}$	0.004		0.004		0.001		0.003		0.036**
	(0.195)		(0.231)		(0.048)		(0.134)		(2.272)
ΔNPL_{it-1}	-0.026***	CIR_{it-1}	-0.000	$Size_{it-1}$	-0.002	CR_{it-1}	0.002	NII_{it-1}	0.027**
	(-4.405)		(-0.292)		(-0.685)		(1.170)		(2.513)
ΔNPL_{it-2}	0.006*	CIR_{it-2}	-0.000	$Size_{it-2}$	0.004	CR_{it-2}	0.000	NII_{it-2}	-0.026**
	(1.885)		(-1.043)		(1.484)		(0.118)		(-2.125)
ΔNPL_{it-3}	0.007	CIR_{it-3}	-0.000	$Size_{it-3}$	0.002	CR_{it-3}	-0.002**	NII_{it-3}	-0.029***
	(1.258)		(-0.904)		(0.403)		(-2.161)		(-5.046)
ΔNPL_{it-4}	0.013**	CIR_{it-4}	-0.000	$Size_{it-4}$	-0.004	CR_{it-4}	0.000	NII_{it-4}	0.009***
	(2.561)		(-0.100)		(-1.035)		(1.459)		(3.300)

Table 2.10 GMM estimation results for bank profitability models in the first period (cont'd)

Dep. Variable: *ROA*	(5)		(6)		(7)		(8)		(9)
Panel B: Estimation of long-run coefficients									
ΔGDP	-0.201		-0.166		-0.175		-0.165		-0.065
	(-1.490)		(-1.240)		(-1.390)		(-1.270)		(-0.520)
$INFL$	0.122		0.152*		0.114		0.153*		0.195**
	(1.650)		(1.940)		(1.260)		(1.810)		(2.100)
$\Delta UNEM$	-0.141		-0.145		-0.165		-0.163		-0.008
	(-1.090)		(-1.100)		(-1.180)		(-1.250)		(-0.060)
ΔNPL	0.001	CIR	0.000	$Size$	-0.002	CR	0.003	NII	-0.078
	(0.070)		(-0.780)		(-0.750)		(1.000)		(-0.670)
Observations	928		928		928		928		928
# of banks	29		29		29		29		29
# of instruments	21		21		23		21		27
Hansen J	13.24		14.08		14.88		13.50		21.11
Hansen p-value	0.152		0.119		0.188		0.141		0.134
m_2	-0.573		-0.580		-0.494		-0.540		-0.386
m_2 p-value	0.567		0.562		0.621		0.589		0.699

The results of the dynamic models exploring the relationship between bank profitability and herding for the first period are presented in this table (2002Q4 -2012Q2). Panel A presents the results of individual coefficient estimations and Panel B presents the long-run coefficient estimations. The models are built using system GMM, which is proposed by Blundell and Bond (1998). The macroeconomic and herding variables are assumed as strictly exogenous, but bank-specific variables are rather assumed to be weakly exogenous. In the model generation, robust one-step estimator with orthogonal deviations is used. The validity of the selected instruments is controlled via Hansen J test, which has a null hypothesis of "H0: Overidentifying restrictions are valid". Second-order autocorrelation is tested via Arellano-Bond test (m_2), which has a null hypothesis of "H0: There is no second-order autocorrelation". Four lags of the bank-specific or herding variables are included in each time to account for the effect of the previous year's quarters and to avoid instrument proliferation problem. t-statistics are presented in parenthesis and *, **, *** indicate significance at the 10%,

Table 2.11 GMM estimation results for bank profitability models in the second period

Dep. Variable: ROA	(1)		(2)		(3)		(4)
Panel A: Estimation of individual lag coefficients							
Constant	-3.313***		-3.218***		-3.006***		-3.394***
	(-5.942)		(-6.631)		(-5.968)		(-5.364)
ROA_{t-1}	0.341***		0.356***		0.359***		0.407***
	(3.419)		(4.211)		(3.882)		(4.251)
ΔGDP_{t-1}	-0.337		-4.410		2.709		-0.722
	(-0.165)		(-1.600)		(0.903)		(-0.460)
ΔGDP_{t-2}	-2.238		-5.087**		0.692		-2.440*
	(-1.033)		(-2.502)		(0.245)		(-1.716)
$INFL_{t-1}$	3.471		9.128**		1.075		3.848*
	(1.363)		(2.503)		(0.415)		(1.764)
$INFL_{t-2}$	1.169		-3.620		0.104		2.567
	(0.798)		(-1.165)		(0.056)		(1.352)
$\Delta UNEM_{t-1}$	-0.344		-5.807		-3.705		0.548
	(-0.153)		(-1.593)		(-1.347)		(0.239)
$\Delta UNEM_{t-2}$	3.323**		0.816		2.124		4.143***
	(2.120)		(0.429)		(0.954)		(2.780)
		LSV_{t-1}	-0.860	$Sias_{t-1}$	0.105*	EA_{it-1}	-0.780
			(-1.091)		(2.007)		(-0.645)
		LSV_{t-2}	-1.717	$Sias_{t-2}$	0.124*	EA_{it-2}	1.449*
			(-1.531)		(1.820)		(1.869)
		LSV_{t-3}	1.344*	$Sias_{t-3}$	0.114	EA_{it-3}	3.182**
			(1.787)		(1.575)		(2.172)
		LSV_{t-4}	0.903*	$Sias_{t-4}$	-0.029	EA_{it-4}	-2.261
			(1.783)		(-0.328)		(-0.921)

Table 2.11 GMM estimation results for bank profitability models in the second period (cont'd)

Dep. Variable: ROA	(1)		(2)		(3)		(4)
Panel B: Estimation of long-run coefficients							
ΔGDP	-3.909		-14.742**		5.309		-5.335
	(-0.630)		(-2.490)		(0.580)		(-1.090)
$INFL$	7.043**		8.551***		1.840		10.825***
	(2.290)		(2.880)		(0.500)		(3.220)
$\Delta UNEM$	4.523		-7.748		-2.469		7.917**
	(1.650)		(-1.090)		(-0.400)		(2.170)
		LSV	-0.513	$Sias$	0.491**	EA	2.682***
			(-0.200)		(2.360)		(5.100)
Observations	427		404		404		404
# of banks	27		27		27		27
# of instruments	13		19		15		25
Hansen J	6.694		8.572		2.815		16.62
Hansen p-value	0.244		0.285		0.421		0.217
m_2	-0.663		-0.465		-0.549		-0.556
m_2 p-value	0.507		0.642		0.583		0.578

Table 2.11 GMM estimation results for bank profitability models in the second period (cont'd)

Dep. Variable: ROA	(5)		(6)		(7)		(8)		(9)
Panel A: Estimation of individual lag coefficients									
Constant	-3.267***		-2.659***		-5.781*		-3.178***		-3.142***
	(-5.469)		(-5.426)		(-2.013)		(-4.522)		(-4.906)
ROA_{t-1}	0.366***		0.486***		0.334***		0.467***		0.372***
	(3.533)		(6.579)		(5.068)		(4.557)		(3.631)
ΔGDP_{t-1}	-1.066		-0.815		0.041		-0.912		-0.741
	(-0.587)		(-0.493)		(0.025)		(-0.527)		(-0.507)
ΔGDP_{t-2}	-2.635		-2.486		-1.331		-2.887		-4.194**
	(-1.353)		(-1.401)		(-0.789)		(-1.546)		(-2.149)
$INFL_{t-1}$	3.309		2.834		1.924		4.385*		4.472**
	(1.449)		(1.292)		(0.689)		(1.893)		(2.180)
$INFL_{t-2}$	1.637		1.903		3.290*		1.866		-0.502
	(0.860)		(0.887)		(1.771)		(0.893)		(-0.226)
$\Delta UNEM_{t-1}$	0.887		1.001		1.290		0.465		-12.152*
	(0.313)		(0.365)		(0.508)		(0.177)		(-1.849)
$\Delta UNEM_{t-2}$	3.754**		4.511**		4.105**		4.301**		4.556
	(2.620)		(2.524)		(2.420)		(2.439)		(1.210)
ΔNPL_{it-1}	-0.197	CIR_{it-1}	0.001	$Size_{it-1}$	0.201	CR_{it-1}	0.048	NII_{it-1}	15.452*
	(-0.250)		(0.472)		(0.342)		(0.359)		(1.990)
ΔNPL_{it-2}	2.093*	CIR_{it-2}	-0.001	$Size_{it-2}$	-0.533*	CR_{it-2}	0.137	NII_{it-2}	3.891
	(1.988)		(-0.892)		(-1.915)		(1.574)		(0.816)
ΔNPL_{it-3}	-0.352	CIR_{it-3}	-0.000	$Size_{it-3}$	-0.417	CR_{it-3}	0.143	NII_{it-3}	-18.269**
	(-0.922)		(-0.420)		(-0.967)		(1.686)		(-2.733)
ΔNPL_{it-4}	-0.743***	CIR_{it-4}	-0.000	$Size_{it-4}$	0.892*	CR_{it-4}	0.099	NII_{it-4}	7.384
	(-2.846)		(-0.712)		(1.991)		(1.010)		(1.035)

Table 2.11 GMM estimation results for bank profitability models in the second period (cont'd)

Dep. Variable: *ROA*	(5)		(6)		(7)		(8)		(9)
Panel B: Estimation of long-run coefficients									
ΔGDP	-5.833		-6.423		-1.937		-7.130		-7.856
	(-1.030)		(-1.000)		(-0.400)		(-1.070)		(-1.670)
$INFL$	7.797**		9.218**		7.833**		11.730***		6.321*
	(2.520)		(2.790)		(2.080)		(3.170)		(1.800
$\Delta UNEM$	7.317*		10.728**		8.105*		8.945**		-12.093
	(1.790)		(2.130)		(1.990)		(2.270)		(-1.260)
ΔNPL	1.262*	CIR	-0.001	$Size$	0.215	CR	0.802***	NII	13.467
	(1.890)		(-0.410)		(0.890)		(4.180)		(0.690)
Observations	404		404		404		404		404
# of banks	27		27		27		27		27
# of instruments	25		22		22		22		23
Hansen J	17.49		15.61		14.36		12.64		12.65
Hansen p-value	0.178		0.111		0.157		0.244		0.317
m_2	-0.691		-0.717		-0.348		-0.528		-0.705
m_2 p-value	0.490		0.473		0.728		0.598		0.481

The results of the dynamic models exploring the relationship between bank profitability and herding for the second period are presented in this table (2012Q3 -2017Q4). Panel A presents the results of individual coefficient estimations and Panel B presents the long-run coefficient estimations. The models are built using system GMM, which is proposed by Blundell and Bond (1998). The macroeconomic and herding variables are assumed as strictly exogenous, but bank-specific variables are rather assumed to be weakly exogenous. In the model generation, robust one-step estimator with orthogonal deviations is used. The validity of the selected instruments is controlled via Hansen J test, which has a null hypothesis of "H0: Overidentifying restrictions are valid". Second-order autocorrelation is tested via Arellano-Bond test (m_2), which has a null hypothesis of "H0: There is no second-order autocorrelation". Four lags of the bank-specific or herding variables are included in each time to account for the effect of the previous year's quarters and to avoid instrument proliferation problem. t-statistics are presented in parenthesis and *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively.

We also look at the cumulative effect of the crisis-herding interaction on profitability to see if there is any evidence to back up the discussion that herding has more harmful effects on profitability, especially during turbulent periods when information efficiency is low. As a result, we build the models in Table 2.12 and plot the long-run marginal effects of the crisis-herding interaction on profitability for the LSV and Sias herding measures, respectively. The horizontal axis in Figure 2.1 represents the level of LSV herding, while the vertical axis represents the marginal effect of this interaction during a crisis. Because the confidence interval encompasses the origin, the observed influence of the interaction does not have a significant effect on profitability, as shown in Figure 2.1. Figure 2.2 can be used to get the same conclusion about the crisis-Sias herding interaction. As a result, there is little evidence to support the claim that herding harms profitability during turbulent periods.

Table 2.12 Crisis-herding interaction models in the first period

Dep. Variable: ROA	(1)		(2)
Panel A: Estimation of individual lag coefficients			
Constant	0.009***		0.005*
	(3.457)		(1.714)
ROA_{t-1}	0.772***		0.772***
	(22.466)		(23.614)
ΔGDP_{t-1}	0.035		0.008
	(1.402)		(0.261)
ΔGDP_{t-2}	-0.009		-0.051**
	(-0.411)		(-2.319)
$INFL_{t-1}$	0.061***		0.087***
	(3.752)		(3.187)
$INFL_{t-2}$	-0.011		-0.060***
	(-0.930)		(-3.064)
$\Delta UNEM_{t-1}$	-0.027		-0.072*
	(-0.775)		(-1.838)
$\Delta UNEM_{t-2}$	-0.026		-0.018
	(-0.792)		(-1.419)
$Crisis$	-0.011**		-0.005**
	(-2.677)		(-2.713)
LSV_{t-1}	-0.046	$Sias_{t-1}$	-0.002
	(-1.422)		(-0.675)
LSV_{t-2}	-0.040	$Sias_{t-2}$	-0.001
	(-1.327)		(-0.346)
LSV_{t-3}	-0.078**	$Sias_{t-3}$	-0.003
	(-2.208)		(-1.108)
LSV_{t-4}	-0.022	$Sias_{t-4}$	-0.002
	(-1.080)		(-0.392)
$Crisis \times LSV_{t-1}$	0.038	$Crisis \times Sias_{t-1}$	0.001
	(1.123)		(0.268)
$Crisis \times LSV_{t-2}$	0.056	$Crisis \times Sias_{t-2}$	-0.000
	(1.648)		(-0.271)
$Crisis \times LSV_{t-3}$	0.070	$Crisis \times Sias_{t-3}$	0.007**
	(1.591)		(2.295)
$Crisis \times LSV_{t-4}$	0.035	$Crisis \times Sias_{t-4}$	0.003
	(1.605)		(0.676)

Table 2.12 Crisis-herding interaction models in the first period (cont'd)

Dep. Variable: ROA	(1)		(2)
Panel B: Estimation of long-run coefficients			
ΔGDP	0.117		-0.187
	(0.660)		-0.970
$INFL$	0.217**		0.118
	(2.120)		0.830
$\Delta UNEM$	-0.231		-0.395**
	(-0.900)		-2.250
$Crisis \times LSV$	-0.047+0.872 LSV	$Crisis \times Sias$	-0.022+0.049 $Sias$
Observations	928		928
# of banks	29		29
# of instruments	19		19
Hansen J	3.796		3.716
Hansen p-value	0.150		0.156
m_2	-0.585		-0.659
m_2 p-value	0.559		0.510

The results of the dynamic models exploring the cumulative effect of crisis-herding interaction on profitability for the first period are presented in this table (2002Q4 -2012Q2). Panel A presents the results of individual coefficient estimations and Panel B presents the long-run coefficient estimations. The models are built using system GMM, which is proposed by Blundell and Bond (1998). Following Brambor et al. (2006), all constitutive terms are included in the specification of the interaction terms to prevent a misspecified model. In the model generation, robust one-step estimator with orthogonal deviations is used. The validity of the selected instruments is controlled via Hansen J test, which has a null hypothesis of "H0: Overidentifying restrictions are valid". Second-order autocorrelation is tested via Arellano-Bond test (m_2), which has a null hypothesis of "H0: There is no second-order autocorrelation". Four lags of the herding and interaction variables are included to account for the effect of the previous year's quarters and to avoid instrument proliferation problem. t-statistics are presented in parenthesis and *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively. The 95% confidence intervals of the marginal effect of herding on profitability are shown in Figure 2.1 and 2.2.

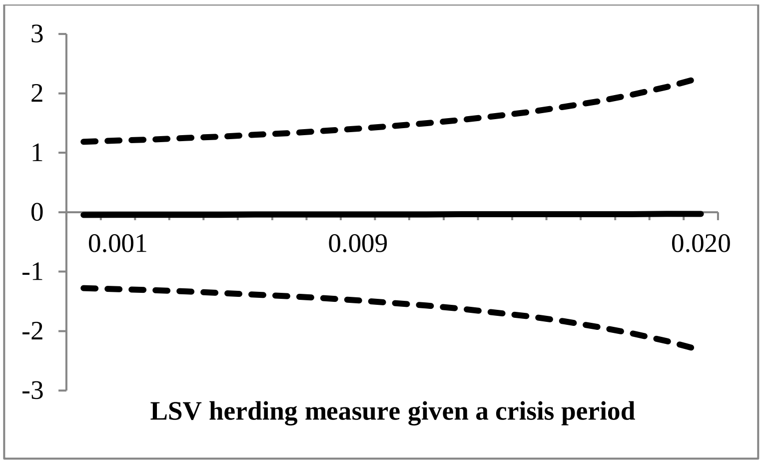

Figure 2.1 Marginal effect of LSV herding on profitability given a crisis period

Notes. The horizontal axis in the figure represents the level of LSV herding, while the vertical axis represents the marginal effect of herding-profitability interaction during the crisis periods (i.e., subprime (2007Q3-2008Q4) and European sovereign debt (2009Q4-2012Q4) crises).

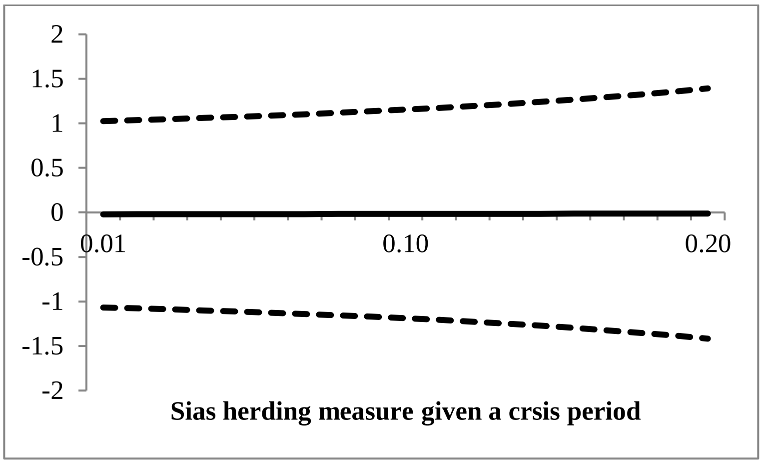

Figure 2.2 Marginal effect of Sias herding on profitability given a crisis period

Notes. The horizontal axis in the figure represents the level of Sias herding, while the vertical axis represents the marginal effect of herding-profitability interaction during the crisis periods (i.e., subprime (2007Q3-2008Q4) and European sovereign debt (2009Q4-2012Q4) crises).

Tables 2.13 and 2.14 show the results of estimation for loan quality models for the first and second periods, respectively, starting with baseline models that only incorporate macroeconomic variables and lagged dependent variable as regressors. The model results demonstrate that for the first period, the long-run coefficient estimation for the inflation variable is significantly negative at the 1% significance level, which contradicts the findings of previous studies that find a positive relationship between inflation and NPLs (Klein, 2011; Škarica, 2013). When herding and bank-specific regressors are incorporated into the system, however, this relationship loses its stability. GDP growth, on the other hand, is fairly stable and significantly negative in the first period for all models except the baseline model. GDP growth is predicted to be negative in these models, implying that bank asset quality will improve as the economy grows (Klein, 2011). Table 2.14 shows that we are not able to draw any conclusions about the link between macro factors and NPLs for the second period because the long-run coefficients are not statistically significant. According to Fang et al. (2021), herding is expected to have harmful effects on bank profitability, and the magnitude of these effects is expected to be higher during volatile times such as crisis and election periods. To bolster these claims, it is reasonable to infer a causal relationship between bank profitability and asset quality, as declining profitability may be the result of declining loan quality over these times. Furthermore, herding intensity may grow when the economic climate is stable or during an expansionary phase, because banks may wish to avoid falling victim to the increased competition during such times. Assuming that lending evaluation criteria are relaxed during these times, it is reasonable to foresee a gradual decrease in loan quality. As a result, we should expect a positive relationship between herding and NPLs. In both periods, we find no significant relationship between herding intensity and NPLs, demonstrating that herding intensity is not a factor that affects loan quality.

The remaining models in Tables 2.13 and 2.14 show the estimation results when bank-specific variables are included. We test the “bad management” and “skimping” hypotheses by looking at the significance of the cost-to-income ratio coefficient. Increasing cost inefficiency implies ineffective management, which leads to more problem loans in the future. As a result, the “bad management” hypothesis is supported by a positive cost-to-income ratio. Banks that allocate fewer resources to examine loan quality may be more cost-efficient, but they will suffer from an increase in bad loans in the long run. As a result, the "skimping" hypothesis is supported by a negative cost-to-income ratio. We cannot confirm the "bad management" and "skimping" hypotheses, because we do not find a significant coefficient for the cost-to-income ratio in both periods. According to the "moral hazard" hypothesis, managers of thinly capitalized banks tend to increase the riskiness of their loan portfolios to create incentives. When we look at the long-run coefficient estimation for equity to assets ratio, we see that it is statistically significant and has a negative sign, which supports the moral hazard hypothesis. Even though Louzis et al. (2012) find no evidence for the moral hazard hypothesis for Greek banks, our findings show a positive association between a bank's capitalization and asset stability in the first period, but no such relationship in the second. Diversification is emphasized as a factor that reduces credit risk (Louzis et al., 2012). The significance of the non-interest income ratio and size variables are used to test the "diversification" hypothesis, and both variables are expected to have a negative sign. However, in neither period do we find significant findings for both coefficients. We test the "bad management-II" and "procyclical credit policy" hypotheses via the significance of ROE's coefficient. A significantly negative sign implies the inverse relationship between the management quality measured by the bank's profitability and the bank's asset stability. A positive sign, on the other hand, suggests that the bank's managers may inflate current earnings to persuade the market of the bank's profitability at the expense of future problem loans. We do not find a significant coefficient for either period; hence the "bad management-II" or "procyclical credit policy" hypotheses cannot be confirmed.

Table 2.13 GMM estimation results for loan quality models in the first period

Dep. Variable: ΔNPL	(1)		(2)		(3)		(4)
Panel A: Estimation of individual lag coefficient							
Constant	0.007*		0.010		0.012*		0.012
	(1.932)		(1.387)		(1.733)		(1.543)
ΔNPL_{it-1}	-0.081		-0.092		-0.088		-0.090
	(-1.261)		(-1.530)		(-1.626)		(-1.507)
ΔGDP_{t-1}	-0.091***		-0.127**		-0.125		-0.107**
	(-3.239)		(-2.721)		(-1.635)		(-2.757)
ΔGDP_{t-2}	-0.064		-0.099**		-0.071		-0.079
	(-0.901)		(-2.129)		(-0.971)		(-1.141)
$INFL_{t-1}$	0.068		0.043		0.031		0.069
	(1.334)		(0.791)		(0.657)		(1.279)
$INFL_{t-2}$	-0.139		-0.198		-0.154		-0.201
	(-1.583)		(-1.359)		(-1.198)		(-1.418)
$\Delta UNEM_{t-1}$	-0.001		0.029		-0.015		0.006
	(-0.008)		(0.831)		(-0.298)		(0.097)
$\Delta UNEM_{t-2}$	0.007		0.040		0.007		0.027
	(0.069)		(0.469)		(0.077)		(0.274)
		LSV_{t-1}	0.051	$Sias_{t-1}$	-0.004*	CIR_{it-1}	-0.000
			(1.175)		(-1.948)		(-0.442)
		LSV_{t-2}	0.046	$Sias_{t-2}$	0.001	CIR_{it-2}	0.000
			(1.382)		(0.262)		(0.542)
		LSV_{t-3}	0.012	$Sias_{t-3}$	-0.003	CIR_{it-3}	-0.000
			(0.217)		(-0.803)		(-0.495)
		LSV_{t-4}	-0.007	$Sias_{t-4}$	0.004	CIR_{it-4}	0.000
			(-0.138)		(0.654)		(0.410)

Table 2.13 GMM estimation results for loan quality models in the first period (cont'd)

Dep. Variable: ΔNPL	(1)		(2)		(3)		(4)
Panel B: Estimation of long-run coefficients							
ΔGDP	-0.144		-0.208***		-0.180*		-0.171*
	(-1.690)		(-3.740)		(-1.790)		(-1.940)
$INFL$	-0.065*		-0.142		-0.113		-0.121
	(-1.790)		(-1.080)		(-1.250)		(-1.540)
$\Delta UNEM$	0.006		0.064		-0.007		0.030
	(0.050)		(0.660)		(-0.060)		(0.240)
		LSV	0.094	$Sias$	-0.002	CIR	0.000
			(0.630)		(-0.200)		(-0.270)
Observations	957		928		928		928
# of banks	29		29		29		29
# of instruments	11		14		19		21
Hansen J	3.01		1.840		8.037		11.55
Hansen p-value	0.390		0.398		0.329		0.240
m_2	0.900		1.024		1.018		1.021
m_2 p-value	0.370		0.306		0.309		0.307

Table 2.13 GMM estimation results for loan quality models in the first period (cont'd)

Dep. Variable: ΔNPL	(5)		(6)		(7)		(8)
Panel A: Estimation of individual lag coefficients							
Constant	0.022		0.014*		0.011		0.053
	(1.675)		(1.908)		(1.585)		(0.961)
ΔNPL_{it-1}	-0.091		-0.088		-0.090		-0.088
	(-1.692)		(-1.491)		(-1.530)		(-1.501)
ΔGDP_{t-1}	-0.103***		-0.115***		-0.112***		-0.119**
	(-3.098)		(-2.820)		(-3.097)		(-2.399)
ΔGDP_{t-2}	-0.093		-0.099		-0.080		-0.088
	(-1.533)		(-1.613)		(-1.174)		(-1.305)
$INFL_{t-1}$	0.043		0.065		0.070		0.072
	(1.062)		(1.423)		(1.154)		(1.426)
$INFL_{t-2}$	-0.185		-0.234		-0.198		-0.234
	(-1.468)		(-1.614)		(-1.250)		(-1.342)
$\Delta UNEM_{t-1}$	-0.018		0.000		-0.005		0.009
	(-0.309)		(0.005)		(-0.094)		(0.142)
$\Delta UNEM_{t-2}$	0.068		0.023		0.019		0.024
	(0.811)		(0.254)		(0.213)		(0.235)
EA_{it-1}	-0.014	NIR_{it-1}	-0.014	ROE_{it-1}	-0.007	$Size_{it-1}$	-0.002
	(-0.493)		(-0.853)		(-0.381)		(-0.175)
EA_{it-2}	-0.187	NIR_{it-2}	0.009	ROE_{it-2}	0.006	$Size_{it-2}$	-0.004
	(-1.149)		(1.053)		(0.399)		(-1.525)
EA_{it-3}	0.140	NIR_{it-3}	0.021	ROE_{it-3}	0.019	$Size_{it-3}$	-0.002
	(1.252)		(1.012)		(1.055)		(-0.632)
EA_{it-4}	0.001	NIR_{it-4}	-0.010	ROE_{it-4}	-0.010	$Size_{it-4}$	0.006
	(0.115)		(-0.846)		(-0.563)		(0.663)

Table 2.13 GMM estimation results for loan quality models in the first period (cont'd)

Dep. Variable: ΔNPL	(5)		(6)		(7)		(8)
Panel B: Estimation of long-run coefficients							
ΔGDP	-0.180**		-0.197**		-0.176**		-0.190**
	(-2.330)		(-2.670)		(-2.070)		(-2.200)
$INFL$	-0.130		-0.156*		-0.118		-0.149
	(-1.580)		(-1.730)		(-1.340)		(-1.340)
$\Delta UNEM$	0.046		0.021		0.013		0.031
	(0.430)		(0.190)		(0.120)		(0.230)
EA	-0.054*	NIR	0.006	ROE	0.008	$Size$	-0.002
	(-1.990)		(0.910)		(0.400)		(-0.890)
Observations	928		928		928		928
# of banks	29		29		29		29
# of instruments	24		21		21		24
Hansen J	16.40		14.20		11.84		18.54
Hansen p-value	0.174		0.115		0.223		0.100
m_2	1.053		1.027		1.022		1.019
m_2 p-value	0.292		0.304		0.307		0.308

The results of the dynamic models exploring the relationship between loan quality and herding for the first period are presented in this table (2002Q4 - 2012Q2). Panel A presents the results of individual coefficient estimations and Panel B presents the long-run coefficient estimations. The models are built using system GMM, which is proposed by Blundell and Bond (1998). The macroeconomic and herding variables are assumed as strictly exogenous, but bank-specific variables are rather assumed to be weakly exogenous. In the model generation, robust one-step estimator with orthogonal deviations is used. The validity of the selected instruments is controlled via Hansen J test, which has a null hypothesis of "H0: Overidentifying restrictions are valid". Second-order autocorrelation is tested via Arellano-Bond test (m_2), which has a null hypothesis of "H0: There is no second-order autocorrelation". Four lags of the bank-specific or herding variables are included in each time to account for the effect of the previous year's quarters and to avoid instrument proliferation problem. t-statistics are presented in parenthesis and *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 2.14 GMM estimation results for loan quality models in the second period

Dep. Variable: ΔNPL	(1)		(2)		(3)		(4)
Panel A: Estimation of individual lag coefficient							
Constant	-0.015		0.003		0.005		-0.001
	(-1.003)		(0.477)		(0.787)		(-0.113)
ΔNPL_{it-1}	-0.312		0.015		0.017		0.022
	(-1.593)		(0.137)		(0.151)		(0.194)
ΔGDP_{t-1}	-0.245*		-0.260		-0.188		-0.095
	(-1.740)		(-1.100)		(-1.387)		(-0.834)
ΔGDP_{t-2}	-0.212		-0.060		-0.039		-0.007
	(-1.412)		(-0.382)		(-0.705)		(-0.180)
$INFL_{t-1}$	0.286		0.265		0.120		0.116
	(1.551)		(0.850)		(1.088)		(0.613)
$INFL_{t-2}$	-0.036		-0.188		-0.131		-0.077
	(-0.207)		(-1.044)		(-0.836)		(-0.453)
$\Delta UNEM_{t-1}$	0.219		0.134		0.157		0.217
	(0.754)		(0.850)		(0.871)		(0.836)
$\Delta UNEM_{t-2}$	0.262		0.108		0.002		0.059
	(1.142)		(0.539)		(0.018)		(0.516)
		LSV_{t-1}	-0.034	$Sias_{t-1}$	0.005	CIR_{it-1}	-0.000
			(-0.673)		(1.084)		(-0.863)
		LSV_{t-2}	-0.072	$Sias_{t-2}$	-0.004	CIR_{it-2}	-0.000***
			(-1.159)		(-0.607)		(-5.160)
		LSV_{t-3}	0.019	$Sias_{t-3}$	0.004	CIR_{it-3}	0.000
			(0.646)		(0.713)		(0.716)
		LSV_{t-4}	-0.061	$Sias_{t-4}$	0.005	CIR_{it-4}	0.000
			(-0.676)		(1.241)		(0.054)

Table 2.14 GMM estimation results for loan quality models in the second period (cont’d)

Dep. Variable: ΔNPL	(1)		(2)		(3)		(4)
Panel B: Estimation of long-run coefficients							
ΔGDP	-0.3477		-0.324		-0.231		-0.105
	(-1.700)		(-0.800)		(-1.330)		(-0.650)
$INFL$	0.1905		0.079		-0.011		0.040
	(1.230)		(0.540)		(-0.140)		(0.400)
$\Delta UNEM$	0.3669		0.245		0.162		0.282
	(1.290)		(1.970)		(1.450)		(1.080)
		LSV	-0.151	$Sias$	0.009	CIR	0.000
			(-1.070)		(0.740)		(-1.200)
Observations	487		459		459		459
# of banks	28		27		27		27
# of instruments	10		16		17		25
Hansen J	2.149		5.929		7.013		19.05
Hansen p-value	0.342		0.204		0.220		0.121
m_2	-0.177		1.007		1.012		1.010
m_2 p-value	0.860		0.314		0.311		0.312

Table 2.14 GMM estimation results for loan quality models in the second period (cont'd)

Dep. Variable: ΔNPL	(5)		(6)		(7)		(8)
Panel A: Estimation of individual lag coefficients							
Constant	-0.017		0.003		0.005		0.101
	(-1.225)		(0.388)		(0.935)		(0.765)
ΔNPL_{it-1}	0.002		0.014		0.030		0.039
	(0.013)		(0.137)		(0.238)		(0.234)
ΔGDP_{t-1}	-0.134		-0.101		-0.076		-0.140
	(-1.164)		(-0.857)		(-0.726)		(-0.991)
ΔGDP_{t-2}	-0.049		-0.020		-0.011		-0.068
	(-0.978)		(-0.408)		(-0.310)		(-0.845)
$INFL_{t-1}$	0.167		0.184		0.075		0.192
	(0.746)		(0.825)		(0.418)		(0.681)
$INFL_{t-2}$	-0.061		-0.146		-0.063		-0.101
	(-0.360)		(-0.929)		(-0.386)		(-0.490)
$\Delta UNEM_{t-1}$	0.157		0.221		0.209		0.147
	(0.609)		(0.839)		(0.746)		(0.641)
$\Delta UNEM_{t-2}$	0.103		0.071		0.010		0.065
	(0.970)		(0.651)		(0.102)		(0.494)
EA_{it-1}	-0.166***	NIR_{it-1}	0.002	ROE_{it-1}	0.031	$Size_{it-1}$	0.029*
	(-2.827)		(0.968)		(0.396)		(1.816)
EA_{it-2}	0.172	NIR_{it-2}	-0.030**	ROE_{it-2}	-0.094	$Size_{it-2}$	-0.021*
	(1.463)		(-2.530)		(-0.906)		(-2.034)
EA_{it-3}	0.007	NIR_{it-3}	0.002	ROE_{it-3}	0.151	$Size_{it-3}$	0.004
	(0.066)		(0.380)		(1.618)		(0.165)
EA_{it-4}	0.064	NIR_{it-4}	0.008	ROE_{it-4}	-0.138*	$Size_{it-4}$	-0.019
	(0.691)		(0.696)		(-1.810)		(-0.604)

Table 2.14 GMM estimation results for loan quality models in the second period (cont'd)

Dep. Variable: ΔNPL	(5)		(6)		(7)		(8)
Panel B: Estimation of long-run coefficients							
ΔGDP	-0.183		-0.123		-0.090		-0.216
	(-1.030)		(-0.710)		(-0.750)		(-0.830)
$INFL$	0.106		0.038		0.013		0.095
	(0.880)		(0.320)		(0.170)		(0.740)
$\Delta UNEM$	0.261		0.296		0.226		0.221
	(1.000)		(1.090)		(0.890)		(0.980)
EA	0.077	NIR	-0.018	ROE	-0.051	$Size$	-0.007
	(1.490)		(-1.020)		(-0.750)		(-0.690)
Observations	459		459		459		459
# of banks	27		27		27		27
# of instruments	22		23		23		21
Hansen J	13.03		14.39		17.13		12.40
Hansen p-value	0.222		0.212		0.104		0.192
m_2	0.946		0.957		1.321		1.080
m_2 p-value	0.344		0.339		0.187		0.280

The results of the dynamic models exploring the relationship between loan quality and herding for the second period are presented in this table (2012Q3 - 2017Q4). Panel A presents the results of individual coefficient estimations and Panel B presents the long-run coefficient estimations. The models are built using system GMM, which is proposed by Blundell and Bond (1998). The macroeconomic and herding variables are assumed as strictly exogenous, but bank-specific variables are rather assumed to be weakly exogenous. In the model generation, robust one-step estimator with orthogonal deviations is used. The validity of the selected instruments is controlled via Hansen J test, which has a null hypothesis of "H0: Overidentifying restrictions are valid". Second-order autocorrelation is tested via Arellano-Bond test (m_2), which has a null hypothesis of "H0: There is no second-order autocorrelation". Four lags of the bank-specific or herding variables are included in each time to account for the effect of the previous year's quarters and to avoid instrument proliferation problem. t-statistics are presented in parenthesis and *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively.

To strengthen the above result, we include a crisis-herding interaction to reveal whether herding has a harmful effect given a crisis period. The results for interaction models are shown in Table 2.15. We also show the long-run marginal effects of the crisis-herding interaction on loan quality for the LSV and Sias herding measures, respectively, in Figures 2.3 and 2.4. The horizontal axis in Figure 2.3 represents the level of LSV herding, whereas the vertical axis represents the marginal effect of this interaction during a crisis. Because the confidence interval encompasses the origin, the observed impact of the interaction does not have a significant effect on loan quality, as shown in Figure 2.3. A similar conclusion can be drawn from the crisis-Sias herding interaction shown in Figure 2.4. As a result, we cannot confirm a reinforced effect of herding on loan quality during crisis periods.

Table 2.15 Crisis-herding interaction models NPL in the first period

Dep. Variable: ΔNPL	(1)		(2)
Panel A: Estimation of individual lag coefficients			
Constant	0.018		0.020**
	(1.525)		(2.059)
ΔNPL_{it-1}	-0.092		-0.090
	(-1.537)		(-1.546)
ΔGDP_{t-1}	-0.126		-0.039
	(-1.546)		(-0.410)
ΔGDP_{t-2}	-0.080		-0.072
	(-1.547)		(-0.765)
$INFL_{t-1}$	0.045		0.093*
	(1.355)		(1.784)
$INFL_{t-2}$	-0.219		-0.194
	(-1.204)		(-1.352)
$\Delta UNEM_{t-1}$	0.039		-0.114*
	(0.995)		(-1.822)
$\Delta UNEM_{t-2}$	0.040		-0.141
	(0.390)		(-0.867)
$Crisis$	-0.008*		-0.011*
	(-1.803)		(-1.719)
LSV_{t-1}	0.049	$Sias_{t-1}$	-0.008
	(0.582)		(-1.303)
LSV_{t-2}	0.001	$Sias_{t-2}$	0.007
	(0.038)		(0.497)
LSV_{t-3}	0.013	$Sias_{t-3}$	-0.005
	(0.129)		(-1.524)
LSV_{t-4}	-0.032	$Sias_{t-4}$	-0.015
	(-0.465)		(-1.029)
$Crisis \times LSV_{t-1}$	-0.008	$Crisis \times Sias_{t-1}$	0.002
	(-0.137)		(0.282)
$Crisis \times LSV_{t-2}$	0.077	$Crisis \times Sias_{t-2}$	-0.018
	(1.347)		(-0.848)
$Crisis \times LSV_{t-3}$	-0.026	$Crisis \times Sias_{t-3}$	0.006
	(-0.250)		(0.730)
$Crisis \times LSV_{t-4}$	0.024	$Crisis \times Sias_{t-4}$	0.018
	(0.454)		(1.002)

Table 2.15 Crisis-herding interaction models NPL in the first period (cont'd)

Dep. Variable: ΔNPL	(1)		(2)
Panel B: Estimation of long-run coefficients			
ΔGDP	-0.189		-0.102
	(-2.210)		(-0.580)
$INFL$	-0.159		-0.093
	(-1.100		(-0.830)
$\Delta UNEM$	0.072		-0.234
	(0.750)		(-1.280)
$Crisis \times LSV$	-0.008+0.061 LSV	$Crisis \times Sias$	-0.010+0.007 $Sias$
Observations	928		928
# of banks	29		29
# of instruments	23		23
Hansen J	7.743		7.906
Hansen p-value	0.258		0.245
m_2	1.029		1.030
m_2 p-value	0.303		0.303

The results of the dynamic models exploring the cumulative effect of crisis-herding interaction on loan quality for the first period are presented in this table (2002Q4 -2012Q2). Panel A presents the results of individual coefficient estimations and Panel B presents the long-run coefficient estimations. The models are built using system GMM, which is proposed by Blundell and Bond (1998). Following Brambor et al. (2006), all constitutive terms are included in the specification of the interaction terms to prevent a misspecified model. In the model generation, robust one-step estimator with orthogonal deviations is used. The validity of the selected instruments is controlled via Hansen J test, which has a null hypothesis of "H0: Overidentifying restrictions are valid". Second-order autocorrelation is tested via Arellano-Bond test (m_2), which has a null hypothesis of "H0: There is no second-order autocorrelation". Four lags of the herding and interaction variables are included to account for the effect of the previous year's quarters and to avoid instrument proliferation problem. T-statistics are presented in parenthesis and *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively. The 95% confidence intervals of the marginal effect of herding on profitability are shown in Figure 3 and 4.

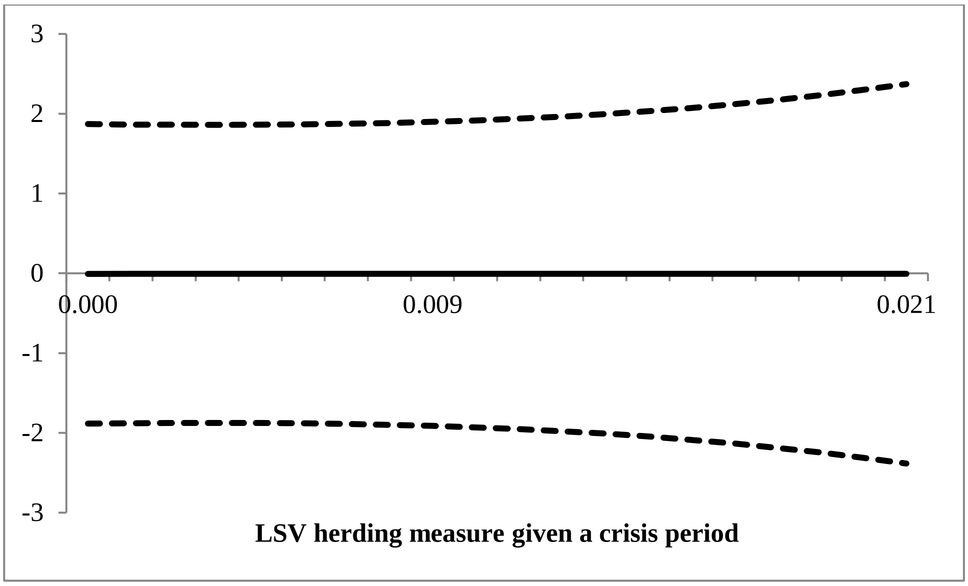

Figure 2.3 Marginal effect of LSV herding on loan quality given a crisis period

Notes. The horizontal axis in the figure represents the level of LSV herding, while the vertical axis represents the marginal effect of herding-loan quality interaction during the crisis periods (i.e., subprime (2007Q3-2008Q4) and European sovereign debt (2009Q4-2012Q4) crises).

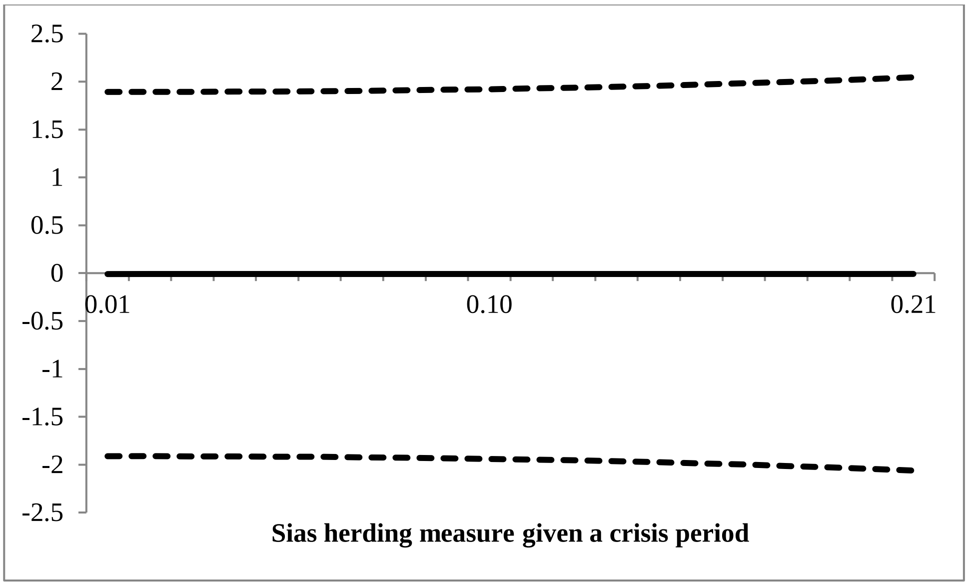

Figure 2.4 Marginal effect of Sias herding on loan quality given a crisis period

Notes. The horizontal axis in the figure represents the level of Sias herding, while the vertical axis represents the marginal effect of herding-loan quality interaction during the crisis periods (i.e., subprime (2007Q3-2008Q4) and European sovereign debt (2009Q4-2012Q4) crises).

2.4.3 Macroprudential policy (MPP) applications in Turkey

Literature shows that regulation is one of the major actors defining banks' action plans and may cause herding. According to Haiss (2005), the combination of certain regulatory and governance rules may force banks into herding behavior. Tran et al. (2017) indicate that regulatory pressure in the form of higher capital after the global financial crisis reduces the available profitable activities for banks in Australia. Therefore, banks engage in research of remaining available channels. The increase in herding for household loans after the post-crisis period is an example of this research activity. Stellinga (2020) points out that risk models may be a source of procyclicality since they are very much based on market data which contribute to excessive optimism during boom and panic in the boost times. Although policymakers do not willingly harmonize banks' risk assessment practices, they may lead to an unwanted harmonization via the standardization of risk assessment approaches. As a result, model uniformity may increase the risk of herding.

Following the 2001 financial crisis, Turkey implemented many structural reforms, both monetary and prudential in nature. These reforms improved the macroeconomic indicators and simultaneously encouraged fund inflows into the country in connection with the increased global liquidity. As a result, during the 2000s, Turkey experienced rapid credit growth (Kara, 2016).

Many regulations and supervisory actions were enacted throughout the banking industry during this period of rapid credit growth. The Banking Regulation and Supervision Agency (BRSA) focused on individual banks and took a microprudential approach. The Central Bank of the Republic of Turkey (CBRT) released a financial stability report with a macro perspective, but the monetary policy was still based on conventional inflation-targeting regime, which left macro-financial vulnerabilities unaddressed.

Following the global financial crisis of 2008, quantitative easing programs of advanced economies encouraged emerging markets to loosen their external financial conditions. Large capital inflows exacerbated internal and external imbalances in those economies during this period, resulting in lower interest rates and currency appreciation (Küçükbıçakcı et al., 2020). Meanwhile, by the end of 2010, the private credit to GDP ratio in Turkey had risen to 40%, accompanied by a quick appreciation of the Turkish lira. All of these factors contributed to the economy's overheating, highlighting the necessity for macroprudential policy tools (Kara, 2016). As a result, at the end of 2010, CBRT was in charge of controlling macro-financial risks. The CBRT changed its conventional inflation-targeting regime by focusing on financial stability. As a result, the principal goal of the new strategy was to combat the negative consequences of capital inflow volatility.

There are two crucial points in this time frame that are related to loan herding. First, because the increase in global liquidity resulted in credit growth, the loan herding that we observe during this period may be entirely rational, or at least has a rational portion. Second, following CBRT's leadership, several policy instruments, including reserve requirements, a flexible interest rate corridor, and a reserve option mechanism, entered the stage. These instruments were designed to counteract macroeconomic volatility caused by global liquidity cycles and the interaction of capital flows, exchange rates, and credit expansion in an economy with currency mismatches (Kara, 2016). The most visible outcome of these policy instruments' deployment related to credit growth was a slowing of credit growth acceleration after the first half of 2011. Because this result reveals that macroprudential regulations intervened in credit growth cycles, we may assume that policy applications have an impact on our loan herding values.

Considering these two potential points of interaction, we intend to test the following hypothesis:

H_{MPP}: We observe rational loan herding due to the increase in global liquidity and the associated macroprudential practices.

Loan herding may contain rational and irrational components, according to Uchida and Nakagawa (2007) and Fang et al. (2021). According to Uchida and Nakagawa (2007), rational banks consider both overall macroeconomic and industry-specific conditions while making lending decisions. Even though the overall lending trend is deducted from the total herding value in the LSV measure; the remainder may still have effects due to industry-specific rational reasons. As a result, they adjust the LSV measure by regressing it on industry-specific proxies such as industry-based GDP growth and land prices and using the residual as the herding value's irrational component. Fang et al. (2021) follow Uchida and Nakagawa's (2007) perspective by enhancing the proxy base (i.e. they consider industrial profitability and credit ratings as two additional factors). To extract the irrational herding component, we also follow Uchida and Nakagawa's (2007) steps for both using LSV and Sias measures. In our setup, we use global liquidity and MPP practices as the factors that may lead banks to herd rationally in their lending decisions. The international component of credit, in the form of cross-border and local loans denominated in foreign currencies, is of particular importance for assessing global liquidity, according to the Bank for International Settlements (BIS). This is because the foreign component frequently serves as a secondary source of finance in the run-up to financial crises. Although the international component of credit is small in comparison to overall credit, its cyclicality can amplify domestic trends and is closely linked to global financial booms and busts. As a result, we use the quarterly change in international claims on all sectors denominated in US dollars (i.e., bank and non-bank sectors) provided by the BIS to measure global liquidity. We use the macroprudential policy index in the iMaPP database for MPP practices, which was created by Alam et al. (2019) by merging existing IMF databases with the IMF's Macroprudential Policy Survey. Equation (12) depicts the model used to separate the effects of increased global liquidity and MPP practices from loan herding:

$$Herding_t = \beta_1 \Delta Liq_t + \beta_2 MPP_{t-1} + \varepsilon_t \tag{12}$$

where $Herding$ is the loan herding intensity for quarter t, ΔLiq is the growth of global liquidity in quarter t, and MPP is the macroprudential policy index value for the quarter $t-1$.MPP is included in the model with one lag to account for the time delay between policy decisions and their observable effects on lending decisions, as well as any potential endogeneity issues between loan herding and MPP implementations. ε_t is the residual portion of the herding measure after the effects of global liquidity changes and MPP implementations are isolated from the total loan herding.

Table 2.16 shows the one-sample t-test results for residual series when the herding measure is LSV[5] (H0: Residual mean is equal to zero). According to the findings, the residual fraction of the herding measure is not statistically different from zero for both periods after excluding the effects of the global liquidity increase and associated macroprudential policy applications. This result leads us to conclude that banks collectively herd in their lending decisions due to the increase in global liquidity and prudential measures that the regulatory authorities employ. As a result, this collective behavior can be explained as rational herding because the banks' collective activity is due to their being affected by the same environment, observing similar global signals, and being exposed to the same regulatory applications.

Table 2.16 Herding measure after the effects of global liquidity and macroprudential policy applications are removed

	Period 1	Period 2
Herding measure: LSV		
Mean	0.000	0.000
t-Stat	(0.000)	(0.000)
Median	-0.004	-0.002

This table presents the one-sample t-test results for the residual term as indicated in equation 12. Periods 1 and 2 stand for 2002Q4 -2012Q2 and 2012Q3 -2017Q4, respectively. t-statistics are presented in parenthesis and *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively.

[5] Our preliminary test results show that the Sias herding value cannot be explained significantly for the first period. For the second period, Table 2.5 provides that the mean of the Sias herding is not statistically different from zero. Therefore, we only report the results for LSV herding in Table 2.16.

2.5 Conclusion

In this study, we analyze whether banks herd in their lending decisions and whether loan herding is one of the elements that influence bank performance and loan quality. Using LSV and Sias herding measures, we analyze two periods between 2002Q4 and 2017Q4. While we look at the impact of herding intensity on bank performance and loan quality, we also look at a group of widely discussed hypotheses in the literature that look into the same topics. Even though we estimate individual lag coefficients, as well as long-run coefficients for macroeconomic, bank-specific, and herding variables on bank profitability and loan quality, the sign and statistical evidence we offer are based on long-run coefficients. The findings of the analysis on bank performance-herding relationships show that for the first period, the coefficient of the LSV herding measure is significantly negative. This finding indicates that herding has harmful effects on bank performance in the first period. When the analysis is redone with the Sias herding measure, however, we cannot detect a statistically significant coefficient. As a result, this finding suggests that following the lending decisions of other banks in subsequent quarters has no impact on profitability in the first period. However, we are unable to obtain significant coefficients for both the LSV and Sias measures in the second period. In both periods, we find evidence of a positive association between inflation and bank performance, which is consistent with earlier research findings. Only for the second period do we find evidence for a positive relationship between capital and bank performance. Furthermore, we provide evidence for the second period that contradicts earlier research findings on the association between credit risk and bank performance. Furthermore, we validate the findings of Athanasoglou et al. (2008), namely that the size of a bank has no bearing on its performance. Long-run marginal effects plots are used to examine the cumulative effect of the crisis-herding relationship on profitability. The marginal effects shown in these graphs suggest that we cannot validate the hypothesis that herding has a greater detrimental influence on profitability during turbulent periods such as crises. We find no significant relationship between herding intensity and loan quality for either period. In terms of macro variables, we observe a significantly negative sign for the GDP growth coefficient in the first period, as expected, but we cannot draw the same conclusion for the second period because the estimation results for the macro variables are not statistically significant. We only find evidence for the "moral hazard" hypothesis in the first period among the other hypotheses evaluated. We compute the long-run marginal effect of herding on loan quality given a crisis period to examine the cumulative effect of the crisis-herding interaction on loan quality. The marginal effect plots reveal that a reinforced effect of herding on loan quality during crisis periods cannot be confirmed.

Following the 2001 crisis, macro indicators improved as a result of structural reforms with monetary and prudential components, resulting in fund inflows into the country due to the encouraging effect of increased global liquidity. This development led to a rapid credit growth era during the 2000s. The structural improvements were insufficient in terms of coverage for macro-financial risks because they initially served to support the conventional inflating targeting regime. Following the global financial crisis of 2008, massive money inflows to emerging economies as a result of advanced economies' quantitative easing policies caused these economies to overheat, necessitating the deployment of macroprudential controls. We assumed that the statistically significant herding values would be completely rational, or at least contain a rational component because the direct or indirect consequences of the developments during this period might have an impact on banks’ lending decisions. For this reason, we isolated the herding (i.e., LSV herding) from the effects of the global liquidity increase and the applied prudential policies, and looked at whether the remaining part (i.e., the irrational component) is still statistically significant. According to our findings, when the effects of the global liquidity increase and related macroprudential policy measures are separated from the herding variable, the remaining fraction is not statistically significant. This revealed that the herding in lending decisions in both periods occurred for rational reasons. The results of this study are crucial because they demonstrate how herding behavior, that develops in a context of rising liquidity and new regulations, negatively affects profitability at a period of considerable changes in Turkey's banking sector and economy.

Additionally, this study adds to the literature by noting how regulators' preventive measures may lead to collective behavior, demonstrating the importance of the policymaker as a game-changer.

CHAPTER 3

MUTUAL FUND HERDING IN INDUSTRIES

3.1 Introduction

Herding has been studied from a variety of perspectives in the literature. The changing effects of buy and sell-side transactions on the overall herding (Wermers, 1999), the distinction between herding as a result of following own transactions and following the transactions by other funds (Choi and Sias, 2009; Sias, 2004), the effect of fund flows on herding (Celiker et al., 2015; Choi and Sias, 2009; Coval and Stafford, 2007), the effect of different trading strategies on herding (Demirer and Zhang, 2019; Grinblatt et al., 1995; Wermers, 1999), and the impact of herding on stock prices (Brown et al., 2014; LSV, 1992) are those that can be counted at first glance.

Although many studies focus on the US fund markets (LSV, 1992; Sias, 2004; Ukpong et al., 2021), some studies focus on more concentrated markets (Holmes et al., 2013; Walter and Weber, 2006; Wylie, 2005). According to Holmes et al. (2013), examining herding in concentrated markets with a small number of funds and stocks might make sense. They indicate that the possibility that money managers in concentrated markets are familiar with one another's behavior and relative strength is much higher than in a large market, making the setting convenient for intentional herding. The mutual fund market in Turkey can be considered concentrated, thus the factors driving the herding that Holmes et al. (2013) identify may also apply to the Turkish case. Furthermore, given information disclosure regulations and the prevalence of family firms, it is reasonable to believe that there are some factors that hinder the production of reliable information in emerging markets, which may cause herding behavior due to noisy information. According to Morck et al. (2000), stock prices move together more in emerging markets compared to developed markets, indicating that less firm-specific information is produced in emerging markets. Chan and Hameed (2006) claim that several factors, including lack of information disclosure enforcement by regulation, lack of corporate transparency and voluntary disclosure, and lack of reliable information production due to the prevalence of family-owned businesses, contribute to the lack of firm-specific information in emerging markets. Given the different characteristics of emerging markets, herding behavior and its potential reasons that were examined in developed fund markets have been analyzed for the Turkish case as an example for emerging economies.

Choi and Sias (2009) examine institutional investors' industry herding. One of their goals is to determine whether the same factors that cause herding in individual stocks also contribute to it on an industry-wide scale. Second, they show that not all stock prices in an industry reflect information simultaneously, allowing investors in that industry to infer knowledge about a stock from other stocks in that sector. This asynchronous price incorporation argument is also examined by Moskowitz and Grinblatt (1999). They demonstrate that industries that did well (or poorly) in the preceding six months tend to do so in the subsequent twelve months. They suggest that this is because stock prices in the same industry might not incorporate information at the same time. They suggest that large firms' prices adopt information first, followed by the pricing of other firms. As a result, the observed momentum impact in industry returns may be due to this lead and lag effect, which could also generate herding at the industry level. This study investigates whether mutual funds herd in sectors and also whether herding has a major effect on industry valuations, with similar goals to Choi and Sias (2009). Although we follow Choi and Sias (2009) in concentrating on institutional industry herding, our work is more akin to that of Celiker et al. (2015), as we examine the trade of mutual funds that invest extensively in stocks rather than full-scope institutions that invest in stocks. In this study, we examine elements that Choi and Sias (2009) and Celiker et al. (2015) have previously discussed and that have the potential to be interpreted as industry herding, but our work differs from theirs in the following ways: First, we shift the focus to an emerging market, which has distinct characteristics in terms of the money manager base, the number of alternative stocks to invest in, and the availability of an environment to herding due to limitations in reliable information production. Second, we do not cover the whole universe of mutual funds but rather focus on equity-intensive funds to explore industry herding by using a more standardized fund group with an investment structure to invest at least 80% of holdings in the stock market. Third, unlike similar studies that employ quarterly datasets, we make use of a distinct dataset with monthly granularity, allowing us to incorporate the interim trading actions of money managers in the system.

We use LSV and Sias herding measures in our analyses. When applied to industry herding, the LSV measure compares the number of buy/sell trades in a specific industry during a given period to the expected number of buy/sell trades across all industries for that specific period. However, the Sias herding measure finds out how closely investors (i.e., in our case mutual funds) follow each other's trade in adjacent periods. Our findings indicate that the overall industrial herding among mutual funds becomes statistically significant when the LSV measure is used. In contrast, we do not find significant evidence for overall industry herding when we apply the Sias measure. We also investigate how buy and sell herding contributes to the overall herding and find that the impacts vary depending on the applied herding measure. Our analysis of the investor flows provides that industry herding is not a result of investors' fund flows. We also show that single-stock herding is not a strong driver of industry herding. Our findings also show that style investing is not the main cause of industry herding. We further demonstrate that there is no evidence of return reversals for the top-ranking buy and sell herding industries, demonstrating that mutual fund herding is not a factor to destabilize industry returns.

The remainder of the chapter is organized as follows: The data and methodology are discussed in Section 2, the findings of our analyses are presented in Section 3, and we conclude in Section 4.

3.2 Data and methodology

3.2.1 Data

Our sample consists of the portfolio holdings of all stock-weighted mutual funds (i.e., 37 mutual funds) acquired from Takasbank between December 2015 and December 2019. According to the Capital Markets Board of Turkey's "Communiqué on Principles Regarding Investment Funds", stock-weighted mutual funds are obliged to invest at least 80% of the fund's portfolio value in stocks traded at The Borsa Istanbul (BIST). Therefore, it is a good source to examine institutional investors' tendency to herd into industries. We observe that most of the funds in our sample used to have different trading strategies (i.e., investing in a certain type of stock or an index) and name tags (e.g., Type A stock fund) before December 2015. Thus, we determine December 2015 as a milestone and the beginning of our data set. To avoid an already focused stock investment position, all index and sector funds are eliminated from our sample.

During the sample period, 4 out of 37 funds have been terminated and merged with other funds, while 1 out of 37 funds has been merged with two funds that are not in our sample. Regardless of the underlying rationale, these mergers may lead to an additional increase or decrease in the acquirer funds' portfolio holdings. Without adjustment after the period of a merger, the acquirer funds may erroneously seem like a "buyer" or a "seller" fund for particular industries. Therefore, we perform adjustments[6] to prevent classification errors during the month of the merger and the following month.

[6] Please see the appendices for the adjustment steps.

The stock price data are obtained from Yahoo Finance and Refinitiv Eikon. Yahoo Finance is a publicly available source and can be reached easily via third-party programming packages (i.e., yfinance package developed for python environment). Yahoo Finance provides data directly from BIST with 15 minutes-delay and adjusts closing prices for corporate actions such as dividends and splits (i.e., Yahoo Finance applies Center for Research in Security Prices (CRSP) standards while adjusting closing stock prices). We use Refinitiv Eikon for the delisted stocks that are held by mutual funds in our sample. The stock prices provided by Refinitiv Eikon are also adjusted for corporate actions. Table 3.1 shows descriptive statistics about mutual funds and their stock holdings.

Table 3.1 Descriptive statistics of mutual funds and their stock holdings

Year	2015	2016	2017	2018	2019
Number of mutual funds	29	32	33	35	36
Number of traded stocks	142	171	200	205	221
Number of industry months	20	240	240	240	240
Mean value of mutual fund holdings (monthly, in million TRY)	3.612	3.045	2.731	2.844	2.951
Median value of mutual fund holdings (monthly average, in million TRY)	2.013	1.465	1.383	1.542	1.397

This table presents descriptive statistics about mutual funds and their stock holdings. The data sample covers the stock holdings of stock-weighted mutual funds which are trading stocks between December 2015 and December 2019.

The Public Disclosure Platform of Turkey (KAP), Sectoral Classifications are used to classify the stocks that mutual funds invest in. The KAP initially categorizes industries into 13 main groups and 37 sub-groups. To form the final industry groups for our sample, we apply the following additional adjustment steps:

(1) We eliminate main industry groups with fewer than 5 stocks. Our goal is to avoid the creation of an industry group dominated by a few stocks.

(2) If any of the industries' sub-groups has fewer than five stocks, we maintain them in the main group. Again, the goal is to avoid any industry classification that is dominated by a few stocks.

(3) After the first two steps, we apply a final elimination to the remaining industries, to remove the industries in which none of the funds have an active investment for at least one period.

After the above stages, we are left with 20 industries, which are listed in Table 3.2.

Table 3.2 Industry classification

No	Industry
1	Basic Metal Companies
2	Brokerage Houses
3	Banks
4	Electricity, Gas and Water Companies
5	Financial Leasing and Factoring Companies
6	Real Estate Investment Trusts
7	Food, Beverage and Tobacco Companies
8	Holding and Investment Companies
9	Construction and Public Works Companies
10	Paper and Paper Products, Printing and Publishing Companies
11	Chemicals, Petroleum, Rubber and Plastic Products Companies
12	Fabricated Metal Products, Machinery, Electrical Equipment, and Transportation Vehicles Companies
13	Wood Products Including Furniture Companies
14	Consumer Trade Companies
15	Insurance Companies
16	Non-metallic Mineral Products Companies
17	Technology Companies
18	Textile, Wearing Apparel and Leather Companies
19	Wholesale Trade Companies
20	Transportation, Storage and Telecommunication Companies

This table presents the industry classifications used for placing stocks into business sectors and is based on the sectoral classifications of the Public Disclosure Platform (KAP).

3.2.2 Methodology

3.2.2.1 LSV herding measure

Our first measure is developed by LSV (1992) to evaluate the herding behavior among pension funds. This measure utilizes the imbalance between the buy and sell trades. Following Choi and Sias (2009), for the calculation of the LSV measure, we classify a fund as a buyer in an industry k if:

$$\sum_{i=1}^{I_{k,t}} P_{i,t-1}(Shares_{n,i,t} - Shares_{n,i,t-1}) > 0 \tag{1}$$

where $I_{k,t}$ is the number of securities in industry k at month t, $P_{i,t-1}$ is the adjusted closing price of the stock i at the beginning of the month, and $Shares_{n,i,t}$ and $Shares_{n,i,t-1}$ are the number of shares of stock i that are adjusted for corporate actions and held by the fund n at the beginning and end of month t, respectively. Even if the fund does not actively trade, the monetary value of its position in an industry may change as stock prices fluctuate. To eliminate such passive momentum, we follow Choi and Sias (2009) and use the product of previous month-end prices and the change in the number of shares to compute the monetary value of the change in the fund's holdings for that particular industry. After determining the buyer and seller funds for an industry, we compute the ratio of the number of buyers to several active funds in that industry k during month t as

$$p_{k,t} = \frac{B_{k,t}}{(B_{k,t} + S_{k,t})} \tag{2}$$

where $B_{k,t}$ $(S_{k,t})$ is the number of buyer (seller) funds in industry k at month t. Using this fraction, we calculate the LSV measure for industry k at month t as

$$LSV_{k,t} = |p_{k,t} - p_t| - AF_{k,t} \tag{3}$$

where p_t is the cross-sectional average of the percentage of buyers for all industries at month t. $AF_{k,t}$ is an adjustment factor that assumes that the number of buyers follows a binomial distribution with p_t as the likelihood of being a buyer among the active funds in an industry.

3.2.2.2 Sias herding measure

Herding intensity is calculated in the LSV measure based on the difference between the actual and expected number of trades in the same direction for that month. However, the Sias measure examines the cross-sectional correlation between the ratios of buyers to all active traders in the adjacent months. The Sias herding is presented as

$$\rho\left(p_{k,t}, p_{k,t-1}\right) = \left[\frac{1}{(K-1)\sigma(p_{k,t})\sigma(p_{k,t-1})}\right]\sum_{k=1}^{K}(p_{k,t}-p_t)(p_{k,t-1}-p_{t-1}) \tag{4}$$

where $\rho\left(p_{k,t}, p_{k,t-1}\right)$ is the cross-sectional correlation between the ratios of buyers to all active traders in the adjacent months. K is the number of industries, $\sigma(p_{k,t})$ is the standard deviation of the ratio of buyers to all active traders across industries for month t, and $p_{k,t}$ is the ratio of the number of buyers to the number of active funds in that industry k during month t as previously mentioned in equation (2). This cross-sectional correlation term will be positive if the funds follow the previous month trades of other funds or their own previous month trades. To be able to distinguish between the portions of herding due to following own trades and following others' trades, The cross-sectional correlation is split into two components by Sias (2004):

$$\begin{aligned}\rho\left(p_{k,t}, p_{k,t-1}\right) &= \left[\frac{1}{(K)\sigma\left(p_{k,t}\right)\sigma\left(p_{k,t-1}\right)}\right] \times \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}}\frac{(D_{n,k,t}-p_t)(D_{n,k,t-1}-p_{t-1})}{N_{k,t}N_{k,t-1}}\right] \\ &+ \left[\frac{1}{(K)\sigma\left(p_{k,t}\right)\sigma\left(p_{k,t-1}\right)}\right] \times \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}}\sum_{m=1,m\neq n}^{N_{k,t-1}}\frac{(D_{n,k,t}-p_t)(D_{m,k,t-1}-p_{t-1})}{N_{k,t}N_{k,t-1}}\right]\end{aligned} \tag{5}$$

The cross-sectional correlation that results from the funds following their own trades from the previous month is represented by the first term on the right-hand side of equation (5), while the second term represents the cross-sectional correlation that results from the funds following the trades of other funds from the previous month. $D_{n,k,t}$ is a dummy variable that takes 1 (0) if the fund n buys industry k in month t.

3.3 Evidence for industry herding by mutual funds

3.3.1 Overall herding measure

We first test the null hypothesis of "no industrial herding by mutual funds" against the alternative hypothesis of "mutual funds herd in industries". Table 3.3 presents the mean and median levels for LSV and Sias herding measures. The mean values of LSV and Sias herding measures are 3.8% and -5.7% respectively (i.e., overall Sias herding is displayed by "Beta") and only the LSV herding measure is significant at 1% level. It is appropriate that we observe these conclusions simultaneously because LSV and Sias measures involve two different timing concerns. LSV measure checks the overall deviation from the expected buy/sell trades during a given period. Therefore, the results indicate that when examined with LSV measure the realized number of buy/sell industry trades significantly deviates from the number of expected buy/sell industry trades. Sias measure, however, checks whether current period buy/sell trades are linked to the trades that happened one period earlier. As a result, our findings indicate that when measured with the Sias method the trades of two consecutive periods are not significantly linked together. It is observed from Table 3.3 that the effect of following own previous trades to the overall Sias measure is not statistically significant (with 1.4 %). Nevertheless, the effect of following trades by other funds is -7.1% and significant at 5% level. Having a negative contribution from following other funds' trade means that the second portion of the equation (5) is also negative. According to Sias (2004), if mutual funds sell (buy) industries that other mutual funds bought (sold) the previous month, this percentage will be negative. Thus, this negative sign is an indicator that mutual funds reverse their previous position in the current month.

Table 3.3 Evidence of herding, LSV and Sias measures

	LSV	Sias		
		Beta	Own	Other
Mean	0.038***	-0.057	0.014	-0.071**
t-Stat	(7.934)	(-1.339)	(0.522)	(-2.236)
Median	0.036	-0.067	-0.011	-0.092

This table presents the mean and median values for unconditional LSV and Sias herding measures. t-Stats for mean values are presented in parentheses. ***, **, and * stand for 1, 5, and 10% significance levels, respectively.

3.3.2 Buy and sell herds

The original LSV measure in equation (3) calculates herding based on the mismatch between the buyer and seller count in an industry but does not account for the side of the trade (i.e. whether it is a buy or a sell trade). Wermers (1999) proposes the following extension to LSV measure to account for buy and sell herds:

$$LSV_{k,t}^{buy} = LSV_{k,t} | (p_{k,t} - p_t) > 0 \quad (6)$$

$$LSV_{k,t}^{sell} = LSV_{k,t} | (p_{k,t} - p_t) < 0 \quad (7)$$

Wermers (1999) uses a five-fund threshold for a stock-quarter, arguing that simply two or three funds trading in the same direction do not appear to qualify as a herd. Following Wermers (1999), we present the results for industry-months traded by at least 5, 10, and 20 mutual funds in Table 3.4. The mean values of the LSV measures are reported as 3.8%, 4.1%, 3.3%, and 2.1% for the unconditional case (i.e., no fund threshold) and at least 5, 10, and 20 active funds cases, respectively. All the reported means are significant at the 1% level. In Panel A, we demonstrate the existence of industry herding using LSV measure for related active fund criteria. Panel B displays the mean and median values for industry-months traded by all active funds and at least 5, 10, and 20 active mutual funds. Buy-herding figures are shown to be a little higher than sell-herding figures. The difference between the buy and sell herding means decreases as the number of active funds increases.

Table 3.4 Evidence of herding using LSV measure with buy/sell herding and active fund breakdown

	Unconditional	>= 5 active mutual funds	>= 10 active mutual funds	>= 20 active mutual funds
Panel A. Overall herding results				
Mean	0.038***	0.041***	0.033***	0.021***
t-Stat	(7.934)	(9.129)	(7.514)	(4.448)
Median	0.036	0.036	0.031	0.010
Panel B. Buy- and sell-herding results				
Buy-herding				
Mean	0.049***	0.049***	0.038***	0.026***
t-Stat	(7.170)	(7.748)	(6.817)	(4.175)
Median	0.045	0.040	0.025	0.016
Sell-herding				
Mean	0.032***	0.039***	0.035***	0.024***
t-Stat	(6.378)	(7.669)	(6.466)	(4.482)
Median	0.032	0.039	0.032	0.019

This table presents the mean and median values for LSV herding measure in buy/sell herding and the number of active funds detail. t-Stats for mean values are presented in parentheses. ***, **, and * stand for 1, 5, and 10% significance levels, respectively.

To decompose the buy and sell herds for the Sias measure, we follow the method proposed by Choi and Sias (2009). First, we group industries according to the institutions that bought and sold over the prior time period $p_{k,t-1} > 0.5$ and $p_{k,t-1} < 0.5$, respectively. Then, we divide equation (5) into buy- and sell-herding to calculate the contribution of each side to the overall correlation. The herding values calculated using the Sias measure are shown in Table 3.5. As previously stated, the Sias measure accounts for the cross-sectional correlation between the buyers to all active traders ratios in the adjacent months. Furthermore, the impact of funds following both their own industry trades and the industry trades of other funds is divided into two components. Celiker et al. (2015) indicate that the primary point of interest while examining the Sias method results is the contribution of funds following other mutual funds' industry trades. In Table 3.5, Panel A displays the mean and median values for the overall Sias measure. The mean values of the cross-sectional correlations are -5.3%, -8.6%, -10.2%, and -3.1%, respectively. The mean value for the unconditional case seems to be not statistically significant, which is an indication of "no herding". The fraction of the cross-sectional correlation that results from funds trading their own previous industries is reported in Panel B (the first component of the equation (5)), and Panel C reports the portion that is the result of funds following other funds' industry trades (the second component of the equation (5)). According to Panel B and C, following own industry trades has a positive impact, whereas following other funds' industry trades has a negative impact. Sias (2004) indicates that own contribution will be positive if an investor buys or sells the industry in the adjacent periods. The contribution from following other funds' industry trades will be negative if investors buy (sell) industries sold (purchased) in the previous period. From Panel B and C, we observe that the absolute contribution by following other funds' trades is greater than the contribution due to following own industry trades.

We then divide the total cross-sectional correlation and its components of following own and others' industry trades into the effects of buy and sell herding. Panels D, E, and F of Table 5 display the impact of buy- and sell-herding on the total cross-sectional correlation, the impact of following own industry trades, and the impact due to following other funds' industry trades, respectively. From the panels, we observe no major difference between the impacts of buy- and sell-herding both for the total cross-sectional correlation and its two components (i.e., own and other figures).

Table 3.5 Evidence of herding using Sias measure with buy/sell herding and active fund breakdown

	Unconditional	>= 5 active mutual funds	>= 10 active mutual funds	>= 20 active mutual funds
Panel A. Total Sias measure				
Mean	-0.053	-0.086**	-0.102***	-0.031
t-Stat	(-1.251)	(-2.406)	(-3.623)	(-1.534)
Median	-0.072	-0.099	-0.047	-0.022
Panel B. Impact of funds following own industry trades				
Mean	0.021	-0.031***	-0.029***	-0.009*
t-Stat	(0.760)	(-4.530)	(-5.910)	(-1.935)
Median	-0.010	-0.029	-0.029	-0.002
Panel C. Impact of funds following other funds' industry trades				
Mean	-0.074**	-0.055	-0.073**	-0.022
t-Stat	(-2.282)	(-1.650)	(-2.688)	(-1.103)
Median	-0.086	-0.067	-0.051	-0.006
Panel D. Total Sias measure				
Impact of buy				
Mean	-0.036	-0.049**	-0.043**	-0.020
t-Stat	(-1.365)	(-2.067)	(-2.641)	(-1.514)
Median	-0.081	-0.047	-0.037	-0.019
Impact of sell				
Mean	-0.018	-0.037*	-0.058***	-0.011
t-Stat	(-0.711)	(-1.737)	(-3.056)	(-0.798)
Median	-0.006	-0.008	-0.046	0.000

Table 3.5 Evidence of herding using Sias measure with buy/sell herding and active fund breakdown (cont'd)

	Unconditional	>= 5 active mutual funds	>= 10 active mutual funds	>= 20 active mutual funds
Panel E. Impact of funds following own industry trades				
Impact of buy				
Mean	-0.006	-0.018***	-0.012***	-0.008**
t-Stat	(-0.385)	(-3.103)	(-4.657)	(-2.689)
Median	-0.018	-0.019	-0.011	-0.004
Impact of sell				
Mean	0.027	-0.013***	-0.016***	-0.001
t-Stat	(1.372)	(-3.323)	(-4.036)	(-0.420)
Median	-0.003	-0.013	-0.013	0.000
Panel F. Impact of funds following other funds' industry trades				
Impact of buy				
Mean	-0.030	-0.032	-0.031*	-0.013
t-Stat	(-1.434)	(-1.436)	(-1.866)	(-0.952)
Median	-0.058	-0.035	-0.031	0.000
Impact of sell				
Mean	-0.044**	-0.023	-0.042**	-0.010
t-Stat	(-2.233)	(-1.188)	(-2.343)	(-0.737)
Median	-0.045	0.004	-0.028	0.009

This table presents the mean and median values for Sias herding measure in buy/sell herding and the number of active funds detail. Buy and sell herdings are displayed according to the impact of funds following own industry trades and other funds' industry trades. t-Stats for mean values are presented in parentheses. ***, **, and * stand for 1, 5, and 10% significance levels, respectively.

3.3.3 Fund flows

Choi and Sias (2009) and Celiker et al. (2015) indicate that institutional industry herding may be the reflection of underlying investors' flows. Therefore, if the herding is due to transactions by underlying investors, the results is expected to be weaker when the effect of these transactions is isolated. According to Coval and Stafford (2007, p. 482), "Funds experiencing large inflows tend to increase their existing positions…". Likewise, when mutual funds experience cash outflows, they liquidate their holdings. Qian and Tanyeri (2017) state that fund runs may take place as a result of reactions to litigation. Loss of confidence in the quality of management and the desire to minimize damage in the event of a fire sale may lead funds to experience abnormal outflows. As a result, if both cash inflows and outflows are centered on funds with holdings in related industries, these flows may induce funds to trade in the same direction, creating an imbalance between buy and sell trades, akin to herding.

To compensate for the impacts of flows on herding, we investigate changes in funds' industry portfolio weights, as suggested by Choi and Sias (2009) and Celiker et al. (2015). If a fund adjusts its portfolio concentration in the exact direction as its transactions throughout an industry-month, we classify it as an active trader. Then, we recalculate LSV and Sias herding measures based on this new "active fund" classification. In Table 3.6, Panel A presents the LSV herding measure levels for the overall case and in buy/sell herding breakdown. According to Panel A, the mean values for the LSV measure are 4.1%, 4.3%, and 4.0% for industry-months when there is no active fund limit and when there are at least five and ten active mutual funds[7], respectively. The mean and median statistics for buy- and sell-herding are also presented in the same panel. The values presented in Panel A are noticeably higher than those reported in Table 3.4, and still significant at the 1% level. The

[7] The case with at least twenty active funds could not be reported due to incalculable industry-month values as a result of the new "active fund" constraint.

associated mean Sias measures are displayed in Panel B as 0.1%, -4.8%, and 0.1% respectively, and the measures are also presented in the contribution of following own trades and following other funds' trades breakdown. We observe that after taking transactions by underlying investors, Sias measure still shows evidence for "no cross-sectional correlation".

Table 3.6 Herding results after controlling for fund flows

		Unconditional	>= 5 active mutual funds	>= 10 active mutual funds
Panel A. LSV herding results				
Mean		0.041***	0.043***	0.040***
t-Stat		(6.990)	(8.597)	(7.804)
Median		0.041	0.040	0.038
Buy herding results				
Mean		0.042***	0.049***	0.043***
t-Stat		(5.596)	(7.361)	(7.090)
Median		0.039	0.043	0.036
Sell herding results				
Mean		0.043***	0.043***	0.044***
t-Stat		(6.836)	(8.045)	(6.841)
Median		0.043	0.040	0.044
Panel B. Sias herding results				
Total cross-sectional correlation	Mean	0.001	-0.048	0.001
	t-Stat	(0.021)	(-1.489)	(0.026)
	Median	0.011	-0.040	0.008
Following own trades	Mean	0.006	-0.025***	-0.012***
	t-Stat	(0.406)	(-5.375)	(-3.229)
	Median	0.009	-0.030	-0.020
Following other funds' trades	Mean	-0.005	-0.023	0.013
	t-Stat	(-0.154)	(-0.740)	(0.460)
	Median	-0.045	0.003	0.033

This table presents the mean and median values for LSV and Sias herding measures after controlling for underlying investors transactions. t-Stats for mean values are presented in parentheses. ***, **, and * stand for 1, 5, and 10% significance levels, respectively.

3.3.4 Individual stock herding

Choi and Sias (2009) acknowledge that some industries are extremely concentrated, with a single stock accounting for a considerable portion of the industry. Therefore, the industry herding could just be herding for that particular stock. Additionally, according to Celiker et al. (2015, p. 8), "…even in the presence of individual stock herding mutual funds might herd at the industry level". These two studies reveal that individual stock herding is not an indicator of institutional industry herding. Following Choi and Sias (2009) and Celiker et al. (2015), we examine the hypothesis that "the herding by mutual funds is the evidence of single stock herding". Celiker et al. (2015) first excluded the stock with the highest degree of herding for each industry-period before reapplying the LSV approach to test the hypothesis. After removing the stock with the highest level of herding, it is hypothesized that any evidence of industry herding would remain, proving that individual stock herding is not the cause of the observed industry herding. Our findings show that; after excluding the stock with the highest level of herding in each industry-month, the mean LSV herding measure becomes 1.079 % and is statistically significant at a 5% level.

To test the hypothesis using the Sias method, we follow Choi and Sias (2009). They first define the capitalization-weighted institutional demand for a stock. Therefore, the first step in determining capitalization-weighted demand is to determine the buyer fraction for each stock i in month t:

$$\Delta_{i,t} = \frac{Number\ of\ funds\ buying\ stock\ i\ in\ month\ t}{Number\ of\ funds\ either\ buying\ or\ selling\ stock\ i\ in\ month\ t} \quad (8)$$

We then define the weighted demand of funds for industry k, as the market-capitalization-weighted average of stocks within that industry (where $w_{i,t}$ is the stock i's capitalization weight in industry k at the beginning of month t):

$$\Delta^*_{k,t} = \sum_{i=1}^{I_{k,t}} w_{i,t}\Delta_{i,t} \tag{9}$$

We break down the cross-sectional correlation into four components because this weighted demand is a linear function of institutional demand for each stock in that industry. These components include the portions that correspond to herding because investors are following one another or themselves into the same stock and the portions that correspond to herding because investors are following one another or themselves into different stocks within the same industry. Thus, the cross-sectional correlation stated in equation (5) can take the following form:

$$\begin{aligned}
&\rho\left(\Delta^*_{k,t}, \Delta^*_{k,t-1}\right) = \\
&\frac{1}{K\sigma(\Delta^*_{k,t})\sigma(\Delta^*_{k,t-1})}\sum_{k=1}^{K}\left(\sum_{i=1}^{I_{k,t}}\left(w_{i,t}w_{i,t-1}\left(\sum_{n=1}^{N_{i,t}}\left(\frac{D_{n,i,t}-\overline{\Delta^*_{k,t}}}{N_{i,t}}\times\frac{D_{n,i,t-1}-\overline{\Delta^*_{k,t-1}}}{N_{i,t-1}}\right)\right)\right)\right)+ \\
&\frac{1}{K\sigma(\Delta^*_{k,t})\sigma(\Delta^*_{k,t-1})}\sum_{k=1}^{K}\left(\sum_{i=1}^{I_{k,t}}\left(w_{i,t}w_{i,t-1}\left(\sum_{n=1}^{N_{i,t}}\sum_{m=1,m\neq n}^{N_{i,t-1}}\frac{D_{n,i,t}-\overline{\Delta^*_{k,t}}}{N_{i,t}}\times\frac{D_{m,i,t-1}-\overline{\Delta^*_{k,t-1}}}{N_{i,t-1}}\right)\right)\right)+ \\
&\frac{1}{K\sigma(\Delta^*_{k,t})\sigma(\Delta^*_{k,t-1})}\sum_{k=1}^{K}\left(\sum_{i=1}^{I_{k,t}}\sum_{j=1,j\neq i}^{I_{k,t-1}}\left(w_{i,t}w_{j,t-1}\left(\sum_{n=1}^{N_{i,t}}\frac{D_{n,i,t}-\overline{\Delta^*_{k,t}}}{N_{i,t}}\times\frac{D_{n,j,t-1}-\overline{\Delta^*_{k,t-1}}}{N_{j,t-1}}\right)\right)\right)+ \\
&\frac{1}{K\sigma(\Delta^*_{k,t})\sigma(\Delta^*_{k,t-1})}\sum_{k=1}^{K}\left(\sum_{i=1}^{I_{k,t}}\sum_{j=1,j\neq i}^{I_{k,t-1}}\left(w_{i,t}w_{j,t-1}\left(\sum_{n=1}^{N_{i,t}}\sum_{m=1,m\neq n}^{N_{j,t-1}}\frac{D_{n,i,t}-\overline{\Delta^*_{k,t}}}{N_{i,t}}\times\frac{D_{m,j,t-1}-\overline{\Delta^*_{k,t-1}}}{N_{j,t-1}}\right)\right)\right)
\end{aligned} \tag{10}$$

The correlation that results from funds replicating their own trades into the same stock is shown in equation (10), first term on the right-hand side. The second term is the portion that emerges from funds tracking other funds' trades into the same stocks. The third term is the portion that states the correlation due to funds' trades in the form of following their previous trades into different stocks in the same industry. The last term in the equation presents the fraction of correlation that arises from funds following others' trades into different stocks in the same industry. The first, second, third, and fourth components of equation (10) have mean values of -0.5%, -10.2%, 0.4%, and -0.7%, respectively, as shown in Table 3.7. Only the second component, which shows the fraction of cross-sectional correlation due to tracking other funds' trades in the same stock, is found to be significant at the 1% significance level. The means of the remaining components do not significantly deviate from 0. According to Celiker et al. (2015), only the fourth component can be classified as real industry herding since it shows the fraction of cross-sectional correlation due to funds following others' trades into different stocks in the same industry. The one-sample t-test results on the fourth component demonstrate that industrial herding is not significantly led by herding to a particular stock.

Table 3.7 Results of single stock herding in Sias framework

	Same stock	Different stock in the same industry	Total
Following themselves	-0.005 (-0.215)	0.004 (1.429)	-0.001 (-0.036)
Following others	-0.102*** (-4.179)	-0.007 (-0.456)	-0.109*** (-4.218)
Total	-0.107*** (-3.303)	-0.003 (-0.180)	-0.110*** (-2.953)

This table presents the mean values of single stock herding by funds using the Sias method. The total cross-sectional correlation is divided into four components depending on whether funds are following each other or themselves into the same stocks or different stocks in the same industry. t-Stats for mean values are presented in parentheses. ***, **, and * stand for 1, 5, and 10% significance levels, respectively.

3.3.5 Style investing

Two reasons stand out for the relationship between style investing and herding (Celiker et al., 2015). First, in terms of market capitalizations (size) and book-to-market ratios (B/M), companies within a certain sector typically share a number of comparable traits. Therefore, funds that have style targets such as size and B/M may invest in the same industries. Second, information received by managers related to industries may have size and B/M components. As a result, industry herding may be driven by mutual funds' style investing selections.

Following Choi and Sias (2009), we first classify stocks under six styles, based on the size of their market equities and B/M[8]. Two groups are based on the median market capitalization across all stocks for the relevant month, and three groups are formed using the 30th and 70th percentiles of B/M across all stocks for the relevant month. We then decompose the impact of funds that track other funds' trades into other stocks in the same industry, which is stated in the last component of equation (10), into two to see the effect of style investing: (1) different stocks from the same industry that share the same style group; (2) different stocks from the same industry that are also from different style groups. As a result of this decomposition, the last component of equation (10) takes the following form:

$$\frac{1}{K\sigma(\Delta^*_{k,t})\sigma(\Delta^*_{k,t-1})}\sum_{k=1}^{K}\left(\sum_{i=1}^{I_{k,t}}\sum_{j=1,j\neq i}^{I_{k,t-1}}\left(w_{i,t}w_{j,t-1}\left(\sum_{n=1}^{N_{i,t}}\sum_{m=1,m\neq n}^{N_{j,t-1}}\frac{D_{n,i,t}-\overline{\Delta^*_{k,t}}}{N_{i,t}}\times\frac{D_{m,j,t-1}-\overline{\Delta^*_{k,t-1}}}{N_{j,t-1}}\right)\right)\right)=$$
$$\frac{1}{K\sigma(\Delta^*_{k,t})\sigma(\Delta^*_{k,t-1})}\sum_{k=1}^{K}\left(\sum_{i=1,i\in s}^{I_{k,t}}\sum_{j=1,j\neq i,j\in s}^{I_{k,t-1}}\left(w_{i,t}w_{j,t-1}\left(\sum_{n=1}^{N_{i,t}}\sum_{m=1,m\neq n}^{N_{j,t-1}}\frac{D_{n,i,t}-\overline{\Delta^*_{k,t}}}{N_{i,t}}\times\frac{D_{m,j,t-1}-\overline{\Delta^*_{k,t-1}}}{N_{j,t-1}}\right)\right)\right)+$$
$$\frac{1}{K\sigma(\Delta^*_{k,t})\sigma(\Delta^*_{k,t-1})}\sum_{k=1}^{K}\left(\sum_{i=1,i\in s}^{I_{k,t}}\sum_{j=1,j\neq i,j\notin s}^{I_{k,t-1}}\left(w_{i,t}w_{j,t-1}\left(\sum_{n=1}^{N_{i,t}}\sum_{m=1,m\neq n}^{N_{j,t-1}}\frac{D_{n,i,t}-\overline{\Delta^*_{k,t}}}{N_{i,t}}\times\frac{D_{m,j,t-1}-\overline{\Delta^*_{k,t-1}}}{N_{j,t-1}}\right)\right)\right) \quad (11)$$

where $i \in s$ shows that the stock i is in the style group s.

The first line in Table 3.8 shows the contribution of funds to the correlation that is related to following different stocks that are from the same industry and are in the same or different style groups. The average actual impact of funds tracking other funds' trades into the same style category and different style category is -0.5% and -0.2%, respectively, and both are statistically insignificant. Finding insignificant

[8] Market capitalizations and B/M ratios are obtained from the Bloomberg and Refinitiv Eikon platforms. B/M ratios are available at a monthly frequency, but market capitalization data are available at a quarterly frequency. Therefore, the quarter-end market capitalizations are assumed to be the same as for the previous two months of the relevant quarter. To sort stocks according to the medians of their market capitalizations and B/M ratios, Froot and Teo (2008) use the data of t-1, and they state that they use those timing conventions to ensure that accounting variables are known before the sort (i.e., also suggested in Fama and French (1992)). We follow Froot and Teo (2008) in the timing of the sort for market capitalizations and B/M ratios.

results is not a major surprise given that these percentages are derived from the breakdown of the fourth component of equation (10) as indicated in the previous section. Therefore, this outcome shows that no major herding is revealed even if the investment by funds in different stocks in the same industry is broken down into investing in the same- and different-style stocks.

According to Choi and Sias (2009), it is not enough to show whether style herding fully explains industry herding, but it is also required to test whether style herding contributes to industry herding. To test whether style herding contributes to industry herding, we first compute the expected contributions of the same and different style groups. The assumption here is that if style investing does not add to industry herding, then a fund manager would purchase stocks regardless of the style group of stocks that are purchased by other managers. The second line in Table 3.8 shows the expected contributions[9] due to tracking other funds' trades into stocks from the same and different style groups, and the last line in Table 3.8 the discrepancy between the actual and predicted contributions from following other funds into the same and different style stocks. Following the same and different style stocks is expected to contribute -0.3% and -0.4%, respectively. The differences between the actual and expected figures are -0.2% and 0.2%, and these differences are not statistically significant. This finding suggests that style investing isn't the primary cause of industry herding.

[9] Please see Choi and Sias (2009) for the equation of expected contributions.

Table 3.8 Effect of style investing on industrial herding

	Same style	Different style
Actual contribution	-0.005 (-0.538)	-0.002 (-0.210)
Expected contribution	-0.003 (-0.565)	-0.004 (-0.392)
Actual - expected	-0.002 (-0.278)	0.002 (0.278)

This table presents reports the contribution of style investing to industrial herding. The first line shows the actual contribution of funds to correlation that is related to following different stocks which are from the same industry and same or different style groups. The second line presents the expected contributions due to following other funds into stocks from same and different style groups, and the last line is the difference between the actual and expected contributions. t-Stats for mean values are presented in parentheses. ***, ** and * stand for 1, 5 and 10% significance levels, respectively.

3.3.6 Effect of industry herding on industry values

Previous research suggests both that institutional herding leads the price to deviate from its fundamental values (Dasgupta et al., 2011; Gutierrez and Kelley, 2011) and that it does not lead to such a deviation (Nofsinger and Sias, 1999; Sias, 2004; Wermers, 1999). Choi and Sias (2009) and Celiker et al. (2015) both point out that herding can occur as a result of the timeliness of information transmission among money managers and the process of incorporating new information into prices. According to Choi and Sias (2009), it makes sense to believe that institutional demand is correlated with current industry returns and inversely correlated with future returns if we assume that institutional herding occasionally affects industry returns and is not always directly affected by the integration of information into prices. However, if institutional industry herding is the result of the information acquisition process, Choi and Sias (2009, p.28) state that "…institutional demand should be positively correlated with contemporaneous industry returns and not inversely related to subsequent industry returns." Since alternative explanations of herding are not mutually exclusive, institutional industry herding may reflect the information dissemination process and non-information factors at different times.

We investigate the claim that industry herding does not cause industry values to diverge from fundamental values. To test the hypothesis in the LSV framework, we first order industries according to the previous month's buy and sell LSV herding results and then form portfolios using the highest five buy (sell) LSV herding. We also form a difference portfolio that buys the highest five buy and sells the highest five sell herding industries. Following the formation (i.e., ranking) month, we then compute the equal-weighted average of value-weighted industry returns for these portfolios. Then, we compute the average returns of industry portfolios for coinciding observations using Jegadeesh and Titman's (1993) calendar time aggregation method. We test the abnormal returns generated by portfolios using CAPM and Fama-French three-factor[10] (Fama and French, 1993) alphas. To test the hypothesis in the Sias framework, we start calculating each industry's contribution (Choi and Sias, 2009) to the cross-sectional correlation across consecutive months, as shown in equation (12):

$$Industry\ k'scontribution = \left[\frac{1}{K\sigma\left(p_{k,t}\right)\sigma\left(p_{k,t-1}\right)}\right](p_{k,t} - \overline{p_{k,t}})(p_{k,t-1} - \overline{p_{k,t-1}}) \tag{12}$$

Then we define securities as buy-herding industries if the final two terms of equation (12) are both positive (i.e., funds are buying more than the overall industry in both periods). After that we select the highest five buy-herding industries that add most to the herding measure. Likewise, we classify the securities for which the last two terms of equation (12) are negative, as sell-herding industries. We then select the highest five sell-herding industries that add most to the herding measure. After that, we follow the same procedure as in the LSV measure case, to calculate the portfolio returns.

Table 3.9 shows the monthly average raw returns, CAPM, and FF 3-factor alphas for the top buy/sell and difference industry portfolios, respectively, based on LSV and Sias herding rankings. According to the first line of Panel A, difference

[10] The FF 3-factors are own calculations.

portfolios do not have significant raw and abnormal returns in the formation period following LSV rankings. In Panel B however, we observe significantly negative raw return and CAPM alpha for the difference portfolios in the formation period following Sias rankings. In terms of the significance of difference portfolio returns in the formation period, this result is consistent with prior studies (Both Choi and Sias, 2009, and Celiker et al., 2015 find significantly positive difference portfolio returns in the formation period). We don't observe any statistically significant differences in portfolio returns in the subsequent periods of both panels. This result is also in line with the findings of Celiker et al. (2015), who find that a different portfolio does not earn significant returns in subsequent periods. As a result, we draw the conclusion that there is no evidence of return reversals in industries with high levels of buy- and sell-herding, indicating that mutual fund herding does not have a destabilizing effect on industry returns.

Table 3.9 Fund herding and industry returns

	Raw Industry Returns			CAPM alphas			FF-3 Factor alphas		
	Buy	Sell	Difference	Buy	Sell	Difference	Buy	Sell	Difference
Panel A. LSV herding measure									
0-Months	0.009	0.017*	-0.008	-0.002	0.004	-0.017	-0.001	0.006	-0.011
	(1.115)	(1.925)	(-1.018)	(-0.334)	(0.808)	(-1.474)	(-0.108)	(1.103)	(-0.969)
1-Months	0.015*	0.012	0.003	0.003	-0.001	-0.007	0.004	-0.001	-0.001
	(1.705)	(1.317)	(0.433)	(0.542)	(-0.154)	(-0.620)	(0.637)	(-0.134)	(-0.076)
3-Months	0.013	0.012	0.001	0.000	0.001	-0.012	0.000	0.001	-0.006
	(1.586)	(1.480)	(0.209)	(-0.119)	(0.141)	(-1.447)	(0.107)	(0.159)	(-0.701)
6-Months	0.013*	0.013	0.001	0.000	0.000	-0.010	0.001	0.001	-0.005
	(1.729)	(1.588)	(0.231)	(0.121)	(0.066)	(-1.331)	(0.361)	(0.148)	(-0.595)
9-Months	0.013*	0.013	0.001	0.000	0.000	-0.010	0.001	0.000	-0.005
	(1.717)	(1.567)	(0.316)	(0.101)	(0.058)	(-1.347)	(0.282)	(0.104)	(-0.614)
12-Months	0.014*	0.012	0.002	0.001	0.000	-0.009	0.002	0.000	-0.003
	(1.878)	(1.502)	(1.093)	(0.371)	(-0.056)	(-1.142)	(0.636)	(0.041)	(-0.416)
Panel B. Sias herding measure									
0-Months	0.010	0.025***	-0.014*	-0.001	0.012**	-0.023**	0.004	0.013**	-0.014
	(1.147)	(3.522)	(-1.947)	(-0.097)	(2.344)	(-2.289)	(0.679)	(2.617)	(-1.421)
1-Months	0.012	0.010	0.002	-0.002	-0.004	-0.009	0.002	-0.002	-0.001
	(1.209)	(1.263)	(0.321)	(-0.281)	(-0.582)	(-1.114)	(0.359)	(-0.253)	(-0.193)
3-Months	0.013	0.012	0.002	0.000	0.000	-0.011	0.003	0.000	-0.002
	(1.607)	(1.560)	(0.279)	(-0.033)	(-0.051)	(-1.193)	(0.727)	(-0.006)	(-0.227)
6-Months	0.016**	0.014*	0.002	0.003	0.001	-0.009	0.006	0.003	-0.002
	(2.055)	(1.847)	(0.630)	(0.569)	(0.138)	(-1.058)	(1.442)	(0.690)	(-0.300)
9-Months	0.015*	0.014*	0.001	0.002	0.001	-0.010	0.005	0.004	-0.003
	(1.984)	(1.956)	(0.240)	(0.439)	(0.277)	(-1.186)	(1.287)	(0.839)	(-0.403)
12-Months	0.016**	0.014*	0.002	0.003	0.001	-0.008	0.006	0.003	-0.002
	(2.172)	(1.928)	(0.607)	(0.700)	(0.178)	(-1.064)	(1.590)	(0.803)	(-0.302)

This table presents reports on the mean raw returns and CAPM and FF 3-factor alphas for top 5 buy, top 5 sell, and difference portfolios. Panel A shows the returns in the LSV framework and Panel B shows the returns in the Sias framework. The first lines of both Panel A and B show the mean returns in the formation periods. The remaining lines show the returns for different holding periods for the portfolios developed using Jegadeesh and Titman's (1993) calendar time aggregation method. t-Stats for mean values are presented in parentheses. ***, **, and * stand for 1, 5, and 10% significance levels, respectively.

3.4 Conclusion

The presence of industrial herding among mutual funds in Turkey has been investigated in this study. On a unique data set obtained from Takasbank, we apply LSV and Sias herding measures. We uncover evidence of mutual fund herding in industries across the period of concern when using the LSV measure. In contrast, when the Sias measure is used, there is no overall significant industry herding among mutual funds. Furthermore, contrary to past studies' findings (Choi and Sias, 2009; Celiker et al., 2015), as is evident from the significantly negative correlation coefficient for the component standing for “following others’ trades”, mutual funds drift away from their earlier holdings in subsequent quarters. When we examine buy- and sell-herdings with the LSV measure, we observe that buy herds are slightly higher than sell herds when there are no restrictions on the number of active funds (i.e., unconditional case). However, this gap gets closer when the number of funds in the active fund criterion rises. When the evaluation is based on the Sias measure, however, we cannot reach the same result. We find no evidence that fund flows are driving industry herding. Two findings result from our examination of how single stock trading affects industry herding: Even after omitting the top herding stocks from the sample when the herding measure is LSV, there is still a significant amount of industry herding. However, using the Sias measure, we show that funds do not track other funds’ trades into different stocks in the same industry, proving that single-stock herding does not significantly affect industry herding. Our findings also show that style investing is not the main driver of industry herding. The top-ranking buy and sell herding industries do not show any indication of return reversals, which shows that mutual fund herding is not a factor that destabilizes industry returns.

The findings of this study are significant because they reveal the implications of a concentrated market with fewer funds and stocks traded than in developed markets. The results indicate that the Turkish scenario, which serves as a typical of emerging markets, responds similarly to the reasons for industry herding and the other characteristics that have been identified for developed markets and can be perceived as herding. As a result, potential factors of information asymmetry such as the lack of a reliable information production environment (Morck et al., 2000; Chan and Hameed, 2006) and the dynamics of a concentrated market with a small number of funds and stocks do not have a significant contribution to the herding behavior of money managers.

According to Brown et al. (1996), managers' judgments on portfolio construction can be influenced by mutual funds' competitive nature without any additional financial incentives. As a result, mutual fund markets are tournaments where managers compete against one another to achieve their investing goals. Further, according to Chevalier and Ellison (1997), there is a direct correlation between the fund's capital inflows and its previous performance. Because of this connection, fund managers are motivated to alter the risk and distribution of their funds in order to keep them appealing. Because the algorithm used to attract potential investors is primarily based on fund performance, fund managers who are reluctant to share their genuine capabilities may exhibit herding behavior due to career concerns (Popescu and Xu, 2017). The fund tournament literature can be related to herding literature in future research studies because of the relationship between flow and career concerns.

During the study, we referred to the generation of reliable information about stocks on the market as one of the key distinctions between a developed and emerging economy (Chan and Hameed, 2006; Morck et al., 2000). An environment conducive to herding results from this distinction. Knowing this, it could also be interesting to look at the other way around as a future research subject: how herding influences investor behavior in developed and emerging economies to see the differences.

Only the LSV measure can provide a measure in industrial category breakdown, while both the LSV and Sias measures use cross-sectional averages to compute the final herding measure. None of these measures can, however, produce computations based on the sample's agents (i.e., funds). It's crucial to be able to calculate herding in agent details since it gives researchers the chance to identify the variables that influence how herding differs among agents. Examining the lagged herding behavior would also be interesting for determining whether the behavior is persistent between periods. Future studies could potentially look at these two arguments.

In this study, we do not use an index like the HHI to assess the market concentration for mutual funds. Instead, we make inferences on the level of concentration based on the number of active funds, the number of fund managers, and the number of stocks traded by the funds. Although there are studies also expressing market concentration via these parameters (Gavriildis et al., 2013; Holmes et al., 2013), we believe that market concentration might also be highlighted using concentration ratios or indices in future research papers.

REFERENCES

Acharya, V. V., Yorulmazer, T., 2007. Too many to fail-An analysis of time-inconsistency in bank closure policies. J. Financ. Intermediation. https://doi.org/10.1016/j.jfi.2006.06.001

Aiken, L.S., West, S.G., Reno, R.R., 1991. Multiple Regression: Testing and Interpreting Interactions. Sage.

Alam, Z., Alter, A., Eiseman, J., Gelos, G., Kang, H., Narita, M., Nier, E., Wang, N., 2019. Digging Deeper--Evidence on the Effects of Macroprudential Policies from a New Database.

Arellano, M., Bond, S., 1991. Employment Equations Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. Rev. Econ. Stud. 58, 277–297.

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. J. Econom. 68, 29–51.

Athanasoglou, P.P., Brissimis, S.N., Delis, M.D., 2008. Bank-specific, industry-specific and macroeconomic determinants of bank profitability. J. Int. Financ. Mark. Institutions Money 18, 121–136. https://doi.org/10.1016/j.intfin.2006.07.001

Banerjee, A. V, 1992. A Simple Model of Herd Behavior. Q. J. Econ. 107, 797–817.

Barber, B. M., Odean, T., Zhu, N., 2008. Do retail trades move markets?. The Review of Financial Studies, 22(1), 151-186.

Barberis, N., Shleifer, A., 2003. Style investing. J. financ. econ. 68, 161–199. https://doi.org/10.1016/S0304-405X(03)00064-3

Barron, J.M., Valev, N.T., 2000. International Lending by US Banks. J. Money, Credit Bank. 32, 357–381.

Berger, A.N., Demirgüç-Kunt, A., Levine, R., Haubrich, J.G., 2004. Bank Concentration and Competition: An Evolution in the Making. J. Money, Credit Bank. 36, 433–451.

Berger, A.N., Deyoung, R., 1997. Problem loans and cost efficiency in commercial banks. J. Bank. Financ. 21, 849–870.

Berger, A.N., Udell, G.F., 2004. The institutional memory hypothesis and the procyclicality of bank lending behavior. J. Financ. Intermediation. https://doi.org/10.1016/j.jfi.2004.06.006

Bernardo, A.E., Welch, I., 2004. Liquidity and Financial Market Runs. Q. J. Econ. 119, 135–158.

Bernhardt, D., Campello, M., Kutsoati, E., 2006. Who herds? J. financ. econ. 80, 657–675. https://doi.org/10.1016/j.jfineco.2005.07.006

Bikhchandani, S., Hirshleifer, D., Welch, I., 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. J. Polit. Econ. https://doi.org/10.1086/261849

Bikhchandani, S., Sharma, S., 2000. Herd Behavior in Financial Markets. IMF Staff Pap. 47, 279–310.

Blake, D., Sarno, L., Zinna, G., 2017. The market for lemmings: The herding behavior of pension. J. Financ. Mark. 36, 17–39. https://doi.org/10.1016/j.finmar.2017.03.001

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. J. Econom. 87, 115–143.

Blundell, R., Bond, S., Windmeijer, F., 2000. Estimation in dynamic panel data models: improving on the performance of the standard GMM estimator, IFS Working Papers.

Borio, C., Furfine, C., Lowe, P., 2001. Procyclicality of the financial system and financial stability: issues and policy options. BIS Pap. 1(3), 1–57.

Boyd, N.E., Büyükşahin, B., Haigh, M.S., Harris, J.H., 2015. The Prevalence, Sources, and Effects of Herding. J. Futur. Mark. 36, 671–694. https://doi.org/10.1002/fut.21756

Boyson, N.M., 2010. Implicit incentives and reputational herding by hedge fund managers. J. Empir. Financ. 17, 283–299. https://doi.org/10.1016/j.jempfin.2009.10.005

Brambor, T., Clark, W.R., Golder, M., 2006. Understanding Interaction Models: Improving Empirical Analyses. Polit. Anal. 14, 63–82. https://doi.org/10.1093/pan/mpi014

Brealey, R. A., Kaplanis, E., 2001. Hedge funds and financial stability: An analysis of their factor exposures. International Finance, 4(2), 161-187.

Brennan, M.J., 1990. Latent assets. J. Finance 45, 709–730.

Brown, K.C., Harlow, W.V. and Starks, L.T., 1996. Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry. The Journal of Finance, 51(1), pp.85-110.

Brown, N.C., Wei, K.D., Wermers, R., 2014. Analyst recommendations, mutual fund herding, and overreaction in stock prices. Manage. Sci. 60, 1–20. https://doi.org/10.1287/mnsc.2013.1751

Brunnermeier, M.K., Nagel, S., 2004. Hedge funds and the technology bubble. The journal of Finance, 59(5), 2013-2040.

Caparrelli, F., D'Arcangelis, A. M., Cassuto, A., 2004. Herding in the Italian stock market: a case of behavioral finance. The Journal of Behavioral Finance, 5(4), 222-230.

Caporale, G. M., Economou, F., & Philippas, N., 2008. Herd behaviour in extreme market conditions: the case of the athens stock exchange.

Castro, V., 2013. Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI. Econ. Model. 31, 672–683. https://doi.org/10.1016/j.econmod.2013.01.027

Celiker, U., Chowdhury, J., Sonaer, G., 2015. Do mutual funds herd in industries? J. Bank. Financ. 52, 1–16. https://doi.org/10.1016/j.jbankfin.2014.11.006

Chan, K., Hameed, A., 2006. Stock price synchronicity and analyst coverage in emerging markets. J. financ. econ. 80, 115–147. https://doi.org/10.1016/j.jfineco.2005.03.010

Chang, C., 2010. Herding and the role of foreign institutions in emerging equity markets. Pacific-Basin Finance Journal, 18(2), 175-185.

Chang, E.C., Cheng, J.W., Khorana, A., 2000. An examination of herd behavior in equity markets: An international perspective. J. Bank. Financ. 24, 1651–1679.

Chang, E. C., Dong, S., 2006. Idiosyncratic volatility, fundamentals, and institutional herding: Evidence from the Japanese stock market. Pacific-Basin Finance Journal, 14(2), 135-154.

Chen, Q., Goldstein, I., Jiang, W., 2010. Payoff complementarities and financial fragility: Evidence from mutual fund outflows. Journal of Financial Economics, 97(2), 239-262.

Chevalier, J., Ellison, G., 1997. Risk Taking by Mutual Funds as a Response to Incentives. J. Polit. Econ. 105, 1167–1200.

Chiang, T.C., Zheng, D., 2010. An empirical analysis of herd behavior in global stock markets. J. Bank. Financ. 34, 1911–1921. https://doi.org/10.1016/j.jbankfin.2009.12.014

Choe, H., Kho, B. C., Stulz, R. M., 1999. Do foreign investors destabilize stock markets? The Korean experience in 1997. Journal of Financial economics, 54(2), 227-264.

Choi, I., 2001. Unit root tests for panel data. J. Int. Money Financ. 20, 249–272.

Choi, N., Sias, R.W., 2009. Institutional industry herding. J. financ. econ. 94, 469–491. https://doi.org/10.1016/j.jfineco.2008.12.009

Christie, W.G., Huang, R.D., 1995. Following the Pied Piper: Do Individual Returns Herd around the Market? Financ. Anal. J. 51, 31–37.

Clement, M. B., Tse, S. Y., 2005. Financial analyst characteristics and herding behavior in forecasting. The Journal of finance, 60(1), 307-341.

Coval, J., Stafford, E., 2007. Asset fire sales (and purchases) in equity markets. J. financ. econ. 86, 479–512. https://doi.org/10.1016/j.jfineco.2006.09.007

Danışman, G., 2018. Determinants of Bank Stability: A Financial Statement Analysis. Sosyoekonomi 26, 87–103. https://doi.org/10.17233/sosyoekonomi.2018.04.06

Dasgupta, A., Prat, A., Verardo, M., 2011. Institutional Trade Persistence and Long-Term Equity Returns. J. Finance 66, 635–653. https://doi.org/10.1111/j.1540-6261.2010.01644.x

Dass, N., Massa, M., Patgiri, R., 2008. Mutual funds and bubbles: The surprising role of contractual incentives. The Review of Financial Studies, 21(1), 51-99.

Demirer, R., Kutan, A.M., 2006. Does herding behavior exist in Chinese stock markets?. J. Int. Financ. Mark. Institutions Money 16, 123–142. https://doi.org/10.1016/j.intfin.2005.01.002

Demirer, R., Zhang, H., 2019. Industry Herding and the Profitability of Momentum Strategies During Market Crises. J. Behav. Financ. 20, 195–212. https://doi.org/10.1080/15427560.2018.1505728

Devenow, A., Welch, I., 1996. Rational herding in financial economics. Eur. Econ. Rev. https://doi.org/10.1016/0014-2921(95)00073-9

Diamond, D.W., Dybvig, P.H., 1983. Bank runs, deposit insurance, and liquidity. J. Polit. Econ. https://doi.org/10.1086/261155

Fama, E.F., French, K.R., 1992. The Cross-Section of Expected Stock Returns. J. Finance. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. financ. econ. 33, 3–56. https://doi.org/10.1016/0304-405X(93)90023-5

Fang, H., Lee, Y.H., Shen, C.H., Chung, C.P., 2019. Motivations for Loan Herding by Chinese Banks and Its Impact on Bank Performance. China World Econ. 27, 29–52. https://doi.org/10.1111/cwe.12285

Fang, H., Lu, Y.C., Shieh, J.C.P., Lee, Y.H., 2021. The existence and motivations of irrational loan herding and its impact on bank performance when considering different market periods. Int. Rev. Econ. Financ. 73, 420–443. https://doi.org/10.1016/j.iref.2021.01.015

Flannery, M.J., Hankins, K.W., 2013. Estimating dynamic panel models in corporate finance. J. Corp. Financ. 19, 1–19. https://doi.org/10.1016/j.jcorpfin.2012.09.004

Frey, S., Herbst, P., Walter, A., 2014. Measuring mutual fund herding – A structural approach. J. Int. Financ. Mark. Institutions Money 32, 219–239. https://doi.org/10.1016/j.intfin.2014.05.006

Froot, K., Teo, M., 2008. Style investing and institutional investors. J. Financ. Quant. Anal. 43, 883–906. https://doi.org/10.1017/S0022109000014381

Fung, W., Hsieh, D. A., 2000. Measuring the market impact of hedge funds. Journal of Empirical Finance, 7(1), 1-36.

Gavriilidis, K., Kallinterakis, V., Leire-Ferreira, M.P., 2013. On the impact of style investing over institutional herding: evidence from a highly concentrated market. Investment Management and Financial Innovations, 10(4), pp.27-42.

Gebka, B., Wohar, M.E., 2013. International herding: Does it differ across sectors?. J. Int. Financ. Mark. Institutions Money 23, 55–84. https://doi.org/10.1016/j.intfin.2012.09.003

Gleason, K.C., Mathur, I., Peterson, M.A., 2004. Analysis of intraday herding behavior among the sector ETFs. J. Empir. Financ. 11, 681–694. https://doi.org/10.1016/j.jempfin.2003.06.003

Graham, J.R., 1999. Herding among Investment Newsletters: Theory and Evidence. J. Finance 54, 237–268.

Granger, C. W., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica: journal of the Econometric Society, 424-438.

Grinblatt, B.M., Titman, S., Wermers, R., 1995. Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior. Am. Econ. Rev. 85, 1088–1105.

Gutierrez, R.C., Kelley, E.K., 2011. Institutional Herding and Future Stock Returns. SSRN Electron. J. https://doi.org/10.2139/ssrn.1107523

Haiss, P.R., 2005. Banks, Herding and Regulation, in: Paper for Presentation at the Workshop on Informational Herding Behavior, Copenhagen.

Haiss, P., 2010. Bank Herding and Incentive Systems as Catalysts for the Financial Crisis. IUP J. Behav. Financ.

Hansen, L.P., 1982. Large Sample Properties of Generalized Method of Moments Estimators. Econometrica 50, 1029–1054.

Henker, J., Henker, T., Mitsios, A., 2006. Do investors herd intraday in Australian equities?. International Journal of Managerial Finance.

Hirshleifer, D., Hong Teoh, S., 2003. Herd behaviour and cascading in capital markets: A review and synthesis. Eur. Financ. Manag. https://doi.org/10.1111/1468-036X.00207

Hirshleifer, D., Subrahmanyam, A., Titman, S., 1994. Security Analysis and Trading Patterns when Some Investors Receive Information Before Others. J. Finance 49, 1665–1698.

Holmes, P., Kallinterakis, V., Ferreira, M.P.L., 2013. Herding in a concentrated market: A question of intent. Eur. Financ. Manag. 19, 497–520. https://doi.org/10.1111/j.1468-036X.2010.00592.x

Holtz-Eakin, D., Newey, W., Rosen, H.S., 1988. Estimating Vector Autoregressions with Panel Data. Econom. J. Econom. Soc. 56, 1371–1395.

Hong, H., Kubik, J.D., Solomon, A., 2000. Security Analysts' Career Concerns and Herding of Earnings Forecasts. RAND J. Econ. 31, 121–144.

Hwang, S., Salmon, M., 2004. Market stress and herding. J. Empir. Financ. 11, 585–616. https://doi.org/10.1016/j.jempfin.2004.04.003

Iihara, Y., Kato, H. K., Tokunaga, T., 2001. Investors' herding on the Tokyo stock exchange. International Review of Finance, 2(1-2), 71-98.

Jain, A.K., Gupta, S., 1987. Some Evidence on " Herding " Behavior of U.S. Banks. J. Money, Credit Bank. 19, 78–89.

Jegadeesh, N., Kim, W., 2010. Do Analysts Herd? An Analysis of Recommendations and Market Reactions. Rev. Financ. Stud. 23, 901–937. https://doi.org/10.1093/rfs/hhp093

Jegadeesh, N., Titman, S., 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance, Vol. 48, No. 1 (Mar., 1993), pp. 65-91.

Judson, R.A., Owen, A.L., 1999. Estimating dynamic panel data models: a guide for macroeconomists. Econ. Lett. 65, 9–15.

Kara, H., 2016. Turkey’s experience with macroprudential policy. BIS Pap. 123–139.

Keane, M.P., Runkle, D.E., 1998. Are Financial Analysts’ Forecasts of Corporate Profits Rational? J. Polit. Econ. 106, 768–805.

Kim, K. A., & Nofsinger, J. R., 2005. Institutional herding, business groups, and economic regimes: Evidence from Japan. The Journal of Business, 78(1), 213-242.

Kim, C., Pantzalis, C., 2003. Global/industrial diversification and analyst herding. Financial Analysts Journal, 59(2), 69-79.

Kim, W., Wei, S. J., 2002. Foreign portfolio investors before and during a crisis. Journal of international economics, 56(1), 77-96.

Klein, N., 2011. Non-performing loans in CESEE: Determinants and impact on macroeconomic performance.

Koch, A., 2017. Herd Behavior and Mutual Fund Performance. Manage. Sci. 63, 3849–3873.

Küçükbıçakcı, F.P.E., Ozen, E., Ünalmış, İ., 2020. Are Macroprudential Policies Effective Tools to Reduce Credit Growth in Emerging Markets?. World J. Appl. Econ. 6, 73–89. https://doi.org/10.22440/wjae.6.1.5

Lakonishok, J., Shleifer, A., Vishny, R.W., 1992. The impact of institutional trading on stock prices. J. financ. econ. 32, 23–43. https://doi.org/10.1016/0304-405X(92)90023-Q

Lamont, O. A., 2002. Macroeconomic forecasts and microeconomic forecasters. Journal of economic behavior & organization, 48(3), 265-280.

Li, D. D., Yung, K., 2004. Institutional herding in the ADR market. Review of Quantitative Finance and Accounting, 23(1), 5-17.

Li, W., Rhee, G., Wang, S. S., 2017. Differences in herding: Individual vs. institutional investors. Pacific-Basin Finance Journal, 45, 174-185.

Lin, W.T., Tsai, S.C., Lung, P.Y., 2013. Investors' herd behavior: Rational or irrational? Asia-Pacific J. Financ. Stud. https://doi.org/10.1111/ajfs.12030

Liu, C., 2014. Herding Behavior in Bank Lending: Evidence from US Commercial Banks. SSRN.

Louzis, D.P., Vouldis, A.T., Metaxas, V.L., 2012. Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. J. Bank. Financ. https://doi.org/10.1016/j.jbankfin.2011.10.012

Lu, R., Shen, C.-H., Fang, H., 2014. The Loan Herding of Chinese Banks for Industrial Lending and the Subsequent Economic Impact. Asian Financ. Assoc. (Asian FA) 2014 Conf. Pap.

Lu, R.Y.-C., Shen, C.-H., Fang, H., 2013. Exploration into Banks' Herding on Industrial Loans in Taiwan. SSRN Electron. J. https://doi.org/10.2139/ssrn.2220347

Maddala, G.S., Wu, S.W., 1999. A comparative study of unit root tests with panel data and a new simple test. Oxf. Bull. Econ. Stat. 61, 631–652.

Merkl, C., Stolz, S., 2013. Banks' regulatory buffers, liquidity networks and monetary policy transmission. Appl. Econ. 41, 2013–2024. https://doi.org/10.1080/00036840802360245

Morck, R., Yeung, B., Yu, W., 2000. The information content of stock markets: Why do emerging markets have synchronous stock price movements? J. financ. econ. 58, 215–260. https://doi.org/10.1016/s0304-405x(00)00071-4

Moskowitz, T.J., Grinblatt, M., 1999. Do industries explain momentum? J. Finance 54, 1249–1290. https://doi.org/10.1111/0022-1082.00146

Nakagawa, R., 2008. Herd behavior by Japanese banks in local financial markets. Res. Cent. Socionetwork Strateg. Discuss. Pap. Ser. 71.

Nakagawa, R., Oiwa, H., Takeda, F., 2012. The Economic Impact of Herd Behavior in the Japanese Loan Market. Pacific Basin Financ. J. 20, 600–613. https://doi.org/10.1016/j.pacfin.2012.01.002

Nakagawa, R., Uchida, H., 2011. Herd behaviour by Japanese banks after financial deregulation. Economica 78, 618–636. https://doi.org/10.1111/j.1468-0335.2010.00870.x

Nickell, S., 1981. Biases in Dynamic Models with Fixed Effects. Econom. J. Econom. Soc. 49, 1417–1426.

Nofsinger, J.R., Sias, R.W., 1999. Herding and feedback trading by institutional and individual investors. J. Finance 54, 2263–2295. https://doi.org/10.1111/0022-1082.00188

Petria, N., Capraru, B., Ihnatov, I., 2015. Determinants of Banks' Profitability: Evidence from EU 27 Banking Systems. Procedia Econ. Financ. 20, 518–524. https://doi.org/10.1016/s2212-5671(15)00104-5

Popescu, M. and Xu, Z., 2018. Mutual fund herding and reputational concerns. Journal of Economics and Finance, 42, pp.550-565.

Qian, M., Tanyeri, B., 2017. Litigation and mutual-fund runs. Journal of Financial Stability, 31, 119-135.

Raddatz, C., Schmukler, S.L., 2013. Deconstructing Herding: Evidence from Pension Fund Investment Behavior. J. Financ. Serv. Res. 43, 99–126. https://doi.org/10.1007/s10693-012-0155-x

Rajan, R.G., 1994. Why Bank Credit Policies Fluctuate: A Theory and Some Evidence. Q. J. Econ. 109, 399–441.

Rajan, R.G., 2006. Has finance made the world Riskier? Eur. Financ. Manag. https://doi.org/10.1111/j.1468-036X.2006.00330.x

Richardson, S., Teoh, S.H., Wysocki, P.D., 2004. The Walk-down to Beatable Analyst Forecasts: The Role of Equity Issuance and Insider Trading Incentives. Contemp. Account. Res. 21, 885–924.

Roodman, D., 2009. How to do xtabond2 : An introduction to difference and system GMM in Stata. stata J. 9, 86–136.

Scharfstein, D.S., Stein, J.C., 1990. Herd Behavior and Investment. Am. Econ. Rev. 80, 465–479.

Shehzad, C.T., Haan, J. De, Scholtens, B., 2010. The impact of bank ownership concentration on impaired loans and capital adequacy. J. Bank. Financ. 34, 399–408. https://doi.org/10.1016/j.jbankfin.2009.08.007

Sias, R.W., 2004. Institutional Herding. Rev. Financ. Stud. 17, 165–206. https://doi.org/10.1093/rfs/hhg035

Škarica, B., 2013. Determinants of non-performing loans in Central and Eastern European countries. Financ. theory Pract. 38, 37–59. https://doi.org/10.3326/fintp.38.1.2

Staikouras, C.K., Wood, G.E., 2011. The Determinants of European Bank Profitability. Int. Bus. Econ. Res. J. 3, 57–68. https://doi.org/10.19030/iber.v3i6.3699

Stellinga, B., 2020. The open-endedness of macroprudential policy. Endogenous risks as an obstacle to countercyclical financial regulation. Bus. Polit. 22, 224–251. https://doi.org/10.1017/bap.2019.14

Stuart, A., Ord, K., 1998. Kendall's Advanced Theory of Statistics. Arnold.

Tan, L., Chiang, T. C., Mason, J. R., Nelling, E., 2008. Herding behavior in Chinese stock markets: An examination of A and B shares. Pacific-Basin finance journal, 16(1-2), 61-77.

Tan, Y., Floros, C., 2012. Bank profitability and inflation: the case of China. J. Econ. Stud. 39, 675–696. https://doi.org/10.1108/01443581211274610

Tran, V.T., Nguyen, H., Lin, C.T., 2017. Herding behaviour in the Australian loan market and its impact on bank loan quality. Account. Financ. 57, 1149–1176. https://doi.org/10.1111/acfi.12183

Trueman, B., 1994. Analyst forecasts and herding behavior. The review of financial studies, 7(1), 97-124.

Uchida, H., Nakagawa, R., 2007. Herd behavior in the Japanese loan market: Evidence from bank panel data. J. Financ. Intermediation 16, 555–583. https://doi.org/10.1016/j.jfi.2007.03.007

Ukpong, I., Tan, H., Yarovaya, L., 2021. Determinants of industry herding in the US stock market. Financ. Res. Lett. 43, 101953. https://doi.org/10.1016/j.frl.2021.101953

Voronkova, S., Bohl, M. T., 2005. Institutional traders' behavior in an emerging stock market: Empirical evidence on polish pension fund investors. Journal of Business Finance & Accounting, 32(7-8), 1537-1560.

Walter, A., Weber, F.M., 2006. Herding in the German Mutual Fund Industry. Eur. Financ. Manag. 12, 375–406.

Welch, I., 1992. Sequential Sales, Learning, and Cascades. J. Finance 47, 695–732.

Welch, I., 2000. Herding among security analysts. J. financ. econ. 58, 369–396.

Wermers, R., 1999. Mutual fund herding and the impact on stock prices. J. Finance 54, 581–622. https://doi.org/10.1111/0022-1082.00118

Wylie, S., 2005. Fund manager herding: A test of the accuracy of empirical results using U.K. data. J. Bus. 78, 381–403. https://doi.org/10.1086/426529

Zitzewitz, E., 2001. Measuring herding and exaggeration by equity analysts and other opinion sellers.

APPENDICES

A. SELECTED EMPIRICAL STUDIES ON HERDING IN FINANCIAL MARKETS

Table A.1 Selected empirical studies on herding in financial markets

Author (year)	Field of study	Data	Method	Findings
LSV (1992)	Pension funds	Quarterly portfolio holdings of 769 all-equity pension funds in US for the 1985-1989 period.	LSV	No significant evidence is found for herding and positive-feedback trading in large stocks by pension fund managers. Weak evidence of herding and somewhat stronger evidence of positive-feedback trading are found for smaller stocks. No solid evidence is found to support that institutional investors destabilize prices of individual stocks.
Grinblatt et al. (1995)	Mutual funds	Quarterly portfolio holdings for 274 mutual funds from US that existed on December 31, 1974.	LSV and modified-LSV measure created by Grinblatt et al. (1995)	Significant evidence showing momentum trading is found. However, findings do not support herding.

Table A.1 Selected empirical studies on herding in financial markets (cont'd)

Author (year)	Field of study	Data	Method	Findings
Wermers (1999)	Mutual funds	Periodic portfolio holdings of mutual funds that existed any time between 1974 and 1994 and based in USA.	LSV and modified-LSV measure created by Wermers (1999)	A low level of herding by mutual funds in the average stock is found. A much higher level of herding in trades of small stocks and in trading by growth-oriented fund is found.
Nofsinger and Sias (1999)	Institutional investors	Annual fraction of shares for all NYSE firms held by institutional investors for the 1977 to 1996 period.	Nofsinger and Sias (1999)	There is strong positive relation between annual changes in institutional ownership and returns. This relation may be due to either institutional investors engage in intrayear positive feedback trading more than individual investors and/or institutional investors' level of herding has a greater impact on returns than individual investors' herding.
Sias (2004)	Institutional investors	Quarterly institutional ownership data from March 1983 through December 1997.	Sias (2004)	Institutional investors tend to follow their own and each other's trades. The tendency to follow own lag trades does not result from correlation in their net flows and investing net flows in their portfolios, but is related to trading costs. They also tend to follow momentum strategies, but only little of their herding stems from momentum trading.
Li and Yung (2004)	ADR market	Number of ADR shares held by institutional investors between 1985 and 1998.	Nofsinger and Sias (1999)	There is a strong positive relation between changes in institutional ownership of ADR shares and ADR returns over the same period, and this relation persists after controlling for market momentum.

Table A.1 Selected empirical studies on herding in financial markets (cont'd)

Author (year)	Field of study	Data	Method	Findings
Choi and Sias (2009)	Institutional investors	Quarterly data for institutional ownership of US stocks between 1983 and 2005.	Sias (2004)	The evidence shows that institutional herding has an industry component. The findings also suggest that institutions herd into industry styles and such herding has impact on prices. The evidence also indicates that industry herding is not related to underlying investors' flows, but with managers' decisions. Another finding is that there is institutional industry momentum trading, however, it does not explain the herding behavior.
Celiker et al. (2015)	Mutual funds	Portfolio holdings data for all mutual funds excluding international and non-equity funds for the 1980-2013 period.	LSV (1992) and Sias (2004)	The evidence shows the existence of industrial herding by mutual funds. The industry herding is not due to fund flows of underlying investors and not related to individual stock herding. Further, the industry herding is not a result of style investing. It is shown that industry returns are positively related to industry herding. Additionally, industry momentum profits are positively related to the herding during the formation of winner and loser industry periods.
Gutierrez and Kelley (2011)	Institutional investors	Institutional ownership data of US stocks between 1980 and 2005.	LSV (1992)	The findings suggest that buy herds predict negative abnormal returns two and three years after the herding. However, herding on the sell side has no relation with the future returns.

Table A.1 Selected empirical studies on herding in financial markets (cont'd)

Author (year)	Field of study	Data	Method	Findings
Wylie (2005)	Mutual funds	Portfolio holdings of 268 UK firms, taken from semiannual reports for the period between 1986 and 1993.	LSV (1992)	A similar level of herding to that reported in studies of US is found. The evidence shows that the herding level increases with the number of managers trading a particular stock over a period and is larger for the smallest and largest stocks.
Kim and Nofsinger (2005)	Institutional investors	Annual institutional ownership data for Japanese countries for the years 1975-2001.	Nofsinger and Sias (1999)	The evidence shows that the level of herding in Japan is only one-third the level in the US. However, the price impact of the herding is much higher in Japanese case. There is no evidence showing that Japanese institutions are feedback traders.
Iihara et al. (2001)	Institutional investors	Annual fraction of shares held by individual, institutional and foreign investors in Tokyo Stock Exchange during the period from 1975 and 1996.	Nofsinger and Sias (1999)	It is found that both institutional and foreign investors' herding has more impact on stock prices than that of individual investors' herding. The impact of foreign investors' herding on stock prices increases when the effect of individual investors is minimized. Further, evidence for feedback trading is found for large firm stocks.
Chang and Dong (2006)	Institutional investors	Institutional ownership data of all non-financial companies listed on the Tokyo Stock Exchange.	Nofsinger and Sias (1999)	Strong evidence is found that firms for which institutional investors herd have high idiosyncratic volatility. Further, evidence shows that firms with very high or very low earnings have high idiosyncratic volatility.

Table A.1 Selected empirical studies on herding in financial markets (cont'd)

Author (year)	Field of study	Data	Method	Findings
Walter and Weber (2006)	Mutual funds	Portfolio holdings of 60 mutual funds which are mostly located or operated in Germany and investing in German stocks. The sample period is between 1997 and 2002.	LSV (1992)	There is herding in the trade of German stocks by mutual funds which is slightly higher than the herding levels found in studies analyzing the US and the UK markets. The measured level of herding increases with the number of active funds in a stock. The evidence shows that buy-side herding is more visible during boom periods and sell-side herding is more pronounced during crash period. The results provide no evidence for destabilizing effect of herding on stock prices.
Voronkova and Bohl (2005)	Pension funds	Portfolio holdings of pension funds (i.e., from annual and semi-annual reports) in Polish market for the period from 1999 to 2002.	LSV (1992)	The estimated herding and feedback trading measures are found to be higher than corresponding values reported for mature markets. The reason for this result is provided as the highly regulated environment of Polish pension fund industry.
Chang (2010)	Institutional investors	Weekly order flow and holdings data from Taiwan Economic Journal (TEJ) database between 2000 and 2005.	Relation between order flows and overshoot in prices	It is found that when qualified foreign institutional investors increase (decrease) their holdings' weight in particular sectors; dealers, margin traders, and mutual funds follow them during the same and following weeks. This behavior can have a destabilizing effect as asset prices initially overshoot and later revert.

Table A.1 Selected empirical studies on herding in financial markets (cont'd)

Author (year)	Field of study	Data	Method	Findings
Choe et al. (1999)	Foreign investors	Foreign ownership, percentage of daily trade volume and price-setting trade volume for 414 stocks listed in Korean Stock Exchange from 1996 to 1997.	LSV (1992) and Wermers (1999)	The evidence shows that foreign investors engage in positive feedback trading and herd before the Korean crisis over the last months of 1997. The results indicate that crisis does not affect the intensity of herding. Further, positive feedback trading and herding do not have destabilizing effect on prices.
Holmes et al. (2013)	Mutual funds	Monthly portfolio holdings of 45 mutual funds trading in Portuguese market.	Sias (2004)	The overall results suggest that herding is significant in a concentrated market. The evidence suggests that herding is more intense when market returns are low or market declines. Further, the main reasons for the herding might be the reputational concerns of managers and quarterly performance management.
Brunnermeier and Nagel (2004)	Hedge funds	Quarterly stock holdings of hedge funds between 1998 and 2000 for US market.	Two-factor return regressions	The findings suggest that hedge funds intentionally prefer to ride on technology stock bubbles. They decrease their positions before the bubble deflates and utilize the predictability of investor sentiment in their trades. The findings challenge the efficient markets notion that rational speculators always stabilize prices.

Table A.1 Selected empirical studies on herding in financial markets (cont'd)

Author (year)	Field of study	Data	Method	Findings
Fung and Hsieh (2000)	Hedge funds	Monthly returns of large hedge funds from the October 1987 stock market crash to the Asian Currency Crisis of 1987.	Estimated hedge fund positions	The evidence suggests that there are periods (i.e., ERM crisis in 1992, the European bond market rally in 1993 and decline in 1994) that hedge fund activities cause market impact. There is no evidence that hedge funds perform positive feedback trading. Hedge funds do not act as a single group. There are different style classes, which chase unrelated trades. Further, hedge funds do not lead other traders to herd in similar trades.
Brealey and Kaplanis (2001)	Hedge funds	Monthly returns of 146 hedge funds from Tass Management database which has a continuous observation beginning no later than January 1994 and ending in September 1999.	Return regressions showing funds' exposure to markets	In each investment strategy class, funds tend to make similar changes to their factor exposures, which is an indication of herding. However, it is not easy to identify speculative portfolio shifts using returns, as it is not possible to clearly date the changes with precision and it is difficult to distinguish the effects that result from active fund management and from those that characterize a passive portfolio.

Table A.1 Selected empirical studies on herding in financial markets (cont'd)

Author (year)	Field of study	Data	Method	Findings
Boyson (2010)	Hedge funds	Monthly return data for hedge funds from Lipper Tass database for the period between January 2004 and December 2004.	Tracking error deviation, beta deviation and total risk	The evidence indicates that senior managers that deviate from the herd are more likely to be terminated and do not experience higher fund inflows than less experienced managers. Further, more experienced managers herd more than less-experienced managers.
Graham (1999)	Analyst recommendations	5293 market timing recommendations made by 237 newsletters.	Dynamic measure of reputation with Bayesian updating functions	Herding decreases with the precision of private information. It is more likely to expect an analyst to herd on Value Line's recommendation, when his/her reputation is high, ability is low, or signal correlation is high.
Boyd et al. (2015)	Hedge funds	Daily positions data of hedge funds from CFTC for 30 futures markets between July 2004 and July 2009.	LSV (1992)	The evidence suggests that herding in futures markets is similar but slightly higher than levels found in equity markets. Further, herding decreases with a greater number of traders in the market. There is some positive feedback trading among hedge fund managers, but it is more related with number of traders rather than with net buying imbalances among traders.

Table A.1 Selected empirical studies on herding in financial markets (cont'd)

Author (year)	Field of study	Data	Method	Findings
Kim and Wei (2002)	Foreign investors	Month-end share holding by individual investors for each stock listed in Korea Stock Exchange, between December 1996 and June 1998.	LSV (1992) method with Wylie (1997) correction	The findings suggest that heterogeneity among foreign investors is a significant factor for feedback trading and herding. The Korean branches/subsidies of foreign institutions or foreign individual investors who are resident in Korea are less likely to engage in feedback trading and herding than their non-resident counterparts.
Barber et al. (2008)	Individual investors	Transaction data for AMEX and NYSE stocks for the period between 1983 and 1992 and NASDAQ data for the period between 1987 and 2000.	LSV (1992)	The findings suggest that using small trades as a proxy for the individual trades, it is observed that buy transactions are highly correlated. In both short and long horizons, retail trade imbalances forecast future returns.
Tan et al. (2008)	Individual and institutional investors	Stock price, trading volume and earnings per share data for all firms listed in Shanghai Stock Exchange and Shenzhen Stock Exchange over the period between July 1994 and December 2003.	CSAD by Chang et al. (2000)	The findings show that there is herding in A and B share markets on the Shanghai and Shenzhen exchanges, and the herding is relevant for short horizons. Further evidence shows that herding is present when markets are rising, and when volume and volatility are high.

Table A.1 Selected empirical studies on herding in financial markets (cont'd)

Author (year)	Field of study	Data	Method	Findings
Li et al. (2017)	Individual and institutional investors	Complete transaction records of 180 component stocks traded in Shanghai Stock Exchange from July 2002 to December 2004.	Dispersion of trading volume	The findings suggest that less informed individual investors tend to trade towards the market movement and less selectively among different stocks. Both the individual and institutional herding measures are negatively related to absolute market return and positively related to average trade volume. Further, institutional herding is Granger-caused by both its own lagged trades and those of individual investors.
Christie and Huang (1995)	Market activity	Daily (NYSE and AMEX firms between July 1962 and December 1988) and monthly (NYSE firms between 1925 and 1988) returns of US stocks.	Dispersion of equity returns	The findings suggest that dispersions increase significantly during periods of large average price changes, which indicates that the observed herding level is low during stressful periods. Further, it is concluded that herding is not an important factor while determining equity returns during periods of market stress.

Table A.1 Selected empirical studies on herding in financial markets (cont'd)

Author (year)	Field of study	Data	Method	Findings
Chang et al. (2000)	Market activity	Daily stock price data for all NYSE and AMEX firms between January 1963 and December 1997, daily price series for stocks in Hong Kong (January 1981 - December 1995), Japan (January 1976 - December 1995), South Korea (January 1978 - December 1995) and Taiwan (January 1976 - December 1995) markets.	CSAD by Chang et al. (2000)	The findings suggest that during periods of extreme price movements, equity return dispersions for the US, Hong Kong and Japan tend to increase, which is evidence against the presence of herding behavior. However, for South Korea and Taiwan, significant evidence for herding is documented. Further, it is stated that macroeconomic information is more effective on investor behavior than firm-specific information in markets which exhibit herding.
Hwang and Salmon (2004)	Market activity	Daily price series for US and South Korean stock markets from January 1993 to November 2002.	A new approach based on the cross-sectional dispersion of the factor sensitivity of assets within a given market	There is evidence for significant and persistent herding independent from given market conditions. Macro-factors provide almost no help in explaining herding patterns. It is shown that herding is available both when market is rising and falling. Further, market stress helps efficient pricing in the market.

Table A.1 Selected empirical studies on herding in financial markets (cont'd)

Author (year)	Field of study	Data	Method	Findings
Gleason et al. (2004)	ETFs	Tick by tick transaction data from the NYSE's TAQ database for the period April 1999 to September 2002.	CSSD by Christie and Huang (1995) and CSAD by Chang et al. (2000)	The findings show that when the up and down markets are analyzed in aggregate, no herding is observed. During periods of market stress, it is shown that ETF traders trade away the market consensus. Further, weak evidence of asymmetric reaction to news during periods of stress in up markets and down markets is found.
Caporale et al. (2008)	Market activity	Daily, weekly and monthly returns for the stocks in Athens Stock Exchange from January 1998 to December 2007.	CSSD by Christie and Huang (1995) and CSAD by Chang et al. (2000)	The findings suggest weak evidence for herding when weekly and monthly returns are used, which is an indication that herding is a short-term phenomenon. Further, herding is found to be stronger during rising markets. It is shown that herding behavior exists both during and after stock market crisis of 1999, and investors act closer to rational profile after 2002.
Caparrelli et al. (2004)	Capital markets	The return data of 151 stocks from Italian Stock Market for the period from September 1988 to January 2001.	CSSD by Christie and Huang (1995)	The findings suggest that herding is present for the Italian market during extreme market conditions in terms of both sustained growth rate and high stock levels.

Table A.1 Selected empirical studies on herding in financial markets (cont'd)

Author (year)	Field of study	Data	Method	Findings
Henker et al. (2006)	Stock market	Intraday trading data for 160 largest stocks trading at Australian Stock Exchange from 2001 to 2002.	CSSD by Christie and Huang (1995) and CSAD by Chang et al. (2000)	There is no evidence of herding both for the entire market and for industry sectors. It is also suggested that as the information dissemination is well in the Australian equity market, herding is limited.
Dass et al. (2008)	Mutual funds	The stock holdings (i.e., traded in Nasdaq) of American mutual funds for the period from 1997 to 2003.	Grinblatt et al. (1995)	The findings suggests that the efficient contractual incentives make managers invest less in bubble stocks. In this manner, higher incentives prevent managers to engage in herding behavior.
Hong et al. (2000)	Analyst recommendations	Earnings estimates by 8421 analysts covering 4527 firms between 1983 and 1996.	Deviation from consensus estimates	It is documented that experienced and inexperienced analysts face different incentives and inexperienced analysts are punished harder for poor forecasting performance and forecast boldness. Therefore, inexperienced analysts herd more than their more experienced counterparts.

Table A.1 Selected empirical studies on herding in financial markets (cont'd)

Author (year)	Field of study	Data	Method	Findings
Welch (2000)	Analyst recommendations	50 thousand individual buy/sell recommendations issued during the 1989-1994 period.	Propensity to follow consensus recommendations	It is found that an analyst's recommendation revision has a positive impact on the next two analysts' revisions. This impact is stronger when short-run ex-post returns are predicted close enough and the newest revision occurs recently. The impact of the consensus is not strong when it is a predictor of subsequent returns. The impact of the consensus is strong when market is bullish.
Kim and Pantzalis (2003)	Analyst recommendations	Analyst forecasts for US companies with a coverage of 1980-1998 period.	Dispersion of analysts' forecasts	The findings suggest that geographically or industrially diversified companies tend to herd more than domestic or industrially focused companies. Further, the market penalizes security analysts' herding behavior by degrading market valuations, and this effect is stronger when diversified companies are the concern.
Jegadeesh and Kim (2010)	Analyst recommendations	Stock recommendations for US stocks between November 1993 and December 2005.	Deviation from consensus recommendation	It is found that the reaction to analysts' recommendation revision is stronger when the revised recommendation is not close to consensus. Moreover, the level of herding is higher in downgrades than that of upgrades. Another finding is that analysts from more reputable brokerage houses tend to herd more than those from less reputable ones.

Table A.1 Selected empirical studies on herding in financial markets (cont'd)

Author (year)	Field of study	Data	Method	Findings
Bernhardt et al. (2006)	Analyst recommendations	Individual analysts' quarterly forecasts of earnings from 1989 to 2001.	Deviation of the forecast from the best estimate	The findings suggest that analysts systematically issue biased anti-herding forecasts, which is biasing their forecasts away from the consensus.
Uchida and Nakagawa (2007)	Loan herding	A data set of loans derived from Japanese banks' balance sheets for the period from 1975 through 2000.	LSV (1992)	Herding in the lending decisions of Japanese banks is observed for the sample period. Herding is observed especially during stressful periods such as second oil crisis in the late 1970s, the bubble period in the late 1980s, and during stagnation period coming after.
Nakagawa et al. (2012)	Loan herding	The loan data of Japanese banks and other financial institutions during the 1975-1999 period.	Regressing a vector of economic factors on change of amount of loans outstanding	The evidence states that Japanese financial institutes engage in inefficient herding during the asset-price bubble in the late 1980s. Further, loans as a result of inefficient herding are negatively correlated with GDP and land prices in the following years, which is the indication of negative impact of herding on Japanese economy.
Liu (2014)	Loan herding	Quarterly bank loan information of US banks obtained from the Call Reports published by Federal Reserve, over the period from 1976 to 2010.	LSV (1992) and FHW (2014)	The results indicate herding in the entire period. Further, the regression results indicate that banks tend to herd more during economically stressful periods. Herding is found to be positively correlated with off-balance sheet activities, and large banks observed to herd more than small banks.

Table A.1 Selected empirical studies on herding in financial markets (cont'd)

Author (year)	Field of study	Data	Method	Findings
Lu et al. (2014)	Loan herding	Transaction information on business lending by Chinese state-owned commercial banks, joint-equity banks and city banks for the period 2006-2011.	Sias (2004)	Herding is found to be more common among banks with a higher portion of risky assets, a higher portion of non-performing loans, a lower capitalization and a lower ROE. Habit lending is observed as a result of government's support on some industries. Both reputational and characteristic herding are observed for city banks as a result of focusing on same type industries to avoid credit risk in their local and small loan base. Further, it is observed that herding in lending has negative impact on macroeconomic and financial parameters.

Table A.1 Selected empirical studies on herding in financial markets (cont'd)

Author (year)	Field of study	Data	Method	Findings
Fang et al. (2019)	Loan herding	Information related to consumer and business loans from all types of Chinese banks for the 2006-2012 period.	Sias (2004)	The findings indicate that joint-stock commercial banks tend to engage in herding in large-capitalization industries, but city commercial banks engage in herding in small-capitalization industries. Evidence of investigative herding and informational cascades are found for joint-stock and city commercial banks, respectively. Further, it is found that herding in loans has harmful effects on the capital adequacy, asset quality, managerial capability, total earnings and liquidity of city commercial banks. However, herding has no negative impact on the performance of joint-stock commercial banks.
Jain and Gupta (1987)	Loan herding	The net loan figures of banks classified according to their sizes for the years 1977 to 1982.	Granger (1969) causality	The findings suggest that regional banks follow the international lending decisions of top nine and next fifteen banks. However, the level of herding is quite low.

B. DATA ADJUSTMENT STEPS FOR THE MERGED FUNDS

Without adjustments following the merger time, the acquirer funds can mistakenly appear to be a "buyer" or a "seller" fund for specific industries. We make the following adjustments for the month of the merger and the month after to avoid these classification errors:

a. If the acquirer fund's holdings of "stock-A" in the month after the merger exceed the sum of its holdings in the merger month plus the holdings of the merger fund in the merger month, it indicates that the fund is voluntarily growing its stock-A holdings. The final number of shares held by the acquirer fund for stock-A is therefore determined by summing the number of shares of stock-A held by the acquirer fund during the merger month plus the number of additional shares of stock-A remaining after the merger fund's contribution is subtracted.
b. If the number of stocks of "stock-A" held by the acquirer fund in the month following the merger is less than the total of its holdings in the merger month plus the holdings of the merger fund in the merger month, that means the fund is selling a portion of stock-A coming from the merger fund. When we look at the acquiring funds' trading patterns over the past months, we see that they primarily trade to keep a target monetary amount defined for stocks. Therefore, we maintain the market value of stock-A held by the merger fund in the merger month at the same level and adjust the number of stock-A stocks in the following month in accordance with the change in the price of stock-A between the merger and the following month.

c. If the number of stocks of “stock-A” held by the acquirer fund in the following month is just increased by the number of stocks held by the merger fund in the month of merger, it means the acquirer fund is not actively trading stock-A. As a result, we maintain the level of stock-A stocks from the merger month.

C. TURKISH SUMMARY / TÜRKÇE ÖZET

Finansal kuruluşların risk alma, varlık edinimi ve yatırım kararlarında benzer stratejiler benimseme eğilimi, finans piyasalarında ve finansal kurumlarda sürü davranışı olarak bilinir. Pek çok çalışma sürü davranışının altında yatan teorik temelleri incelemiştir. Bunların arasından öne çıkan Haiss (2010)'e ait çalışmada, sürü davranışı rasyonel ve davranışsal nedenler olmak üzere iki grup nedene bağlanır. Rasyonel görüşe göre yatırım kararları, doğru bilgi eksikliği, kurum yetkililerinin kazanç ve itibar yapısı ve bazı dış faktörler nedeniyle sekteye uğrar. Davranışsal bakış açısı ise, karar vericilerin bilgi edinme ve işleme maliyetlerini azaltmak için "sezgisel yöntemler" kullanma eğiliminin yanı sıra yatırımcı psikolojisi gibi rasyonelliklerini sınırlayan iç ve/veya dış değişkenlere odaklanır. Bu iki grup görüş çerçevesi içinde, bu tez çalışmasında banka kredileri ve yatırım fonları gibi iki farklı finansal ekosistemde sürü davranışı ve etkileri incelenmiştir.

Literatürdeki ampirik çalışmalarda öne çıkan yöntemler incelendiğinde LSV (1992) çalışmasında öne sürülen yöntemin ardından gelen literatüre de öncülük ettiği söylenebilir. LSV (1992)'de söz konusu sürü davranışı ölçümü, bir grup para yöneticisinin aynı dönemde belirli hisseleri satın alma (satma) eğilimlerinin ortalaması olarak tanımlanır. LSV (1992), sürü davranışını test etmek için 341 yatırım yöneticisi tarafından yönetilen 769 vergiden muaf ABD hisse senedi fonunun yatırım davranışını kullanır. Örneklemdeki fonların çoğunluğunu emeklilik fonları oluşturmaktadır. Veri seti, 1985 ve 1989 arasındaki dönem için bu fonların çeyrek sonu varlıklarından oluşmaktadır. LSV'nin (1992) analiz aşaması üç adıma ayrılabilir. İlk adımda sürü davranışını değerlendirmek amacıyla yatırım yöneticilerinin hisse senetleri için alım ve satım eylemleri arasındaki korelasyon derecesi incelenmektedir. İkinci aşamada yatırım yöneticilerinin hisse senedi talepleri ile önceki yatırım performansları arasındaki ilişkiye bakarak pozitif geri bildirimli ticaretin seviyesi test edilmektedir. Çalışmanın sonuçlarına göre yatırım yöneticilerinin büyük hisse senedi işlemlerinde göreceli olarak daha az sürü davranışı gösterdikleri ortaya konulmuştur. Küçük hisse senedi işlemleri sürü davranışının seviyesinin biraz daha yüksek olmasına karşılık, bu seviye yine de dramatik olarak kabul edilebilecek bir seviye değildir. Küçük hisse senetlerinde pozitif geri bildirim stratejilerinin varlığını destekleyen kanıtlar görülse de büyük hisse senetleri için benzer kanıtlara rastlanmaz. Son olarak, bir hisse senedi için kurumsal talep fazlası ile fiyat değişikliği arasındaki ilişkinin oldukça zayıf olduğu gösterilmiştir.

Literatürde önce çıkan bir diğer yöntem de Sias (2004) çalışmasında sunulmaktadır. Bu çalışmada kurumsal yatırımcıların alım satım işlemlerinin zaman içindeki korelasyonu araştırılmaktadır. Sias'a (2004) göre kurumsal yatırımcılar, ardışık periyotlarda kendi işlemlerini ya da diğer kurumsal yatırımcıların işlemlerini takip edebilirler. Sias'a (2004) göre gerçek sürü davranışı diğer kurumsal yatırımcıların işlemlerinin takip edilmesidir, çünkü kendi işlemlerini takip eden yatırımcılar bir ticaret stratejisini sürdürüyor olabilirler. Çalışmada kullanılan NYSE, AMEX ve NASDAQ hisselerine ait getiri, hisse senedi sayısı ve şirket büyüklüğü verileri CRSP'den alınmıştır. Her bir hisse senedine ait kurumsal yatırımcı sahipliğine ilişkin bilgiler ise CDA-Spectrum ve 13F raporlamalarından edinilmiştir. Kurumsal hisse senedi sahipliği için Mart 1983-Aralık 1997 dönemi baz alınmıştır. Sias (2004) bu zaman aralığı boyunca modellediği kesitsel regresyonlardan yola çıkarak korelasyon katsayılarını hesaplar. Ayrıca bu metotta Sias (2004), yatırımcının kendi işlemlerini takip etmesinin korelasyona katkısı ile diğer yatırımcıların aynı hisse senediyle olan işlemlerinin takip edilmesinin katkısını ayrıştırmaya fırsat tanır. Analiz sonuçlarına göre, ardışık dönemlerde kurumsal yatırımcılar aynı hisse senetleri için hem kendi hem de diğer kurumsal yatırımcıların işlemlerini takip etmektedir. Ayrıca analizler, kurumların kendi işlemlerini takip etme eğilimlerinin net akışları (alışkanlık yatırımı) veya mevcut portföylerindeki net yatırım akışları ile ilişkili olmadığını ortaya koymaktadır. Momentum ticareti için ortaya konan kanıtlar ise bu faktörün sürü davranışının önemli bir bölümünü açıklamadığını göstermektedir. Ayrıca bulgular, kurumsal düzeydeki sürü davranışının hisse senedi fiyatlarını temel değerlerinden uzaklaştıran bir faktör olmadığı göstermiştir.

Çalışmanın ilk ampirik kısmında, banka kredilerinin verilmesi sürecindeki sürü davranışı incelenmiştir. Banka kredilerinde sürü davranışı, bankaların diğer bankalara ait kredi verme kararlarını takip etme eğilimi olarak tanımlanır. Bankaları kredi verme kararlarında diğer bankları takip etmeye yönlendiren motivasyon kaynakları bilgi temelli, itibar temelli ve banka karakteristiği temelli kaynaklar olarak üç başlıkta gruplandırılabilir. Bilgi temelli hipotez, kredi talep edenlerin içsel değerindeki belirsizliğin, kredi verme kararını etkilediği ve dolayısıyla sürü davranışına neden olduğunu öne sürmektedir. Kredi talep edenin mali durumu ile ilgili belirsizlik seviyesinin yüksek olduğu durumlarda, bankalar kredi talep eden ile ilgili kendi bilgilerini bir kenara bırakarak sürü ile birlikte karar verirler (informational cascades). Bunun aksine, kredi talep edenler ile ilgili içsel değerlemeler halka açık ve şeffaf ise, bankalar benzer rasyonel kararlar alarak aynı tipteki kredilere ya da aynı endüstri kollarına kredi vermeye odaklanabilirler (investigative herding). İtibar temelli hipoteze göre, bir banka, bezer özellikler gösteren diğer bankalar bir endüstri ya da kredi tipindeki kredi varlıklarını arttırıyor (azaltıyor) diye, sürü ile hareket etmemenin yaratacağı itibari etkileri hesaplayarak kendi kredi varlıklarını da arttırabilir (azaltabilir). Banka karakteristiği temelli hipotez, belirli banka türlerinin belirli özelliklere sahip endüstrilere borç vermeyi tercih edebileceğine vurgu yapar. Bu hipoteze göre, aynı türden bankalar, benzer algılama ve değerlendirme standartlarını paylaştıkları için aynı sektöre kredi verecek şekilde kümelenebilirler.

Banka kredilerindeki sürü davranışının sebep ve etkilerini inceleyen yaklaşımları üç ana başlıkta toplayabiliriz. İlk yaklaşım, bankaları sürü davranışına yönlendiren ekonomik, düzenleyici ve bankalara özgü faktörleri incelemektedir (Liu, 2014; Tran et al., 2017). İkinci yaklaşım, kredilerdeki sürü davranışının makroekonomik ve reel sektör değişkenleri üzerindeki etkilerini araştırmaktadır (Nakagawa, 2008; Nakagawa and Uchida, 2011; Uchida and Nakagawa, 2007). Üçüncü yaklaşım, kredilerdeki sürü davranışının banka verimliliği ve performansı üzerindeki etkilerini incelemektedir (Fang et al., 2019; Lu et al., 2013).

Ampirik çalışma için Türkiye'deki 30 adet ticari bankanın nakdi kredi verileri (ihtisas dışı krediler) kullanılmıştır. Nakdi kredi verilmesi sürecince sürü davranışı olup olmadığı incelenmiş ve sürü davranışının banka performansı ile kredi kalitesi üzerindeki etkisi analiz edilmiştir. LSV (1992) ile Sias (2004) sürü davranışı ölçümleme metotları kullanılarak 2002Ç4 ve 2017Ç4 arasındaki dönem incelenmiştir. BDDK (Bankacılık Düzenleme ve Denetleme Kurumu)'nın Haziran 2012'deki yönetmeliği, kredi sınıflandırmalarında değişikliğe neden olduğu için bu dönem 2002Ç4-2012Ç2 ve 2012Ç3-2017Ç4 olarak ikiye bölünmüştür. Kredi verileri, Türkiye Bankalar Birliği veri sisteminde yer alan finansal tablolardan edinilmiş ve bankaların çeyreklik finansal raporları ile de hatalara karşı kontrol edilmiştir. Bankalara ait finansal oranlar da yine Türkiye Bankalar Birliği'nin veri sisteminden edinilmiştir. Makroekonomik değişkenlere ilişkin veriler ise Refinitiv Eikon ve Türkiye İstatistik Kurumu (TÜİK) veri sistemlerinden alınmıştır.

Sürü davranışını tespit etmekte kullanılan yöntemlerden ilki yukarıda da bahsedilen LSV yöntemidir. Bu yöntemin temel varsayımı, bankalar arasında sürü davranışı olmadığında, kredi verme kararının tüm kredi tipleri arasında rastgele dağılmasıdır. Bu varsayım temel alınarak belirli bir j kredi kategorisinde t zamanında LSV ölçümü aşağıdaki gibi olur:

$$LSV_{j,t} = |p_{j,t} - p_t| - E|p_{j,t} - p_t|$$
$$= \left|\frac{X_{j,t}}{N_{j,t}} - \frac{\sum_{j=1}^{n} X_{j,t}}{\sum_{j=1}^{n} N_{j,t}}\right| - E\left[\left|\frac{\widetilde{X_{j,t}}}{N_{j,t}} - p_t\right| ; \tilde{X}_{j,t} \sim B(p_t, N_{j,t})\right] \quad (1)$$

Bu eşitlikteki $p_{j,t}$ t çeyreğinde, j kredi kategorisindeki mevcut kredi miktarını arttıran bankaların oranıdır. Dolayısıyla $X_{j,t}$, t çeyreğinde, j kredi kategorisindeki mevcut kredi miktarını arttıran banka sayısını ve $N_{j,t}$ de aynı çeyrekteki aktif banka sayısını ifade etmektedir. p_t, t çeyreğinde tüm kredi tipleri baz alındığında kredi varlıklarını arttıran banka sayısının kesitsel ortalamasıdır. n, toplam kredi kategorisi sayısıdır. Sonuç olarak p_t, t çeyreği boyunca genel kredi verme eğilimi için bir referans olarak kabul edilebilir. (1) no'lu eşitliğin ilk kısmı, her banka t çeyreğinde, j kredi kategorisindeki mevcut kredi varlığını arttırırsa (ya da azaltırsa) 0'a yaklaşır. Dolayısıyla, $p_{j,t}$ terimi, eğer bankalar sürü davranışı gösterip birlikte hareket ederlerse p_t teriminden farklılaşacaktır. (1) no'lu eşitliğin ikinci kısmı ise bankaların kredi verme kararlarının dağılımını dikkate almak için eklenmiş bir ayar faktörüdür.

LSV metodu, aynı yöndeki eylemlerin sayısı (belirli bir kredi kategorisinde varlıklarını arttıran veya azaltan bankaların sayısı) ile söz konusu dönem için aynı yönde beklenen eylem sayısı arasındaki farka odaklanmaktadır. Sias yönteminde ise ardışık dönemler arasındaki kesitsel korelasyon kullanılarak sürü davranışı hesaplanır. Ayrıca bu yöntemde, sürü davranışında bir bankanın kendi faaliyetlerinin etkisi diğer bankaların faaliyetlerinin etkisinden ayrıştırılabilir. Sias yöntemi aşağıdaki şekilde ifade edilebilir:

$$\rho(p_{k,t}, p_{k,t-1}) = \left[\frac{1}{(K-1)\sigma(p_{k,t})\sigma(p_{k,t-1})}\right] \sum_{k=1}^{K} (p_{k,t} - p_t)(p_{k,t-1} - p_{t-1}) \tag{2}$$

Burada $\rho(p_{k,t}, p_{k,t-1})$, ardışık çeyreklerde k kredi kategorisindeki kredi varlıklarını arttıran bankalar ile tüm bankalar arasındaki kesitsel korelasyonu göstermektedir. $p_{k,t}$, t çeyreğinde k kredi kategorisindeki varlıklarını arttıran bankaların o kategoride aktif tüm bankalara oranını ifade etmektedir. K, toplam kredi kategorisini göstermektedir. Eğer bir banka k kredi kategorisindeki varlıklarını, kendisine ait ya da diğer bankaların önceki çeyrekteki kredi verme kararlarını takip ederek arttırırsa (azaltırsa) $\rho(p_{k,t}, p_{k,t-1})$ terimi pozitif bir değer alır. Sias metodu, bankaların kendilerine ait ve diğer bankalara ait eylemlerin $\rho(p_{k,t}, p_{k,t-1})$ kesitsel korelasyonuna etkilerini ayrıştıracak şekilde ikiye bölünebilir:

$$\rho(p_{k,t}, p_{k,t-1}) = \left[\frac{1}{(K)\sigma(p_{k,t})\sigma(p_{k,t-1})}\right] \times \sum_{k=1}^{K} \left[\sum_{n=1}^{N_{k,t}} \frac{(D_{n,k,t} - p_t)(D_{n,k,t-1} - p_{t-1})}{N_{k,t}N_{k,t-1}}\right]$$

$$+ \left[\frac{1}{(K)\sigma(p_{k,t})\sigma(p_{k,t-1})}\right] \times \sum_{k=1}^{K} \left[\sum_{n=1}^{N_{k,t}} \sum_{m=1,m\neq n}^{N_{k,t-1}} \frac{(D_{n,k,t} - p_t)(D_{m,k,t-1} - p_{t-1})}{N_{k,t}N_{k,t-1}}\right] \tag{3}$$

Burada eşitliğin ilk kısmı, bankaların kendi kredi kararlarını takip etmelerinin, ikinci kısmı ise diğer bankaların kredi kararlarını takip etmelerinin kesitsel korelasyondaki etkisini göstermektedir. $D_{n,k,t}$ terimi, eğer n bankası t çeyreğinde k kredi kategorisindeki varlıklarını arttırıyorsa (azaltıyorsa) 1 (0) değerini alan bir kukla değişkendir.

LSV metodu daha önce ifade edilen kredi verilerine uygulandığında 2002Ç4-2012Ç2 ve 2012Ç3-2017Ç4 periyotlarının ikisinde de istatistiksel açıdan anlamlı derecede sürü davranışı tespit edilmiştir. Aynı veriler Sias metodu ile değerlendirildiğinde 2002Ç4-2012Ç2 periyodunda istatistiksel açıdan anlamlı derecede sürü davranışı bulunurken, 2012Ç3-2017Ç4 periyodunda anlamlı bir sürü davranışına rastlanmamıştır. Burada Sias ölçümü değerlendirilirken, toplam kesitsek korelasyonun, bir bankanın diğer bankaların kredi verme davranışlarını takip edip etmediğini gösteren kısmının analiz edildiği vurgulanmalıdır. Çünkü, Sias'a (2004) göre sürü davranışı bir finansal kuruluşun kendi geçmiş aksiyonlarını değil, aynı alanda faaliyet gösteren diğer finansal kuruluşların aksiyonlarının takip etmesi ile ortaya çıkmaktadır.

Sürü davranışının varlığına ilişkin analizlerden sonra, sürü davranışının banka kârlılığı ve kredi kalitesi üzerindeki etkileri incelenmiştir. Bu etkileri analiz edebilmek için panel veri metotlarına başvurulmuştur. Bağımlı değişkenlerdeki (banka kârlılığı ve takipteki krediler) zamana bağlı kalıcılığın hesaba katılabilmesi için dinamik bir model tercih edilmiştir. Modellerin oluşturulmasında Arellano ve Bover (1995) ile Blundell ve Bond (1998) tarafından geliştirilen sistem GMM metodu, dayanıklı standart hata terimi ile kullanılmıştır. Modellerin oluşturulmasında tek-adımlı tahmin edici kullanılmıştır. İki–adımlı tahmin edici esasında asimptotik olarak tek-adımlı tahmin ediciye göre daha etkili kabul edilmektedir ve hataların homoskedastisitesi varsayımı iki-adımlı tahmin edici ile tolere edilmektedir. Ancak, iki-adımlı tahmin edici kullanmanın etkisi istatistiksel açıdan önem arz edecek bir seviyede değildir (Arellano ve Bond, 1991; Blundell vd., 2000; Blundell ve Bond, 1998). Seçilen enstrüman değişkenlerin geçerliliğini kontrol etmek için ise Hansen testi kullanılmıştır. Oluşturulan modellerde, gecikmeli bağımlı değişken, makroekonomik değişkenler, banka özelindeki değişkenler ve sürü davranışını gösteren değişken, bağımsız değişkenler olarak seçilmiştir. Bağımsız değişkenlerin gecikme periyodu sayısı belirlenirken, kesitsel birim ve enstrüman değişken sayıları arasındaki ilişki ve ilgili literatürde (Louzis vd., 2012) izlenen yollar dikkate alınmıştır. Bu çerçevede, banka özelindeki değişkenler ve sürü davranışında kullanılan değişkenler için önceki yılın dinamik etkilerini de dikkate alabilmek için Berger ve Deyoung (1997) ile Louzis vd. (2012)'nin da önerdiği şekilde dört adet gecikme periyodu kullanılmıştır. Enstrüman değişken sayısının kesitsel grup sayısını geçmemesini garantilemek için Holtz-Eakin et al. (1988) tarafından öne sürülen "collapsing" metodu uygulanmıştır. Ayrıca kullanılan panel verisinde boşluklar bulunması nedeniyle (unbalanced panel) Roodman (2009) tarafından önerilen ortogonal sapmalar da kullanılmıştır.

Modellerde kullanılan makro ve mikro seviye değişkenlere ek olarak, bu değişkenlerin kümülatif uzun dönem etkisini de analiz edebilmek için değişkenlerin uzun dönem katsayıları da oluşturulmuştur. Louzis vd.'ye (2012) göre, uzun dönem katsayı varyansı tahmin edilirken gecikmeli değişkenlerin katsayı tahminleri arasındaki kovaryans da dikkate alınır. Bu sayede gecikmeli regresörlerin kümülatif etkisi için daha kesin ve sağlam bir istatistiksel yorum oluşturulabilir. Uzun dönemli standart hatalar kullanıldığında, çoklu doğrusal bağlantı temelli bireysel gecikmeli değişkenlerin istatistiksel açıdan önemsiz oluşu gibi problemler de hesaba katılmış olur. Tüm bu açıklamalar doğrultusunda hipotez testleri, uzun dönemli değişkenlerin katsayıları temel alınarak gerçekleştirilmiştir.

Regresörlerin bağımlı değişken üzerindeki etkisi, kriz dönemleri gibi faktörlerden etkilenebilir (Fang vd., 2021). Bu nedenle sürü davranışının banka kârlılığı/takipteki krediler üzerindeki etkisinin, analize konu olan dönemin bir kriz dönemine rastlamasıyla değişip değişmediği etkileşim terimleri kullanılarak incelenmiştir.

Banka performansı ile sürü davranışı arasındaki ilişkiyi temel alan analizlerin sonuçlarına göre incelenen ilk dönemde (2002Ç4-2012Ç2) LSV metodu ile hesaplanan sürü davranışı değişkeninin katsayısı negatif olarak bulunmuştur. Bu sonuç, sürü davranışının banka performansını ilk dönemde negatif etkilediğini göstermektedir. Ancak, analiz Sias metodu ile hesaplanan sürü davranışı değişkeni kullanılarak tekrarlandığında istatistiksel olarak anlamlı bir katsayı bulunamamıştır. Bu sonuç da ardışık çeyrek dönemler söz konusu olduğunda, diğer bankaların kredi verme kararlarını takip etmenin incelenen ilk dönemde banka kârlılığı üzerinde bir etkisi olmadığını göstermiştir. Ancak ikinci dönemde (2012Ç3-2017Ç4), hem LSV hem de Sias ölçümleri için istatistiksel açıdan anlamlı katsayılar elde edilememiştir. Her iki dönemde de daha önceki araştırma bulgularıyla da tutarlı olarak, bank performansı ve enflasyon arasında pozitif bir ilişki olduğuna dair kanıtlar elde edilmiştir. Ayrıca, sadece ikinci dönemde, sermaye ve banka performansı arasında pozitif bir ilişkinin var olduğu gösterilmiştir. Kredi riski ve banka performansını değerlendiren analiz sonuçları, ikinci dönemde daha önceki araştırma sonuçlarıyla çelişen bir durum olduğunu ortaya koymuştur (beklenen ilişkinin yönü negatif iken, ikinci dönemde uzun dönem katsayısı pozitif işaret almıştır). Ayrıca, Athanasoglou vd.'nin (2008), bir bankanın büyüklüğünün bankanın performansı üzerinde hiçbir etkisi olmadığına ilişkin bulgusu da doğrulanmıştır. Uzun dönem marjinal etki analizleri, krizler gibi çalkantılı dönemlerde sürü davranışının banka kârlılığı üzerinde daha fazla zararlı etkiye sahip olacağına dair hipotezin doğrulanabilmesi için yeterli kanıt olmadığını göstermiştir.

Kredi kalitesi ile sürü davranışı arasındaki ilişkiyi temel alan analizlerin sonuçlarına göre, incelen her iki dönemde de anlamlı bir ilişkiye dair kanıt sunulamamıştır. Makro değişkenler ile kredi kalitesi arasındaki ilişki incelendiğinde, ilk dönemde gayri safi yurt içi hasıla (GSYİH) büyüme katsayısı ile beklendiği gibi istatistiksel açıdan anlamlı bir negatif ilişki gözlemlenmiştir. Ancak bu ilişki ikinci dönemde devam etmemektedir. Değerlendirilen tüm hipotezler arasında sadece ilk dönemde “ahlaki tehlike” (moral hazard) hipotezine ilişkin kanıtlar bulunabilmiştir. Uzun dönem marjinal etki analizleri, kriz döneminde sürü davranışının kredi kalitesi üzerinde daha güçlü bir etkisi olduğuna dair bir kanıt ortaya koyamamıştır.

Literatürdeki çalışmalar, bankacılık sistemine yönelik düzenlemelerin, bankaların stratejik aksiyonlarını belirlerken dikkate aldıkları ana faktörlerden olduklarını ve sürü davranışına neden olabileceğini göstermektedir (Haiss, 2005; Tran vd., 2017; Stellinga, 2020). Kural koyucular regülasyon uygulamalarında doğrudan bankacılık sistemini belirli kazanç kanallarına koşullandırmak istemeseler bile, konulan kurallar ekosistem içindeki mevcut kazançlı aktivite sayısının azalmasına ve dolayısıyla bankaların kalan kârlı aktivitelerin etrafında toplanmasına neden olabilirler. Bu da sürü davranışının rasyonel nedenleri olabileceği manasına gelir.

2001 malî krizinden sonra, Türkiye’de hem malî hem de ihtiyati nitelikleri olan pek çok yapısal reform uygulamaya alınmıştır. Bu reformlar makroekonomik göstergeleri iyileştirirken, aynı zamanda artan küresel likiditeye bağlı olarak ülkeye fon girişini de teşvik etmiştir. Fon girişinin artmasının bir sonucu olarak da Türkiye 2000’lerde hızlı bir kredi büyümesini deneyimlemiştir. Kredi büyümesinin hızlı olduğu bu dönemde, bankacılık sektöründe pek çok düzenleme ve denetim faaliyeti hayata geçirilmiştir. Bu dönemde Bankacılık Düzenleme ve Denetleme Kurumu (BDDK) bireysel bankaları odaklanmış ve mikro ihtiyati bir yaklaşım benimsemiştir. Yine aynı dönemde merkez bankası (TCMB) makro perspektifli bir finansal istikrar raporu yayımlamış, ancak para politikası hâlâ geleneksel enflasyon hedeflemesi rejimine dayandığı için makro-finansal kırılganlıklar yeterince adreslenememiştir.

2008 küresel finansal krizinin ardından gelişmiş ekonomilerin nicel genişleme programları, gelişmekte olan piyasaları, dış finansal koşullarını gevşetmeye teşvik etmiştir. Bu dönemdeki büyük sermaye girişleri, gelişmekte olan ekonomilerdeki iç ve dış dengesizlikleri şiddetlendirerek daha düşük faiz oranlarına ve para birimlerinin değer kazanmasına neden olmuştur (Küçükbıçakçı vd., 2020). Bu sırada, 2010 yılı sonunda, Türkiye'deki özel kredilerin GSYİH'ya oranı %40'a yükselmiş ve buna Türk Lirası'nın hızlı şekilde değer kazanması eşlik etmiştir. Tüm bu faktörler, ekonominin aşırı ısınmasına katkıda bulunarak makro ihtiyati politika araçlarının gerekliliğini ortaya koymuştur (Kara, 2016). 2010 yıl sonu itibarıyla makro-finansal risklerin kontrolünden TCMB sorumlu olmuştur. TCMB bu dönemde finansal istikrara odaklanarak geleneksel enflasyon hedeflemesi rejimini değiştirmiştir. Sonuç olarak, yeni stratejinin temel amacı, sermaye girişindeki oynaklığın olumsuz sonuçlarıyla mücadele etmek olarak belirlenmiştir.

Bu çalışmada 2000'lerin başından itibaren hızlanan sermaye girişleri, global düzeyde artan likidite ve uygulanan düzenleyici politikalar ile sürü davranışı arasındaki ilişki de incelenmiştir. Öncelikle, küresel likidite artışı kredi büyümesi ile sonuçlandığından, bu zaman diliminde gözlemlenen sürü davranışı tamamen rasyonel olabilir veya en azından rasyonel bir kısma sahip olabilir. Yine bu dönemde TCMB'nin liderliğini takiben zorunlu karşılıklar, esnek faiz koridoru ve rezerv opsiyon mekanizması gibi bir dizi politika aracı devreye girmiştir. Bu araçlar, küresel likidite döngülerinin neden olduğu makroekonomik oynaklık ile para birimi uyuşmazlığı olan bir ekonomide sermaye akımları, döviz kurları ve kredi genişlemesi arasındaki etkileşime karşı mücadele edebilmek için tasarlanmıştır (Kara, 2016). Bu politika araçlarının kredi genişlemesine yönelik uygulanmasının en belirgin sonucu, 2011'in ilk yarısından sonra kredi büyüme ivmesinin azalması olmuştur. Bu sonuç, makro ihtiyati düzenlemelerin kredi büyüme döngülerini etkilediğini gösterdiğinden, politika uygulamalarının bankaların kredi verme kararı üzerinde etkili olduğu varsayılabilir. Bu potansiyel etkileşim noktaları düşünülerek "Küresel likiditedeki artış ve buna bağlı makro ihtiyati uygulamalar nedeniyle kredi verme kararında rasyonel bir sürü davranışı gözlemlenmektedir" hipotezi test edilmiştir.

Hipotez testi sırasında küresel likiditeyi ölçmek için Bank for International Settlements (BIS)'ın yayımladığı ABD doları cinsinden ifade edilen tüm sektörler (yani banka ve dışı sektörler) üzerindeki uluslararası alacaklardaki çeyreklik değişim kullanılmıştır. Makro ihtiyati politika uygulamaları için ise Alam vd. (2019) tarafından IMF veri tabanındaki mevcut veriyi ve IMF'in Makro İhtiyati Politika Anketi sonuçlarını birleştirerek oluşturulan iMaPP veri tabanındaki makro ihtiyati politika endeksi kullanılmıştır. Kurulan model ile, sürü davranışı ölçümünden küresel likidite artışı ve makro ihtiyati politika uygulamalarının etkileri izole edilip kalan kısmın istatistiksel olarak manalı olmayı sürdürüp sürmediği incelenmiştir. Analiz sonuçlarına göre, küresel likidite artışının ve makro ihtiyati politika uygulamalarının etkileri sürü davranışı ölçümünden ayrıştırıldığında geriye kalan kısmın istatistiksel olarak anlamlı olmadığı görülmüştür. Bu sonuç da incelenen dönemde kredi verme kararlarındaki sürü davranışının rasyonel nedenlerle gerçekleştiğini ortaya koymaktadır.

Çalışmanın ikinci ampirik kısmında, yatırım fonlarının endüstri özelindeki sürü davranışları incelenmiştir. Endüstri özelinde sürü davranışı araştırmaları, yatırımcıların özellikle hisse senedi yatırımlarında, belirli bir grup endüstride faaliyet gösteren şirketlerin hisse senetlerini irrasyonel nedenlerle tercih edip etmediklerini inceler. Bu alandaki öncü makalelerinde Choi ve Sias (2009) motivasyon kaynaklarından birini, bireysel hisse yatırımında sürü davranışına neden olan faktörlerin aynı zamanda endüstri seviyesinde de sürü davranışına neden olup olmadığını analiz etmek olarak tarif ederler. Choi ve Sias (2009)'ın diğer motivasyonu ise hisse senetlerinde endüstriyel düzeyde bir bilgi asimetrisi olabileceğine dair görüştür. Bu görüş, yeni bilginin endüstri içindeki tüm hisse fiyatlarına eş zamanlı olarak yansımayacağına, dolayısıyla bir yatırımcının endüstri içindeki bir hisse fiyatındaki değişime bakarak diğer bir hissenin fiyatı hakkında çıkarımda bulunmasına neden olabileceğine işaret eder. Bilginin fiyatlara asenkron olarak dahil olması argümanı Moskowitz ve Grinblatt (1999) tarafından da incelenmiştir. Çalışmalarında önceki altı ayda iyi (kötü) performans gösteren sektörlerin sonraki on iki ayda da iyi (kötü) performans göstermeye devam ettiğini ortaya koymuşlardır. Bu duruma açıklama olarak, piyasadaki bilginin aynı endüstrideki her hisse senedinin fiyatına eş zamanlı yansımamış olabileceğini sunmuşlardır. Moskowitz ve Grinblatt'a (1999) göre bilgi önce büyük fimaların hisse fiyatlarına yansır ve ardından diğer firmaların hisse fiyatları bu bilgi ile yeniden değerlenir. Bu yüzden bu öncü ve artçı etki, endüstri getirilerinde gözlemlenen momentum etkisinin ve endüstri düzeyinde sürü davranışının nedeni olabilir.

Choi ve Sias (2009) ile benzer motivasyonları paylaşan bu çalışma, yatırım fonlarının sektörel bazda sürü davranışı izleyip izlemediğini ve sürü davranışının sektörlerin değerlemeleri üzerinde istatistiksel olarak önemli bir etkiye sahip olup olmadığını analiz etmektedir. Bu çalışmada, finansal kurumların endüstri seviyesine sürü davranışına odaklanması konusunda Choi ve Sias'ın (2009) çalışmalarındaki yöntem ve akış takip edilmektedir. Ancak, çalışma ağırlıklı olarak hisse senetlerine yatırım yapan yatırım fonlarını konu edinip Choi ve Sias'ta (2009) olduğu gibi hisse senedi yatırımı yapan tüm finansal kurumları analiz etmediği için, Celiker vd. (2015) çalışmasına daha yakındır. Öte yandan bu çalışmada, literatürdeki pek çok çalışmanın tercih ettiği ABD fon piyasası yerine (LSV, 1992; Sias, 2004; Ukpong vd., 2021) Türkiye fon piyasası gibi daha konsantre bir piyasa tercih edilmiştir. Holmes vd.'ne (2013) göre konsantre piyasalardaki fon yöneticilerinin büyük piyasalardakilerine göre birbirlerinin davranış ve stratejilerine aşina olmaları daha olasıdır. Bu da konsantre piyasalardaki ortamın bilinçli bir sürü davranışına daha açık olmasına neden olur. Türkiye'deki fon piyasası da konsantre bir piyasa sayılabileceğinden, çalışmanın bu kısmının amaçlarından biri de ABD piyasaları gibi köklü ve gelişmiş piyasalarda sürü davranışına neden olan faktörlerin Türkiye gibi bir piyasada da benzer etkiyi yaratıp yaratmadığının incelenmesidir.

Çalışmada kullanılan örneklem Takasbank'tan alınan tüm hisse senedi ağırlıklı yatırım fonlarının Aralık 2015 ve Aralık 2019 tarihleri arasındaki portföy varlıklarından oluşmaktadır. Sermaye Piyasası Kurulu (SPK)'nun "Yatırım Fonlarına İlişkin Esaslar Tebliği"ne göre, hisse senedi ağırlıklı yatırım fonları, fon portföy değerlerinin en az %80'i ile Borsa İstanbul (BİST)'da işlem gören hisse senetlerine yatırım yapmak zorundadır. Bu nedenle seçilen örneklem kurumsal yatırımcıların sektörel sürü davranışını inceleyebilmek için uygun bir kaynaktır. Yatırım fonlarının portföylerinde bulunun hisse senetlerinin sektörlere göre gruplandırılabilmesi için Kamuyu Aydınlatma Platformu'nun (KAP) sektör sınıflandırmaları kullanılmıştır. Bu gruplandırma sonucunda hisse senetleri 20 sektör başlığı altında toplanmıştır.

Sürü davranışını değerlendirmek için LSV ve Sias metotları kullanılmıştır. Endüstri seviyesinde sürü davranışını tespit için uygulandığında LSV yöntemi, belirli bir dönem ve endüstrideki alım/satım işlemlerinin söz konusu dönemde tüm endüstrilerdeki alım/satım işlemleri ile karşılaştırmasını yapar. Öte yandan Sias yöntemi, yatırımcıların ardışık dönemlerde birbirlerinin ticaret işlemlerini ne kadar yakından takip ettiğini inceler. Çalışmada öncelikle "yatırım fonları endüstri seviyesinde sürü davranışı göstermez" sıfır hipotezine karşılık, "yatırım fonları endüstri seviyesinde sürü davranışı gösterir" alternatif hipotezi test edilmiştir. Analiz sonucuna göre sadece LSV ölçümünün istatistiksel açıdan anlamlı olduğu görülmüştür. Bu sonuç, LSV metodu ile ölçüldüğünde gerçekleşen alım/satım yönlü endüstri bazında ticaret işlemi sayısının incelenen gruptan beklenen alım/satım yönlü endüstri bazında ticaret işlemi sayısından istatistiksel olarak anlamlı seviyede sapma gösterdiği anlamına gelmektedir. Sias ölçümü ardışık dönemlerdeki kesitsel korelasyonu gösterdiği için analiz sonucuna göre ardışık iki periyottaki ticaret işlemleri birbirleriyle istatistiksel açıdan anlamlı bir ilişkili içinde değildir.

LSV metodu sürü davranışını ölçümlerken alım ve satım işlem sayıları arasındaki dengesizliğe odaklanır, ancak doğrudan işlem yönünü hesaba katmaz. Wermers'in (1999) çalışmasında LSV yöntemine yaptığı eklemeyle, alım ve satım yönlü işlemlerin hangisinde sürü davranışının daha yoğun gözlemlendiğini anlamak mümkün olmuştur. Wermers'in (1999) yöntemi kullanılarak yapılan analiz sonuçlarına göre alım yönlü sürü davranışı ölçümünün satım yönlü sürü davranışı ölçümünden biraz daha yüksek olduğu görülmektedir. Bu fark analiz sırasında baz alınan aktif fon sayısı kriteri arttıkça kapanmaktadır. Sias metodunu alım ve satım yönlü sürü davranışına göre ayrıştırmak için Choi ve Sias'ın (2009) çalışmasındaki yöntem izlenmiştir. Bu yönteme göre alım ve satım yönlü sürü davranışı arasında belirgin bir farklılık gözlemlenmemiştir.

Sürü davranışının varlığı istatistiksel olarak ortaya konulduktan sonra ölçümlenen vakanın gerçekten sürü davranışı mı yoksa bu imajı yaratan başka bir faktörden mi kaynaklandığını anlamak gerekmektedir. Bu ayrımı yapabilmek için çalışmada ilk incelenen faktör fonların nakit akışladır. Choi ve Sias (2009) ve Celiker vd.'ye (2015) göre endüstri seviyesinde sürü davranışı ölçümü fondaki yatırımcıların nakit hareketlerinden etkilenebilir. Coval ve Stafford'a (2007) göre de yatırım fonları nakit girdisi olduğu zaman halihazırda sahip oldukları hisse senetlerine ekstra yatırım yapmaya daha meyillidirler. Aynı zamanda yatırımcılar fondaki yatırımlarından çıkmak istediklerinde de fonun mevcut varlıklarından satılarak yatırımcıların nakit ihtiyacı karşılanır. Eğer nakit girişi ve çıkışı benzer endüstrilere yatırım yapmış fonlar üzerinde yoğunlaşırsa, bu durum fonların aynı yönde işlem yapmalarına neden olabilir ve alıcı/satıcı sayıları arasındaki dengeyi değiştirebilir. Dolayısıyla fondaki nakit hareketi bu durumun sürü davranışı gibi algılanmasına sebep olabilir. Çalışmada fonlardaki nakit akışının sürü davranışı üzerindeki etkisini inceleyebilmek için Choi ve Sias (2009) ile Celiker vd.'nin (2015) önerdiği gibi aktif yatırımcı tanımında değişikliğe gidilmiştir. Bu yeni tanıma göre bir fonun bir endüstrideki yatırımının portföyündeki ağırlığının değişimi ile yapılan işlemin (alım veya satım) yönü aynı ise bahsi geçen fon ilgili endüstride aktif bir yatırımcı olarak nitelendirilir. LSV ve Sias ölçümleri bu yeni tanıma göre tekrarlandığında çıkan sonuçlar, LSV ölçümünün fondaki nakit akışlarının kontrol edilmediği önceki analizdeki LSV ölçümüne göre dikkate değer ölçüde daha yüksek değerler aldığını göstermiştir. Ayrıca LSV ölçümü istatistiksel olarak anlamlı olmaya devam ettiği için fonlardaki nakit akışının, ölçüm metodu LSV iken sürü davranışını etkilemediği ortaya konmuştur. Sias ölçümü sonucu ise fondaki nakit akışlarının kontrol edilmediği önceki analiz sonuçlarına benzer şekilde, istatistiksel olarak anlamlı bir kesitsel korelasyon ortaya koyamamıştır.

Bazı endüstriler son derece yoğundur ve bir hisse içinde bulunduğu endüstrinin önemli bir kısmını oluşturuyor olabilir. Dolayısıyla yatırımcıların tek bir hisse etrafındaki sürü davranışları endüstri özelinde sürü davranışı gibi gözükebilir. Choi ve Sias (2009) ve Celiker vd. (2015) çalışmalarında bu durum analiz edilmiş ve endüstri seviyesindeki sürü davranışının aslında tekil hisse seviyesinde sürü davranışının bir işareti olmadığı gösterilmiştir. Bu çalışmada da Choi ve Sias (2009) ve Celiker vd. (2015) çalışmalarındaki gibi "yatırım fonlarının endüstri seviyesindeki sürü davranışı tekil hisse özelinde sürü davranışıdır" hipotezi test edilmiştir. Hipotezin LSV metodu ile test edilebilmesi için Celiker vd. (2015) çalışmasında olduğu gibi her periyotta en yüksek sürü davranışı ölçümünü gösteren hisseler örneklemden çıkarılmış ve LSV metodu kalan kümeye yeniden uygulanmıştır. Buradaki mantığa göre en yüksek seviyede sürü davranışı ölçümüne sahip hisseler örneklemden çıkarıldıktan sonra bile endüstri seviyesinde sürü davranışı ölçümleniyorsa, ölçümlenen durum tekil hisse özelinde sürü davranışının kanıtı olamaz. Analiz sonuçlarına göre her periyottaki en yüksek sürü davranışı ölçümü alınan hisseler örneklemden çıkarıldıktan sonra bile kalan kümedeki LSV ölçümü istatistiksel olarak anlamlı gözükmektedir. Bu sonuca göre LSV metodu ile endüstri seviyesinde ölçülen sürü davranışı, tekil hisselerin alım satımından kaynaklanmamaktadır. Analizi Sias metodu ile gerçekleştirmek için Choi ve Sias (2009) çalışmasındaki gibi hisselerin market büyüklüğü ile ağırlıklandırılmış endüstri talepleri oluşturulmuştur. Bu ağırlıklı talep, o sektördeki her hisse senedi için kurumsal talebin doğrusal bir fonksiyonu olduğundan, kesitsel korelasyon bu aşamada dört bileşene ayrılmıştır: aynı hisse senedi için kendilerine ya da diğer yatırım fonlarına ait işlemleri takip edenlerin korelasyona katkıları ile aynı endüstrideki farklı hisse senetleri için kendilerine ya da diğer yatırım fonlarına ait işlemleri takip edenlerin korelasyona katkıları. Celiker vd. (2015) çalışmasına göre yalnızca diğer yatırım fonlarının aynı endüstrideki farklı hisse senetlerinde olan işlemlerinin takip edilmesi sonucu hesaplanan korelasyon katkısı endüstri seviyesinde sürü davranışı olarak adlandırılabilir. Analiz sonuçlarına bakıldığında sadece diğer fonların aynı hisse senedi üzerindeki işlemleri için hesaplanan katkının istatistiksel açıdan anlamlı olduğu görülmektedir. Bu sonuca göre tekil hisse seviyesinde olup endüstri seviyesinde sürü davranışı olarak algılanacak bir durum söz konusu değildir.

Çalışmada yatırım tarzı ve sürü davranışı arasındaki olası ilişki de incelenmiştir. Celiker vd.'ye (2015) göre böyle bir ilişkinin iki temeli olabilir. Birincisi, aynı endüstrideki hisse senetlerinin piyasa değeri ve defter değeri-piyasa değeri oranına ilişkin benzer karakteristikleri söz konusu olabilir. Dolayısıyla piyasa değeri ve defter değeri-piyasa değeri oranına ilişkin yatırım stratejileri olan fonlar aynı endüstrilere yatırım yapabilirler. İkincisi, fon yöneticilerinin değerlendirdikleri piyasa sinyallerinin endüstri ile bağlantılı piyasa değeri ve defter değeri-piyasa değeri oranı bileşenleri olabilir. Dolayısıyla bu bilgileri değerleyen fon yöneticileri de benzer endüstrilere yatırım kararı alabilirler. Her iki durumda da endüstri düzeyindeki sürü davranışı yatırım fonlarının yatırım stillerinden etkilenebilir. Söz konusu durumu analiz edebilmek için Choi ve Sias'ın (2009) çalışmasında olduğu gibi örneklemdeki hisse senetleri önce piyasa değeri ve defter değeri-piyasa değeri oranlarına göre altı gruba bölünmüştür. Bu grupların ikisi ilgili ay için tüm hisse senetlerinin medyan piyasa değeri esas alınarak ve üçü de ilgili ay için tüm hisse senetlerinde defter değeri-piyasa değeri oranının 30. ve 70. yüzdelik dilimleri kullanılarak oluşturulmuştur. Daha sonra Sias yöntemiyle aynı sektördeki diğer fonları farklı hisse senetlerinde takip eden fonların korelasyon katkısını hesaplayan eşitlik yatırım stillerinin etkisi görebilmek için ikiye bölünmüştür: (1) aynı endüstriden aynı stil grubunu paylaşan farklı hisse senetlerini takip etmenin korelasyona katkısı ve (2) aynı endüstriden farklı stil grubunu paylaşan farklı hisse senetlerini takip etmenin korelasyona katkısı. Bu gruplandırmalar ışığında yürütülen analiz sonuçlarına göre yatırım stilinin endüstri düzeyinde sürü davranışını etkileyen faktörlerden birisi olmadığı görülmüştür. Ancak Choi ve Sias (2009) çalışmasına göre endüstri düzeyinde sürü davranışının yatırım stillerinden etkilenmediği göstermek tek başına yeterli değildir. Eğer yatırım stili izlemenin endüstri seviyesinde sürü davranışına bir katkısı yoksa, bu durumda bir fon yöneticisi hisse senedi alımı yaparken diğer fon yöneticileri tarafından alınan hisse senetlerinin stil gruplarına önem vermez. Bu hipotezi değerlendirmek için, diğer fonları aynı ve farklı stil gruplarındaki hisse senetlerine yaptıkları yatırımlarda izlemenin korelasyon katkılarının gerçekleşen ve beklenen değerleri arasındaki farklar analiz edilmiştir. Analiz sonuçlarına göre gerçekleşen ve beklenen değerler arasındaki farklar istatistiksel olarak anlamlı olmadığı için yatırım stillerinin endüstri düzeyinde sürü davranışına neden olmadığı anlaşılmıştır.

Sürü davranışını konu edinen çalışmaların odaklandığı bir nokta da sürü davranışının yatırım yapılan endüstri ya da hisse bazında getiriye olan etkisidir (Dasgupta vd., 2011; Gutierrez ve Kelley, 2011; Nofsinger ve Sias, 1999; Sias, 2004; Wermers, 1999). Choi ve Sias (2009) ve Celiker vd. (2015) çalışmalarında sürü davranışının fon yöneticileri arasındaki bilgi akışının zamanlaması ve yeni bilginin fiyatlanması sürecine bağlı olarak ortaya çıkabileceği vurgulanmaktadır. Choi ve Sias'a (2009) göre, sürü davranışının endüstri getirilerini zaman zaman etkilediğini ve her zaman yeni bilginin fiyatlanmasından etkilenmediğini varsaydığımızda, endüstriye olan kurumsal talebin eş zamanlı endüstri getirileri ile doğrudan ilişkili ve takip eden getirilerle de ters yönlü bir ilişki içinde olduğunu öne sürmek mantıklıdır.

Bununla birlikte, eğer endüstri düzeyindeki sürü davranışı yeni bilginin fiyatlanma süreci ile bağlantılı değilse, kurumsal talep eş zamanlı endüstri getirileri ile doğrudan ilişkili olacaktır; ancak takip eden endüstri getirileri ile de ters yönlü bir ilişkiye sahip olmayacaktır. Sürü davranışı ile ilgili alternatif açıklamalar birbirlerini dışlamadığından, endüstri düzeyinde kurumsal sürü davranışı farklı zamanlarda bilginin akış sürecini ve bilgi haricindeki faktörleri yansıtabilir. Bu çalışmada da endüstri seviyesindeki sürü davranışının endüstri getirisini temel değerlerinden uzaklaştırıp uzaklaştırmadığı analiz edilmiştir. Analizi LSV yöntemi ile gerçekleştirmek için önce sektörler önceki ayın alım (satım) yönlü LSV ölçümlerinin büyüklüklerine göre sıralanmıştır. Daha sonra ilk beş alım (satım) yönlü LSV ölçümüne göre endüstri portföyleri oluşturulmuştur. Buna ek olarak, ilk beş alım yönlü portföyü alıp satım yönlü portföyü de satan fark portföyleri oluşturulmuştur. Daha sonra bu portföyler için portföyün oluşturulduğu ayı takip eden dönemler için değer ağırlıklı endüstri getirilerinin eşit ağırlıklı ortalamaları hesaplanmıştır. Ardından, aynı aya denk gelen gözlemler için endüstri portföylerinin ortalama getirilerini hesaplamak amacıyla Jegadeesh ve Titman'ın (1993) takvim zamanı birleştirme yöntemi kullanılmıştır. Portföylerin anormal getirileri CAPM ve Fama-French üç faktörlü modellerinin alfaları kullanılarak test edilmiştir. Analizi Sias yöntemi ile test etmek için önce Choi ve Sias (2009) çalışmasında gösterildiği şekilde her bir endüstrinin kesitsel korelasyona katkısı hesaplanmıştır. Daha sonra endüstriler gösterdikleri sürü davranışının yönüne göre (alım veya satım) gruplandırılmışladır. Bu aşamadan sonra ölçülen korelasyona en fazla katkısı bulunan beş alım ve satım yönlü endüstri seçilmiştir. Ardından portföy getirilerini hesaplamak için, LSV yöntemi ile analiz gerçekleştirilirken izlenen adımlar takip edilmiştir. Analiz sonuçlarına göre LSV metodu ile yapılan sıralama dikkate alındığında portföyün oluşturulma periyodunda, fark portföyü için temel ve anormal getirilerin istatistiksel olarak anlamlı olmadığı görülmektedir. Ancak, Sias metodu ile yapılan sıralama dikkate alındığında, temel getiri ve CAPM alfasının fark portföyü için negatif ve istatistiksel olarak anlamlı sonuçlandığı görülmektedir. Öte yandan, portföy oluşturma periyodunu takip eden dönemlerde fark portföyünü getirilerinin istatistiksel olarak anlamlı olmaması (Celiker vd., 2015) ve anlamlı getirilerin sadece portföyün oluşturulma dönemi ile sınırlı kalması (Choi ve Sias, 2009; Celiker vd.,

2015) literatürdeki benzer çalışmalarla da tutarlıdır. Sonuç olarak, yüksek düzeyde alım veya satım yönlü sürü davranışı ölçümü gösteren endüstrilerde, getirilerin tersine çevrildiğine ve başka bir deyişle yatırım fonlarındaki sürü davranışının endüstri getirileri üzerinde istikrarsızlaştırıcı bir etkisi bulunduğuna dair bir kanıt bulunamamıştır.

Çalışmanın bu kısmının önemli olmasının nedenlerinden biri gelişmiş piyasaların aksine daha az fon ve işlem gören hisse senedine sahip konsantre bir piyasayı incelemesi ve böyle bir piyasada da gelişmiş piyasalarda görülen sürü davranışı etkilerinin olup olmadığını analiz etmesidir. Çalışmanın bulguları yatırımcıların, yatırım fonu yöneticilerinin sektör ve hisse seçimi sırasında aldığı kararları anlamaları açısından da önemlidir. Çalışmada endüstri seviyesinde sürü davranışına etkisi olabilecek faktörlerden önemli bir kısmı analiz edilmiştir, ancak piyasa ve/veya fon yöneticisi özelindeki bir grup faktöre değinilmemiştir. Morck vd. (2000) çalışmasına göre, gelişmiş piyasalara kıyasla gelişmekte olan piyasalarda hisse senedi fiyatlarının hareketi daha fazla paralellik arz eder. Bu da gelişmekte olan piyasalarda daha az firma bazlı bilgi üretimi ve akışı olduğunun bir göstergesidir. Chan ve Hameed (2006) çalışmasında gelişmekte olan piyasalarda firma özelinde bilgi eksikliğinin, mevzuat tarafından zorunlu kılınmış bir bilgi açıklama yükümlülüğünün olmaması, kurumsal şeffaflık ve gönüllü bilgi açıklama ilkesinin istenilen seviyede olmaması ve çok sayıda aile şirketinin var olması nedeniyle güvenilir bilgi üretiminin istenilen seviyede olmaması gibi faktörlere bağlı olduğu vurgulanmaktadır. Belirtilen bu noktalara, belirli hisse senetleri üzerinde yoğunlaşan analist kapsamı ve fon yöneticilerinin yatırım kararlarında kullandıkları veri setlerinin benzerliği gibi faktörler eklendiğinde, sürü davranışı oldukça beklenen ve anlaşılabilir bir hal alır. Bu faktörlerin incelenmesi ve etkinliklerinin araştırılması, gelecekteki çalışmalar için potansiyel araştırma kapsamı olarak düşünülebilir.

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PUBLICATIONS

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CONFERENCE PRESENTATIONS

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3. *City Index Relations in Istanbul Stock Exchange*, Global Business and Technology Association Fourteenth Annual Conference, New York City, July 2012.
4. *Business Failure Predictions in Istanbul Stock Exchange*, Global Business and Technology Association Eleventh Annual Conference, Prague, July 2009.

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