Herding Behavior across Different Market Return and Volatility Conditions

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Abstract
Herding behavior is one of the most prominent behavioral biases in financial markets, potentially leading to asset price deviations from fundamental values and increasing market instability. This study investigates the linear and nonlinear effects of market returns and market volatility on investors' herding behavior in the Tehran Stock Exchange (TSE). To this end, daily data for the TSE Total Index and the TSE Top 50 Active Companies Index over the period from March 2015 to March 2021 were employed. Herding behavior was measured using the Cross-Sectional Absolute Deviation (CSAD) approach, and the relationships were estimated using Ordinary Least Squares (OLS) and Quantile Regression (QR) techniques. The OLS results reveal that the nonlinear market return coefficient is negative and statistically significant for both indices, providing robust evidence of herding behavior in the Iranian stock market. Furthermore, the nonlinear volatility coefficient is also negative and significant, suggesting that heightened market volatility is associated with stronger herding tendencies among investors. The quantile regression findings indicate that the intensity of herding behavior varies across different segments of the CSAD distribution. Specifically, herding behavior is more pronounced in the lower and middle quantiles, whereas its significance diminishes in the upper quantiles. In addition, the impact of market volatility on herding behavior is found to be nonlinear and state-dependent, becoming stronger under conditions of elevated uncertainty. Overall, the findings suggest that herding behavior in the Tehran Stock Exchange is not uniform across market conditions and that periods of heightened volatility may intensify investors' tendency to follow collective market sentiment through increased uncertainty and stronger information cascades.
Keywords: Herding Behavior; Market Volatility; Market Return; Quantile Regression; CSAD; Tehran Stock Exchange.
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1.Introduction

The capital market is one of the most important components of a country's financial system, playing a vital role in mobilizing and allocating financial resources, financing corporate activities, promoting investment, and fostering economic growth. The efficient functioning of capital markets largely depends on investors' behavior and their responses to new information. Traditional finance theory assumes that investors are fully rational agents who make decisions based on all available information and the fundamental values of assets. Under this framework, asset prices fully reflect available information, leaving little room for persistent deviations from intrinsic value. However, extensive empirical evidence suggests that actual investor behavior often deviates from the assumptions of perfect rationality, with psychological and behavioral factors playing a significant role in investment decisions (Kahneman & Tversky, 1979; Shefrin, 2000). In response to the limitations of traditional financial theories, behavioral finance has emerged as one of the most influential fields in modern finance. This approach argues that investors are frequently affected by cognitive biases, behavioral distortions, and prevailing market conditions, leading them to make decisions that are inconsistent with

the predictions of the Efficient Market Hypothesis (Thaler, 1999; Barberis & Thaler, 2003). Among the most extensively studied phenomena in behavioral finance is herding behavior, which occurs when investors follow the actions and decisions of other market participants rather than relying on their own information and analysis (Banerjee, 1992; Bikhchandani et al., 1992).

Herding behavior arises when investors, due to uncertainty, informational constraints, or concerns about the consequences of independent decision-making, use the behavior of others as the basis for their own investment decisions. Under such circumstances, investors tend to disregard their private information and personal assessments and instead conform to the dominant market trend. Keynes (1936), through his well-known "beauty contest" analogy, argued that investors often select assets not because they personally consider them valuable, but because they believe other market participants will perceive them favorably. Consequently, investment decisions become driven more by expectations regarding the behavior of others than by fundamental valuations. Herding behavior is of particular importance because it can cause asset prices to deviate from their fundamental values, increase market volatility, generate speculative bubbles, and reduce market efficiency (Bikhchandani & Sharma, 2000). Many episodes of financial crises and periods of severe market instability have been accompanied by widespread collective and imitative behavior among investors. Accordingly, identifying the factors that contribute to the emergence and intensification of herding behavior has become a central issue in the behavioral finance literature.

Among the various determinants of herding behavior, market returns and market volatility are particularly important. Changes in market returns provide valuable information about overall market conditions and influence investors' expectations regarding future market performance. During periods of high returns, investors may become more inclined to imitate the behavior of other market participants as they observe broad-based increases in asset prices. Conversely, during market downturns or periods of declining returns, investors may also follow the actions of others in an attempt to avoid potential losses. Therefore, the relationship between market returns and herding behavior may vary across different market conditions. In addition to market returns, market volatility is widely recognized as one of the most influential factors affecting investor behavior. Higher volatility is generally associated with increased uncertainty and risk, which may impair investors' ability to process information effectively. Under such conditions, investors are more likely to rely on the actions of other market participants rather than on their own information and analysis. Consequently, a substantial body of empirical research has examined the relationship between market volatility and herding behavior. The findings generally suggest that herding intensifies during periods of market turbulence and heightened volatility, when investors increasingly engage in collective behavior (Christie & Huang, 1995; Chang et al., 2000; Hwang & Salmon, 2004; Chiang & Zheng, 2010).

Despite the growing literature on herding behavior, existing studies indicate that both the intensity and nature of herding vary across market conditions. Some studies report stronger herding during bullish market periods, whereas others find that herding becomes more pronounced during market downturns and periods of elevated volatility (Gebka & Wohar, 2013; Clements et al., 2017). These mixed findings suggest that the relationship between market returns, market volatility, and herding behavior may not be uniform across different segments of the herding distribution. In other words, factors that exert only limited influence under normal market conditions may become substantially more important during extreme market episodes. The Iranian stock market has experienced considerable fluctuations in recent years, including multiple episodes of sharp booms and severe downturns. The dominance of retail investors, informational frictions, information asymmetry, and the market's sensitivity to economic and political news create favorable conditions for the emergence of collective and imitative investor behavior. Therefore, examining herding behavior under varying return and volatility conditions can contribute significantly to a better understanding of investor behavior and the underlying sources of

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fluctuations in the Tehran Stock Exchange. From a methodological perspective, conventional mean-based approaches such as Ordinary Least Squares (OLS) may fail to capture the heterogeneity inherent in the relationship between market conditions and herding behavior. In contrast, quantile regression provides a more comprehensive framework by allowing the effects of market returns and volatility on herding behavior to be examined across different points of the herding distribution. This approach reveals whether the influence of explanatory variables differs across low, medium, and high levels of herding behavior, thereby offering deeper insights into the behavioral mechanisms governing financial markets (Koenker & Bassett, 1978).

Despite extensive research on herding behavior, three major gaps remain in the existing literature. First, most previous studies have primarily focused on identifying the existence of herding behavior, while paying relatively little attention to the nonlinear effects of market returns and volatility on the formation and intensity of herding and how these effects vary across different market conditions. Second, the majority of existing studies employ mean-based estimation techniques that are unable to capture the heterogeneous behavior of investors under varying market environments. Third, empirical evidence from the Iranian stock market, particularly regarding the nonlinear effects of market returns and volatility across different quantiles of the Cross-Sectional Absolute Deviation (CSAD) distribution, remains limited. To address these gaps, the present study employs an extended herding behavior model combined with a quantile regression framework. The contribution of this study is threefold. First, unlike most previous studies that focus solely on the role of market returns in explaining herding behavior, this study simultaneously incorporates both the linear and nonlinear effects of market returns and market volatility within a unified herding framework. Second, herding behavior is examined across two major stock market indices in Iran, namely the Tehran Stock Exchange Total Index and the Top 50 Most Active Companies Index. Third, by employing quantile regression, the study investigates how the effects of market returns and volatility vary across different levels of herding behavior.

Given the importance of the research question, this study utilizes daily data from the Tehran Stock Exchange covering the period from March 2015 to March 2021 and employs the extended herding model of Chang et al. (2000) to examine the linear and nonlinear effects of market returns and volatility on investor herding behavior. Furthermore, quantile regression is used to explore the heterogeneity of these relationships across different segments of the herding distribution. The findings are expected not only to contribute to the behavioral finance literature in emerging markets but also to provide useful implications for regulatory policy design, market risk management, and the enhancement of informational efficiency in the Tehran Stock Exchange.

The remainder of the paper is organized as follows. Section 2 and 3 review the theoretical background and related literature. Section 4 describes the methodology and data. Section 5 presents and discusses the empirical results. Finally, Section 6 concludes and offers policy implications.

2. Literature Review

2.1. Herding Behavior and Its Conceptual Foundations

Behavioral finance emerged largely in response to criticisms directed at the assumptions of classical finance by scholars such as Kahneman and Tversky (1979). According to behavioral finance theory, investors are influenced by psychological factors when making financial decisions and do not rely solely on economic models and rational criteria. Instead, beliefs, emotions, and cognitive biases play a significant role in the decision-making process. As a result, investors' choices may deviate from fully rational behavior, causing asset prices to diverge from their intrinsic values. Consequently, determining the fundamental value of assets often becomes challenging. Some researchers argue that irrational investors exert only a limited influence on market prices because their actions are largely random and tend to offset one another over time. Moreover, from this perspective, irrational investors often display similar behavioral patterns, while rational investors eliminate mispricing through arbitrage activities.

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However, Shiller (1984) demonstrated that irrational investors can significantly affect financial markets by driving prices away from their fair and fundamental values. This suggests that capital markets may be influenced by psychological and sociological factors and, therefore, may not always exhibit perfect informational efficiency (Salzman & Trifan, 2005).

Herding behavior is one of the central concepts in behavioral finance and refers to investors' tendency to follow the actions and decisions of other market participants without sufficiently relying on their own information and analysis. The theoretical roots of this concept can be traced back to Keynes' (1936) discussion of collective expectations in financial markets. Subsequently, herding behavior was extensively developed by scholars such as Shiller (1987), Banerjee (1992), and Bikhchandani et al. (1992), becoming one of the most widely studied topics in behavioral finance. Broadly speaking, herding occurs when investors base their investment decisions on the observed actions of others rather than on their own independent information and judgment. This phenomenon tends to intensify during periods characterized by heightened uncertainty, information ambiguity, and market turbulence, as investors increasingly regard the behavior of others as a substitute source of information (Banerjee, 1992; Bikhchandani et al., 1992; Chaffai & Medhioub, 2018). Numerous studies suggest that herding behavior may contribute to increased price volatility, deviations from fundamental values, the formation of speculative bubbles, and ultimately reduced market efficiency (Chang et al., 2000; Bekiros et al., 2017).

Banerjee (1992) defines herding as a situation in which individuals follow the actions of others even when their own information and beliefs suggest an alternative course of action. Similarly, Devenow and Welch (1996) and Sciubba (2000) describe herding as correlated behavioral patterns among individuals, leading investors to make similar and synchronized decisions. Along the same lines, Chang et al. (2000) argue that herding occurs when market participants base their investment decisions on collective market actions while disregarding their own private information and beliefs. Patterson and Sharma (2007) further suggest that herding arises when a group of investors simultaneously trades in the same direction over a given period or abandons private information in favor of mimicking the actions of others. The common element across these definitions is that investors rely on the observed behavior of other market participants rather than on independent information and judgment.

The theoretical literature identifies several factors contributing to the emergence of herding behavior. Hirshleifer et al. (1994) argue that herding may result from investors relying on similar information sources and interpreting information in comparable ways. When market participants are exposed to the same information or process market signals similarly, the likelihood of making similar decisions increases, giving rise to correlated behavioral patterns. In addition, information asymmetry, the growing influence of institutional investors, concentration in similar asset classes, compensation structures, career concerns, information quality, and the level of development and sophistication of financial markets have all been identified as important drivers of herding behavior (Black, 1986; Rajan, 1994; Scharfstein & Stein, 1990; Trueman, 1988; Demirer & Kutan, 2006; Patterson & Sharma, 2006).

Two principal perspectives dominate the literature regarding the nature of herding behavior. The first views herding as an irrational phenomenon driven by individuals' innate tendency to imitate collective actions. According to this perspective, investors are influenced by emotions, social pressure, and behavioral biases, leading them to follow others without adequately considering fundamental information. The second perspective considers herding a rational response whereby investors deliberately follow others because they believe that other market participants possess superior information or more accurate analyses. Proponents of this view argue that, under conditions of uncertainty, following others may represent a rational strategy for reducing decision-making risk (Bikhchandani & Sharma, 2000).

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Herding behavior can emerge in both conscious and unconscious forms (Devenow & Welch, 1996; Rook, 2006). From a conscious perspective, investors face cognitive limitations and constraints in processing the vast amount of information available in financial markets. This condition, often referred to as information overload, encourages investors to use the decisions and actions of other market participants as a shortcut for decision-making in order to reduce information acquisition and processing costs (DellaVigna, 2007; Hirshleifer et al., 2009). Under such circumstances, following the majority may be perceived as less risky than relying solely on individual judgment. Furthermore, aligning with the prevailing market consensus may reduce reputational and career-related risks associated with making unconventional decisions, thereby encouraging investors to conform to collective behavior (Trueman, 1994). In some cases, imitation may also help investors preserve economic benefits or avoid potential losses, particularly in contexts such as liquidity trading and depositor behavior during banking crises (Admati & Pfleiderer, 1988; Diamond & Dybvig, 1983).

From an unconscious perspective, herding behavior is rooted in social and psychological mechanisms. Individuals tend to align their beliefs, expectations, and decisions with prevailing social norms and dominant opinions because their perceptions of economic and social reality are influenced by majority views (Martin & Hewstone, 2001; Rook, 2006). Such conformity may occur even when investors possess private information or analyses that contradict prevailing market sentiment (Zhang, 2010). From an evolutionary standpoint, imitation can be viewed as an adaptive mechanism that enables individuals to benefit from the collective knowledge and experience of others (Gibson & Höglund, 1992). Moreover, the dissemination of news and information in financial markets can generate emotions such as fear, anxiety, optimism, and excitement among investors, which may spread through social interactions and communication networks (Hirshleifer & Teoh, 2003; Stieglitz & Dang-Xuan, 2013). Consequently, when prevailing market expectations are aligned with the direction of new information and news flows, the likelihood of collective behavior and intensified herding increases substantially.

2.2. Market Returns, Market Volatility, and Herding Behavior

Herding behavior is one of the most prominent phenomena in behavioral finance, referring to situations in which investors base their decisions on the actions of the majority rather than on their own information and analysis. In other words, investors tend to follow the prevailing market consensus even when their personal assessments differ from the dominant market view (Kessous & Valette-Florence, 2019; Barrera & Ponce, 2021). The theoretical roots of this phenomenon can be traced to the bandwagon effect introduced by Leibenstein (1950), which suggests that individuals often prefer to align themselves with the majority because doing so reduces the psychological burden of decision-making and provides a greater sense of security. Herding behavior in financial markets can also be explained within several major theoretical frameworks in financial economics. Traditional finance theories, particularly the Efficient Market Hypothesis (EMH), assume that investors behave rationally, process available information efficiently, and incorporate all relevant information into asset prices. Under this framework, stock returns are expected to respond primarily to new information, while cross-sectional differences in returns reflect variations in firms' risk characteristics and fundamentals. However, financial markets do not always conform to this rational benchmark. In many instances, large market movements and heightened volatility are driven less by fundamental information and more by collective, imitative, and sentiment-driven investor behavior (Bikhchandani & Sharma, 2000).

One of the most influential theoretical explanations for herding behavior is the information cascade theory. According to this framework, investors make decisions sequentially, and the actions of earlier investors serve as informational signals for those who follow (Banerjee, 1992; Bikhchandani et al., 1992). Consequently, investors rely not only on their private information but also on information inferred from the observed behavior of others. When a sufficient number of market participants buy or

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sell in the same direction, subsequent investors may conclude that those traders possess superior information. As a result, investors may disregard their own private signals and follow the crowd, even when their personal information suggests a different course of action. Bikhchandani et al. (1992) argue that information cascades emerge through a sequential process in which the decisions of a small number of early investors influence the choices of subsequent market participants. As this process unfolds, private information gradually loses its role in decision-making, and collective behavior replaces independent analysis. From this perspective, herding may represent a rational response to information inferred from others' actions. Similarly, Welch (1992) contends that investors may rationally conclude that information embedded in the actions of other traders is more valuable than their own private information. Therefore, following the crowd is not necessarily irrational but may constitute an optimal strategy under conditions of uncertainty.

Nevertheless, information cascades and herding behavior are not identical concepts. Smith and Sorensen (2000) argue that an information cascade occurs when individuals completely disregard their private information, whereas herding refers more broadly to convergence in investor decisions, even when private information continues to play some role. Accordingly, every information cascade constitutes a form of herding, but not all herding behavior originates from information cascades. One of the most important consequences of information cascades is the disruption of information aggregation and the deterioration of market efficiency. When investors rely primarily on the actions of others rather than on their own information, new information may not be accurately incorporated into asset prices, causing prices to diverge from their fundamental values. Cipriani and Guarino (2008) demonstrate that information cascades can distort price discovery and contribute to persistent mispricing. Consequently, information cascade theory provides an important framework for explaining herding behavior, excess volatility, and the formation of speculative bubbles in financial markets.

The relationship between market returns and herding behavior can be understood within this theoretical framework. Based on the standard asset-pricing models, larger absolute market returns should be associated with greater cross-sectional dispersion of stock returns because firms differ in their risk exposure, financial structure, liquidity, and sensitivity to market information (Chang et al., 2000). In a rational market, substantial market movements should therefore generate heterogeneous stock responses. However, if return dispersion decreases—or increases less than expected—during periods of extreme market returns, such a pattern may signal herding behavior, as investors follow the overall market direction rather than evaluating firm-specific information.

Behavioral finance theories suggest that investors often exhibit reactions to abnormal market returns that extend beyond the predictions of conventional financial models. During bull markets, rapidly rising prices may generate optimistic expectations and fear of missing out (FOMO), encouraging investors to follow prevailing market trends. Conversely, during bear markets, fear of losses and heightened uncertainty may induce widespread selling behavior. In both cases, investor decisions become increasingly influenced by the actions of others rather than by fundamental information (Christie & Huang, 1995; Chang et al., 2000).

Based on this reasoning, Christie and Huang (1995) and Chang et al. (2000) propose measuring herding behavior through the relationship between cross-sectional return dispersion and market returns. In the model developed by Chang et al. (2000), a significantly negative nonlinear relationship between return dispersion and the squared market return provides evidence of herding. The intuition is straightforward: under rational trading, periods of large market movements should increase return dispersion across stocks. However, when investors herd, individual stock returns converge toward the overall market return, causing dispersion to decline. Therefore, a negative and statistically significant coefficient on the squared market return indicates that investor behavior becomes increasingly synchronized during periods of substantial market movements.

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Market volatility also plays a critical role in fostering herding behavior. Volatility reflects the level of uncertainty, perceived risk, and difficulty associated with forecasting future asset prices. As volatility increases, the investment environment becomes more complex, and investors' ability to assess fundamental values diminishes. Under such circumstances, investors may rely more heavily on the behavior of other market participants as a decision-making guide. Consequently, higher volatility can strengthen herding behavior by increasing uncertainty and reducing confidence in individual judgment (Shiller, 1990; Bekiros et al., 2017).

This relationship can also be explained through Prospect Theory. According to Kahneman and Tversky (1979), investors are more sensitive to losses than to gains. During periods of elevated risk and uncertainty, fear of losses may encourage investors to imitate the actions of others rather than bear the responsibility of making independent decisions. In this sense, herding behavior serves as a psychological coping mechanism through which investors perceive their decisions as being aligned with the majority, thereby reducing the personal burden associated with potential losses. At the same time, herding behavior may itself contribute to greater market volatility. When a large number of investors simultaneously buy or sell a particular asset, excess demand or supply pressure amplifies price fluctuations. Koubaa and Slim (2019) show that increases in trading activity are often associated with higher volatility, and herding behavior can reinforce this relationship. Under such conditions, volatility clustering may emerge, whereby periods of high volatility tend to be followed by similarly volatile periods, while tranquil periods also persist over time (Perez & Gerry, 2018). Thus, the relationship between herding and volatility is inherently bidirectional: volatility can intensify herding behavior, while herding behavior can further increase market volatility.

The limits-to-arbitrage theory also provides insight into the relationship between volatility and herding. Even when rational investors recognize deviations of asset prices from their fundamental values, they may be unable or unwilling to correct these mispricing. During periods of elevated volatility, the risks associated with trading against prevailing market trends increase substantially. Arbitrageurs may therefore refrain from taking contrarian positions due to capital constraints, liquidity risk, or concerns that mispricing may persist for an extended period. Under such circumstances, collective market behavior remains largely unchecked, and even rational investors may choose to move with the crowd rather than oppose it. Consequently, limits to arbitrage can contribute to the persistence and amplification of herding behavior during turbulent market conditions (Shleifer & Vishny, 1997).

The relationship between volatility and herding can also be explained by theories of speculative bubbles and noise trader models. According to these perspectives, asset prices may deviate from their fundamental values for prolonged periods and become increasingly driven by collective investor expectations. In such environments, investors make trading decisions based on the observed behavior of others rather than on fundamental information. This process can amplify mispricing, fuel speculative bubbles, and increase market volatility. When expectations eventually reverse and prices begin reverting toward their fundamental values, the same collective behavior can trigger sharp market corrections and bubble collapses. Consequently, herding behavior is widely recognized as one of the key mechanisms underlying both the formation and bursting of financial bubbles (Shiller, 1984; De Long et al., 1990; Bikhchandani & Sharma, 2000; Zhou & Sornette, 2009).

2.3. Theoretical Framework and Research Hypotheses

Theoretical explanations of herding behavior suggest that investors' decisions are influenced not only by fundamental information but also by informational constraints, psychological biases, and prevailing market conditions (Kahneman & Tversky, 1979; Shleifer, 2000; Barberis & Thaler, 2003). Although different theoretical perspectives provide distinct explanations for why investors herd, they share a common mechanism: when uncertainty increases and the ability to process information independently becomes limited, investors tend to rely more heavily on the actions and beliefs of other market

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participants (Banerjee, 1992; Bikhchandani et al., 1992). Therefore, herding behavior can be viewed as a state-dependent phenomenon whose intensity may vary according to market conditions.

Information cascade theory provides one of the fundamental explanations for the emergence of herding behavior. According to Banerjee (1992) and Bikhchandani et al. (1992), investors make decisions sequentially and may interpret the actions of previous investors as valuable information. Once a sufficient number of market participants follow a particular direction, subsequent investors may disregard their own private information and imitate the observed behavior of others. In financial markets, large movements in market returns can generate strong signals regarding market sentiment and future expectations, increasing the likelihood that investors follow collective market behavior. Within the Cross-Sectional Absolute Deviation (CSAD) framework introduced by Chang et al. (2000), rational price movements are expected to increase the dispersion of individual stock returns because firms differ in their fundamental characteristics and responses to market information. However, when investors herd, stock returns become increasingly aligned with market movements, causing return dispersion to increase less than proportionally. Therefore, a negative and statistically significant coefficient of the nonlinear market return term provides evidence of herding behavior. Market volatility and herding behavior may be associated through a complex relationship in which volatility reflects prevailing uncertainty and stress conditions affecting investor behavior. On the one hand, intentional herding driven by imitation, reputation concerns, or excessive reliance on other investors' actions can amplify price movements and contribute to higher market volatility (Scharfstein & Stein, 1990; Bikhchandani & Sharma, 2001). On the other hand, volatility itself may create an environment characterized by greater uncertainty, information ambiguity, and difficulties in processing private signals, thereby encouraging investors to rely more heavily on collective market behavior. However, the impact of herding on market stability depends on the underlying source of collective behavior. While intentional herding may destabilize markets by reinforcing excessive price movements, unintentional herding may arise when investors rationally respond to similar information signals or common fundamental factors, potentially improving market adjustment and reducing volatility (Hirshleifer et al., 1994). Recent evidence by Fei and Liu (2021) further highlights the complex relationship between herding and volatility by showing that different forms of herding may have asymmetric implications for market stability. Therefore, rather than assuming a strictly causal direction, this study considers volatility as an important state variable reflecting prevailing uncertainty and stress conditions that may be associated with different intensities of herding behavior across market environments.

The relationship between market returns and herding is also expected to be nonlinear. Under normal market conditions, investors generally have greater incentives and opportunities to collect information, evaluate firm fundamentals, and make independent decisions. However, during periods of extreme market movements, psychological pressures and uncertainty may reduce the reliance on private information and increase dependence on market consensus. Prospect theory developed by Kahneman and Tversky (1979) provides a behavioral explanation for this mechanism by showing that investors' preferences and risk perceptions change under uncertainty, particularly when potential losses become salient. Consequently, extreme positive or negative market returns may increase investors' tendency to imitate others, resulting in stronger behavioral convergence.

Beyond its potential feedback relationship with herding, volatility can also affect investor behavior through an informational mechanism. Volatility reflects uncertainty regarding future market conditions and reduces the precision of available information. Under highly volatile conditions, investors face greater difficulties in interpreting market signals and evaluating the accuracy of their own information. As a result, the observed actions of other investors may become an alternative source of information. This argument is consistent with the information cascade framework, which suggests that uncertainty

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strengthens the tendency of investors to follow collective decisions (Bikhchandani et al., 1992; Bikhchandani & Sharma, 2001).

The limits-to-arbitrage perspective further explains why herding behavior may persist even when investors' decisions deviate from fundamental values. According to Shleifer and Vishny (1997), arbitrageurs face significant risks and constraints that limit their ability to correct mispricing generated by irrational trading behavior. During periods of high volatility, these constraints become more severe because uncertainty regarding the timing and direction of price corrections increases. Consequently, market inefficiencies generated by collective investor behavior may persist for longer periods. Similarly, noise trader models suggest that correlated beliefs and sentiment-driven trading can generate excessive price movements and contribute to deviations from fundamental values (De Long et al., 1990).

Based on these theoretical arguments, the present study does not interpret volatility as a purely exogenous determinant of herding behavior. Rather, volatility is considered as an indicator of prevailing market uncertainty and stress conditions that may influence investors' tendency to follow collective market signals. Accordingly, the objective of this study is therefore to examine whether different volatility conditions are associated with variations in the intensity of herding behavior. This approach is consistent with previous studies that investigate the relationship between return dispersion, herding, and market volatility (Fei & Liu, 2021). Furthermore, since the influence of market conditions may differ across tranquil and turbulent periods, herding behavior is expected to be nonlinear and heterogeneous across the distribution of return dispersion. Ordinary Least Squares (OLS) estimation captures only the average relationship and may overlook important differences between low and high herding states. Therefore, quantile regression developed by Koenker and Bassett (1978) provides an appropriate framework for examining whether the effects of market returns and volatility vary across different levels of the CSAD distribution.

Drawing on the theoretical framework discussed above, three testable hypotheses are formulated. First, information cascade theory and behavioral finance perspectives suggest that the relationship between market movements and investor behavior is unlikely to be linear. During periods of extreme market movements, investors may increasingly rely on collective market signals rather than private information, leading to greater synchronization of stock returns and a decline in cross-sectional return dispersion. Therefore, the first hypothesis is proposed as follows:

H1: Market returns exhibit a nonlinear relationship with investors' herding behavior.

Second, market volatility represents a condition of heightened uncertainty and informational constraints. Under such circumstances, investors may find it more difficult to process information independently and may rely more heavily on the observed actions of other market participants. Accordingly, volatility is expected to influence the intensity of herding behavior. Thus, the second hypothesis is formulated as:

H2: Market volatility is significantly associated with investors' herding behavior, and this relationship is nonlinear across different market conditions.

Finally, because herding is a state-dependent behavioral phenomenon, the influence of market returns and volatility may differ across various market conditions. Specifically, the effects of these factors may vary between periods characterized by low, moderate, and high levels of return dispersion. Therefore, quantile regression is employed to examine this heterogeneity, leading to the third hypothesis:

H3: The effects of market returns and market volatility on herding behavior are heterogeneous across different levels of the CSAD distribution.

2.4. Empirical Literature

Herding behavior has been one of the most extensively examined topics in behavioral finance over the past three decades. Nevertheless, despite substantial advances in its theoretical foundations, empirical

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evidence regarding the existence, intensity, and determinants of herding remains mixed and, in many cases, inconclusive.

Early empirical studies in this area focused primarily on the behavior of institutional investors. Lakonishok et al. (1992), examining the trading behavior of 769 pension funds in the United States over the period 1985–1989, found no significant evidence of herding and concluded that institutional investors' decisions were largely based on independent information. Grinblatt et al. (1995), analyzing the trading behavior of 155 U.S. mutual funds between 1974 and 1984, reported only limited evidence of herding. However, they found that a considerable proportion of funds followed momentum-based strategies and tended to buy stocks with strong past performance. Similarly, Patterson and Sharma (2005), using intraday data from the New York Stock Exchange over the period 1998–2001, found no significant evidence of herding and interpreted their findings as being consistent with the efficient market hypothesis. Although these early studies provided only limited support for the existence of herding, they laid the groundwork for the development of more refined empirical approaches to measuring this phenomenon.

From a methodological perspective, the seminal contributions of Christie and Huang (1995) and Chang et al. (2000) represent a major turning point in the herding literature. Christie and Huang (1995) introduced the Cross-Sectional Standard Deviation (CSSD) of returns and argued that, under herding behavior, the dispersion of individual stock returns around the market return should decline during periods of extreme market movements. Their results for the U.S. stock market did not provide significant evidence of herding. Chang et al. (2000) subsequently extended this approach by proposing the Cross-Sectional Absolute Deviation (CSAD), which allows for the detection of nonlinear herding behavior. Examining equity markets in the United States, Hong Kong, Japan, South Korea, and Taiwan over the period 1963–1997, they found limited evidence of herding in developed markets but significant evidence in the emerging markets of South Korea and Taiwan. This study remains one of the most influential empirical contributions documenting differences in investor behavior between developed and emerging markets and continues to serve as a foundation for subsequent research.

Subsequent studies have examined herding behavior across a wide range of markets. Demirer and Kutan (2006), using the CSSD and CSAD approaches, investigated the Chinese stock market but found no evidence of herding. Their findings were consistent with those of Chen et al. (2003) and supported the market efficiency hypothesis. In contrast, Yao et al. (2014), examining the Chinese stock market over the period 1999–2008, found evidence of herding and showed that herding was stronger at the industry level and among both large and small firms than at the aggregate market level. These mixed findings suggest that the detection of herding behavior is highly sensitive to the level of analysis, sample period, and market-specific characteristics.

A substantial strand of the literature has focused on small, emerging, and relatively illiquid markets. Zaharyeva (2009) reported significant evidence of herding in the Ukrainian stock market, while Duasa and Kassim (2008) found similar evidence in the Malaysian capital market. Serra and Lobão (2002), Barros (2009), and Leite (2011) also confirmed the presence of herding in the Portuguese capital market. These findings suggest that limited liquidity, information asymmetry, lower information transparency, and underdeveloped market structures may increase the likelihood of imitative investor behavior. By contrast, many studies conducted in large and developed markets, such as the United States and Hong Kong, as well as in certain Japanese industries, have reported weak evidence of herding, which is broadly consistent with the predictions of the efficient market hypothesis (Patterson & Sharma, 2005, 2007).

More recent research has shifted from merely detecting herding behavior toward identifying its key determinants. Investor sentiment is one of the most important factors examined in this regard. Blasco et al. (2012), studying the Spanish stock market, showed that herding behavior is influenced by past

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returns, investor sentiment, and investors' tendency to imitate other market participants. Vieira and Pereira (2014) examined the relationship between investor sentiment and herding in the Portuguese capital market and found that investor sentiment exerts only a limited effect on the intensity of herding. In emerging markets and new asset classes, Jia et al. (2022) analyzed the cryptocurrency market and found that extreme investor sentiment significantly strengthens herding behavior, particularly during periods of crisis and heightened uncertainty.

As the behavioral finance literature has expanded, market returns and volatility have received increasing attention as key determinants of herding behavior. Theoretical studies suggest that heightened market volatility increases investor uncertainty and encourages reliance on the observed behavior of other market participants. In this context, Bekiros et al. (2017), using the CSAD approach and quantile regression for the U.S. stock market, showed that herding behavior is mainly observed in the tails of the return distribution and during periods of heightened market uncertainty. By incorporating implied volatility indices into their model, they demonstrated that market fear and uncertainty play an important role in intensifying herding behavior. Their findings further indicate that the strength of herding is not uniform across market conditions and increases markedly during crisis and extreme market episodes.

Subsequent studies have extended this line of inquiry. Litimi (2017), employing GARCH and CSAD models, found that herding behavior in the French stock market occurs mainly during financial crises and only in certain industries. Chaffai and Medhioub (2018), using GARCH models and quantile regression for Gulf Cooperation Council stock markets, found that herding is more pronounced during upward market phases than during downward phases. In contrast, Patwarani and Husodo (2023), examining six Asian markets over the period 2019–2023, showed that herding behavior is primarily strengthened during bearish markets and the COVID-19 pandemic. These divergent findings suggest that the relationship among market returns, volatility, and herding behavior may depend on market structure, financial development, and macroeconomic conditions.

In recent years, the herding literature has increasingly moved toward nonlinear and regime-dependent approaches. Klein (2013) showed that herding intensity in the U.S. market differs significantly between crisis and tranquil periods. Wu and Fu (2021), applying a Markov-switching framework to the Chinese stock market, found that herding is stronger in high-volatility regimes, whereas reverse herding emerges during tranquil periods. Jiang et al. (2022) reported similar evidence for Asian equity markets. One of the most comprehensive recent studies is that of Lakshminarayana et al. (2026), who examined the Indian stock market using a combination of CSAD, VAR, EGARCH, Markov-switching, and quantile-on-quantile regression models. Their results show that herding behavior is strongly influenced by market returns, volatility, trading volume, and market regimes. They further demonstrate that herding intensifies during high-volatility regimes, bearish markets, and crisis periods, and that the relationship between market variables and herding behavior is nonlinear and asymmetric. In the context of Iran, Aghaei (2025) examined herding behavior in the Tehran Stock Exchange over the period 2015–2021 and showed that the intensity of herding is affected by various economic and social conditions, including sharp exchange rate fluctuations, the COVID-19 pandemic, and bullish and bearish market states. However, existing studies have largely focused on detecting the presence of herding, while the roles of market returns and volatility as direct explanatory factors of herding behavior have received limited attention.

Overall, the literature review reveals three important gaps. First, most previous studies have focused on whether herding behavior exists, while relatively less attention has been paid to market returns and volatility as explanatory drivers of herding. Second, much of the existing literature relies on mean-based approaches such as OLS, which are unable to capture heterogeneity in investor behavior across different market conditions. This limitation is particularly important because recent evidence suggests

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that the relationship among returns, volatility, and herding is nonlinear, asymmetric, and varies across different segments of the herding distribution. Third, despite the growing literature on herding in developed and emerging markets, empirical evidence from the Tehran Stock Exchange remains limited, and existing studies have mainly examined herding detection or the effects of economic and social shocks. It therefore remains unclear how, and to what extent, market returns and volatility explain investors' herding behavior across different levels of the herding distribution. By applying a quantile regression framework to the Tehran Stock Exchange, the present study seeks to fill this gap and provide new evidence on the heterogeneous relationship among market returns, volatility, and herding behavior.

4. Research Model and Methodology

To evaluate herding behavior, Christie and Huang (1995) and Chang et al. (2000) employed a modeling framework based on the cross-sectional dispersion of stock returns. The approaches adopted in both studies are founded on the premise that, in the presence of herding behavior, individual stock returns tend to converge toward the overall market return. Consequently, herding behavior reduces the divergence between individual stock returns and the market portfolio return. This convergence can be measured using the Cross-Sectional Standard Deviation (CSSD) and the Cross-Sectional Absolute Deviation (CSAD). The CSSD measure is calculated as follows:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N} \left(R_{i,t} - R_{m,t}\right)^2}{N-1}} \quad (1)$$

where $R_{i,t}$denotes the daily return of stock i at time t, and $R_{m,t}$ represents the market portfolio return at time t. In this study, the Tehran Stock Exchange (TSE) Total Index is used as a proxy for the market return. Daily returns are computed using the following logarithmic return formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \times 100 \quad (2)$$

where $P_t$and P_{t-1}represent the index values at times $t$and $t-1$, respectively.

The CSSD model measures the dispersion of stock returns during periods of extreme market movements. When investors follow the overall market trend and behave in line with the majority of market participants, return dispersion is expected to decline. In highly volatile periods, investors may ignore their private information and individual valuation signals and instead rely on collective market behavior. Following Chang et al. (2000), herding behavior can be examined using the following specification:

$$CSSD_t = \alpha + \beta_1 D_t^U + \beta_2 D_t^L + \varepsilon_t \quad (3)$$

where $D_t^U$and $D_t^L$are dummy variables representing the upper and lower tails of the market return distribution, respectively. Herding behavior is indicated by negative and statistically significant estimates of $\beta_1$and β_2. Such results imply that return dispersion decreases during extreme upward or downward market movements. Conversely, positive coefficients suggest the absence of herding behavior. Due to several limitations of the CSSD framework, including its reliance on extreme market conditions and its inability to adequately capture herding behavior during relatively stable periods, this study employs the CSAD model. The CSAD framework extends the CSSD approach by incorporating the cross-sectional absolute deviation of returns, which is defined as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} \mid R_{i,t} - R_{m,t} \mid \quad (4)$$

where $R_{i,t}$denotes the return of stock $i$at time t, and $R_{m,t}$represents the market return. The CSAD measure provides a more general alternative to CSSD. By using absolute deviations rather than squared deviations, it reduces sensitivity to extreme observations and outliers. Moreover, the model accommodates potential nonlinearities in the relationship between return dispersion and market returns. The CSAD framework is conceptually rooted in the Capital Asset Pricing Model (CAPM), which

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assumes a linear relationship between individual stock returns and the market portfolio return (Sharpe, 1964). Following Bekiros et al. (2017), the CSAD model can be expressed as:

$$CSAD_t = \alpha + \gamma_1 \mid R_{m,t} \mid + \gamma_2 R_{m,t}^2 + \varepsilon_t \quad (5)$$

where $CSAD_t$measures the cross-sectional dispersion of stock returns and serves as the primary indicator of herding behavior. A nonlinear decline in CSAD following large market movements is interpreted as evidence of behavioral convergence among investors and, consequently, the existence of herding behavior. In this specification, $R_{m,t}$ denotes the market return calculated from the TSE Total Index, $\mid R_{m,t} \mid$represents the absolute market return, and $R_{m,t}^2$captures the nonlinear effect of market returns. The coefficient $\gamma_2$plays a crucial role in identifying herding behavior (Gebka & Wohar, 2013). A negative and statistically significant estimate of $\gamma_2$indicates the presence of herding behavior, implying that investors increasingly align their decisions with the market consensus during periods of substantial market movements (Bekiros et al., 2017). Although the original CSAD framework introduced by Chang et al. (2000) provides an effective approach for identifying herding behavior through the nonlinear relationship between market returns and return dispersion, it does not explicitly account for the role of market uncertainty. Therefore, the present study extends the baseline CSAD specification by incorporating volatility measures to examine whether different volatility environments provide additional information regarding the intensity of herding behavior. The extended specification is not intended to replace the original model but rather to capture the state-dependent nature of herding behavior under different market conditions. To evaluate whether the inclusion of volatility terms provides additional explanatory power beyond the original CSAD specification, a joint significance test of the volatility coefficients was conducted. Specifically, the null hypothesis $H_0: \beta_3 = \beta_4 = 0$was tested against the alternative hypothesis that volatility terms jointly contribute to explaining cross-sectional return dispersion. Rejection of the null hypothesis indicates that the extended model provides additional information beyond the original Chang et al. (2000) framework and supports the inclusion of volatility measures in analyzing the state-dependent nature of herding behavior.

Using the CSAD framework, herding behavior can be examined over the entire sample period, including both highly volatile and relatively tranquil market conditions. The nonlinear component of herding is captured by the coefficient γ_2. Specifically, as market participants increasingly converge toward the market consensus, cross-sectional return dispersion declines below its rational benchmark level. This phenomenon is reflected in a negative and statistically significant value of γ_2. Conversely, a positive and statistically significant value of $\gamma_2$indicates the presence of adverse or reverse herding. In such circumstances, investors do not follow the market consensus and instead disregard information conveyed by broad market price movements. As a result, they engage in excessive trading of a subset of assets, leading to an abnormal increase in cross-sectional return dispersion. Reverse herding is therefore identified by a positive and statistically significant estimate of γ_2(Klein, 2013).

Based on the existing theoretical foundations, the role of market returns and volatility in shaping herding behavior is not expected to be uniform across different market conditions. Under normal circumstances, investors generally have greater opportunities to process information and make independent investment decisions. However, during extreme market conditions—such as periods of exceptionally high returns, sharp market declines, or elevated volatility—psychological and informational pressures intensify, increasing the likelihood of investors following the behavior of the crowd. Consequently, the relationship between market returns, volatility, and herding behavior is inherently nonlinear and asymmetric. From this perspective, the application of Quantile Regression (QR) is theoretically well justified. Conventional mean-based approaches such as Ordinary Least Squares (OLS) only capture the average effect of market returns and volatility on herding behavior. However, herding is a state-dependent phenomenon, and its intensity may vary substantially across the

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lower, middle, and upper tails of the CSAD distribution. Quantile regression enables the effects of market returns and volatility to be examined across different levels of herding intensity and provides a more comprehensive understanding of whether these relationships differ between tranquil and turbulent market conditions.

Accordingly, the theoretical framework of this study assumes that abnormal market returns and heightened market volatility may contribute to the emergence and intensification of herding behavior by increasing uncertainty, strengthening informational cascades, constraining arbitrage opportunities, and amplifying behavioral responses among investors. To investigate these relationships, this study employs the Quantile Regression (QR) estimator developed by Koenker and Bassett (1978). Quantile regression provides a more comprehensive representation of the conditional distribution of the dependent variable and overcomes several limitations associated with OLS estimation (Barnes & Hughes, 2002; Zhou & Anderson, 2013). Unlike mean-based estimators, QR models the response of the dependent variable at different conditional quantiles, denoted by τ, making it particularly suitable for analyzing non-normal distributions and heterogeneous relationships across the distribution (Alexander, 2008; Allen et al., 2013; Xiao, 2012). Furthermore, this approach allows researchers to examine whether the effects of explanatory variables differ across various quantiles. The general form of the linear quantile regression model is given by:

$$y_i = \theta X_i + \varepsilon_i \quad (6)$$

where $y_i$is the dependent variable, $X_i$denotes the vector of explanatory variables, θrepresents the parameter vector, and $\varepsilon_i$is the error term. Given θ_τ^*, the τ-th conditional quantile function of $y_i$can be expressed as:

$$Q_Y(\tau \mid X) = \theta_\tau^* X^T$$

The quantile regression estimator is obtained by minimizing a weighted sum of absolute residuals:

$$\hat{\theta}(\tau) = \min_{\theta}\left[\sum_{\{i|y_i \geq X_i\theta\}} \tau|y_i - X_i\theta| + \sum_{\{i|y_i < X_i\theta\}}(1-\tau)|y_i - X_i\theta|\right] \quad (7)$$

The minimization problem in Equation (7) can be solved using linear programming techniques. In quantile regression, the median regression ($\tau = 0.5$) is obtained by minimizing a symmetrically weighted sum of absolute residuals, whereas other quantiles are estimated through asymmetric weighting schemes whose weights vary according to the quantile under consideration.

This study employs the standard quantile regression estimator proposed by Koenker and Bassett (1978), which differs from the censored quantile regression approaches introduced by Buchinsky and Hahn (1998) and Zhang and Zhu (2013). The QR framework enables the relationship between market returns, volatility, and herding behavior to be examined across the entire conditional distribution of CSAD, ranging from the 0.05 quantile to the 0.95 quantile.

Accordingly, the quantile regression specifications used to examine the effects of market returns and volatility on herding behavior are defined as follows:

$$Q_\tau(CSAD_t) = \alpha_\tau + \beta_{1,\tau} \mid R_{m,t} \mid + \beta_{2,\tau} R_{m,t}^2 + \beta_{3,\tau} \mid V_{m,t} \mid + \beta_{4,\tau} V_{m,t}^2 \quad (8)$$

$$Q_\tau(CSAD_t) = \alpha_\tau + \beta_{1,\tau} \mid R_{m,t} \mid + \beta_{2,\tau} R_{m,t}^2 + \beta_{3,\tau} \mid V_{50,t} \mid + \beta_{4,\tau} V_{50,t}^2 \quad (9)$$

In Equations (8) and (9), $Q_\tau(CSAD_t)$denotes the τ-th conditional quantile of the CSAD measure, which serves as the proxy for herding behavior. $R_{m,t}$represents the market return at time t, $\mid R_{m,t} \mid$is the absolute market return, and $R_{m,t}^2$captures the nonlinear effect of market returns. The variables $V_{m,t}$and $V_{50,t}$represent the volatility of the TSE Overall Index and the TSE Top 50 Active Companies Index,

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respectively. Market volatility is measured using the rolling standard deviation of returns. The volatility of the overall market index is calculated as follows:

$$V_{m,t} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(R_{m,t-i} - \bar{R}_m\right)^2} \quad (10)$$

where $V_{m,t}$denotes market volatility at time t, $R_{m,t-i}$represents lagged market returns, $\bar{R}_m$is the mean market return within the rolling estimation window, and $n$denotes the number of observations used to compute volatility[1]. Similarly, the volatility of the Top 50 Active Companies Index $(V_{50,t})$is calculated using the rolling standard deviation of its returns. The inclusion of both linear and nonlinear return and volatility terms is motivated by the premise that investor responses to market conditions are unlikely to be purely linear. Herding behavior tends to emerge more strongly during periods of extreme returns and heightened market volatility. Therefore, the existence of nonlinear relationships between market conditions and herding behavior is evaluated through the coefficients $\beta_{2,\tau}$and $\beta_{4,\tau}$.

Based on the theoretical foundations of herding behavior, investors are expected to place greater weight on the actions of other market participants and rely less on their private information during periods of extreme market returns and heightened volatility. Consequently, the nonlinear return and volatility coefficients, namely $\beta_{2,\tau}$and $\beta_{4,\tau}$, are expected to be statistically significant across different quantiles of the CSAD distribution. Negative and statistically significant coefficients indicate a reduction in the cross-sectional dispersion of returns and, therefore, stronger herding behavior. In contrast, positive coefficients suggest greater heterogeneity in investors' decisions and a weakening of herding tendencies. The quantile regression framework allows these relationships to be examined simultaneously across different market conditions and varying levels of herding intensity. Within this framework, the coefficients $\beta_{3,\tau}$and $\beta_{4,\tau}$capture the linear and nonlinear effects of market volatility on the CSAD measure, respectively. The statistical significance of these coefficients indicates the existence of a relationship between market volatility and herding behavior, while their signs determine the direction of this relationship. Specifically, a negative and statistically significant coefficient for $\beta_{4,\tau}$ indicates that the positive association between volatility and return dispersion diminishes at higher levels of market uncertainty. This suggests that under extremely volatile market conditions, individual stock returns tend to converge more closely relative to periods of normal volatility. Such convergence may be consistent with increased reliance on common market signals and collective behavior among investors; however, it may also reflect the effect of market-wide information shocks that simultaneously influence individual stocks. (Bekiros et al., 2017; Bikhchandani et al., 1992)

Specifically, a negative and statistically significant coefficient for $\beta_{4,\tau}$implies that increasing market volatility reduces the cross-sectional dispersion of returns, suggesting that investors increasingly align their decisions with the prevailing market consensus rather than relying on firm-specific information. Conversely, a positive and statistically significant value of $\beta_{4,\tau}$suggests an increase in return dispersion and a decline in behavioral convergence among investors, thereby indicating a weakening of herding behavior in the market.

Table 1. Definition of Variables

Variable	Description
CSADtotal	Cross-Sectional Absolute Deviation of Returns for the TEPIX (Total Market Index)
CSAD50	Cross-Sectional Absolute Deviation of Returns for the Top 50 Most Active Companies Index
Rtotal	Return of the TEPIX (Total Market Index)
R50	Return of the Top 50 Most Active Companies Index

[1] n this study, market volatility is measured as the rolling standard deviation of daily returns calculated over a 20-trading-day window. Accordingly, n = 20 is used in the volatility estimation.

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Variable	Description
Vtotal	Volatility of the TEPIX Return
V50	Volatility of the Return of the Top 50 Most Active Companies Index

5. Empirical Results

5.1. Descriptive Statistics

The variables employed in this study include the cross-sectional absolute deviation of returns for the TEPIX (CSADtotal), the cross-sectional absolute deviation of returns for the Top 50 Most Active Companies Index (CSAD50), market returns for both indices (Rtotal and R50), and their corresponding return volatilities (Vtotal and V50). The analysis is based on daily time-series data covering the period from March 2015 to March 2021. Descriptive statistics for all variables are reported in Table 2.

Table 2. Descriptive Statistics of the Variables

Statistic	CSADtotal	Rtotal	Vtotal	CSAD50	R50	V50
Mean	1.6642	0.2495	0.8637	1.4318	0.2472	0.9092
Median	1.5029	0.0647	0.5968	1.2229	0.0726	0.4623
Maximum	10.0682	6.9685	2.7551	19.6868	8.1136	7.6930
Minimum	0.0000	-4.8277	0.0999	0.0000	-5.6717	0.0000
Standard Deviation	0.8333	1.2204	0.6840	1.0986	1.3173	1.1291
Skewness	2.3140	0.5796	1.0318	5.5114	0.4955	2.2419
Kurtosis	15.4465	6.6110	2.9304	70.4307	6.7923	9.0085

Source: Authors' calculations.

Table 2 presents the descriptive statistics of the variables employed in the empirical analysis. The average values of the cross-sectional absolute deviation of returns (CSAD) are 1.6642 for the TEPIX Total Market Index and 1.4318 for the Top 50 Most Active Companies Index. These values indicate a considerable degree of return dispersion around the market return during the sample period, suggesting that individual stock returns did not always move proportionally with overall market movements. In addition, the median values are lower than the corresponding means for both indices, implying that the distributions are affected by episodes of unusually high return dispersion. Such episodes may reflect periods of substantial market uncertainty, changes in investor expectations, and heterogeneous responses to new information.

A comparison between the two indices reveals that the Top 50 Most Active Companies Index experienced greater extreme fluctuations in return dispersion than the overall market index. Specifically, the maximum value of CSAD50 reached 19.6868, compared with 10.0682 for CSADtotal. This finding suggests that, despite representing larger and more actively traded firms, the stocks included in the Top 50 index experienced substantial divergence in investor responses during certain periods. Such behavior may be related to differences in firm-specific information, sensitivity to market developments, and variations in investors' perceptions regarding large-cap stocks.

Regarding market returns, the average daily returns of the TEPIX and the Top 50 Most Active Companies Index were 0.2495% and 0.2472%, respectively, indicating an overall positive performance of the Iranian stock market during the sample period. However, the relatively high standard deviations of returns compared with their average values (1.2204 for TEPIX and 1.3173 for the Top 50 Index) demonstrate considerable fluctuations in stock prices and confirm the presence of substantial uncertainty and risk in the market. The slightly higher volatility of returns in the Top 50 Index suggests that actively traded large-cap stocks were also exposed to significant market fluctuations.

The volatility measures, calculated as the rolling standard deviation of daily returns, are positive by construction. The average volatility of the Top 50 Most Active Companies Index (0.9092) is slightly higher than that of the TEPIX (0.8637), indicating a greater degree of return variability among the most

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actively traded firms. Furthermore, the higher standard deviation of V50 (1.1291) compared with Vtotal (0.6840) suggests that volatility fluctuations were more pronounced within the Top 50 segment of the market. This pattern may reflect the greater sensitivity of actively traded stocks to market news, macroeconomic developments, and changes in investor sentiment. The distributional characteristics provide additional insights into the behavior of the variables. All variables exhibit positive skewness, indicating a greater probability of observing extreme positive values. In particular, the skewness coefficients of CSAD50 (5.5114) and CSADtotal (2.3140) reveal a pronounced right-skewed distribution, suggesting that periods of exceptionally high return dispersion occurred occasionally during the sample period. These extreme observations are consistent with episodes of heightened uncertainty and substantial changes in market conditions. Moreover, the kurtosis values of CSAD50 (70.4307) and CSADtotal (15.4465) are considerably higher than the benchmark value of three, indicating heavy-tailed distributions and the presence of extreme observations in return dispersion. In contrast, the kurtosis of Vtotal (2.9304) is close to the normal distribution benchmark, while V50 (9.0085) exhibits more pronounced extreme movements.

Overall, the descriptive statistics indicate that the Tehran Stock Exchange was characterized by considerable return dispersion, substantial market fluctuations, asymmetric distributions, and occasional extreme observations during the study period. These distributional features suggest that investor behavior varied significantly across different market conditions and provide justification for employing nonlinear and distribution-sensitive approaches, such as quantile regression, to examine the relationship between market returns, volatility, and herding behavior.

5.2. Stationarity Tests

To ensure the validity of the econometric estimations and avoid spurious regression problems, the stationarity properties of all variables were examined using the Augmented Dickey–Fuller (ADF) and Ng–Perron unit root tests. The results are reported in Table 3.

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Table 3. Unit Root Test Results

Panel A. Augmented Dickey–Fuller (ADF) Test

Variable	CSADtotal	Rtotal	Vtotal	CSAD50	R50	V50
ADF Statistic	-5.2365***	-14.1150***	-18.5225***	-7.7246***	-14.0740***	-18.2133***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)

Panel B. Ng–Perron Test

Statistic	CSADtotal	Rtotal	Vtotal	CSAD50	R50	V50
MZa	-7.3721	-27.3357	-10.7351	-10.1341	-27.0895	-11.8653
MZt	-1.8519	-11.6069	-2.3033	-2.2117	-11.5428	-2.4166
MSB	0.2512	0.0424	0.2145	0.2182	0.0426	0.2036
MPT	3.5785	0.1885	2.3368	2.5758	0.2031	2.1412
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)

Critical Values						
Significance Level	ADF	KPSS	MZa	MZt	MSB	MPT
1%	-3.435	0.739	-13.800	-2.580	0.174	3.578
5%	-2.863	0.463	-8.100	-1.980	0.233	3.170
10%	-2.567	0.347	-5.700	-1.620	0.275	4.450

Source: Authors' calculations.

The results of the ADF and Ng–Perron unit root tests are reported in Table 3. According to the ADF test, the calculated test statistics for all variables exceed the corresponding critical values in absolute terms at conventional significance levels, leading to the rejection of the null hypothesis of a unit root. Consequently, all variables are found to be stationary in levels. The findings of the Ng–Perron test further confirm these results. The values of the MZa, MZt, MSB, and MPT statistics consistently indicate that the null hypothesis of non-stationarity can be rejected for all variables included in the

analysis. The consistency between the ADF and Ng–Perron test outcomes strengthen the reliability of the stationarity assessment.

Overall, the empirical evidence suggests that the cross-sectional absolute deviation measures (CSAD), market return variables, and market volatility variables for both the TEPIX and the Top 50 Most Active Companies Index are stationary at level, implying an order of integration of I(0). The stationarity of all variables indicates that their statistical properties, including the mean and variance, remain stable over the sample period. From an econometric perspective, these findings imply that the estimated relationships are unlikely to suffer from spurious regression problems. Therefore, the necessary conditions for applying level-based econometric techniques, including the CSAD herding model and quantile regression framework, are satisfied, and the subsequent analysis can be conducted without differencing the data.

Before estimating the extended CSAD herding models, the potential multicollinearity problem among the explanatory variables was examined using the Variance Inflation Factor (VIF) test. Since the extended specification incorporates both linear and nonlinear transformations of market returns and volatility, including $|R_m|$, R_m^2, $|V_m|$, and V_m^2, some degree of correlation among these variables is theoretically expected. However, excessive multicollinearity may increase the variance of coefficient estimates and affect the reliability of statistical inference. Therefore, VIF statistics were calculated separately for the Total Market Index and the Top 50 Most Active Companies Index.

Table 4. Variance Inflation Factor (VIF)

	Total Market Index (TEPIX)		Top 50 Most Active Companies Index	
Variable	VIF	1/VIF	VIF	1/VIF
|Rm|	4.22	0.24	4.90	0.20
R_m^2	3.64	0.27	4.28	0.23
|Vm|	3.58	0.28	4.90	0.20
V_m^2	3.03	0.33	4.32	0.23
Mean VIF	3.62		4.60	

Source: Authors' calculations

As reported in Table 4, the mean VIF values are 3.62 for the Total Market Index and 4.60 for the Top 50 Most Active Companies Index. Furthermore, all individual VIF values remain well below the conventional threshold of 10, while the corresponding tolerance values ($1/VIF$) are above 0.20. These results indicate that multicollinearity is not a serious concern in the extended specification and that the estimated coefficients can be interpreted with reasonable confidence.

5.3. The role of market returns and volatility in shaping herding behavior

This section presents the empirical results of the herding behavior models. In the first step, the existence of herding behavior in the Iranian stock market is examined using the CSAD framework proposed by Chang et al. (2000). Subsequently, quantile regression models are estimated across different segments of the CSAD distribution to investigate the role of market returns and market volatility in shaping herding behavior. The use of quantile regression allows the effects of market returns and volatility to be assessed under varying market conditions, ranging from relatively tranquil periods to episodes characterized by intense herding behavior. The estimation results are reported separately for the Tehran Stock Exchange Total Market Index (TEDPIX) and the Top 50 Most Active Companies Index. Furthermore, given the inherently nonlinear nature of herding behavior, the analysis considers not only the linear effects of market returns and volatility but also their nonlinear components. This approach provides a more comprehensive understanding of how changes in market conditions influence investors' tendency to follow collective market behavior.

Table 5. The role of market returns and volatility in shaping herding behavior: TEPIX (Total Market Index)

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Model	α	β_1	β_2	β_3	β_4	Adj. R^2
OLS	1.078*	0.613*	-0.099*	0.380*	-0.026**	0.3815
	(35.93)	(10.96)	(-6.82)	(7.37)	(-2.18)	
	α_τ	$\beta_{1,\tau}$	$\beta_{2,\tau}$	$\beta_{3,\tau}$	$\beta_{4,\tau}$	
QR ($\tau = 0.01$)	0.482*	0.948	-0.210*	-0.780	0.029**	0.2283
	(14.69)	(15.54)	(-13.37)	(-1.42)	(2.33)	
QR ($\tau = 0.05$)	0.553*	0.856*	-0.192*	0.144*	-0.015	0.2587
	(21.47)	(17.87)	(-15.50)	(3.25)	(-1.45)	
QR ($\tau = 0.25$)	0.771*	0.824*	-0.180*	0.187*	-0.007	0.2955
	(37.28)	(21.39)	(-18.07)	(5.26)	(-0.87)	
QR ($\tau = 0.50$)	0.915*	0.767*	-0.157*	0.438*	-0.040*	0.3021
	(33.89)	(15.70)	(-12.46)	(9.71)	(-3.87)	
QR ($\tau = 0.75$)	1.177*	0.735*	-0.128*	0.506*	-0.038**	0.2728
	(28.17)	(9.45)	(-6.38)	(7.05)	(-2.27)	
QR ($\tau = 0.95$)	1.668*	0.722*	-0.019	0.912*	-0.121**	0.2591
	(14.00)	(3.26)	(-0.32)	(4.46)	(-2.59)	
QR ($\tau = 0.99$)	2.339*	1.460*	-0.118	1.253**	-0.193***	0.2956
	(7.75)	(2.71)	(-0.85)	(2.53)	(-1.70)	

Source: Authors' calculations. **Note:** $\beta_{1,\tau}$corresponds to $|R_{m,t}|$, $\beta_{2,\tau}$corresponds to $R^2_{m,t}$, $\beta_{3,\tau}$corresponds to $|V_{m,t}|$(or $|V_{50,t}|$in the Top 50 Index model), and $\beta_{4,\tau}$corresponds to $V^2_{m,t}$(or $V^2_{50,t}$in the Top 50 Index model). Values in parentheses are t-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The estimation results for the impact of market returns and market volatility on herding behavior in the Tehran Stock Exchange Total Market Index (TEDPIX) are reported in Table 5. Before discussing the empirical findings, it is important to note that the model employed in this study represents an extended version of the herding model originally proposed by Chang et al. (2000). In the original framework, herding behavior is identified through the nonlinear relationship between the Cross-Sectional Absolute Deviation of returns (CSAD) and market returns. The baseline specification is expressed as:

$$SAD_t = \alpha + \beta_1|R_{m,t}| + \beta_2(R_{m,t})^2 + \varepsilon_t$$

In this framework, the coefficient (β_2) serves as the primary indicator of herding behavior. According to the approach developed by Chang et al. (2000), when herding behavior exists, investors tend to follow the collective behavior of the market rather than rely on their own information and private assessments during periods of substantial market fluctuations. Consequently, the cross-sectional dispersion of returns increases less than would normally be expected. Therefore, a negative and statistically significant value of (β_2) provides evidence of herding behavior. In contrast, a positive and significant coefficient indicates the presence of adverse herding or behavioral divergence among investors. Given that the primary objective of this study is to investigate the role and impact of market returns and market volatility on herding behavior, the original model of Chang et al. (2000) is extended by incorporating both linear and nonlinear measures of market volatility. The final empirical specification employed in this study is given by:

$$CSAD_t = \alpha + \beta_1 | R_{m,t} | + \beta_2 R^2_{m,t} + \beta_3 | V_{m,t} | + \beta_4 V^2_{m,t} + \varepsilon_t$$

In this specification, (β_1) and (β_2) capture the linear and nonlinear effects of market returns, respectively, whereas (β_3) and (β_4) measure the linear and nonlinear effects of market volatility. Within this framework, (β_2) remains the principal indicator of herding behavior, while (β_3) and (β_4) reveal how market volatility may strengthen or weaken herding tendencies. Since the intensity of herding behavior may vary across different market conditions, the analysis employs both Ordinary Least Squares (OLS) and Quantile Regression (QR). In the quantile framework, the coefficients $\beta_{2,\tau}$, $\beta_{3,\tau}$, and $\beta_{4,\tau}$ capture the existence of herding behavior and the effects of market returns and market volatility across different segments of the conditional distribution of CSAD.

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The OLS estimation results indicate that the coefficient associated with the nonlinear market return term ($\beta_2 = -0.099$) is negative and statistically significant at the 1% level. According to the criterion proposed by Chang et al. (2000), this finding provides evidence of herding behavior in the Tehran Stock Exchange Total Market Index over the sample period. In other words, as market return fluctuations intensify, the cross-sectional dispersion of stock returns increases less than would normally be expected, suggesting that investors tend to align their decisions with the overall direction of the market. This result implies that a considerable proportion of market participants in the Iranian stock market follow the collective behavior of other investors rather than relying solely on their own information and independent analyses. In addition, the joint significance of the volatility terms was examined using a Wald test. The null hypothesis that the volatility coefficients are jointly equal to zero ($H_0: \beta_3 = \beta_4 = 0$) was rejected (Wald statistic = 22.14, p-value < 0.001). This result confirms that the inclusion of volatility measures significantly improves the explanatory power of the extended CSAD model relative to the original specification of Chang et al. (2000). Therefore, market volatility provides additional information regarding the variation in return dispersion and the intensity of herding behavior beyond the nonlinear effects of market returns alone. Furthermore, the coefficient of the linear market return term ($\beta_1 = 0.613$), is positive and statistically significant, indicating that an increase in market returns initially leads to a rise in the cross-sectional dispersion of stock returns. However, the negative and significant coefficient of the squared return term demonstrates that this relationship is inherently nonlinear. At higher levels of market returns, the growth in return dispersion gradually slows and eventually declines. This pattern is fully consistent with the herding literature, where investor behavior becomes increasingly synchronized during periods of extreme market movements. The results also reveal an important role for market volatility in shaping investor behavior. The coefficient of the linear volatility term ($\beta_3 = 0.380$), is positive and statistically significant, suggesting that a moderate increase in market volatility is initially associated with greater cross-sectional return dispersion. This finding implies that, during the early stages of rising uncertainty, investors react differently to incoming information, resulting in a more heterogeneous set of market expectations and trading decisions. Nevertheless, the coefficient of the nonlinear volatility term (β□=-0.026) is negative and statistically significant, indicating that the positive relationship between volatility and cross-sectional return dispersion weakens at higher levels of market uncertainty. This suggests that during highly volatile periods, individual stock returns tend to exhibit greater convergence relative to normal volatility conditions. Such convergence is consistent with the possibility that investors rely more heavily on common market signals under stressed conditions; however, it may also reflect the influence of market-wide shocks affecting individual stocks simultaneously. From a behavioral finance perspective, this finding is consistent with the information cascade framework, which suggests that uncertainty may increase investors' reliance on observed market behavior. However, the observed reduction in return dispersion may also partly reflect the effect of common market-wide shocks during stressed periods. Under highly uncertain conditions, investors become more inclined to rely on the observed actions of other market participants rather than on their own private information and independent judgment.

The quantile regression results provide a more nuanced picture of this phenomenon. The coefficient of the squared market return term ($\beta_{2,\tau}$), is negative and statistically significant at the 1% level for the 0.01, 0.05, 0.25, 0.50, and 0.75 quantiles. This finding indicates that herding behavior exists across a substantial portion of the conditional distribution of CSAD and is not confined to specific market conditions. However, the absolute magnitude of the coefficient declines from -0.210 at the 0.01 quantile to -0.128 at the 0.75 quantile, suggesting a gradual weakening of herding intensity as the cross-sectional dispersion of returns increases. In other words, when the market exhibits a higher degree of consensus, investors are more likely to follow the behavior of other market participants. As

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heterogeneity in expectations and differences in the interpretation of information increase, the strength of herding behavior diminishes.

An important observation is that in the two upper-tail quantiles (0.95 and 0.99), although the coefficient of the squared return term remains negative, it is no longer statistically significant. This result suggests that under extremely turbulent market conditions, when return dispersion reaches its highest levels, investor behavior departs from the herding pattern and becomes increasingly driven by firm-specific information, heterogeneous expectations, and differing interpretations of market conditions. Therefore, the empirical evidence indicates that herding behavior in the Tehran Stock Exchange is primarily a phenomenon associated with normal and moderately stressed market conditions, while its explanatory power weakens during periods of extreme volatility and dispersion. With respect to market returns, the coefficient of the linear return term ($\beta_{1,\tau}$), is positive and statistically significant across all quantiles. This finding indicates that higher market returns are associated with greater cross-sectional dispersion of stock returns. Nevertheless, the negative coefficient of the squared return term across most quantiles confirms that this relationship is nonlinear. At higher levels of market returns, the rate of increase in return dispersion slows, and investors gradually move toward more collective patterns of behavior.

The analysis of market volatility also reveals several noteworthy findings. In the OLS specification, the coefficient of the linear volatility term ($\beta_{3,\tau}$), is positive and statistically significant, whereas the coefficient of the nonlinear volatility term ($\beta_{4,\tau}$), is negative and statistically significant. This result implies that although an initial increase in volatility leads to greater return dispersion, at higher levels of volatility investors gradually exhibit more similar behavioral patterns, resulting in a decline in cross-sectional return dispersion. Consequently, severe market volatility can create conditions associated with stronger behavioral convergence among investors.

The quantile regression estimates further indicate that the impact of volatility is not uniform across the distribution of herding behavior. At the lowest quantile of the distribution (τ=0.01), the coefficient of the nonlinear volatility term is positive and statistically significant, suggesting that under relatively calm market conditions, higher volatility increases return dispersion and reduces behavioral convergence among investors. However, moving toward the middle and upper quantiles, the sign of the coefficient changes, becoming negative and statistically significant from the 0.50 quantile onward. Moreover, the absolute magnitude of the coefficient increases across higher quantiles, reaching -0.193 at the 0.99 quantile. This finding indicates that when the market is characterized by higher levels of dispersion and uncertainty, severe volatility is associated with greater convergence in investors' decisions. Although this pattern is consistent with stronger collective behavior, it may also reflect the impact of common market-wide information or shocks affecting individual stocks simultaneously.

Overall, the results reported in Table 4 demonstrate the presence of herding behavior in the Tehran Stock Exchange Total Market Index. However, the intensity of this behavior varies across different segments of the market behavior distribution. Furthermore, the effect of market volatility on herding behavior is both nonlinear and asymmetric. While volatility under tranquil market conditions does not necessarily intensify herding behavior, during periods characterized by heightened uncertainty and elevated dispersion, it plays a significant role in reinforcing imitative behavior and promoting convergence in investors' decisions.

However, the quantile regression results indicate that the relationship between market returns, market volatility, and herding behavior is not uniform across the entire distribution of CSAD. The coefficient of the squared market return term ($\beta_{2,\tau}$), is negative and statistically significant at the 1% level across all quantiles from (τ = 0.01) to (τ = 0.75), providing robust evidence of herding behavior. This finding suggests that herding is not confined to normal market conditions but is present throughout a substantial portion of the distribution of market behavior. Nevertheless, the intensity of herding varies

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across quantiles. The magnitude of the coefficient declines from -0.210 at the 0.01 quantile to -0.128 at the 0.75 quantile, indicating that herding behavior is stronger at low and moderate levels of return dispersion than at higher levels of dispersion. In the two upper-tail quantiles, namely (τ = 0.95) and (τ = 0.99), although the coefficient of $\beta_{2,\tau}$, remains negative, it is no longer statistically significant. This result suggests that at the highest levels of return dispersion, there is insufficient evidence to support the existence of herding behavior. In other words, when the market is exposed to extremely unusual or turbulent conditions, investors tend to exhibit more heterogeneous behavior, and the degree of reliance on collective market actions diminishes. This finding is consistent with the results reported by Bekiros et al. (2017) and Klein (2013), who argue that herding behavior is not necessarily persistent across all crisis conditions and may give way to heterogeneous investor responses under extreme levels of uncertainty.

Regarding the effect of market volatility, the quantile regression results also reveal an interesting pattern. The coefficient of the linear volatility term ($\beta_{3,\tau}$), is positive and statistically significant across most quantiles, increasing from 0.144 at the 0.05 quantile to 1.253 at the 0.99 quantile. This finding indicates that the direct effect of volatility on return dispersion becomes substantially stronger in the upper segments of the CSAD distribution. Put differently, when the market experiences greater dispersion and uncertainty, volatility plays a more prominent role in explaining investor behavior.

On the other hand, the coefficient of the nonlinear volatility term ($\beta_{4,\tau}$), is negative and statistically significant at the 0.50, 0.75, 0.95, and 0.99 quantiles, whereas it is statistically insignificant at the lower quantiles. This result suggests that the herding-enhancing effect of market volatility emerges primarily at moderate and high levels of market dispersion. In other words, once the market enters a period of heightened stress, further increases in volatility lead to greater convergence in investors' decisions and a stronger tendency toward herding behavior. Therefore, market volatility is not only an important determinant of herding behavior, but its effect is also heterogeneous and conditional upon the level of return dispersion prevailing in the market.

Overall, the results reported in Table 4 indicate that herding behavior exists throughout a substantial portion of the CSAD distribution in the Tehran Stock Exchange Total Market Index. Moreover, market volatility—particularly at moderate and high levels of return dispersion—plays a significant role in shaping the degree of return convergence among investors. These findings suggest that rising uncertainty and market volatility can contribute to stronger collective behavior in the Iranian stock market by increasing investors' reliance on common market signals and information cascades. The results are also consistent with the findings of Bekiros et al. (2017), Chaffai and Medhioub (2018), and Lakshminarayana et al. (2026), all of whom report that heightened uncertainty and market volatility can encourage investors to follow collective market behavior rather than rely on their own independent assessments.

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Table 6. The role of market returns and volatility in shaping herding behavior: Top 50 Most Active Companies Index

Model	α	β_1	β_2	β_3	β_4	Adj. R^2
OLS	0.852*	0.513*	-0.077*	0.425*	-0.041*	0.1994
	(19.14)	(6.70)	(-4.26)	(6.24)	(-2.91)	
	α_τ	$\beta_{1,\tau}$	$\beta_{2,\tau}$	$\beta_{3,\tau}$	$\beta_{4,\tau}$	
QR (τ = 0.01)	0.189*	0.633*	-0.135*	0.074	-0.006	0.1752
	(4.54)	(8.86)	(-7.99)	(1.16)	(-0.45)	
QR (τ = 0.05)	0.295*	0.757*	-0.162*	0.026	0.007	0.1990
	(13.19)	(19.72)	(-17.86)	(0.74)	(0.93)	
QR (τ = 0.25)	0.439*	0.819*	-0.169*	0.190*	-0.018***	0.2344
	(19.65)	(21.33)	(-18.65)	(5.56)	(-2.55)	
QR (τ = 0.50)	0.591*	0.889*	-0.177*	0.379*	-0.047*	0.2369
	(20.56)	(18.00)	(-15.12)	(8.62)	(-5.28)	

Model	α	β_1	β_2	β_3	β_4	Adj. R^2
QR ($\tau = 0.75$)	0.940*	0.720*	-0.115*	0.480*	-0.0388*	0.2148
	(22.08)	(9.84)	(-6.63)	(7.73)	(-2.95)	
QR ($\tau = 0.95$)	1.639*	0.594	-0.058	0.737*	-0.047	0.1285
	(10.40)	(2.12)	(-0.87)	(2.96)	(-0.93)	
QR ($\tau = 0.99$)	3.544*	1.585	-0.415	1.333	0.104	0.0752
	(4.33)	(1.10)	(-1.42)	(1.05)	(0.40)	

Source: Authors' calculations. Notes: Values in parentheses are t-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The results concerning the impact of market returns and market volatility on herding behavior in the Top 50 Active Companies Index of the Tehran Stock Exchange are presented in Table 6. As discussed earlier, the primary criterion for identifying herding behavior in this study is the coefficient of the nonlinear market return term (β_2), where a negative and statistically significant coefficient indicates the existence of herding behavior and convergence in investors' decisions. In addition, the coefficients β_3 and β_4 capture the linear and nonlinear effects of market volatility on the intensity of herding behavior, respectively.

The OLS estimation results show that β_2=-0.077 and is statistically significant at the 1% level. Therefore, the hypothesis of herding behavior in the Top 50 Active Companies Index is supported. This finding suggests that investors trading the shares of large and influential firms tend to follow the general direction of the market rather than rely solely on their own information and independent analysis when responding to changes in market returns. Although herding behavior is confirmed in this index, as in the Total Market Index, the magnitude of the coefficient suggests that the intensity of herding is somewhat weaker in the Top 50 Active Companies Index. Specifically, β_2=-0.099 for the Total Market Index, whereas, β_2=-0.077for the Top 50 Active Companies Index. This result may indicate that the shares of larger firms are less susceptible to imitative behavior because of greater information transparency, broader analyst coverage, and higher levels of liquidity.

The coefficient of the linear market return term (β_1=0.513), is also positive and statistically significant, indicating that under normal market conditions, an increase in market returns is associated with a rise in the cross-sectional dispersion of stock returns. However, the negative sign of β_2 suggests that this relationship reverses at higher levels of market returns, leading investors to move toward collective market behavior. This finding is consistent with the theoretical predictions of the model proposed by Chang et al. (2000) as well as the theoretical foundations of information cascades.

With regard to market volatility, the OLS results indicate that the coefficient of the linear volatility term ($\beta_3 = 0.425$), is positive and statistically significant, whereas the coefficient of the nonlinear volatility term ($\beta_4 = -0.041$), is negative and statistically significant. This result suggests that during the initial stages of rising volatility, investor responses are heterogeneous and return dispersion increases. However, as volatility intensifies and uncertainty rises, investors' decisions become more synchronized, resulting in greater convergence in stock returns. In other words, severe market volatility plays an important role in increasing return convergence among large-cap stocks, which may be consistent with stronger collective behavior. Furthermore, since the absolute value of β_4 is larger for the Top 50 Active Companies Index than for the Total Market Index, it can be inferred that herding behavior among large firms is more sensitive to episodes of extreme market volatility.

The quantile regression results also provide important evidence of heterogeneity in investor behavior across different segments of the CSAD distribution. An examination of the coefficient $\beta_{2,\tau}$ reveals that it is negative and statistically significant at the 1% level across all quantiles from τ =0.01 to $\tau = 0.75$. Therefore, herding behavior is present throughout a substantial portion of the distribution of market behavior. The magnitude of $\beta_{2,\tau}$ increases from -0.135 at the 0.01 quantile to-0.177 at the 0.50 quantile

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and subsequently declines to -0.115 at the 0.75 quantile. This pattern indicates that the intensity of herding behavior is strongest in the middle segments of the CSAD distribution. In other words, when market conditions are relatively normal, investors exhibit the greatest tendency to follow the collective behavior of other market participants.

At the τ= 0.95 quantile, the coefficient $\beta_{2,\tau}$ remains negative but is no longer statistically significant. Similarly, at τ= 0.99 although the coefficient is relatively large (-0.415), it lacks statistical significance. This finding suggests that under the most extreme market conditions and at the highest levels of return dispersion, there is insufficient evidence to support the existence of herding behavior. Under such circumstances, investors respond more differently to new information, leading to greater behavioral heterogeneity. This result is consistent with the findings obtained for the Total Market Index and suggests that herding behavior is primarily observed under normal and moderately turbulent market conditions, while it tends to weaken during extremely adverse market episodes.

The coefficients associated with market volatility also reveal several noteworthy patterns. The coefficient of the linear volatility term ($\beta_{3,\tau}$), is statistically insignificant at the lower quantiles of τ=0.01 and $\tau = 0.05$, but becomes positive and statistically significant from $\tau = 0.25$ onward. Moreover, its magnitude increases progressively from 0.190 at the 0.25 quantile to 0.737 at the 0.95 quantile and 1.343 at the 0.99 quantile. This pattern indicates that as the market moves toward higher levels of dispersion and uncertainty, volatility becomes increasingly important in explaining investor behavior. On the other hand, the coefficient of the nonlinear volatility term ($\beta_{4,\tau}$), is negative and statistically significant at the 0.25, 0.50, and 0.75 quantiles. However, this convergence should not necessarily be interpreted as pure herding, as simultaneous reactions to common market shocks may also reduce return dispersion. The strongest volatility-induced herding effect is observed at the median quantile ($\tau = 0.50$), where $\beta_{4,\tau}$ = -0. 047. However, at the two upper-tail quantiles ($\tau = 0.95$) and ($\tau = 0.99$), the coefficient is no longer statistically significant. This finding indicates that under extremely turbulent market conditions, the influence of volatility on herding behavior weakens and investors exhibit more heterogeneous responses to market information.

Although the estimated coefficients are relatively small in magnitude, their economic interpretation should be considered within the CSAD framework, where the dependent variable represents return dispersion rather than asset returns themselves. The negative and significant nonlinear return coefficients indicate that, as market movements become stronger, the increase in return dispersion is lower than the level predicted by rational asset pricing behavior. Therefore, even relatively small reductions in CSAD can represent meaningful deviations from the benchmark relationship implied by the CAPM framework. Moreover, the persistence of negative and statistically significant coefficients across multiple quantiles suggests that the observed effect is systematic rather than driven by isolated observations.

Overall, the results reported in Table 5 indicate that herding behavior is widespread within the Top 50 Active Companies Index of the Tehran Stock Exchange and is evident across most segments of the CSAD distribution. Furthermore, market volatility plays a significant role in strengthening behavioral convergence among investors, particularly at moderate and relatively high levels of the herding distribution. A comparison of these findings with those obtained for the Total Market Index suggests that although the intensity of herding behavior is slightly weaker among large firms, its sensitivity to market volatility shocks is greater. Consequently, during periods of heightened uncertainty, investor behavior in large-cap stocks shifts more rapidly toward collective and imitative patterns.

These findings imply that even among the largest and most liquid firms in the Iranian stock market, severe volatility can create favorable conditions for the emergence of information cascades and the intensification of herding behavior. The results are also consistent with the findings of Xiang (2011)

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and Bekiros et al. (2017), supporting the view that herding behavior constitutes one of the major drivers of asset price bubbles and asymmetric deviations of market prices from their fundamental values.

6. Conclusion and Policy Implications

This study investigated the impact of market returns and market volatility on investor herding behavior in the Tehran Stock Exchange. To this end, daily stock market data covering the period from March 2015 to March 2021 were employed. Herding behavior was measured using the Cross-Sectional Absolute Deviation of returns (CSAD) within the theoretical framework proposed by Chang et al. (2000). To examine the role of market returns and volatility in the emergence and intensification of herding behavior, the baseline CSAD model was extended by incorporating both linear and nonlinear effects of market returns and market volatility. The estimations were conducted separately for the Tehran Stock Exchange Total Market Index and the Top 50 Active Companies Index. Furthermore, to capture potential heterogeneity in investor behavior under different market conditions, both Ordinary Least Squares (OLS) and Quantile Regression (QR) techniques were employed.

The OLS results indicate that the coefficient of the nonlinear market return term (β_2) is negative and statistically significant for both the Total Market Index and the Top 50 Active Companies Index. According to the criterion proposed by Chang et al. (2000), this finding confirms the existence of herding behavior in the Tehran Stock Exchange. In other words, during periods characterized by substantial market return fluctuations, the cross-sectional dispersion of stock returns increases less than would normally be expected, suggesting that investors become more inclined to align their decisions with the overall market direction. This result implies that a portion of investment decisions in the Iranian stock market is driven by the collective behavior of market participants rather than by independent information processing and individual analysis. For the Total Market Index, the estimated nonlinear return coefficient is β_2=-0.099, which is statistically significant. The quantile regression results further reveal that this coefficient remains negative and statistically significant across quantiles ranging from τ=0.01 to τ=0.75, while losing statistical significance at the upper-tail quantiles τ=0.95 and τ=0.99. Therefore, herding behavior in the Total Market Index is primarily observed in the lower, middle, and moderately high segments of the CSAD distribution but weakens under the most extreme levels of return dispersion. This finding suggests that investor responses are not necessarily convergent during highly turbulent market episodes. Instead, differences in expectations, private information, and heterogeneous interpretations of market conditions may lead to greater behavioral divergence.

Regarding the role of market volatility in the Total Market Index, the results indicate that the linear volatility coefficient is positive and statistically significant, whereas the nonlinear volatility coefficient is negative and statistically significant in the OLS model. These findings imply that an initial increase in market volatility leads to greater return dispersion; however, as volatility intensifies and uncertainty increases, the positive relationship between volatility and return dispersion weakens, resulting in greater convergence of individual stock returns. This convergence may reflect stronger reliance on common market signals, although the influence of market-wide shocks affecting individual stocks simultaneously cannot be ruled out. The quantile regression estimates further show that the nonlinear effect of volatility is negative and statistically significant primarily in the middle and upper quantiles. Accordingly, the influence of market volatility on return convergence and collective investor behavior in the Total Market Index is nonlinear and highly dependent on prevailing market conditions.

The results for the Top 50 Active Companies Index also provide clear evidence of herding behavior. The nonlinear market return coefficient estimated by OLS is β_2=-0.077, which is statistically significant and confirms the presence of herding among large and actively traded firms. Nevertheless, the intensity of herding appears to be somewhat weaker than that observed in the Total Market Index. This outcome may be attributed to the greater information transparency, higher liquidity, and broader analyst coverage typically associated with large firms. The quantile regression results similarly indicate

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that herding behavior remains significant across most quantiles, particularly between τ=0.01 and $\tau = 0.75$, while becoming weaker at the extreme upper-tail quantiles.

With respect to the effect of market volatility on herding behavior in the Top 50 Active Companies Index, the results reveal that the nonlinear volatility coefficient is negative and statistically significant in the OLS model. Furthermore, the quantile regression estimates show that this coefficient is negative and significant at the $\tau = 0.25, \tau = 0.50, and\ \tau = 0.75$ quantiles. These findings suggest that severe market volatility at moderate and relatively high levels of the CSAD distribution reduces cross-sectional return dispersion and increases behavioral convergence among investors. However, this convergence may reflect both stronger collective responses among investors and the effect of common market-wide shocks during turbulent periods. Therefore, even among large and highly liquid firms, periods of elevated volatility can create conditions that are consistent with stronger collective behavior and information cascades.

Overall, the findings demonstrate that herding behavior exists in the Tehran Stock Exchange, although its intensity varies across different market conditions. The nonlinear market return component provides strong evidence of herding behavior, while the effects of market volatility are conditional on the prevailing level of return dispersion. The quantile regression results further reveal that the influence of market returns and volatility is not uniform across the CSAD distribution, highlighting the state-dependent and heterogeneous nature of investor herding behavior. These results suggest that herding behavior in the Iranian stock market is inherently nonlinear, asymmetric, and state-dependent. From a policy perspective, the findings underscore the importance of enhancing information transparency, improving disclosure quality, strengthening financial analysis and research infrastructures, and promoting investor financial literacy. Reducing information asymmetry and increasing investors' ability to conduct independent analyses may help mitigate imitation-driven behavior and emotional overreactions during periods of heightened market volatility. In addition, regulatory authorities should closely monitor periods of excessive volatility and unusual trading activity, as such conditions may facilitate the emergence of information cascades and amplify collective investor behavior. Strengthening market surveillance mechanisms and expanding access to timely, accurate, and transparent information can contribute to more efficient price discovery and reduce the likelihood of herding-induced market distortions.

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