UNIVERSIDADE CATÓLICA PORTUGUESA

Evidence of Herding Behavior in PSI's Utilities Sector

From 2014 to 2024

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Católica Porto Business School
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Resumo

O presente estudo teve como objetivo identificar a presença de herding no setor das Utilities português entre 2014 e 2024, com foco no impacto de grandes eventos económicos e geopolíticos, como a pandemia de COVID-19 e a guerra na Ucrânia. Considerando que o herding tende a surgir em contextos de stress e incerteza nos mercados, este estudo procurou determinar se os investidores deste setor adotaram padrões de decisão coletiva durante esses períodos críticos. Assim, foi utilizado o método CSAD para detetar a presença de herding, medindo se os retornos das ações convergiam para o retorno médio do setor.

Embora a análise do período completo (2014-2024) não revele fortes evidências de herding, a presença significativa deste comportamento durante a pandemia sugere que os investidores do setor reagiram coletivamente face à elevada incerteza. No entanto, a ausência de herding durante a guerra na Ucrânia, aliada ao aumento da dispersão dos retornos, indica que os participantes do setor seguiram estratégias de investimento independentes. Estes resultados contribuem para a compreensão do comportamento dos investidores no setor das Utilities do PSI, reforçando a natureza dependente do contexto do herding na formação de decisões de investimento.

As conclusões sugerem que o herding não é uma resposta universal a crises, mas sim depende da natureza da própria crise e das características do setor, destacando a importância de distinguir herding racional e especulativo nos mercados financeiros. Esta investigação evidencia como a resiliência do sistema financeiro e as estratégias adotadas pelos investidores ajudaram a manter a estabilidade do setor durante o período estudado, oferecendo contributos relevantes para o entendimento das causas e nuances do comportamento de herding no setor das Utilities do PSI.

Palavras-Chave: Herding, psicologia, dispersão de retornos, comportamento em massa, PSI, setor das Utilities.

Abstract

The present study aimed to identify the presence of herding behavior in the Portuguese Utilities sector between 2014 and 2024, with focus on the impact of major economic and geopolitical events, such as the COVID-19 pandemic and the Ukraine war. Given that herding behavior often emerges in response to market stress and uncertainty, this study sought to determine whether investors in this sector exhibited collective decision-making patterns during these critical periods,

Therefore, the CSAD method was used to detect herding behavior, measuring whether stock returns converge towards the sector's return.

While the full-period analysis (2014-2024) does not provide strong evidence of herding, the presence of significant herding behavior during the COVID-19 pandemic suggests that Utilities' investors reacted collectively to heightened uncertainty. However, the absence of herding during the Ukraine war, combined with increased return dispersion, indicates that sector participants pursued independent investment strategies. These results contribute to the understanding of investor behavior in the PSI's Utilities sector by enhancing the context-dependent nature of herding in shaping investor behavior. The findings suggest that herding is not a universal response to crises but rather depends on the nature of the crises itself and sector, highlighting the importance of distinguishing rational from speculative herding in financial markets. This research exposes how the resilience of the financial system and the investors' trading strategies employed helped maintain sector stability during the studied period, providing valuable insights into the causes and nuances of herding behavior in the PSI's Utilities sector.

Keywords: Herding, psychology, return dispersion, mass behavior, PSI, Utilities sector.

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Glossary

ABSrm – Absolute Market Return: A measure of the absolute value of market return, often used in herding studies.

ADF – Augmented Dickey-Fuller Test: A statistical test used to check for stationarity in time series data.

AICEP – Agência para o Investimento e Comércio Externo de Portugal: Portugal's trade and investment agency.

CB – European Central Bank: The central bank responsible for monetary policy in the Eurozone.

CMVM – Comissão do Mercado de Valores Mobiliários: Portuguese Securities Market Commission, responsible for regulating financial markets.

CO2 – Carbon Dioxide: A greenhouse gas emitted through industrial and energy production activities.

CSAD – Cross-Sectional Absolute Deviation: An alternative to CSSD, capturing nonlinear patterns in return dispersion.

CSSD – Cross-Sectional Standard Deviation: A measure used to detect herding behavior by analyzing return dispersions.

EDP – Energias de Portugal: Leading Portuguese utility company involved in electricity generation, distribution, and supply.

EDPR – EDP Renováveis: Renewable energy subsidiary of EDP, specializing in wind and solar power.

EMH – Efficient Market Hypothesis

ERSE – Entidade Reguladora dos Serviços Energéticos: Portugal's energy regulatory authority.

ETF – Exchange-Traded Funds: Investment funds traded on stock exchanges, offering diversified exposure to various assets.

EU – European Union

FOMO – Fear of Missing Out: Psychological behavior in investing where individuals follow trends to avoid missing opportunities.

GALP – Galp Energia: Integrated energy company engaged in oil, gas, and renewable energy sectors.

GDP – Gross Domestic Product: The total monetary value of all goods and services produced in a country within a given period.

LSV – Lakonishok, Shleifer, and Vishny Measure: A measure of institutional herding behavior in financial markets.

OLS – Ordinary Least Squares: A statistical method for estimating relationships between variables in regression models.

PSI – Portuguese Stock Index: Benchmark stock index for Euronext Lisbon, tracking the performance of the largest Portuguese companies.

REN – Redes Energéticas Nacionais: Manages electricity and natural gas transmission networks in Portugal.

Rm – Market Return: The overall return of the market over a given period.

Rm^2 – Squared Market Return: The squared value of market return, used to test nonlinear effects in financial models.

TLTROs – Targeted Longer-Term Refinancing Operations: ECB programs aimed at providing low-interest loans to banks to stimulate lending.

UK – United Kingdom

US – United States

VIF – Variance Inflation Factor: A statistical measure used to detect multicollinearity in regression models.

Chapter 1
Introduction

1. Introduction

1.1. General Background

Human behavior has been continuously researched to understand investors' decision-making process, emerging key financial theories such as the Efficient Market Hypothesis. Fama (1965) defined an "efficient" market as one where prices fully reflect all available information and market participants are fully rational. However, inconsistencies regarding investor rationality and market anomalies were found in these assumptions. As a result, the behavioral finance theory later emerged, incorporating psychological factors into decision-making, embracing investor irrationality and market inefficiency (Sharma & Kumar, 2020). Barberis et al. (1998) provide a review of empirical and psychological studies, explaining the impact of psychological biases in financial decision-making.

Herding behavior emerges from these psychological factors, where investors abandon their personal judgment to mimic their counterparts' trading actions (Spyrou, 2013). Lux (1995) explains how psychological factors can cause blind conformity, exposing herding as a contagious feeling. Herding gained relevance in financial markets after the 1990's financial crises, being classified into rational and irrational herding.

Devenow & Welch (1996) described irrational herding as a set of behavior patterns that are correlated across individuals, caused by basic instincts: mimicry and imitation. Banerjee (1992) contributed to the rational perspective, suggesting that individuals make optimal decisions based on others' actions. Scharfstein & Stein (1990) developed a "learning" model based on rational perspectives, studying forces that cause herding. Herding studies have expanded to various fields, such as cryptocurrency markets (Kaur et al., 2024), digital platforms (Zhang et al., 2024) and geopolitical events, including the Ukraine and Palestine conflicts (Aljifri, 2024; Bougatef & Nejah, 2024; Gavriilidis et al., 2024).

Within this framework, Portugal's financial market presents a unique context for studying herding behavior. Despite its small size, the PSI accounts for 1,5% of Euronext's market capitalization in 2024 (CEIC Data, 2025). Characterized by its institutional and retail investors, low liquidity and overall stability, the PSI is highly concentrated, as few players significantly influence trends. With focus on sustainable energy, the Utilities sector is the PSI's most relevant sector, composed by EDP, EDP Renováveis, Galp and Ren. This sector represents more than 25% of the PSI (Luís Leitão, 2024), with a market cap of 34.33€ billion in March 2025, being considered stable due to consistent demand for essential services (Investing.com, 2025a, 2025b, 2025c, 2025d). However, its concentrated nature makes it vulnerable to market-wide impacts (Luís Leitão, 2024). With high capital requirements and regulations, the sector presents significant entry barriers, reinforcing the dominance of established firms. These firms attract both institutional and retail investors (domestic and international), due to their stable returns, essential services and interest in sustainable investments. With the growing urge for sustainable investing, the Utilities sector plays a central role in the integration of renewable energy sources, smart grid technologies and policy shifts, affecting market performance and investor sentiment, encouraging herding behavior (Trück & Yu, 2016). By focusing on a sector that drives considerable trading volumes and returns, becomes relevant to understand how it impacts investors' behavior in Portugal.

1.2. Research Gaps

By reviewing existing literature, there is a particular interest concerning herding behavior in larger markets like the US, India or China, limiting the global applicability of findings to smaller, less developed and differently regulated markets (Raj & Panja, 2023). This overlooks the potential influence of cultural and regulatory differences on how investors act based on their sentiments across markets (Phan et al., 2023). Similarly, Barros (2023) highlights the need for more research on smaller markets using a larger and more diverse sample, encouraging the study of multiple companies from the Portuguese market.

Furthermore, the latest macroeconomic events, such as the COVID-19 pandemic and the ongoing war in Ukraine (Mohamad, 2024), represent disruptive periods for global markets, with changes in consumer behavior, increase of inflation rates, oil and gas prices and wheat and grain prices. Therefore, the need for more research on the psychological factors influencing herding behavior during these crises is high (Ferreruela & Mallor, 2021).

As one of the most affected sectors, the Utilities sector has a major role in this ongoing recovery. Gebka & Wohar (2013) suggest that the Utilities' sector lacks targeted studies, leaving their investor behavior largely unexamined (Bogdan et al., 2022). Characterized by its stable environment, this sector is commonly overlooked, as herding research is often focused on specific high-volatility sectors (Bekiros et al., 2017).

1.3. Research Question

Considering the shortage of literature regarding herding in smaller markets mentioned by Raj & Panja (2023), the lack of research in the Utilities' sector (Gebka & Wohar, 2013) and lack of extensive time frames (Barros, 2023), we've reached the following primary question: "Is there evidence of Herding behavior in PSI’s Utilities sector from 2014 to 2024?”. As this question approaches crises, recovery and growth periods, two relevant secondary questions emerged: “Is the effect of Herding behavior significantly greater during the COVID-19 pandemic?” and “Is the effect of Herding behavior significantly greater during the Ukraine war?”. These questions address the scarcity of research on herding’s psychological drivers during crises periods, helping us identify patterns and assess whether our findings align with expectations from the revised literature.

1.4. Originality

The original factors are the study of a smaller market, a larger timeframe and the focus on the PSI’s Utilities sector. As global giants (US or China) are the most researched markets regarding herding, like Shen (2018) and BenMabrouk & Litimi (2018), there is a need for studies on smaller markets such as Portugal (Xing et al., 2024). The time frame chosen, from 2014 to 2024, is larger compared to most herding studies such as Chen (2020) and Blasco et al. (2024), with 2 to 5 years ranges. This timeframe enables tracking long-term investor behavior, comparing investor’s reactions to different shocks (Barros, 2023). Finally, by focusing on the PSI’s Utilities sector, we analyze how local factors differ from global herding phenomena, such as supply chain dependencies (Usson, 2022) and regulatory impacts (Mohamad, 2024). After extensive review of the literature, this study appears to be the first to examine herding in Portugal's Utilities sector over a decade (2014–2024), covering the COVID-19 pandemic and the ongoing Ukraine war.

1.5. Contribution to knowledge

This research provides additional empirical evidence for investigators and contributes to the broader field of behavioral finance, debating herding significance in a specific sector and country. The study explores the nuances of herding in smaller markets, opening paths for further investigation in the Utilities sector.

This research offers valuable insights to stakeholders such as investors, company managers and CMVM. Regarding investors, it can improve decision-making, risk management and perception of market dynamics and trends. Company managers can improve their strategic planning through crises management, investor relations and market positioning. Finally, CMVM can improve market regulation, by establishing better policies and trading, contributing to a more efficient and transparent market and promoting investor confidence.

1.6. Introduction to the following chapters

The following chapters will address crucial topics for this research. Chapter 2 will be the literature review, presenting the main concepts and theories, empirical evidence, research context and, lastly, the hypothesis. The chosen methodology will be discussed in Chapter 3, along with the data and software used. The results and discussion of this quantitative analysis will be stated in Chapter 4. Finally, Chapter 5 presents the final conclusions of the paper.

Chapter 2
Literature Review

2. Literature Review

2.1. Herding Definition

Mackay (1869) was one of the first authors to address herding, stating that "Men (…) think in herds; (…) they go mad in herds, while they only recover their senses slowly" (p.3), linking collective investor behavior to financial bubbles. Hirshleifer & Teoh (2003) emphasize the role of sentiment and social influence, describing herding as the tendency for individuals to align their actions due to interactions with others. Alternatively, Rompotis (2018) takes a straightforward approach, where herding represents "a tendency to mimic the actions of other investors when they transact on stock exchanges" (p.483). Lastly, Aharon (2021) defined herding as behavior patterns that are correlated across individuals, emerging when "investors abandon their personal opinions and adopt their counterparts' trading actions" (p.322). When comparing these definitions, all recognize a shift from individual to collective decision-making, differing in emphasis. While Mackay (1869) and Hirshleifer & Teoh (2003) focus on psychological triggers, Rompotis (2018) and Aharon (2021) lean towards observable patterns and market-level behavior. For the purpose of this study, Aharon (2021)'s definition was chosen as it incorporates moderate psychological insights while remaining applicable in empirical market analysis. Its flexibility allows to explore herding from both rational and behavioral finance standpoints, highlighting the conscious/unconscious shift from independent to collective decision-making. Its applicability transcends financial markets, representing a key aspect of this research.

2.2. Main Theories

2.2.1. Efficient Market Hypothesis

The Efficient Market Hypothesis was developed by Fama (1965), an economist known for his work on portfolio theory, asset pricing and the EMH (Fama, 1965). This theory assumes agents are rational and process all information correctly, maximizing utility. Additionally, it assumes market efficiency, where available information is immediately reproduced in stock prices. Finally, it presumes that outperforming the market requires unlikely mechanisms like arbitrage or investment in higher-risk assets. By assuming unbiased market prices, the EMH pushes investors to build diversified portfolios without spending resources on stock picking. Additionally, efficient markets lead to optimal resources allocation, minimizing trading costs, encouraging long-term investments, reducing price manipulation.

The EMH delimits 3 forms of market efficiency, categorizing it into weak, semi-strong, and strong (Fama, 1965). In the weak form, market prices reflect all past information, making it unlikely for investors to gain abnormal profits from historical data. The semi-strong incorporates the weak form, where all publicly available information is reflected rapidly in current prices. In this approach, it's highly unlikely to earn abnormal returns based on fundamental analysis. Finally, the strong form upholds that all public, private and inside information is reflected in market prices, where no investor has monopolistic access to information (Malkiel, 1989).

By promoting fair pricing, this theory reduces arbitrage opportunities, supporting market liquidity and diversification, contributing to a stable and transparent financial system (Naseer & Tariq, 2015).

However, counterfactual assumptions emerged, leading this theory to gain many disbelievers. Merton (1973) introduced the concept of rational expectations while similarly, Jensen & Meckling (1979) explored how agency problems and irrational behavior challenged EMH's assumptions. Malkiel (1989) argued that price changes result from irrational factors rather than solely market fundamentals. Finally, Shiller (2003) found that volatility in stock markets couldn't be explained by changes in fundamental information, highlighting price anomalies that EMH couldn't address and emphasizing the role of psychological factors in decision-making. Recognizing these limitations, Lo (2007) proposed integrating behavioral insights with EMH, addressing rationality assumptions while preserving its core principles. Therefore, EMH was proved insufficient, not accounting for psychological factors, irrationality and market unpredictability (Shiller, 2003), leading to the rise of Behavioral Finance.

2.2.2. Behavioral Finance

Behavioral finance combines psychology and finance to explain how individuals make financial decisions. As psychological factors are intrinsic to human behavior, understanding the neural mechanisms underlying emotions offers valuable insights into investor behavior. Coricelli's et al. (2005) work in neurofinance highlighted the amygdala's role in processing emotions, particularly fear and reward. As it interacts with other brain regions, such as the prefrontal cortex, the amygdala helps assess outcomes and make risk-related judgments, enhancing the brain's role in evaluating past decisions and anticipating future outcomes. Similarly, Peterson (2007) demonstrated how neural representations of expected value affect financial decision-making.

As consequence of these psychological factors, emotions such as fear, stress or panic, as well as biases and heuristics affect market participants' rationality, compromising their decision-making (Daniel et al., 1998). This theory became relevant in the 1980s, suggesting that markets aren't always efficient due to investors' psychological behavior, which isn't always rational. Therefore, inefficiencies arise, creating opportunities for market participants to profit from (Hirshleifer, 2015).

Behavioral finance emerges to explain these inefficiencies. By focusing on individual level biases and heuristics, it justifies investors' irrational decision-making and how the human presence can lead to market bubbles and crashes (Leković, 2020a). Heuristics are mental shortcuts used by individuals to make decisions efficiently, especially under conditions of uncertainty. This process is usually fast but can lead to systematic errors (Tversky & Kahneman, 1974). Alternatively, biases are predictable and represent systematic deviations from rationality that arise when heuristics are applied, exposing the limitations in human reasoning (Agrawal, 2012). Cognitive biases (refer to Table 1 below) emerge due to decision-makers' limited cognitive capacities. There are many types of biases:

Biases/Heuristics	Description	Authors
Overconfidence	Individuals believe that the precision of their forecasts is greater than what is warranted.	(Hirshleifer, 2015)
Overreaction	Overreaction refers to a behavioral tendency where investors excessively adjust their expectations or actions in response to information, often due to consistent patterns of similar data.	(Poteshman, 2001)
Confirmation bias	Overemphasizes the decision maker's existing beliefs, causing them to undervalue or ignore important information that contradicts their position, ultimately impairing their judgement.	(Pompian, 2012)
Hindsight bias	The belief that one predicted an event after it has occurred.	(Biais & Weber, 2009)
Regret	An emotional consequence of the knowledge, ex-post, that a different decision would have had a more favorable outcome than what was done.	(Fooeik et al., 2024)
Representativeness	Making judgments based on how something matches our stereotype.	(Tversky & Kahneman, 1974)
Anchoring	Estimate based on an initial point of reference.	(Tversky & Kahneman, 1974)
Framing	Interpretation changes depending on how the problem is presented.	(Tversky & Kahneman, 1974)
Availability	Rely on easily recalled information when making decisions.	(Tversky & Kahneman, 1974)
Affect	When emotions influence the judgment.	(Tversky & Kahneman, 1974)
Herding	Investors abandon their personal opinions and adopt their counterparts' trading actions.	(Aharon, 2021)
Contagion effect	How interconnections among investors propagate systemic risks and structural shocks in financial markets.	(Park & Oh, 2023)
Informational cascade	An investor ignores private information and follows the common market belief.	(Bikhchandani et al., 1992)

Table 1: Types of biases

Some biases influence decision making by over or underestimating predictions and over adjusting to new information, such as overconfidence and over/underreaction. Confirmation bias and hindsight bias skew judgment by reinforcing existing beliefs or creating false certainty. These promote excessive risk-taking and market volatility, as investors place undue faith in their forecasts and past experiences (Pompian, 2012). Other outlines, such as representativeness, anchoring, and framing, show how individuals rely on stereotypes, distorting information processing, reinforcing market trends rather than correcting mispricing. On the other hand, social influences like herding and informational cascades explore mass behavior, where individuals prioritize market sentiment over individual analysis, exacerbating bubbles and crashes. By understanding these biases, strategies can be developed to mitigate their effects, improving financial stability and investment decisions.

Some authors shaped the understanding of behavioral finance. Tversky & Kahneman (1992) introduced the Prospect Theory, exploring how investors assess potential gains and losses, revealing cognitive biases that influence decision-making under uncertainty. Loss aversion was also addressed, where individuals fear losses more than they value gains, prioritizing loss avoidance irrationally. Mental shortcuts and heuristics were also proven to lead to systematic judgment errors.

Barberis & Thaler (2003) argued that behavioral finance better explains financial phenomena by incorporating partially rational agents. Their theory on the limits of arbitrage explains how constraints prevent rational traders from correcting market inefficiencies, highlighting psychological factors that drive deviations from rational behavior. These apply to aggregate stock markets, individual trading behavior, and corporate finance.

Shiller (2003) expanded these concepts, assessing market volatility and investor types, arguing that market prices often deviate from their fundamental values due to investor emotions and cognitive biases, leading to irrational behavior such as excessive optimism/pessimism. Phenomena such as asset bubbles and crashes demonstrate market inefficiency, shifting the focus from rational models to the complexities of human behavior and psychology.

Finally, Hirshleifer (2015) explored the effects of social influences and impact of psychological biases on market dynamics, studying how investors' inflated beliefs about their knowledge can lead to excessive trading and mispricing of assets.

Overall, behavioral finance helps explain market anomalies and decision-making patterns ignored by classical theories. However, it struggles with integrating psychological factors into traditional models (Mijailović, 2022), overlooking the social status role in investment behavior, focusing more on individual biases than data-driven inefficiencies (Leković, 2020b).

2.2.3. Herding Theories

Research in behavioral finance has increasingly focused on individual biases, with herding emerging on financial markets. Herding is the process where economic agents base their decisions upon the actions of others (Spyrou, 2013). It can be manifested as a group of market participants trading in the same direction and time (Nofsinger & Sias, 1999), or investors abandoning their initial assessments to follow trends (Avery & Zemsky, 1998). Herding includes mutual imitation among investors (Welch, 2000) and correlated trading patterns (Hwang & Salmon, 2004).

Bikhchandani et al. (1992) explain that herding relates to how information is processed and disseminated. Due to information asymmetry or incompleteness, herding is promoted and aggravated among investors (Baddeley et al., 2004). Many authors analyzed the existence of herding in crises periods, concluding that mutual imitation is often observed in these conditions. During heightened uncertainty, investors observe and tend to mimic each other's actions (Ferreruela & Mallor, 2021). Other factors contribute to the appearance of herding such as uniformity of social behavior and FOMO.

In practical terms, some authors state that herding behavior destabilizes markets, increasing the fragility of the financial system by amplifying bubbles and crashes. As prices are driven by collective sentiment, accurately assessing asset prices becomes challenging, making portfolio diversification less effective. This inefficiency arises because diversification strategies rely on assets behaving independently. Because herding behavior increases correlations, it limits the benefits of risk reduction, leading to a decline in market efficiency as prices no longer fully reflect available information. Additionally, aggressive market corrections can emerge from heightened volatility, diminishing investor's confidence, promoting speculation and boosting uncertainty (Ferreruela & Mallor, 2021).

However, according to Kononovicius & Gontis (2015), introducing agents with fundamentalist trading behavior into agent-based herding models reduces market fluctuations and the probability of extreme price deviations. The inclusion of stochastic traders provides an efficient method for minimizing extreme deviations from fundamental values, enhancing that herding can promote equilibrium and mitigate risks in financial systems.

2.2.3.1. Irrational Herding

Keynes (1937) introduced the concept of irrational behavior in capital markets, referring to animal spirits that explain abnormal fluctuations in economic activity, leading to mimicry. According to Devenow & Welch (1996), those who defend irrational herding believe investors follow others blindly without careful analysis or independent thought. Irrational herding portrays investors who recklessly disregard their knowledge and imitate the actions of others without critical thinking (Lin et al., 2013). Despite triggers that lead to imitation behavior such as psychological pressures (peer influence, desire to fit in or FOMO), these lack empirical support to justify their existence (Hirshleifer & Teoh, 2003). Other approaches defend that irrational herding occurs when market participants with insufficient information and inadequate risk evaluation disregard their beliefs and follow other investors' actions (Hung et al., 2010). This process can lead to market inefficiencies, driving asset prices away from fundamental values (Lin et al., 2013). Similarly, Bogdan et al. (2022) believe herding becomes irrational when driven by euphoria and situations of uncertainty, leading to overvaluation or undervaluation of assets. Behavioral biases, such as FOMO or loss aversion often amplify irrational herding during bubbles or crashes. Avery & Zemsky (1998) show how this phenomenon amplifies stock price fluctuations, creating bubbles through investor mimicry.

Irrational herding has been linked to concepts such as trading noise, described as random fluctuations that don't reflect fundamental values arising from investors' irrationality (Admati, 1991). This leads to unpredictable price movements, as investors buy and sell based on market sentiment. When investors have incomplete or incorrect information trade, it adds noise to the market, disrupting price and market stability (Admati, 1991).

2.2.3.2. Rational Herding

On the other hand, rational herding is justified. Investors consciously base their decisions on observable externalities, using market signals or inferred information to guide themselves (Spyrou, 2013). Rational herding can be explained through career concerns, insufficient information or market manipulation. Banerjee (1992) highlighted the concept of observational learning, which leads to mass decision-making, where investors mimic others to minimize risk and align with perceived market wisdom, negatively impacting asset prices.

On another note, Scharfstein & Stein (1990) addressed career concerns among investment managers, explaining how market participants adopt similar investment strategies, staying updated with market developments, protecting their reputation. This rational incentive to herd is a survival strategy in a competitive industry, which is often riskier, especially if they perform worse than their peers.

This phenomenon has been also researched based on psychological factors. Barberis et al. (1998) demonstrated how investors may rationally follow others driven by sentiment shifts, even when individual biases are at play (over or underreaction to market news), reflecting the tendency of investors to misjudge uncertainty. Hong & Stein (1999) illustrates how short-term underreactions transition into long-term overreactions, encouraging strategic mimicking among investors. Daniel et al. (1998) also highlighted how rational herding emerges from individual behavioral biases, with investors strategically responding to both real and perceived signals in the market.

Although rational in the short-term, rational herding can lead to market inefficiencies, including bubbles and volatility, as prices deviate from intrinsic values (Bikhchandani et al., 1992). Moreover, the probability of amplifying inefficiencies during collective misjudgments is higher and riskier (Scharfstein & Stein, 1990), leading to asset prices distortions (Banerjee, 1992), reinforcing herding cycles (Hong & Stein, 1999).

However, Lin et al. (2013) argue that under certain conditions, rational herding aligns prices with fundamental values, improving market efficiency. Bru & Vives (2002) also suggest that herding inefficiencies caused are moderate depending on incentive structures and that herding-based solutions are nearly ideal when the cost of offering incentives is significant. These comparisons highlight the complexity of rational herding, revealing two distinct types: intentional and spurious herding.

2.2.3.2.1. Intentional herding

Intentional herding is the deliberate choice to follow others' actions due to strategic motivations such as reputational concerns or a belief that others have advantageous information. The work of Bikhchandani et al. (1992) established the concept of information cascades, where investors intentionally ignore private information and imitate other agents' behavior, especially when they believe others have superior information. This is promoted by career and reputational concerns, often witnessed among professional investors, as noted by Scharfstein & Stein (1990). Managers may follow their peers to avoid reputational damage if independent choices are risky or unconventional. Strategic trading also represents intentional herding, as it arises from intentional actions of informed traders, whose purpose is to manipulate market expectations. In this context, investors mimic their peers, believing their decisions reflect valuable market information that could improve portfolio performance. However, this behavior is often misinterpreted as irrational behavior (Avery & Zemsky, 1998). This dynamic can lead to fragile markets prone to excessive volatility as well as increased systemic risk, as herding reinforces shared market sentiments rather than objective fundamentals, making markets more susceptible to abrupt shifts in sentiment.

2.2.3.2.2. Spurious herding

Spurious herding happens when investors unintentionally adopt similar behaviors due to correlated information or shared external factors. This is a common reaction to shared signals, if investors trade based on similar information sets (Guo et al., 2020). This type of herding is often seen as an efficient outcome, arising naturally from investors' actions on similar signals or macroeconomic conditions, such as interest rate changes or aggregate market data. With access to equal information, their choices are based on identical data (news, reports, or market analyzes), being likely to react similarly (Devenow & Welch, 1996). Contradicting intentional herding, spurious herding represents a natural response to available information, contributing to a stable market structure. Guo et al. (2020) argue that this rational response is less destabilizing than intentional herding. Hirshleifer & Teoh (2003) highlight the role of spurious herding in improving market efficiency by obtaining data from instinctive individual choices that align with macroeconomic changes.

Spurious herding resembles the EMH, exposing rational responses to shared information (De Long et al., 1990). Hoitash & Krishnan (2008) argue that intentional herding can transition into spurious, when external factors, such as correlated information or trading volumes, result in similar behavior without intentional mimicry. This demonstrates how intentional behavior blends with unintentional actions, leading to price movements that don't reflect intrinsic asset values. Other studies show that herding among institutions is predominantly spurious, due to emotions and structural constraints, with purchase herding being more common for positive signals (upgrades) and selling herding for negative signals (downgrades) (Choi & Sias, 2009). It is also important to mention that similar shared experiences, cultural or educational backgrounds, may lead investors to process information similarly, leading to parallel decisions, intensifying herding behavior (Guo et al., 2020).

2.3. Empirical Evidence

2.3.1. Studies of non-significant herding

Many studies exhibit non-significant herding. Christie & Huang (1995), using the CSSD, argue that extreme market swings often lead to increased return dispersion, reflecting independent decision-making. This suggests some investors maintain autonomy during uncertain times, depending on their access to information and trading strategies.

Lakonishok et al. (1992) and Wermers et al. (1995) found that institutional investors often act independently, especially in highly liquid stocks, with institutions exhibiting herding under industry focus but maintaining independence in large-cap stocks, limiting herding's significance in market volatility. These studies enhance the independence of institutional investors when dealing with large and mature markets. Bikhchandani & Sharma (2000) found that herding is limited in developed markets, often linked to investment managers following momentum strategies. Chiang & Zheng (2010) analyzed herding behavior across international stock markets, showing no significant herding in developed markets (US and the UK). The absence of significant herding relates to market maturity, as developed markets exhibit greater transparency, stronger regulation, and more informed investors, reducing reliance on collective behavior.

Methodology wise, Christie & Huang (1995) and Lakonishok et al. (1992) rely on measures like CSSD or LSV, showing herding is minimal or often explained by rational responses to public information. Differences in methodological sensitivity can also explain why similar studies find herding significant while others don't.

2.3.2. Studies of significant herding

On the other hand, significant herding studies highlight the role of market conditions such as uncertainty, fear and volatility in driving collective behavior. During high uncertainty, investors are prone to herd, especially in smaller portfolios with higher information asymmetry (Aharon, 2021). Studies of southern Europe show significant herding in the Portuguese, Italian, Spanish and Greek markets, heightened during falling markets, high trading activity and extreme volatility (Economou et al., 2011).

Regarding investor type and context, significant studies approach the concept of institutional herding. Evidence suggests US institutional investors herd, with cross-sectional correlations in trading behavior are as high as 40% (Choi & Sias, 2009). Asset structures can also affect herding significance. Rompotis (2018) recognized herding dependence on market conditions, sentiment and asset characteristics, by exposing ETFs' effect on trading behavior, showing that intraday volatility induces herding among ETFs.

Regarding methodology, Hwang & Salmon (2004) and Economou et al. (2011) introduced new approaches, based on the cross-sectional dispersion of assets sensitivity in each market and bias-free datasets, where herding shows significant movements. Evidence of herding in both bull and bear markets was also found.

Despite its differences, both significant and non-significant herding studies converge on the idea that herding is context-dependent, focusing on market factors, information and investor dynamics, as well as herding measurements. While significant herding is often tied to uncertainty, volatility, and asset structures, non-significant herding emphasizes rational reactions to shared information and independent decision-making.

2.3.3. Herding in Crises periods

As herding presence can be aggravated by extreme events, we reviewed studies on herding during crises periods. Tan et al. (2008) suggest herding intensifies during periods of market distress. By studying herding in dual-listed A-share (domestic individual investors) and B-share (foreign institutional investors) Chinese stock market portfolios, evidence shows significant but short-lived herding in both, varying by investor type. Market stress, characterized by volatility and price swings, amplifies herding, especially among less experienced A-share investors. Ferreruela & Mallor (2021) observed herding before and after the 2008 financial crises, but not consistently during it. Data from Spain shows herding predominantly on high-volatility days, particularly after crises, during the pandemic, and under short-selling restrictions. However, in Portugal, herding often appears during low-volatility days, though it also emerges during high-volatility periods like the 2008 financial crises and the pandemic. Similarly, other researchers carried out robustness checks, finding significant herding during COVID-19 (Aljifri, 2024). Studies regarding war periods suggest that emerging markets experience significant herding during early stages of conflicts, driven by proximity to conflict zones or economic reliance on energy markets (Blasco et al., 2024).

These studies align with Chang et al. (2000) findings, where herding tendency is higher during periods of uncertainty and volatility. However, some studies contradict these findings. Hwang & Salmon (2004) believe that, during periods of volatility, herding tends to diminish as investors become less confident, turning to fundamental values for decision-making. The Asian and Russian crises are examples of reduced herding periods, seen as turning points in the literature (Hwang & Salmon, 2004).

2.3.4. Herding in the Portuguese Stock Market

Several studies highlight herding dynamics in the Portuguese market. Leite et al. (2018) showed that herding influenced price fluctuations in the PSI Index between 1998 and 2010, while Kallinterakis & Ferreira (2006) observed herding clustering during the late 1990s in periods of market stability. Caiado (2007) found herding behavior during negative market shocks (2001 index decline), with pronounced effects in daily trading. The findings revealed a significant herding tendency in the Portuguese stock market, due to Portugal's dependency and sensitivity to European and American market variations.

During market stress, studies by Carolino (2018) and Ferreruela & Mallor (2021) found intensified herding, driven by uncertainty and collective risk-averse behavior. As a smaller market, Portugal exhibits similar markets' behavior due to limited liquidity, fewer participants and less efficient price discovery mechanisms (Spyrou, 2013). Additionally, a higher concentration of institutional investors amplifies mimicking behavior due to reputational concerns or limited access to private information (Holmes et al., 2013). This view aligns with Andrikopoulos et al. (2017) who found significant herding in the Portuguese stock market, contrasting with weaker herding tendencies in markets like The Netherlands. Methodology wise, Vieira & Pereira (2015) and Patterson & Sharma (2010) emphasized the sensitivity of herding detection to specific measurement approaches and portfolio structures. Using the Christie & Huang (1995)'s method, Furtado (2012) found herding during market upturns, while Carolino (2018) using Chiang & Zheng (2010)'s model, identified stronger herding in market downturns. Economou et al. (2011) reported mixed findings depending on portfolio structure, with equally weighted portfolios showing no signs of herding behavior, while portfolios with larger market capitalizations exhibited significant herding.

2.3.5. Herding on the Utilities sector

Herding tendency varies across sectors, prevailing in industries sensitive to market uncertainty (Andrikopoulos et al., 2017). Evidence from nine Asian markets suggests that herding is enhanced within specific industries compared to broader domestic or international markets, highlighting the role of information flows, sectorial trends, and investor sentiment in collective decision-making (Zheng et al., 2017).

The Utilities sector can be significant in the context of herding. Although stable and regulated, the energy and oil industries are highly influenced by macroeconomic and geopolitical shifts, leading to volatility cycles (Schmitt & Westerhoff, 2017). Cakan et al. (2019) show that, in emerging markets like Brazil and Russia, the increasing speculation regarding the oil market concerns higher levels of herding, as demand uncertainty drives market consensus. Similarly, Shen (2018) found significant herding in Chinese energy sector during crises periods, driven by emotional contagion and panic. Mohamad (2024) found stronger herding in energy markets during the pandemic than the Ukraine war, suggesting health crises, impacting supply and demand fundamentals, cause more disruption than geopolitical conflicts.

Other papers show that, in the energy sector, herding intensifies during and after a global financial crisis, heightened by oil price fluctuations. Exchange rates impact industrial metals, indicating that herding in the oil and energy sector is not constant but emerges with volatility (Youssef, 2022). Chang et al. (2020) further demonstrate that US fossil fuel markets impact renewable energy markets globally, with diminished herding during extreme downturns.

However, periods of anti-herding behavior exist, particularly when individuals rely on unique private information or during less volatile periods (Ali et al., 2022), suggesting that the balance between herding and independent decision-making is influenced by market conditions.

2.4. Research context

As a small country, with a GDP per capita of 25 277€ and an inflation rate of 5,3% in 2023 (PORDATA, 2024), Portugal integrates both European Union and Eurozone. With a market cap of 89 046,782€ mn in 2024, Euronext Lisbon represents major Portuguese companies, trading stocks, public and private debt securities, ETFs, Warrants, Certificates, Futures and Options (CEIC Data, 2025). In 2024, the PSI, integrated in Euronext Lisbon in 2002, listed 16 companies, with the Utilities sector hosting the most companies (FinancialReports, 2024). Key players include EDP, Galp Energia, and Jerónimo Martins. As of December 2024, the PSI was trading at 6 355,00 points (Euronext, 2025), representing a year-to-date increase of 6,67% (Trading Economics, 2025). The PSI is a highly concentrated market, prevailing a small number of larger companies, where the highest transaction stocks represent most of the total transaction volume (Costa et al., 2021).

The PSI comprises both retail and institutional investors. In the Utilities sector, most investors are institutional, both foreign and domestic, while retail investors hold a significantly smaller share (EDP - Energias de Portugal, 2023; Galp, 2023; REN, 2023). While retail investment has grown through local stocks, real estate, and other financial assets, institutional investors, including foreign participants with support from AICEP, impact larger and more liquid segments. Regulated by the CMVM, the PSI ensures transparency and investor protection, supported by Portugal's open-door policy towards FDI (US Department of State, 2024). Key investors include Spain, Germany, France, the US and China, focusing on energy, infrastructure, and technology sectors.

Over the last decade, Portugal's economy faced significant challenges, including the eurozone crises, the COVID-19 pandemic, and inflationary pressures from energy price shocks and geopolitical conflicts. The ECB applied expansive monetary policies, such as quantitative easing and TLTROs, supporting economic growth, stability, and lowering borrowing costs. However, low bank profitability and high public debt persist. In 2020, the COVID-19 pandemic caused severe economic contraction, rising unemployment, and impacting tourism (Komalasari et al., 2022). To overcome these challenges, the ECB created a 1.85€ trillion Pandemic Emergency Purchase Program.

By 2022, Portugal's GDP improved, but inflation peaked along with energy prices and supply chain disruptions from the Ukraine war, expected to be at 2,6% in 2024 (TPN/Lusa, 2024). ECB raised interest rates to combat inflation, straining purchasing power and increasing borrowing costs in Portugal’s indebted economy. Despite high public debt (94,4% expectancy in 2024 (O’Neill, 2024)) and an aging population, Portugal continues to recover, supported by low ECB interest rates and EU funds, with a decline in unemployment to 6,5% in 2024 (Instituto Nacional De Estatística, 2024). Regarding financial markets, Portugal's stock market sharply declined in 2020’s pandemic, recovering in the following years, remaining stable (Banco De Portugal Eurosistema, 2025).

As the focus of this research, the Utilities sector provides essential services such as electricity and natural gas. With an oligopolistic structure, this sector presents high entry barriers, strict regulatory oversight, and long-term infrastructure investments. Significant players such as EDP in electricity and Galp in natural gas dominate the industry, ensuring reasonable returns on investment. As a major player, EDP generates and distributes electricity, with a market capitalization of 13€ billion (Investing.com, 2025a). EDPR is the fourth-largest renewable energy player in the world (PitchBook, 2024), holding a market capitalization of 8.67€ billion (Investing.com, 2025b). REN, with a market cap of 1.77€ billion and share price of 2,66€ as of March 2025, ensures the efficiency of Portugal's energy transmission network (REN, 2024). Finally, valued at 10.89€ billion with a share price of 15,42€ as of March 2025

(Investing.com, 2025c), Galp is a key player in the oil and gas industry (Galp Energia, 2024). As part of the EU's Green Deal, Portugal committed to carbon neutrality by 2050, encouraging investments in renewable energy, EDP made substantial investments in renewable energy sources, including wind and solar power, complying with EU's emissions regulations. Additionally, the ERSE oversees the electricity and gas markets, attributing penalties for non-compliance with environmental standards. The sector's capital-intensive nature, stable returns and growth prospects attracts both institutional and retail investors, with Utilities stocks like EDP and Galp being among the PSI's most traded. However, the shift towards renewable energy and sustainability, combined with government and EU regulations has redirected investor interest toward green energy companies, reshaping the sector's growth prospects (Trück & Yu, 2016).

2.5. Hypothesis

For this research, the main hypothesis is the following:

H1: Herding behavior is present in the PSI's Utilities sector from 2014 to 2024.

As a highly researched phenomenon, there are opinions in favor (Chang et al., 2020) and against (Hwang & Salmon, 2004) the presence of herding in financial markets during high volatility periods. However, most studies link herding to conditions of uncertainty and information asymmetry (Bikhchandani & Sharma, 2000). Supporting literature states smaller markets exhibit higher levels of herding due to limited liquidity and fewer participants (Spyrou, 2013). Accordingly, Portugal's dependency and highly sensitiveness to European and American variations reveal a significant tendency to herd (Caiado, 2007). Moreover, as enhanced by Economou et al. (2011), due to limited price discovery mechanisms and lower market efficiency, the Portuguese market conditions tend to amplify herding. By representing one of the biggest sectors in the PSI, the Utilities sector can also be prone to this phenomenon, as studies show that herding in the oil and energy sector is not constant but emerges during heightened volatility (Youssef, 2022). Due to its sensitivity to external shocks and systemic risks, herding emerges in these companies during periods of heightened volatility, often linked to external factors such as oil prices and economic instability (Chang et al., 2020). Given the significant weight of Utilities in the PSI, it is plausible that herding behavior is observable in this time frame, encompassing crises and uncertainty periods.

Regarding secondary hypothesis, two were considered:

H2: The effect of Herding behavior is significantly greater during the COVID-19 pandemic.

Periods of crises, such as the COVID-19 pandemic, are marked by heightened uncertainty, fear, and volatility, which tend to exacerbate herding behavior (Tan et al., 2008). Portugal focused studies highlight the presence of herding behavior during the COVID-19 pandemic, driven by collective risk aversion and the search for safer assets (Ferreruela & Mallor, 2021). During the pandemic, investors faced difficulties in predicting market outcomes, relying on collective actions as a safe strategy, aligning with global trends (Noman et al., 2023).

By having traditionally stable cash flows, the Utilities sector became an escape for risk-averse investors during the pandemic. The PSI's Utilities sector remained relatively resilient due to sustained demand for energy and government support for essential services, possibly attracting collective investor behavior, making herding more pronounced during the crisis (Chang et al., 2020).

H3: The effect of Herding behavior is significantly greater during the Ukraine war.

Geopolitical conflicts such as the Ukraine war are periods of higher uncertainty in financial markets, particularly in sectors linked to energy (Chang et al., 2000). Studies suggest that emerging markets experience significant herding during the early stages of conflicts, driven by proximity to conflict zones or economic reliance on energy markets (Blasco et al., 2024). The Ukraine War impacted the Portuguese market due to its reliance on energy imports and exposure to European energy policies, causing sharp increases in energy prices and supply disruptions, which could have amplified collective investor behavior in the Utilities sector. However, recent studies found contradicting evidence, exposing dispersion behavior instead of herding in the energy sector during the war (Mohamad, 2024). Despite this, most of the literature suggests that herding behavior is likely to be found in these circumstances. Therefore, it’s expected to find herding behavior between 2014 and 2024 in the PSI’s Utilities sector, significantly during the COVID-19 pandemic and the Ukraine War.

Chapter 3
Methodology

3. Methodology

3.1. Methodological approach

A quantitative analysis was chosen to test the presence of herding behavior in the Portuguese Utilities' sector, enabling an objective analysis of financial data. The sector's extensive stock market data requires a quantitative approach, enabling the testing of theories within a specific niche. This methodology uses numerical data, makes systematic sampling and statistical analysis to identify patterns and test hypotheses, ensuring objectivity and replicability (Creswell, 2017). By using statistical models, researchers identify patterns in returns, volatility, and the extent of herding behavior during different market conditions, handling large datasets. However, it relies on historical data, overlooking qualitative factors such as investor sentiment, risking oversimplifying complex behaviors (Lakshman et al., 2000).

3.2. Data

For the purpose of this research, we used secondary data, with daily stock return values of the 4 companies constituting the PSI's Utilities sector (EDP, EDP Renováveis, GALP Energia, REN), as well as the benchmark. The total number of observations was 2582, between 01/01/2014 until 31/01/2024. In addition to its availability, secondary data presents validated information, ensuring accuracy and consistency in the analysis, enabling comparisons. While some authors use weekly data (Bogdan et al., 2022), daily data offers greater granularity and statistical precision, making it more suitable for this type of research (Reilly, 2013). Given the analysis of 4 entities within a decade, a panel data analysis took place to assess the cross-sectional and temporal aspects of herding.

Refinitiv Eikon was used as the main source of data, providing high-quality, reliable financial data, including historical and real-time stock prices, financial statements, and market indexes. With global market access, it presents data by sectors, being used by finance professionals (Economou et al., 2015). During the processing of the data, no data manipulation was used, and no outliers nor missing observations were found.

3.3. Variables

The variable used in our model was stock returns. The returns were computed by the following formula:

- $R_{i,t}$ is the log return of firm i on day t, computed based on the equation:

$$R_{i,t} = Ln\ (P(t) / P(t-1))$$

- P(t) and P(t-1) are the closing prices of day t and t-1, respectively

The choice of log returns instead of arithmetic returns relates to its simplification in mathematical modeling, particularly in asset pricing and econometric models (Chen, 2020). The sum of log returns over multiple periods gives the cumulative return, being useful in portfolio theory and when dealing with compounded returns (Black & Scholes, 1972). Moreover, log returns are more normally distributed under certain conditions, making them easier to handle in econometric analysis, particularly when performing regressions (Merton, 1980). It also mitigates bias issues arising from using arithmetic returns over longer time horizons, especially when volatility is high (Jorion, 2009).

3.4. Main Methodology

Despite the use of other approaches by Bikhchandani & Sharma (2000) or Banerjee (1992), most of the current literature employes 2 statistical models to assess return dispersion: Christie & Huang (1995)'s Cross-sectional Standard Deviation and Chang et al. (2000)'s Cross-sectional Absolute Deviation.

The Christie & Huang's (1995) method states that the market alternates between normal and stress markets (periods of abnormally large average price movements). In this approach, in the presence of herding, during periods of market stress, security returns shouldn't deviate substantially from the market's return. To determine the existence of herding during periods of market stress, the CSSD estimates the following linear regression model:

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

Figure 1: CSSD computation formula

$$\text{CSSD}_t = \alpha_0 + \alpha_1 D_t^U + \alpha_2 D_t^L + \varepsilon_t$$

Figure 2: CSSD regression

In this model, DtU (or DtL) represent dummy variables that take the value of 1 if the market return falls in the extreme upper (or lower) tail of the market return distribution; otherwise, it's 0. However, CSSD as a proxy for herding may create bias of outliers (Chen, 2020; Chiang & Zheng, 2010). Additionally, the linearly positive relationship between returns' dispersion and market returns isn't viable, leading to a non-linear relationship.

The CSAD addresses these issues, identifying herding by investigating the non-linear relationship between return dispersion and aggregate market return (Bogdan et al., 2022). CSAD captures return dispersion between different assets at a specific time, being a popular choice among academics (Rompotis, 2018).

The CSAD is defined by the following formula:

$$CSAD_t = \frac{\sum_{i=1}^{N} |R_{i,t} - R_{m,t}|}{N}$$

Figure 3: CSAD computation formula

$$CSAD= a +b1rm + b2 [rm]+b3rm^2 + £$$

Figure 4: CSAD regression

In this nonlinear relationship, herding is represented by a significant and negative coefficient for β3. The beta coefficients were estimated using the Ordinary Least Squares (OLS) method, due to its efficiency in providing unbiased, consistent estimates, assuming no correlation between estimation errors and explanatory variables (Nouri-Goushki & Hojaji, 2023). This method is the most used in the detection of herding behavior using the CSAD. However, it only provides valid results by ensuring these assumptions (Mahaboob et al., 2018). Each beta uncovers different aspects of the relationship between market-wide returns and return dispersion, making the model effective for analyzing herding in financial markets (Faster Capital, 2024). The Durbin-Watson statistics and a VIF test were performed to evaluate autocorrelation in residuals and multicollinearity concerns.

3.5. Software

The software used was Stata, version 18 (College Station, Texas, United States of America), providing tools for data manipulation, regression analysis, and statistical modeling, being easy to learn and use (Baum, 2006). Although Python has the same purpose, the analysis doesn't require advanced custom modeling, being a more complex tool. Moreover, Stata is widely used in finance-related studies, making it easier to replicate results and follow standard methodologies (Chiang & Zheng, 2010).

Chapter 4
Results

4. Results

4.1. Data Overview

4.1.1. Descriptive Statistics

Data regarding 4 companies composing the PSI's Utilities sector was extracted from Refinitiv Eikon, from 2014 to 2024. Table 2 presents the descriptive statistics of the companies in scope, the market benchmark (PSI) and the CSAD of the Utilities' sector's daily returns. The mean and median returns for all companies and the PSI are close to zero, which is expected for daily returns in a stable market, indicating a relatively symmetric distribution of returns. All entities exhibit high kurtosis (from 7,27 to 11,78), indicating heavy tails in the return distributions. This suggests that extreme returns (positive and negative) are more frequent than would be expected in a normal distribution. The skewness values are predominantly negative, indicating a slight tendency for negative returns, being consistent with the asymmetric risk often observed in financial markets. The high kurtosis and negative skewness observed suggest the presence of extreme market movements that could trigger herding (Chiang & Zheng, 2010).

Variables	N	Mean	Median	Standard deviation	Minimum value	Maximum value	Kurtosis	Skewness
EDP.LS	2,582	.0001829	.0003076	.015546	-.148916	.0948463	9.823391	-.6327046
EDPR.LS	2,582	.0005267	.0004309	.0171865	-.1232903	.1000835	7.271162	-.1042123
GALP.LS	2,582	.0000842	.0004138	.0195063	-.1805113	.1603848	9.840726	-.0633675
RENE.LS	2,582	.0000281	0	.0108312	-.099866	.0641103	11.78178	-1.028615
PSI Returns	2,582	.0001939	.0005752	.0113832	-.1093498	.0857761	10.35481	-.7043271
CSAD	2,582	.0087179	.0076116	.0051026	.0004009	.05252	8.476449	1.727877

Table 2: Descriptive Statistics of daily returns from 1/01/2014 to 31/01/2024

4.1.2. Correlation Matrix

The correlation between independent variables shows generally low values, except for the relatively high correlation between ABSrm and Rm2 (0,8032), being expected, as both variables derive from the same measure. Given these results, there is some potential multicollinearity between ABSrm and Rm2, but Rm shows low correlation, indicating that multicollinearity is not a concern overall.

	Rm	ABSrm	Rm2
Rm	1.0000		
ABSrm	-0.1320	1.0000	
Rm2	-0.2197	0.8032	1.0000

Table 3: Correlation Matrix

4.1.3. Stationarity

In time series analysis, stationarity tests are performed to assess whether a series' statistical properties remain unaltered over time. If not stationary, the relationships between variables may appear significant when they aren't. To test for stationarity, the Augmented Dickey Fuller (ADF) test was chosen, due to its ability to run with or without a trend, allowing flexibility analyzing different types of data (Hamilton, 1994). The ADF checks for the presence of a unit root, which indicates non-stationarity, by testing the null hypothesis. If we reject the null hypotheses, all variables are stationary. The ADF tests presented in the appendices show that all null hypotheses were rejected, indicating that all variables are stationary.

4.2. Main Results

4.2.1. CSAD

The CSAD model assessed herding behavior using estimated coefficients, including market return squared (negative coefficient indicating herding) and absolute market return (positive in normal conditions). Market return and intercept were added to control for linear effects and baseline dispersion.

Regression with Newey-West standard errors   Number of obs = 2,582
Maximum lag = 7   F(3, 2578) = 98.42
Prob > F = 0.0000

CSAD	Coefficient	Newey-West std. err.	t	P>|t|	[95% conf.	interval]
Rm	.009664	.0104421	0.93	0.355	-.0108117	.0301397
ABSrm	.3124583	.0279973	11.16	0.000	.2575589	.3673577
Rm2	-.8489882	.5823448	-1.46	0.145	-1.990899	.2929229
_cons	.0062603	.0001792	34.94	0.000	.0059089	.0066117

Table 4: Newey-West General Market Regression

Focusing on General Market regression, the model is globally statistically significant. With an F-statistic of 98,42 and a p-value of 0,0000, it rejects the null hypothesis at the 1% level, confirming that the independent variables help explain the variation in CSAD. The large sample size further enhances the reliability of the estimates and the model's quality for assessing herding behavior.

Although we find a negative market squared return (-0,849), aligning with the expectation of herding behavior. The p-value (0,145) is above the 10% significance level, suggesting no strong evidence of herding behavior over the last decade. The absolute market return coefficient is highly significant (p = 0,000) at the 1% level, indicating that return dispersion increases with market movement, aligning with the predictions of rational asset pricing models.

Regression with Newey-West standard errors — Number of obs = 810
Maximum lag = 5 — F(3, 806) = 41.17
Prob > F = 0.0000

CSAD	Coefficient	Newey-West std. err.	t	P>|t|	[95% conf.	interval]
Rm	.0104359	.0175221	0.60	0.552	-.0239584	.0448302
ABSrm	.3715482	.0412079	9.02	0.000	.2906607	.4524357
Rm2	-1.957108	.6242652	-3.14	0.002	-3.182486	-.7317307
_cons	.0073153	.0003334	21.94	0.000	.0066608	.0079698

Table 5: Newey-West COVID-19 Regression

Regression with Newey-West standard errors — Number of obs = 496
Maximum lag = 4 — F(3, 492) = 38.54
Prob > F = 0.0000

CSAD	Coefficient	Newey-West std. err.	t	P>|t|	[95% conf.	interval]
Rm	.015755	.0222992	0.71	0.480	-.0280584	.0595683
ABSrm	.1479028	.0892224	1.66	0.098	-.0274011	.3232068
Rm2	9.1646	2.764855	3.31	0.001	3.73222	14.59698
_cons	.0072647	.0005046	14.40	0.000	.0062733	.0082561

Table 6: Newey-West Ukraine War Regression

During COVID-19, the squared market return coefficient was -1,957 with a p-value of 0,002, being statistically significant at the 1% level, providing strong evidence of herding behavior during this period. The absolute market return coefficient remained positive and highly significant (p = 0,000) at the 1% level, suggesting that dispersion still rises with market fluctuations. These findings indicate that, while overall market dispersion followed rational asset pricing expectations, there were significant signs of herding during the pandemic.

During the Ukraine War, the squared market return (9,1646), with a p-value of 0,001, was statistically significant at the 1% level. This positive and significant relationship between extreme market movements and return dispersion suggests that return dispersion increased rather than decreased, contradicting herding behavior expectations. The absolute market return coefficient (0,1479) had a p-value of 0,098, being significant at the 10% level, suggesting a weaker but relevant relationship between absolute market returns and dispersion in this period. These results indicate that, unlike the COVID-19 period, the Ukraine war appears to have increased market dispersion, possibly due to varied responses from investors regarding energy sector shocks and geopolitical uncertainty.

Additional statistical tests were conducted to validate the model's reliability. Autocorrelation occurs when past values influence future values, violating the assumption of independent errors. Due to the time-series nature of our data it's relevant to test for autocorrelation, using the commonly used Durbin-Watson statistics. In the appendices below, autocorrelation is present, leading to invalid hypothesis tests unless corrected. To solve this, the Newey West robust estimator was chosen to validate statistical inference.

A VIF test was conducted to analyze the quality of the regression model, showing that the model is free from significant multicollinearity, as expected. The low VIF values align with expectations for a robust regression model, allowing for reliable interpretation of the coefficients. Rm2 (2,93) and ABSrm (2,83) have moderate values, while Rm (1,06) doesn't indicate any multicollinearity concerns. Given that all VIF values remain below the accepted threshold of 5, multicollinearity is not an issue. This suggests that the model is well-specified and the predictor variables are sufficiently independent, supporting the reliability of the coefficients.

Variable	VIF	1/VIF
Rm2	2.93	0.341767
ABSrm	2.83	0.352845
Rm	1.06	0.946161
Mean VIF	2.27	

Table 7: VIF test

4.3. Discussion

Through the tests performed, we found insufficient evidence to establish the presence of herding behavior in the Portuguese Utilities sector between 2014 and 2024, although some exceptions were noted. The results suggest the presence of herding to some extent during the COVID-19 pandemic, aligning with the idea that investors tend to exhibit herding behavior during uncertainty and heightened market stress (Bikhchandani & Sharma, 2000).

The full period analysis (2014-2024) indicates that Utilities' investors didn't consistently exhibit herding, as the coefficient of Rm2 is negative and not statistically significant, agreeing that herding is not a persistent phenomenon but rather emerges in response to specific shocks or crises (Economou et al., 2011). During the COVID-19 pandemic, although herding was present, we observed an increase in return dispersion, which indicates that investors opted for rational herding, where agents respond to shared risk perceptions rather than blindly following market movements (Hirshleifer & Teoh, 2003). This contradicts the speculative herding effect, with Portuguese Utilities' investors aligning with Spyrou (2013)'s vision that investors use market signals or inferred information to guide themselves through uncertain times. Tversky & Kahneman (1974)'s prospect theory helps explain these results and how heightened risk aversion leads to synchronized yet informed trading decisions.

The Ukraine war period contradicts the presence of herding behavior in the Utilities sector, presenting a positive and significant Rm2, indicating an increase in return dispersion. By providing essential services with relatively stable demand, the Utilities sector experienced significant shocks from geopolitical risks and volatility in energy prices, being seen as a defensive investment choice (Schmitt & Westerhoff, 2017). Although the war introduced volatility in energy prices, investors' tendency was to react independently, reflecting divergence in investment strategies. These results align with the recent work of Mohamad (2024) , showing how the Portuguese Utilities sector aligns with global trends.

These findings enhance how herding is an intermittent phenomenon, driven by specific economic and geopolitical conditions (Scharfstein & Stein, 1990). The relative stability of Utilities may shield the sector from speculative herding, although episodes of collective movement still arise in times of crises. This behavior can be explained by information asymmetry, reputational concerns, and external market influences (Banerjee, 1992).

As the uncertainty surrounding the economic impact of the pandemic rose, information imperfections affected investors' ability to assess fundamentals, encouraging herding behavior (Hirshleifer & Teoh, 2003). Additionally, international movements and policy responses encouraged a global synchronized reaction.

In contrast, the Utilities sector was directly affected by fundamental shocks regarding the Ukraine war, particularly in energy supply, regulatory interventions, and government measures to stabilize the market. The rising energy prices and geopolitical uncertainty amplified significant return dispersion among investors. This aligns with Scharfstein & Stein (1990)'s argument that in crises periods, investors engage in "reputational herding" but when fundamental shocks occur, individual strategies tend to diverge based on varying interpretations of risk.

The lack of persistent herding in the Portuguese Utilities' sector throughout the full period suggests that institutional mechanisms and regulatory frameworks played a role in stabilizing the Portuguese Utilities sector, such as market regulations, CMVM and the Eurosystem. This aligns with the findings of De Long et al. (1990), who discussed that market regulations can curb irrational exuberance. The resilience of the financial system may have limited the extent of irrational herding, combined with trading strategies employed by institutional investors and improved access to financial information.

Chapter 5
Conclusions

5. Conclusions

5.1. Main Conclusions

The time frame approached encompassed 2 major geopolitical crises (COVID-19 and Ukraine war), with the purpose of comparing investors' reactions during both events. The CSAD method was used to effectively detect herding behavior, capturing nonlinear patterns across market conditions, offering an advantage over traditional approaches like Christie & Huang (1995), especially in sector-specific analyzes. Using this method, we were able to find overall market dispersion following rational asset pricing expectations throughout the decade, with strong evidence of herding behavior during the COVID-19 period and an increasing return dispersion regarding the Ukraine war period. Therefore, we found insufficient evidence of herding behavior in the Portuguese Utilities sector between 2014 and 2024, the presence of herding to some extent during the COVID-19 pandemic, but an increase of return dispersion during the Ukraine war, contradicting herding expectations. While herding emerged in the early stages of the pandemic, it didn't persist in the later crisis period, indicating that herding is not a structural characteristic of this sector.

By providing empirical evidence on investor behavior in the PSI's Utilities sector, this study reinforces the growing literature that frames herding as a context-dependent and circumstantial phenomenon, emerging in times of extreme uncertainty. The findings align with significant herding studies that highlight herding as a context-dependent phenomenon, such as Economou et al. (2011), who found significant herding in Southern European markets under crises conditions and Aharon (2021) who emphasized the link between uncertainty and collective behavior. However, the absence of generalized herding throughout the full period and the increasing return dispersion during the Ukraine War are consistent with the conclusions of non-significant herding studies, such as Lakonishok et al. (1992) and Bikhchandani & Sharma (2000), who argue that institutional investors in more developed and regulated markets often behave independently.

Therefore, this research's position stands between these theoretical perspectives: although herding behavior arises in situations of extreme crises, as seen during COVID-19, it's not an intrinsic feature of the Portuguese Utilities sector. The increased return dispersion observed during the Ukraine War reinforces the view that herding doesn't emerge in all situations of crises and market volatility, as the nature of the crisis dictates how investors react to it (Mohamad, 2024). In this case, investors reacted independently to energy price fluctuations and geopolitical uncertainty, likely due to the nature of these shocks where clear and differentiated information was available. These conditions allowed investors to assess risks based on their own strategies, risk tolerance, and expectations, unlike the COVID-19 crises, showing that, in certain contexts, investor behavior is driven more by fundamentals than collective decision-making.

5.2. Implications for Stakeholders

The findings suggest that, unlike the pandemic, which encouraged investors to move collectively in search of stability, the war introduced greater uncertainty and distinct investment responses. These insights are particularly relevant for financial regulators (CMVM), as they highlight that while herding can emerge during crises, it does not dominate market behavior. The Portuguese Utilities sector shows resilience, where existing regulations have been effective, however continuous monitoring remains crucial to prevent speculative movements that could distort asset pricing and increase systemic risk. To prevent destabilizing herding behavior, regulators should strengthen mechanisms that enhance market transparency and reduce information asymmetry. By introducing advanced AI surveillance tools, it will be possible to detect abnormal trading patterns indicative of herding, enforcing stricter reporting requirements for institutional investors. Another suggestion is to establish sector-specific emergency liquidity mechanisms that can give response to extreme events, ensuring that liquidity shocks do not trigger unnecessary panic.

For investors, understanding the role of herding in crises periods is essential for portfolio management in the Utilities sector. While herding tendencies were observed during COVID-19, this sector showed signs of fundamental-driven decision-making rather than collective during the Ukraine war, reinforcing the importance of data-driven investment strategies. Institutional investors should recognize that different crises produce different behavioral patterns, adjusting their strategies accordingly. By developing crises-specific portfolio strategies that hedge against geopolitical risks, investors can avoid mass behavior during volatile periods. From a corporate perspective, the results suggest that Utilities companies were not significantly affected by irrational behavior but rather assessed based on their intrinsic value. Despite this fact, corporations should develop adaptable pricing models and contingency plans to manage energy and oil price volatility effectively for future events, as well as invest in sustainability and diversification, making the sector more attractive to long-term investors even during uncertainty.

5.3. Limitations

Despite its relevance to the current literature, this report presents some limitations. Firstly, it estimates herding using only one method, the CSAD. Although appropriate, the CSAD is believed to be market capitalization bias against herding detection (Rubesam & Raimundo, 2022). There are other models without these limitations that can lead to different results (Lakonishok et al., 1992). Additionally, the data was extracted from a single database (Refinitiv-Eikon). Despite being well ranked, Eikon doesn't offer as much textual analysis as some alternative platforms such as S&P Capital IQ (Bennatti, 2023). Another challenge lies in the complexity of human behavior, which models are still unable to fully capture. While this study helps identify patterns of behavior in specific timeframes, understanding the underlying reasons behind them remains difficult.

5.4. Further research

Although the COVID-19 pandemic is over, and its research has been studied, the Ukraine war is still ongoing, as the conflict continues to unfold since 2022. Future research should address the prolonged impact of these events in investors' behavior and market dynamics, along with other periods of economic distress, such as the current conflict Israel-Hamas. Comparative studies of different types of crises— from prolonged wars to regional conflicts—could deepen our understanding of market resilience and investor decision-making under distinct types of stress. Additionally, investigating the role of institutional frameworks, regulatory interventions, and investor diversity in mitigating or amplifying the effects of such crises would offer valuable insights.

AI statement

During the preparation of my written dissertation, "Evidence of Herding Behavior in PSI's Utilities Sector - From 2014 to 2024", the ChatGPT AI tool was used for the following tasks: summarization of academic papers (key take-aways), clarification of concepts, improvement of structure and coherence and bibliography review, with the prompts listed at the end of the document in the Prompt List section. After using this tool, I reviewed and edited the content as necessary and take full responsibility for the publication's content. I also declare that I am aware of and respect the Artificial Intelligence Conduct Rules of the Católica Porto Business School.

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Appendices

Augmented Dickey Fuller (ADF) tests

Augmented Dickey-Fuller test for unit root

Variable: **CSAD** Number of obs = **2,573**
Number of lags = **8**

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	**-10.458**	**-3.430**	**-2.860**	**-2.570**

MacKinnon approximate *p*-value for Z(t) = **0.0000**.

Augmented Dickey-Fuller test for unit root

Variable: **Rm** Number of obs = **2,573**
Number of lags = **8**

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	**-16.376**	**-3.430**	**-2.860**	**-2.570**

MacKinnon approximate *p*-value for Z(t) = **0.0000**.

Augmented Dickey-Fuller test for unit root

Variable: **ABSrm** Number of obs = **2,573**
Number of lags = **8**

H0: Random walk without drift, d = 0

```
Augmented Dickey-Fuller test for unit root

Variable: ABSrm                           Number of obs  = 2,573
                                          Number of lags =     8

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          -------- critical value ---------
              statistic           1%           5%          10%
------------------------------------------------------------------
 Z(t)           -10.241       -3.430       -2.860       -2.570
------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000.

Augmented Dickey-Fuller test for unit root

Variable: Rm2                             Number of obs  = 2,573
                                          Number of lags =     8

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test          -------- critical value ---------
              statistic           1%           5%          10%
------------------------------------------------------------------
 Z(t)            -9.914       -3.430       -2.860       -2.570
------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000.
```

Figure 5: Augmented Dickey-Fuller tests

```
Durbin-Watson d-statistic(  4,  2582) =  1.726021
```

Figure 6: Durbin-Watson d-statistic test

Prompt List Section

1. Research Assistance

- Summarize key findings from studies on herding behavior in financial markets.
- Provide an overview of methodologies used to measure herding, such as CSAD and CSSD.
- Explain the Efficient Market Hypothesis (EMH) and its relation to investor rationality.

2. Writing and Structure Enhancement

- Suggest ways to improve the clarity and conciseness of sentences.
- Help organize the discussion section logically by suggesting a clear structure.

3. Concept Clarification

- Explain how institutional investors contribute to herding behavior in financial markets.
- Clarify the difference between rational and irrational herding in economic terms.
- Define the role of information asymmetry in herding behavior.

4. Methodological Guidance

- Compare the strengths and weaknesses of the CSAD and CSSD methods for detecting herding.
- Explain why the CSAD method is more suitable for sector-specific herding analysis.

5. Ethical and Compliance Support

- Suggest best practices for ensuring academic integrity when using AI in research.

- Provide guidelines for properly citing AI-generated content in academic work.