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Does Algorithmic Trading Induce Herding?

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ABSTRACT

Algorithmic trading (AT) plays a major role in the trading activities of developed markets. This research breaks new ground by investigating how AT influences herding behaviour in stock markets. Utilising the implementation of the Markets in Financial Instruments Directive (MiFID II), we show that AT-induced herding is quantitatively 14 times more pronounced compared to herding triggered by non-AT elements. Algorithmic traders herd more when international volatility and market uncertainty are high, revealing a heightened sensitivity to global market signals. However, during periods of high local volatility, AT seems to disregard these fluctuations, indicating an 'inattention effect'. AT-induced anti-herding is prominent in the volatile aggressive stocks, while no such behaviour is observed in the more stable defensive stocks. The findings carry critical implications for both regulators and market professionals, as we uncover dual behaviours of AT-induced herding and anti-herding in varying market conditions.

JEL Classification: G13, G14, G17

1 | Introduction

Algorithmic trading (AT) now dominates a considerable fraction of trading volumes in advanced stock markets.[1] Although it is widely acknowledged that AT positively influences stock market liquidity and the process of price discovery (see Hendershott, Jones, and Menkveld 2011; Brogaard, Hendershott, and Riordan 2019), recent evidence suggest that AT impacts systemic risk and increases stock market returns and volatility comovements (see Kirilenko et al. 2017; Malceniece, Malcenieks, and Putniņš 2019). It is thus unexpected that the influence of AT on herding within stock markets remains mostly unexamined.

AT might lead to herding for two primary reasons. First, the highly correlated nature of AT strategies (Chaboud et al. 2014) can result in unintentional herding as they uniformly respond to new market data. Such herding arises because these rule-based, preprogrammed strategies react similarly to new information (Bikhchandani and Sharma 2000). This observation aligns with Malceniece, Malcenieks, and Putniņš (2019), who highlight increased comovements in stock returns and liquidity due to correlated trading. Second, within high-frequency trading (HFT) firms, which are a category of AT, a competitive rush exists to quickly exploit arbitrage opportunities (Budish, Cramton, and Shim 2015). HFT firms generally trade in alignment with prominent institutional investor trends (Van Kervel and Menkveld 2019). This suggests a deliberate herding strategy by AT to exploit information asymmetries, representing a rational response to obtain informational benefits (Devenow and Welch 1996).

Detecting AT-induced herding is important because herding has typically been associated with retail investor activity (see Cui, Gebka, and Kallinterakis (2019)). AT activity constitutes a significant portion of trading activities in financial markets. We present a logical argument for its role in inducing herding, contrasting traditional behavioural-based explanations. However, herding has detrimental consequences for asset pricing, market efficiency, and portfolio management, potentially leading to inefficiencies, and elevated risks (Galariotis, Krokida, and Spyrou 2016b; Sibande et al. 2023). In relation to AT, herding could arise from algorithms interpreting market signals uniformly, amplifying systemic risk and market distortion. Conversely, anti-herding algorithms might capitalise on market inefficiencies induced by herding, promoting accurate pricing.

To test our hypothesis that AT induces herding, we expand upon the methodology used by Chang, Cheng, and Khorana (2000) and take advantage of the MiFID II rollout across EU markets, where trading venues are required to keep and maintain records of AT activities for 7–10 years. We utilise a unique dataset comprising all transactions conducted at the Athens Stock Exchange (ASE) during the period immediately following the introduction of MiFID II, covering January 2018 to December 2020. Unlike Hendershott, Jones, and Menkveld (2011) and Boehmer, Fong, and Wu (2021), our dataset includes a specific AT identifier, eliminating the need for proxies to signify AT trading. The Greek stock market, ranking 12th in trading volume among the 28 EU nations, represents the broader EU market, making it a prime candidate for our investigation. Moreover, foreign investors, who make up almost 56% of trading activity in FTSE-Large Cap ASE stocks, exemplify the global shift towards increased institutional investor engagement in trading venues.[2] The ASE relies on an electronic order-driven system, with participation regulated by the ASE's rule book (refer to the ASE website). The trading regulations are completely aligned with the updated MiFID II guidelines, and approximately 12% of the total trading volume in 2018 was executed using AT.

We present novel findings to enrich existing literature. First, we demonstrate that heightened AT intensity promotes herding. Though herding effects of institutional and retail investors are well-documented (Cai et al. 2019; Cui, Gebka, and Kallinterakis 2019), exploration of how AT trading affects stock market herding is still limited. Leveraging the MiFID II implementation, we distinguish between AT and non-AT trading, constructing an AT intensity variable. Our analysis reveals a pronounced AT-induced herding effect, which exhibits a magnitude approximately 14 times stronger than that observed in non-AT herding. Given AT's high-speed and volume characteristics, such pronounced herding may exacerbate trends and heighten market volatility.

Second, utilising the volatility channel of AT, we find that AT-induced herding intensifies under pronounced market volatility and uncertainty, potentially undermining market efficiency. While previous research has explored the nexus between AT and systemic risk, they did so outside of a herding framework (see Kirilenko et al. 2017; Malceniece, Malcenieks, and Putniņš 2019). Contrary to expectations, there's an absence of AT-induced herding during local volatility surges. In contrast, given that foreign investors constitute approximately 56% of the ASE's trading activity, we document a heightened reaction to fluctuations in international volatility compared to those at the local level. Aggressive stocks reveal AT-induced anti-herding, possibly due to their inherent high volatility and market sensitivity. This suggests that, during volatile times, AT investors in aggressive stocks may pivot towards individual judgements rather than market trends. Moreover, a markedly stronger AT-induced herding emerges with heightened international volatility, being significantly more pronounced than non-AT.

Third, through the size channel of AT, we find a significant size effect in AT-induced herding behaviour. Existing literature lacks consensus regarding the interaction between size and herding. Market participants are known to exhibit more herding behaviour when trading small stocks due to their opacity, lower liquidity, and greater information asymmetries (see Wermers 1999; Sias 2004). In contrast, AT-induced herding appears to be more prevalent among large-cap stocks than smaller ones (see Hendershott, Jones, and Menkveld 2011). We categorise stocks to small and large capitalisation portfolios and investigate the effect of AT intensity on stock market herding. We report evidence of a large size effect in AT-induced anti-herding and evidence of small size effect in general herding. This emphasises AT's potential in amplifying liquidity and facilitating price discovery, especially in large-cap stocks.

Lastly, we turn our focus to the liquidity channel of AT. Malceniece, Malcenieks, and Putniņš (2019) highlight AT's positive influence on liquidity and return co-movements. Building on this, and other research noting AT's liquidity enhancement as well as enhanced price discovery (Hendershott, Jones, and Menkveld 2011; Brogaard, Hendershott, and Riordan 2019), we segment our sample based on liquidity. Our findings show that in high liquidity conditions, AT drives an anti-herding effect, suggesting AT's potential in facilitating balanced market sentiment and thus promoting efficiency.

This research contributes to the expanding body of work on AT. While the theoretical connection between AT and stock market efficiency remains ambiguous, numerous empirical studies have shown that AT plays a crucial role in improving liquidity and facilitating price discovery (Hendershott, Jones, and Menkveld 2011; Brogaard, Hendershott, and Riordan 2019). However, more recent investigations suggest that AT can also lead to increased comovement. Notably, a key study by Malceniece, Malcenieks, and Putniņš (2019) on AT and volatility comovements highlights that a significant portion of liquidity comovement in stocks is driven by the intensity of AT activities. Further, Kirilenko et al. (2017) indicate that AT increases systemic risk. In line with this research, we document that AT activities increase the interconnectedness of stocks, thereby decreasing informational efficiency.

Second, we contribute to the expanding research on stock market herding, with a significant portion of the literature examining how herding behaviour varies across different markets and stocks, as well as its changes over time (see Galariotis, Krokida, and Spyrou 2016a; Cui, Gebka, and Kallinterakis 2019). A recent study by Cui, Gebka, and Kallinterakis (2019) indicates that herding behaviour may emerge from interactions among various market participants. We formalise this hypothesis. In particular, we are able to attribute some of the variation of stock market herding to AT. Moreover, this study deepens our insight into the cross-sectional differences in stock market herding, particularly as AT shows greater activity in stocks with specific attributes.

The structure of the article is outlined as follows: Section 2 covers a review of relevant literature and the set of hypotheses for testing. Section 3 details the data collection and methodology. Section 4 presents the findings from our empirical analysis, and Section 5 concludes the study.

2 | Literature Review and Hypotheses

2.1 | Literature Review

There is an extensive literature investigating herding behaviour for a multiple of asset classes (see Galariotis, Krokida, and Spyrou 2016a; Jiang and Verardo 2018; Cai et al. 2019; Voukelatos and Verousis 2019, and Bernales, Verousis, and Voukelatos 2020), across multiple exchanges (see Chiang and Zheng 2010), for closed-end funds (Cui, Gebka, and Kallinterakis 2019) and the FX market (Sibande et al. 2023). It is possible that market participants herd intentionally as they imitate each other's actions (Froot, Scharfstein, and Stein 1992; Bikhchandani and Sharma 2000) or are motivated by career concerns (Clement and Tse 2005). Herding can also be misleading, as noted by Bikhchandani and Sharma (2000), particularly when market participants make similar decisions in response to the same market events. Additionally, behavioural biases might contribute to significant trading correlations and herding, as discussed by Barber, Odean, and Zhu (2008) and further explored by Barber and Odean (2013). On the empirical side, studies by Chang, Cheng, and Khorana (2000) and Chiang and Zheng (2010) have identified herding behaviour directed towards market consensus, while research by Zhou and Lai (2009) along with Gębka and Wohar (2013) has highlighted herding at the industry level. Finally, herding among institutional investors has been well-documented in the United States by Lakonishok, Shleifer, and Vishny (1992) and Wermers (1999), with similar patterns observed in other developed markets globally, as reported by Choi and Skiba (2015) and Galariotis, Rong, and Spyrou (2015).

Herding may reflect a natural response to information asymmetries and future price uncertainty. From this perspective, herding may be a rational strategy to less informed investors (see Chiang and Zheng 2010; Voukelatos and Verousis 2019). In such circumstances, herding persists amid heightened uncertainty and increased costs of information collection, analysis, and due diligence. Indeed, Voukelatos and Verousis (2019), demonstrate that when information about the future price movements is opaque, option investors tend to herd more.

In this article, we examine how AT influences stock market herding. Although intraday herding has been observed (Andrikopoulos et al. 2017), this has been confirmed at the market level and therefore not possible to infer how market participants (i.e., algorithmic traders and non-algorithmic traders in this article) may induce herding. Further, by investigating AT, we can offer a clearer picture of the dynamics and nuances of market behaviour, specifically regarding AT-induced herding and anti-herding tendencies under various market conditions.

There is extensive literature investigating the impact of AT on market quality. AT activity has been investigated in the US equities market (Hendershott, Jones, and Menkveld 2011; Scholtus, van Dijk, and Frijns 2014), international markets (Hendershott and Riordan 2013; Boehmer, Fong, and Wu 2021) and the FX market (Chaboud et al. 2014). The general consensus suggests that AT contributes positively to the price discovery process (Brogaard, Hendershott, and Riordan 2014) and a decline in transaction costs, mainly via the decrease in bid-ask spreads (Hendershott and Riordan 2013). Despite its benefits, AT has also been linked to several negative outcomes, including higher adverse selection costs affecting slower investors (Chaboud et al. 2014). It also contributes to decreased information acquisition (Weller 2017), an increase in systemic risk (Kirilenko et al. 2017; Paulin, Calinescu, and Wooldridge 2019) and increased comovements in returns and volatility (Malceniece, Malcenieks, and Putniņš 2019). In addition to the general consensus on AT's impact on market quality, Haslag and Ringgenberg (2023) found that in U.S. equity exchanges, larger stocks benefit more from AT-related market quality improvements than smaller stocks, a phenomenon linked to trading fragmentation across venues. Conrad, Wahal, and Xiang (2015) discovered that AT can cause significant liquidity drawdowns without degrading market quality. Chakrabarty and Pascual (2023) highlighted the crucial role of algorithmic market makers in sustaining liquidity during market crises. Brogaard et al. (2018) noted that AT selectively provides liquidity to non-algorithmic traders during extreme price movements, primarily in individual stocks. Furthermore, Boehmer, Fong, and Wu (2021) examined how AT affects market volatility and found that although increased AT activity enhances liquidity and informational efficiency, it also unexpectedly raises short-term volatility. This finding highlights AT's flexibility in alternating between providing liquidity and demanding it, particularly under conditions of high volatility (Brogaard et al. 2018), reflecting the complexity of its impact on market dynamics.

Whilst there have been some suggestions that AT may be responsible for herding observed in stock markets around the world (see Chen (2020)), this evidence is speculative at the moment with no attempt to empirically test these propositions. Albeit algorithms lack human attentional limitations, they are bound by capital constraints and the biases of their developers (Chakrabarty, Moulton, and Wang 2022), adding complexity to their market impact. Our investigation into the influence of AT intensity on stock market herding adds to the body of literature connecting AT with market efficiency (Boehmer, Fong, and Wu 2021) as well as with elements of systemic risk (Jain, Jain, and McInish 2016).

2.2 | Hypotheses Development

We develop three testable hypotheses. First, we conjecture that AT intensity is associated with more herding. The existing literature on AT suggests that algorithmic and high-frequency traders typically synchronise their trading activities with enduring price movements, which in turn facilitates the price discovery process (Brogaard, Hendershott, and Riordan 2014). Further, AT strategies often exhibit strong correlations (e.g., Chaboud et al. 2014). These correlated trading strategies lead to increased comovements in returns and liquidity (Malceniece, Malcenieks, and Putniņš 2019). In turn, Choi and Skiba (2015) demonstrate that institutional investors tend to herd based on similar signals derived from fundamental information, indicating that these investors often rely on the same data sources. As a matter of fact, Choi and Skiba (2015) call this type of herding as 'investigative herding' that eventually leads to more efficient markets and we can clearly see the similarities between 'investigative herding' and AT herding as a response to fundamental information. Further, AT strategies engage in a high-frequency arms race as well as in momentum, order anticipation and order following (stealth and gaming) strategies (see Budish, Cramton, and Shim 2015; Van Kervel and Menkveld 2019). In that case, AT trading is expected to induce herding, that is the strategy to imitate the beliefs of others. Drawing from the above findings, we propose the following hypothesis:

Hypothesis 1. *AT intensity increases stock market herding.*

Second, we expect that AT herding will be more pronounced when volatility is high. AT traders are attracted to high volatility environments as high volatility allows them to adopt their market making strategies (see Boehmer, Fong, and Wu 2021). Indeed, the study by Arumugam, Prasanna, and Marathe (2023) demonstrates that spikes in volatility encourages AT activity (HFT and non-HFT). Relatedly, Zhang (2010) shows that AT is pronounced when market uncertainty is high. Boyer, Kumagai, and Yuan (2006) indicate that co-movement has a positive correlation with volatility, Chiang and Zheng (2010) report increased herding when volatility is high, and Cui, Gebka, and Kallinterakis (2019) find that herding behaviour in closed-end funds intensifies when market uncertainty is heightened. Building upon these insights, we develop the following hypothesis:

Hypothesis 2. *AT-induced herding is higher when stock market volatility is high.*

Third, we propose that the interplay between AT intensity and herding behaviour in stock markets is heavily influenced by the source and nature of market volatility. In line with the research by Arumugam, Prasanna, and Marathe (2023), our hypothesis posits that AT strategies become increasingly responsive, thereby amplifying herding behaviour during periods of elevated international volatility. This response can be attributed to AT's propensity to capitalise on global market dynamics and uncertainties, a characteristic highlighted by Boehmer, Fong, and Wu (2021). In contrast, we posit that the influence of AT on herding might be mitigated in scenarios of escalated national volatility, particularly within the context of the ASE. This divergence can be primarily attributed to the unique market dynamics of ASE, as highlighted by Koulakiotis, Babalos, and Papasyriopoulos (2016). Despite being a small and peripheral market within the Eurozone, ASE has attracted considerable attention from large investment funds, with foreign investors contributing significantly to trading volumes. This complex interplay of local and international influences suggests that ASE operates under a set of market stimuli distinct from larger, more established markets. Consequently, while AT strategies are finely tuned to exploit global market trends and broader economic indicators, they may be less sensitive or reactive to localised market fluctuations that are more representative of country-specific economic conditions and investor sentiments. Additionally, the scale and depth of the national market like ASE may not provide the same level of liquidity and trading opportunities that AT strategies require, further diminishing their impact on herding behaviour in such markets. Thus, our next hypothesis suggests that AT's behaviour is influenced not just by the level of volatility, but also by the unique characteristics and scale of the market.

Hypothesis 3. *AT-induced herding intensifies with increased international volatility.*

Last, we expect that AT herding will exhibit company size effects.[3] According to Hendershott, Jones, and Menkveld (2011), stocks of larger companies tend to draw greater AT activity. Large companies' stocks are more liquid with many investors, therefore making it easier for AT to enter and exit the market. Indeed, Menkveld (2013) show that large stocks may attract as much as five times more AT and HFT activity than small stocks. Research on herding suggests a size effect, where smaller stocks tend to experience more pronounced herding than their larger counterparts (Wermers 1999; Sias 2004). This observation aligns with the idea that investors will herd more when information asymmetry and illiquidity is high. On the other hand, Kremer and Nautz (2011) show that short-term herding exists for large stocks. Whilst the above does not allow us to infer a directional hypothesis, we expect that AT-induced herding will exhibit a size effect. We therefore develop the following hypothesis:

Hypothesis 4. *AT-induced herding exhibits a company size effect.*

3 | Data and Methodology

3.1 | Data

We obtained our dataset, covering trades from January 3rd, 2018 to December 31st, 2020, from the ASE, offering a detailed snapshot of the market following MiFID II implementation. The dataset includes 62 stocks, representing a varied cross-section of the FTSE/ATHEX Market Index, with stocks from the Large Cap, Mid Cap, and Small Cap indices.[4] These stocks span 14 different sectors, reflecting a broad spectrum of the Greek market landscape.[5] It's pertinent to note that the FTSE/ATHEX Market Index comprises a total of 85 constituents, indicating that our sample covers a substantial portion of the market. We drop observations before January 10th, 2018, as AT records start from that day. The trade data contain trade price, trade size, a buy/sell indicator, an anonymized stock indicator and a flag to indicate if the trade is an AT (Algo) trade. Data is stamped to the nearest millisecond. We obtain market capitalisation data from Bloomberg. Our final dataset consists of 62 stocks and 36,254,196 trades.[6]

3.1.1 | Regulatory Compliance and Market Participation at the ASE

The ASE operates stock market trading comparable to markets in the US or Europe and adheres strictly to MiFID II policies on

AT (ALGO), direct electronic access (DEA), and high-frequency trading (HFT). Specifically, any trading venue permitting AT must meet certain obligations, as outlined in Article 48 of MiFID II, which details the regulations for venues enabling AT and HFT. The guidelines outlined specify the regulations that trading venues supporting AT and HFT must follow. These regulations are intended to safeguard against market disorder and prevent any potential for market abuse. To comply, trading venues are required to ensure their systems are robust, capable of processing large volumes of orders, and effective under stressed conditions. Moreover, these systems must include circuit breakers to halt or limit trading temporarily during unforeseen price swings.

RTS 7[7] additionally outlines the organisational requirements for trading venues that 'permit or enable AT'. These venues are further detailed in Article 1 of RTS 7 as locations 'where order submission and order matching is facilitated by electronic means'. Recital 3 of RTS 7 identifies that 'specific organisational requirements should be laid down in respect of regulated markets, multilateral trading facilities and organised trading facilities allowing for or enabling AT through their systems. Such trading systems are those where AT may take place as opposed to trading systems in which AT is not permitted, including trading systems where transactions are arranged through voice negotiation'.

AT is permitted under the ASE rulebook and constituted nearly 12% of the total trading volume in 2018. Table 1, Panel A, details the number of notifications sent by firms involved in AT to National Competent Authorities (NCAs) across 18 Member States. Specifically, notifications (246) were directly submitted by local firms authorised for AT by their domestic NCA. Additionally, notifications (872) were received from firms conducting AT across various venues that were authorised by either domestic or foreign NCAs.[8] A firm that engages in AT on a domestic trading venue will be counted in both notification categories. It is obvious that firms participating in ASE follow the EU trend regarding their AT notifications to NCAs (12 report to Greek NCA out of 19 that report to other NCAs including Greek NCA). Additionally, ESMA reports that the proportion of trading venue participants who have informed the NCA about their engagement in AT differs widely across EU jurisdictions. The percentage generally falls between 42% and 60%, but on smaller venues, including those in Nordic countries, it can approach or surpass 50%. At ASE, the rate is around 45%, with 19 out of 42 members engaging in AT.

Panel B in Table 1 illustrates the investor participation over recent years, showcasing the distribution of trading volume among foreign, local private and local institutional investors. Notably, foreign participants have a substantial influence on trading activity within ASE. Since 2018, the participation of foreign investors in market trading activity has been consistently high exceeding 50%. The consistent majority participation of foreign investors further emphasises the need for ASE's trading mechanisms to align with international standards and practices.

TABLE 1 | Algorithmic trading notifications and investor participation in the ASE market.

Panel A: Notifications received by NCAS from firms that engage in ALGO per member state		
Member state	**As NCA of the firm engaging in algorithmic trading**	**As NCA of the trading venue where algorithmic trading takes place**
Austria	3	2
Belgium	2	58
Czech Republic	7	11
Estonia	1	1
Finland	2	43
France	20	79
Germany	81	288
Greece	12	19
Hungary	3	3
Ireland	6	15
Italy	21	57
Malta	3	0
Netherlands	25	60
Norway	2	37
Poland	14	40
Portugal	2	42
Spain	31	74
Sweden	11	43
Total	**246**	**872**

Panel B: Investor participation (%) in the ASE total turnover			
Year	**Foreign investors**	**Local private investors**	**Local institutional investors**
2018	56.00	17.50	22.70
2019	53.70	20.10	25.10
2020	50.80	24.50	23.10
2021	54.30	22.50	21.40
2022	54.90	20.50	22.20
2023	56.10	19.60	22.40

Notes: Data in Panel A is collected from NCAs in the EU Member States under Article 17(2) of MiFID II. Panel B presents the percentage participation of foreign, local private and local institutional investors in the Athens Stock Exchange (ASE) total turnover in the period of 2018–2023.
Source: www.athegroup.gr.

The steady presence of foreign investors not only validates ASE's appeal to international markets but also necessitates the adherence to follow MiFID II regulations that govern algorithmic and HFT activities.

3.2 | Methods

According to Christie and Huang (1995), dispersion is expected to rise in proportion to the absolute size of market returns, as predicted by asset pricing models, due to the varying sensitivities of individual assets to these returns. Conversely, substantial market fluctuations may prompt herding behaviour, leading investors to follow the market consensus rather than relying on their own private signal. This herding behaviour can result in return dispersions growing at a slower rate or even diminishing when herding is particularly intense. To assess this effect, they devised the cross-sectional standard deviation (CSSD) method. However, due to the method's vulnerability to anomalies from squared return deviations, Chang, Cheng, and Khorana (2000) proposed using the cross-sectional absolute deviation (CSAD) as a more reliable alternative, which is less influenced by extreme price movements. This is computed as:

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

where $R_{i,t}$ represents the logarithmic return based on the last daily price of stock i on day t, while $R_{m,t}$ denotes the market return across full sample stocks. Consistent with prior research, we calculate market return as the weighted average of returns across the full set of stocks within our sample (see Chang, Cheng, and Khorana 2000; Chiang and Zheng 2010).

Chang, Cheng, and Khorana (2000) propose that when there are substantial average price movements, investors often follow the general market direction, leading to a non-linear association between CSAD and the average market return. This testing method assumes that prevalent herding behaviour among investors would result in more synchronised returns, reflecting the collective actions within the market. This collective movement, in turn, would result in a reduced dispersion of returns, as individual return paths converge more closely. We employ this methodological framework to uncover evidence of herding behaviour within the market:

$$CSAD_t = \beta_0 + \beta_1\left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + \varepsilon_t \tag{2}$$

Under rational expectations, we expect $\beta_1 > 0$ and $\beta_2 = 0$ (see Black 1972). This scenario suggests that return dispersion correlates positively with market returns, signifying the absence of herding. Herding behaviour represents a departure from rational expectations, thereby suggesting that the coefficient β_2 should exhibit statistical significance. Within the literature on herding, a negative coefficient, accompanied by statistical significance, typically evidence herding behaviour (see Chang, Cheng, and Khorana 2000; Christie and Huang 1995). This demonstrates that return dispersion noticeably decreases during market stress periods, a phenomenon attributable to the correlated trading behaviour among investors. Such a trend suggests that market participants may abandon their individual judgements to align with the market's prevailing consensus. By contrast, if β_2 is positive and statistically significant, it indicates anti-herding (see e.g., Gębka and Wohar 2013). Anti-herding behaviour suggests that participants disregard broad market information and act contrary to the prevailing market sentiment. Factors such as overconfidence and localised herding might cause participants to dismiss the overall market consensus (see Nöth and Weber 2003; Gębka and Wohar 2013).

As outlined in the previous section, our hypothesis posits a positive relationship between AT intensity and stock market herding. To validate this hypothesis, we augment Equation (2) and employ the following equation, applying least squares alongside Newey–West robust standard errors for estimation:

$$\begin{aligned} CSAD_t = {} & \beta_0 + \beta_1\left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + \beta_3 AT\_Intensity_{up10,t} \\ & + \beta_4\left(AT\_Intensity_{up10,t} \times R_{m,t}^2\right) + \varepsilon_t \end{aligned} \tag{3}$$

For each day and stock, we determine the proportion of algo-flagged trades relative to the total trades. $AT\_Intensity_{up10,t}$ is set as a dummy, equating to one on days when the ratio falls within the top 10% of its distribution across the entire sample period, and zero otherwise.

The coefficient of interest here is β_4. In the scenario where AT intensity becomes a driver of herding, the anticipated outcome would be a negative and statistically significant β_4, indicating a convergence of stock returns towards the market consensus. This would suggest that AT strategies are collectively responding to the same market signals, thus moving in tandem. If, instead, β_4 is positive and significant, it would suggest anti-herding—where increased AT activity leads to individual stock returns deviating from the overall market consensus. Anti-herding may arise when algorithmic traders, relying on diverse or contrarian strategies, independently act on different information sets or market perceptions. This independent action could be driven by proprietary algorithms that interpret market data in unique ways, leading to a variety of trading behaviours that counteract the convergent tendencies of herding. Furthermore, anti-herding may reflect a strategic response by ATs to exploit market inefficiencies created by herding behaviour, thus contributing to market correction and enhancing price discovery. If β_3 is statistically significant and negative (positive), it indicates that high levels of AT activity generally correspond to a narrower (wider) dispersion of individual returns.

4 | Results

4.1 | Descriptive Statistics

A detailed summary of the statistics for the number of trades and the AT ratio (defined as the proportion of AT trades relative to total trades) is presented in Table 2, Panel A. We employed daily frequency covering the entire sample period. In addition, we provide key statistical measures, including *CSAD*, $R_{m,t}$ and *AT_Intensity* over the entire sample period on a daily basis, along with descriptive statistics for the three volatility proxies.

TABLE 2 | Descriptive statistics.

Panel A: Summary statistics for the full sample							
	Mean (%)	**Standard deviation (%)**	**Minimum (%)**	**Maximum (%)**	**Skewness**	**Kurtosis**	**Observations**
Variables							
CSAD	1.613	0.629	0.72	6.109	2.8	15	739
$R_{m,t}$	−0.008	1.745	−17.745	8.675	−2.1	25	739
AT_Intensity	0.1	0.3	0	1	2.6	8	739
Total trades and AT							
Total trades	928.8	381.2	238.1	2767.8	1.4	5.8	739
AT ratios	6.173	2.368	1.491	14.59	0.7	3.2	739
Volatility measures							
ASE index	0.005	0.007	0.00002	0.069	4.3	29	739
VIX	20.39	9.88	9.82	82.69	2.6	12	724
TEU	176.5	105.8	43.2	670.5	1.5	6	739

Panel B: Statistics for ratios during the sample periods							
	Mean (%)	**Standard deviation (%)**	**Minimum (%)**	**Maximum (%)**	**Skewness**	**Kurtosis**	**Observations**
Book-to-market ratio	1.752	2.951	0.057	26.67	5.544	39.91	186
Market capitalization	744.06	1589.5	3.985	10959.9	4.198	23.2	186
Beta	0.852	0.366	0.135	2.732	1.438	6.528	186

Panel C: Correlation matrix for volatility			
	(1)	**(2)**	**(3)**
(1) ASE index	1		
(2) VIX	0.43	1	
(3) TEU	0.27	0.77	1

Notes: This table presents the descriptive statistics results. In Panel A, we display the statistic results on average total number of trades and average AT ratios on daily interval, which contains statistics on the mean, standard deviation, minimum values, maximum values, Skewness, Kurtosis, and number of observations for full sample periods. Number of trades and number of algorithmic trades are aggregated on one-minute interval, then we calculate AT ratio as number of algorithmic trades divided by number of trades on each interval. The results are the average value across 62 stocks in our final sample. Statistic results for CSAD and $R_{m,t}$ on daily interval are reported. $CSAD_t = \frac{\sum_{i=1}^{N} \left|R_{i,t} - R_{m,t}\right|}{N-1}$, where $R_{i,t}$ is the return of stock i on day t and $R_{m,t}$ is the market return on day t. Volatility measures detail statistics under national indicator (FTSE ASE index) and international indicators (VIX index and TEU index). ASE index and VIX index data is obtained from Bloomberg, while TEU index is collected from Economic Policy Uncertainty Database. For the daily volatility measure of the ASE index, we employ the intraday high-low price range as a proxy, which is then utilised to develop a sequential dataset indicative of market volatility patterns. For international volatility indicator, we collect Chicago Board Options Exchange's CBOE Volatility Index data from Bloomberg to measure the stock market's expectation of volatility based on S&P 500 index options. TEU index includes daily number of tweets in English involving both Uncertainty terms and Economy terms as investor sentiment indicator. Panel B displays statistics results of book-to-market ratios, market capitalization, and beta values for all stocks across the sample periods. Panel C presents the correlation matrix among volatility indicators.

Our descriptive statistics in Panel B provide a detailed breakdown of the financial characteristics of all stocks during the sample periods. The table highlights the book-to-market ratio alongside market capitalization, providing a detailed insight into the valuation and size of companies in our ASE market sample. For the size effect analysis, we categorise the firms based on their year-end market capitalization, delineating between larger firms with top 30% substantial market presence and smaller firms with lower 30% market capitalization. Furthermore, the classification into aggressive and defensive stocks is based on their beta values, with aggressive stocks bearing a beta greater than one and defensive stocks with a beta less than one, indicating their respective volatility in relation to the market. The correlation matrix among three volatility proxies is shown in Panel C. The matrix demonstrates that there exists moderate positive correlation among national volatility indicator (ASE index), international volatility indicator (VIX index), and investor sentiment indicator (TEU index).

Figure 1 illustrates the CSAD in relation to stock market returns, both for the entire sample and when categorised into large and small stocks. We define large (small) stocks as those within the upper (lower) 30% of market capitalization at the close of each year across the entire sample. The figure suggests potential herding behaviour, with market returns showing a connection to elevated levels of absolute dispersion. Additionally, Figure 2 illustrates the time series of the average ratio of algo-to-total trades across the full sample, as well as individually for large and small stocks.

4.2 | Does AT Induce Herding?

In this section, we investigate the main hypothesis that AT intensity induces stock market herding. The estimation results related to Equation (3) are summarised in Table 3. The adjusted R-squared indicates comparable goodness of fit to herding studies involving financial markets from US, European and Asian countries (Chang, Cheng, and Khorana 2000; Economou, Kostakis, and Philippas 2011). The negative and significant coefficient for β_2 indicates herding behaviour at the ASE, and the statistically significant and negative β_4 coefficient further confirms that higher AT intensity amplifies herding.[9]

4.3 | Is AT-Induced Herding Higher When Volatility Is High?

In particular, we focus on three different proxies of volatility. The first proxy is local volatility, where we estimate the daily range between the ASE index's highest and lowest prices, allowing us to construct a time series that reflects the market's daily fluctuation dynamics. As most of the trading activity in ASE is performed through international based clients, we would expect that foreign investors rely less on local and more on international signals when trading (see Brennan and Cao 1997). Therefore, in separate regressions we include the Volatility Index (VIX) as an international indicator of volatility. Finally, Baker et al. (2021) highlight the evolving landscape of information sources by utilising Twitter for sentiment analysis to construct the Twitter Economic Uncertainty Index (TEU). This novel metric compiles

Cross-Sectional Dispersion and Market Returns

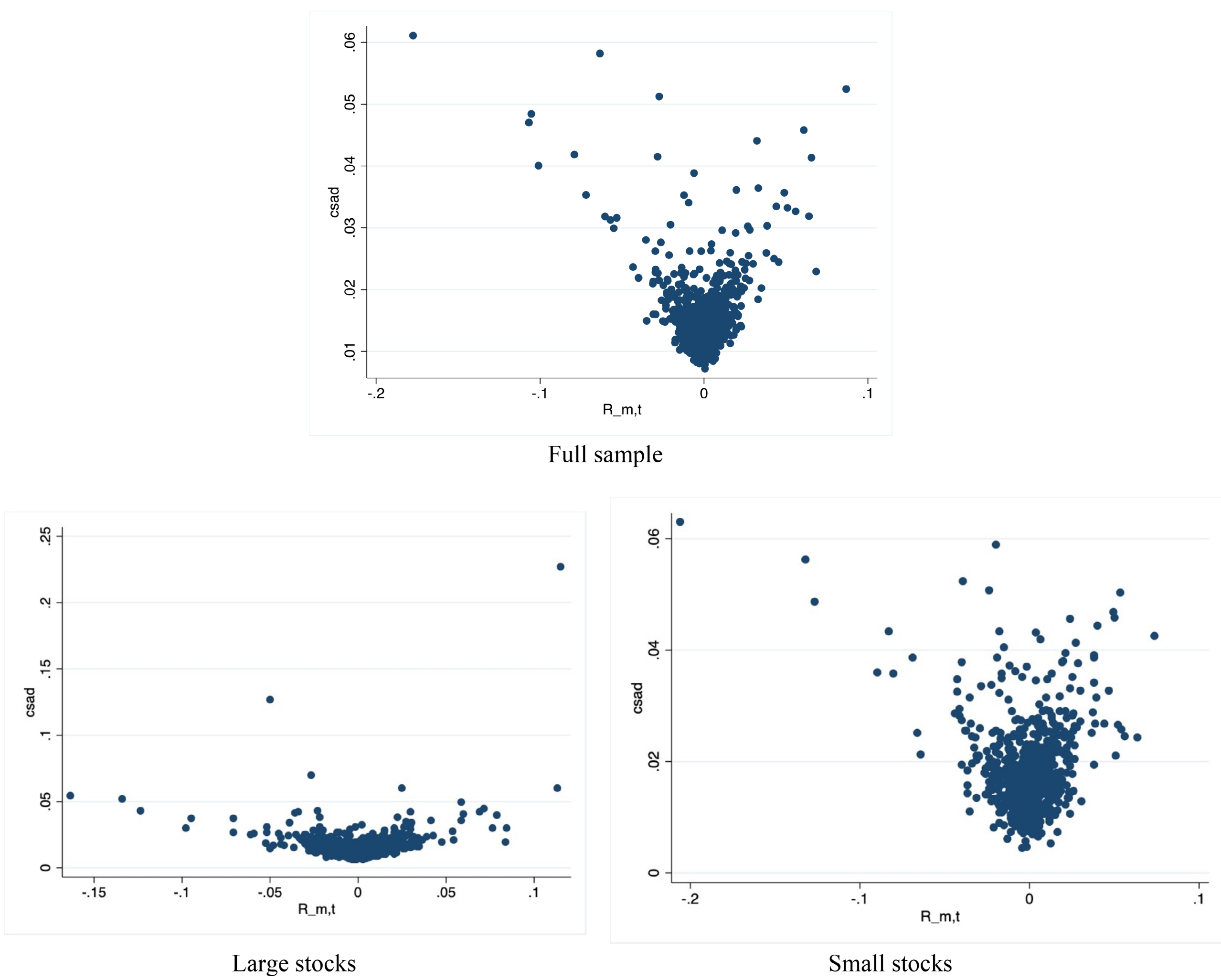

FIGURE 1 | Cross-sectional dispersion and market returns. This figure plots CSAD against the equally-weighted market return between January 2018 and December 2020 for full sample, large stocks and small stocks. Large (Small) stocks are defined as the top (bottom) 30% of market capitalization on each sample year end. [Colour figure can be viewed at wileyonlinelibrary.com]

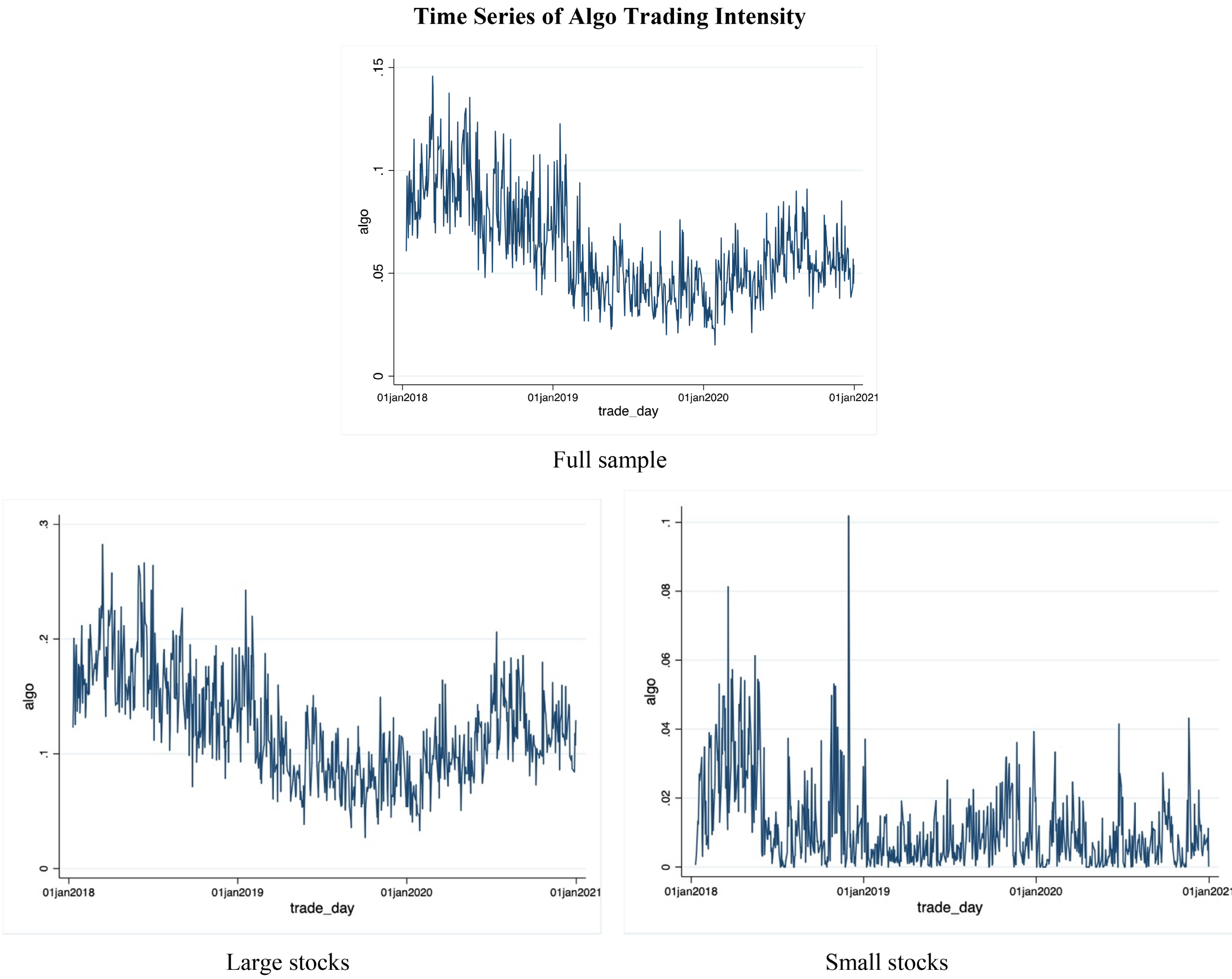

FIGURE 2 | Time series of Algo trading intensity. This figure plots the fraction of algorithmic trading on the daily basis across the sample period from January 2018 to December 2020. Large (Small) stocks are defined as the top (bottom) 30% of market capitalization on each sample year end. [Colour figure can be viewed at wileyonlinelibrary.com]

the daily count of English-language tweets that include keywords associated with uncertainty and economic topics. Considering the link between herding behaviour and market uncertainty, incorporating the TEU in our study offers a multifaceted approach to analysing market volatility dynamics.[10]

The baseline regression results for herding behaviour, segmented by low and high volatility periods, are displayed in Columns 1 and 2 of Table 4. We report some interesting results. The analysis reveals that the herding coefficient β_2 is insignificantly positive during low volatility periods but turns significantly negative under high volatility conditions (β_2 is −0.74 with a t-statistic of −2.58). This implies that during high volatility, investors tend to align with the prevailing market sentiment, whereas they are more prone to disregard it when the market is calmer. Given that the volatility indicator is a national one, this result may reflect the difficulty of investors to price assets in periods of high volatility. More importantly, the results shown in Columns 3 and 4 of Table 4, where Equation (3) is estimated separately for low and high volatility days, indicate no evidence of AT-induced herding, as beta 4 remains statistically insignificant across both volatility conditions.[11] It suggests that Hypothesis 3 is not supported in the context of national volatility. Algorithmic traders operate on a distinct information set compared to national investors. Given the unique market dynamics and integration of the ASE with international markets (Dicle and Levendis 2011; Koulakiotis, Babalos, and Papasyriopoulos 2016), our findings suggest that AT strategies may not be significantly influenced by national volatility factors to the same extent as traditional investors.

In Table 5, we explore the details of herding behaviour by dividing our sample into two distinct stock categories: the aggressive group and the defensive group. The beta values for each stock are collected on 31st December of each sample year. Aggressive stocks, identified by a beta value exceeding 1, exhibit higher volatility compared to the overall market. These stocks tend to move more significantly in response to overall market trends. Column 1 provides evidence of herding within this group, as indicated by a negative and significant β_2 (*t*-statistic of −2.12). When algorithmic trading intensity comes into play (as represented by Equation (3)), the results show a negative and significant β_3 and a positive and significant β_4. The negative β_3 value suggests that under normal market conditions, AT prompts herding behaviour among aggressive stocks. However, a statistically significant and positive β_4 suggests that heightened AT activity in aggressive stocks leads to anti-herding behaviour. In other words, heightened HFT activities in volatile market conditions lead to a broader dispersion in individual stock returns. Aggressive stocks, by their nature, present a fertile ground for the execution of AT strategies. These stocks, due to their greater market sensitivity, are more susceptible to the rapid execution and volume characteristic of AT. This concurs with Boehmer, Fong, and Wu (2021) and Arumugam, Prasanna, and Marathe (2023), who argue that AT is adept at exploiting market dynamics, especially in volatile environments. It appears that during periods of market stress, when aggressive stocks are more sensitive to volatility, AT strategies may avoid the converging behaviour typical of herding, seeking arbitrage opportunities presented by the market's overreaction or underreaction. This behaviour is consistent with the adaptive nature of AT that is programmed to exploit market inefficiencies.

TABLE 3 | Does algorithmic trading induce herding.

	(1)	(2)
$\lvert R_{m,t}\rvert$	0.392***	0.399***
	(13.6)	(13.5)
$R^2_{m,t}$	−0.554***	−0.614***
	(−2.78)	(−3.13)
$AT\_Intensity_{up10,t}$		0.0007
		(1.61)
$AT\_Intensity_{up10,t} \times R^2_{m,t}$		−7.632***
		(−3.52)
Adjusted R^2	0.57	0.58
Observations	739	739

Notes: This table presents the results for the following non-linear regression: $CSAD_t = \beta_0 + \beta_1\lvert R_{m,t}\rvert + \beta_2 R^2_{m,t} + \varepsilon_t$ in Column (1) and $CSAD_t = \alpha + \beta_1 \mid R_{m,t} \mid + \beta_2 R^2_{m,t} + \beta_3 AT\_Intensity_{up10,t} + \beta_4 AT\_Intensity_{up10,t} R^2_{m,t} + \varepsilon_t$ in Column (2), where CSAD is the Cross-Sectional Absolute Deviation, $R_{m,t}$ is the daily market return, and $AT\_Intensity_{up10,t}$ is the dummy variable which takes one when daily fraction of algorithmic trading locate on the top 10% level, otherwise takes zero. Estimations are run from January 2018 to December 2020 for each column. For brevity, we do not include constant value. Newey–West robust *T*-statistics are reported in parentheses. * = significance at the 10% level; ** = significance at the 5% level; *** = significance at the 1% level.

In contrast, defensive stocks (beta < |1|) is absence of herding or anti-herding patterns. Their inherent stability and lower volatility profile may not provide the same speculative or arbitrage opportunities that AT strategies favour, which are abundant in aggressive stocks during turbulent periods. This difference highlights a market response to AT where the behaviour of algorithmic traders is discriminately influenced by the risk profile of the stocks.

The distinction between herding and anti-herding is further underscored by the market environment of the ASE. This observation is consistent with ASE's profile as an emerging market, characterised by substantial participation from foreign investors, as noted by Koulakiotis, Babalos, and Papasyriopoulos (2016). It can be inferred that in such markets, AT strategies may trade on heterogeneous information sets and selectively target stocks more responsive to global market trends rather than those insulated from such fluctuations.

To further investigate this finding, in Table 6, we use VIX and TEU as our volatility proxy and re-estimate Equations (2) and (3) separately for high and low volatility days. When only the baseline regressions are considered from Equation (2) in Table 6 Columns 1 and 2 for VIX (Columns 5 and 6 for TEU), the herding coefficient β_2 is insignificant for low volatility days but signifcantly negative

TABLE 4 | Herding results under high volatility based on ASE index.

	(1)	(2)	(3)	(4)
	Low volatility	**High volatility**	**Low volatility**	**High volatility**
$\lvert R_{m,t}\rvert$	0.171	0.405***	0.164	0.405***
	(1.37)	(7.95)	(1.3)	(7.67)
$R^2_{m,t}$	5.884	−0.74**	5.944	−0.742**
	(1.06)	(−2.58)	(1.05)	(−2.49)
$AT\_Intensity_{up10,t}$			−0.0001	−0.0004
			(−0.03)	(−0.43)
$AT\_Intensity_{up10,t} \times R^2_{m,t}$			3.415	−6.04
			(0.8)	(−0.15)
Adjusted R^2	0.2	0.69	0.2	0.69
Observations	147	147	147	147

Notes: This table reports the results of the herding specification regarding low volatility periods and high volatility periods indicating by national indicator FTSE/ASE large cap index, following the baseline regression $CSAD_t = \beta_0 + \beta_1\lvert R_{m,t}\rvert + \beta_2 R^2_{m,t} + \varepsilon_t$ in Columns (1) and (2), and $CSAD_t = \alpha + \beta_1 \mid R_{m,t} \mid + \beta_2 R^2_{m,t} + \beta_3 AT\_Intensity_{up10,t} + \beta_4 AT\_Intensity_{up10,t} R^2_{m,t} + \varepsilon_t$ in Columns (3) and (4), where CSAD is the cross-sectional absolute deviation at time t, $R_{m,t}$ is the daily market return, $AT\_Intensity_{up10,t}$ is a dummy variable that takes the value of one when the fraction of algorithmic trading over total daily trades (i.e., regardless execution of buy orders or sell orders) is located on the upper 10% tail of its distribution, otherwise takes zero. The national volatility is measured as the standard deviation of daily high and low price of this index. Estimations are run for the top (bottom) 20% of FTSE/ASE index volatility distribution across the full sample as high (low) volatility. For brevity, we do not include constant value. Standard errors are robust to heteroscedasticity and autocorrelation consistent using Newey–West. *T*-statistics in parentheses. * = significance at the 10% level; ** = significance at the 5% level; *** = significance at the 1% level.

TABLE 5 | Herding results from aggressive group and defence group in ASE market.

	(1) Aggressive	(2) Aggressive_AT	(3) Defence	(4) Defence_AT
$\|R_{m,t}\|$	0.315***	0.296***	0.398***	0.397***
	(10.24)	(9.61)	(6.99)	(6.72)
$R^2_{m,t}$	−0.636**	−0.556*	−0.239	−0.228
	(−2.12)	(−1.82)	(−0.69)	(−0.63)
$AT\_Intensity_{up10,t}$		−0.003***		0.000
		(−3.26)		(0.86)
$AT\_Intensity_{up10,t} \times R^2_{m,t}$		3.702**		1.310
		(2.28)		(0.15)
Adjusted R^2	0.335	0.349	0.497	0.498
Observations	739	739	739	739

Notes: This table shows the further test results from ASE market by splitting the full sample into aggressive group and defence group, following the baseline regression $CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2R^2_{m,t} + \varepsilon_t$ in Column (1) for aggressive group and in Column (3) for defence group, and $CSAD_t = \alpha + \beta_1 \mid R_{m,t} \mid + \beta_2R^2_{m,t} + \beta_3AT\_Intensity_{up10,t} + \beta_4AT\_Intensity_{up10,t}R^2_{m,t} + \varepsilon_t$ in Columns (2) and (4), where CSAD is the cross-sectional absolute deviation at time t, $R_{m,t}$ is the daily market return, $AT\_Intensity_{up10,t}$ is a dummy variable that takes the value of one when the fraction of algorithmic trading over total daily trades (i.e., regardless execution of buy orders or sell orders) is located on the upper 10% tail of its distribution, otherwise takes zero. We collect each stock's beta value on 31st December of each sample year. Aggressive group refers to stocks with beta value greater than 1, which indicates these stocks are more volatile than the market. Alternatively, stocks with beta value less than 1 are defence group which are less volatile than the market. For brevity, we do not include constant value. Standard errors are robust to heteroscedasticity and autocorrelation consistent using Newey–West. T-statistics in parentheses. * = significance at the 10% level; ** = significance at the 5% level; *** = significance at the 1% level.

TABLE 6 | Herding results under extreme volatility based on international indicators.

	VIX				TEU			
	(1) Low volatility	(2) High volatility	(3) Low volatility	(4) High volatility	(5) Low volatility	(6) High volatility	(7) Low volatility	(8) High volatility
$\|R_{m,t}\|$	0.276**	0.352***	0.196*	0.351***	0.407***	0.394***	0.434***	0.406***
	(2.13)	(9.29)	(1.72)	(9)	(3.06)	(9.04)	(3.18)	(8.87)
$R^2_{m,t}$	4.629	−0.489***	7.957	−0.499***	−6.817	−0.713***	−8.563	−0.775***
	(0.66)	(−2.69)	(1.22)	(−2.78)	(−1.07)	(−2.84)	(−1.32)	(−2.9)
$AT\_Intensity_{up10,t}$			0.002	−0.001			0.001	0.001
			(1.4)	(−1.43)			(0.96)	(0.58)
$AT\_Intensity_{up10,t} \times R^2_{m,t}$			−2.965	−9.426***			5.459	−1.442***
			(−0.38)	(−3.34)			(1.19)	(−2.71)
Adjusted R^2	0.3	0.67	0.33	0.68	0.23	0.68	0.26	0.68
Observations	145	145	145	145	146	147	146	147

Notes: This table shows the results of herding specification for low volatility and high volatility indicating by international indicator VIX index and TEU index. In Columns (1), (2), (5), and (6), results present from baseline herding specification of market participants in general in ASE market: $CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2R^2_{m,t} + \varepsilon_t$. In Columns (3), (4), (7), and (8), we show results of herding specification on algorithmic traders by including the dummy variable as follows: $CSAD_t = \alpha + \beta_1 \mid R_{m,t} \mid + \beta_2R^2_{m,t} + \beta_3AT\_Intensity_{up10,t} + \beta_4AT\_Intensity_{up10,t}R^2_{m,t} + \varepsilon_t$, where CSAD is the cross-sectional absolute deviation at time t, $R_{m,t}$ is the daily market return, $AT\_Intensity_{up10,t}$ is a dummy variable that takes the value of one when the fraction of algorithmic trading over total daily trades (i.e., regardless execution of buy orders or sell orders) is located on the upper 10% tail of its distribution, otherwise takes zero. Estimations are run for the top (bottom) 20% of VIX and TEU distribution across the full sample as high (low) volatility. For brevity, we do not include constant value. Standard errors are robust to heteroscedasticity and autocorrelation consistent using Newey–West. T-statistics in parentheses. * = significance at the 10% level; ** = significance at the 5% level; *** = significance at the 1% level.

for high volatility days (β_2 is −0.489 with a t-statistic of −2.69 for VIX, β_2 is −0.713 with a t-statistic of −2.84 for TEU), indicating that there is significant herding when volatility is high.

By employing a two-way split between low and high volatility days, as well as AT versus non-AT trading (refer to Table 6, Columns 3 and 4 for VIX and Columns 7 and 8 for

TEU), our analysis from Equation (3) reveals an absence of AT-induced herding during periods of low volatility. However, a significantly negative β_4 was observed (β_4 is −9.426 with a t-statistic of −3.34 for VIX, β_4 is −1.442 with a t-statistic of −2.71 for TEU) in high volatility periods. The absolute value of the β_4 coefficient surpasses that of β_2 (β_2 is −0.449 with a t-statistic of −2.78 for VIX, β_2 is −0.775 with a t-statistic of −2.9 for TEU), suggesting that AT strategies not only respond to volatility but also potentially amplify herding effects during periods of heightened international market uncertainty. These findings support Hypothesis 2, confirming that AT-induced herding becomes more evident when market volatility intensifies. This is consistent with the observations of Chiang and Zheng (2010), who documented an increased propensity for herding during market stress. Furthermore, it echoes the conclusions of Galariotis, Rong, and Spyrou (2015), who highlighted that the factors driving herding behaviour are specific to particular periods. Additionally, consistent with Galariotis, Rong, and Spyrou (2015), our analysis indicates that the triggers for herding behaviour are closely related to market conditions.

Furthermore, the findings reinforce Hypothesis 3, as the pronounced herding behaviour detected during periods of heightened international volatility suggests an intensified impact of AT under such conditions. The distinction in herding patterns, particularly evident under high volatility as measured by international indicators, underscores the differential impact of AT based on the scale and origin of market volatility. The interplay between AT intensity, volatility levels, and market types illustrates a complex landscape where AT's influence on herding behaviour is tied to the broader market context.

4.4 | Does AT-Induced Herding Exhibit a Size Effect?

This section delves into Hypothesis 4 by examining the size effect as an additional channel through which AT impacts herding behaviour. We therefore assign stocks to large and small capitalisation portfolios and re-estimate Equations (2) and (3).

Table 7, Columns 1 and 2, details the results of Equation (2), with separate analyses conducted for small and large stocks. As expected, there is evidence of significant herding effects for small stocks (β_2 is −0.625 with a t-statistic of −3.72). This is in line with established literature on the propensity of investors to follow collective market behaviours in environments characterised by higher opacity and information asymmetry (see Wermers 1999; Sias 2004). The insignificant coefficients for β_2 and β_4 for small stocks indicate that AT are potentially not active in small stocks (see also Figure 2). Conversely, the scenario shifts markedly for large stocks. A significant anti-herding effect emerges among AT participants (β_4 is 13.43 with a t-statistic of 50.32), illustrating a strategic departure from the market consensus. Such distinct behaviour could be attributed to AT participants trading these stocks based on heterogeneous information sets. The ASE exhibits substantial foreign investor participation, which offers fertile ground for AT strategies. Due to their greater transparency and reduced information asymmetry, large stocks are prime candidates for AT to utilise their sophisticated algorithms and high-speed data analytics. This enables AT to independently evaluate market data and induce anti-herding. This behaviour not only demonstrates the informational advantage held by AT but also highlights their role in enhancing market efficiency through divergent trading strategies. Furthermore, the detection of anti-herding among large stocks, rather than

TABLE 7 | Herding and the size effect.

	(1)	(2)	(3)	(4)
	Small	**Small_AT**	**Large**	**Large_AT**
$\lvert R_{m,t} \rvert$	0.368***	0.374***	0.366***	0.378***
	(11.85)	(11.76)	(4.47)	(7.04)
$R^2_{m,t}$	−0.625***	−0.663***	0.565	−0.647*
	(−3.72)	(−3.86)	(0.35)	(−1.71)
$AT\_Intensity_{up10,t}$		−0.0003		−0.001**
		(−0.34)		(−2.25)
$AT\_Intensity_{up10,t} \times R^2_{m,t}$		−4.092		13.43***
		(−1.09)		(50.32)
Adjusted R^2	0.34	0.34	0.36	0.67
Observations	739	739	739	739

Notes: We sort all listed stocks from our full sample (i.e., 62 stocks) each year according to the market capitalization on 31st December, then output small stocks with the lowest 30% of market capitalization and generate large stocks with the highest 30% of market capitalization. Following non-linear regressions $CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R^2_{m,t} + \varepsilon_t$ and $CSAD_t = \alpha + \beta_1 \mid R_{m,t} \mid + \beta_2 R^2_{m,t} + \beta_3 AT\_Intensity_{up10,t} + \beta_4 AT\_Intensity_{up10,t} R^2_{m,t} + \varepsilon_t$, where CSAD is the cross-sectional absolute deviation at time t, $R_{m,t}$ is the daily market return, $AT\_Intensity_{up10,t}$ is a dummy variable that takes the value of one when the fraction of algorithmic trading over total daily trades (i.e., regardless execution of buy orders or sell orders) is located on the upper 10% tail of its distribution, otherwise takes zero. Results in Columns (1) and (2) report the herding specification on small stocks, while results in Columns (3) and (4) present the herding specification on large stocks. Estimations are run from January 2018 to December 2020 for each column. For brevity, we do not include constant value. Standard errors are robust to heteroscedasticity and autocorrelation consistent using Newey–West. T-statistics in parentheses. * = significance at the 10% level; ** = significance at the 5% level; *** = significance at the 1% level.

herding, may be indicative of the AT's capacity to make a stabilising influence on the market. AT potentially mitigates the risk of market bubbles and crashes, thereby contributing to a stable and efficient trading environment.

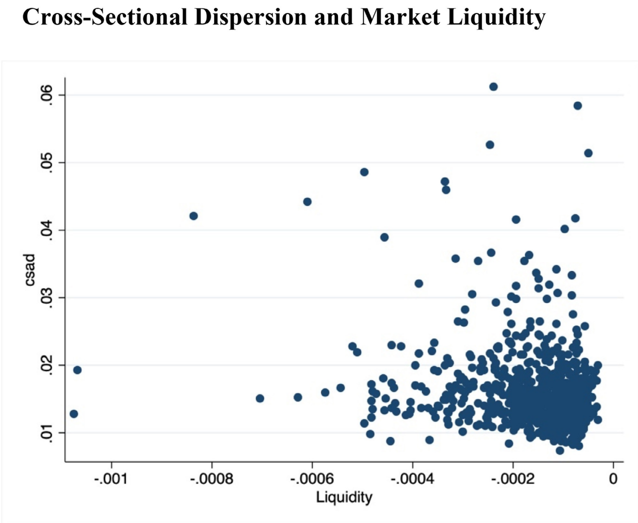

FIGURE 3 | Cross-sectional dispersion and market liquidity. This figure displays scatter plots of the Cross-sectional dispersion and market liquidity of large stocks from 2018 to 2020. We first measure stock liquidity following Amihud liquidity as $Liq_{i,s} = -\log\left(1 + \frac{|R_{i,s}|}{P_{i,s}Vol_{i,s}}\right)$, where $R_{i,s}$, $P_{i,s}$ and $Vol_{i,s}$ is the return, price, and trading volume for stock i on trade s. Then we calculate weighted-average liquidity across the large stocks on day t as $Liq_{m,t} = \frac{1}{N}\sum_1^N Liq_{i,t}$. [Colour figure can be viewed at wileyonlinelibrary.com]

Overall, the regression results in this section confirm Hypothesis 4 that AT-induced herding exhibits a size effect.[12]

4.5 | The Impact of Market Liquidity on AT-Induced Herding

This section delves further into the liquidity channel of AT-induced herding, specifically focusing on large stocks. First, we test if AT-induced herding is higher when liquidity is higher on large stocks. To measure liquidity, we follow Galariotis, Krokida, and Spyrou (2016b) to measure Amihud liquidity as $Liq_{i,s} = -\log\left(1 + \frac{|R_{i,s}|}{P_{i,s}Vol_{i,s}}\right)$, where $R_{i,s}$, $P_{i,s}$ and $Vol_{i,s}$ is the return, price and trading volume for stock i on trade s. Subsequently, we calculate market liquidity on day t by averaging the liquidity across large stocks (see Figure 3).

The results of Equation (2) are shown in Table 8, Columns 1 and 2, specifically separating low and high liquidity days. The herding coefficient β_2 is notably negative during low liquidity periods (β_2 is −2.101 with a t-statistic of −2.21), while herding is not evident in high liquidity periods (β_2 is insignificant). This finding aligns with Hung, Lu, and Lee (2010), indicating that market participants are more prone to follow market consensus when dealing with large stocks during periods of low market liquidity. When we split the sample to AT and non-AT trading (Table 8, Columns 3 and 4, respectively), we find herding evidence in both periods. The significant negative β_2 in Column 3 reflects that non-AT investors often conform to market consensus, resulting in herding during periods of low liquidity. Under high liquidity conditions, AT-induced anti-herding is observed (β_4 is 17.45 with a t-statistic of 3.1), illustrating

TABLE 8 | Herding under extreme market liquidity of large stocks.

	(1)	(2)	(3)	(4)
	Low liquid	**High liquid**	**Low liquid**	**High liquid**
$\lvert R_{m,t}\rvert$	0.58***	0.392***	0.49***	0.317***
	(4.82)	(4.1)	(5.68)	(3.56)
$R^2_{m,t}$	−2.101**	0.217	−1.391**	1.282
	(−2.21)	(0.13)	(−2.12)	(0.82)
$AT\_Intensity_{up10,t}$			−0.002	−0.001
			(−0.86)	(−1.12)
$AT\_Intensity_{up10,t} \times R^2_{m,t}$			26.97	17.45***
			(0.96)	(3.1)
Adjusted R^2	0.51	0.5	0.56	0.55
Observations	147	148	147	148

Notes: Taking into account the elasticity aspect of liquidity, we follow Galariotis, Krokida, and Spyrou (2016b) to measure Amihud liquidity for large stocks as $Liq_{i,s} = -\log\left(1 + \frac{|R_{i,s}|}{P_{i,s}Vol_{i,s}}\right)$, where $R_{i,s}$, $P_{i,s}$, and $Vol_{i,s}$ is the return, price, and trading volume for stock i on trade s. There are 19 stocks defined as large stocks in our sample, which sort as the top 30% of market capitalization on each sample year. We calculate the average liquidity ($Liq_{i,t}$) for each large stock i on day t. The market liquidity is measured across stocks as $Liq_{m,t} = \frac{1}{N}\sum_1^N Liq_{i,t}$. Then we use market liquidity ($Liq_{m,t}$) to define low liquidity (lower 20% of its distribution) and higher liquidity (upper 20% of its distribution). The results of regression $CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R^2_{m,t} + \varepsilon_t$ and $CSAD_t = \alpha + \beta_1 \mid R_{m,t} \mid + \beta_2 R^2_{m,t} + \beta_3 AT\_Intensity_{up10,t} + \beta_4 AT\_Intensity_{up10,t} R^2_{m,t} + \varepsilon_t$ are reported in this table. In Columns (1) and (2), the results show baseline herding specification of market participants in general in ASE market. The results in Columns (3) and (4) indicate herding specification on algorithmic traders by including the dummy variable $Intense_{up10,t}$, which takes the value of one when the fraction of algorithmic trading over total daily trades (i.e., regardless execution of buy orders or sell orders) is located on the upper 10% tail of its distribution, otherwise takes zero. Estimations are run for the top (bottom) 20% of market liquidity for the large stocks sample as high (low) liquidity. For brevity, we do not include constant value. Standard errors are robust to heteroscedasticity and autocorrelation consistent using Newey–West. T-statistics in parentheses. * = significance at the 10% level; ** = significance at the 5% level; *** = significance at the 1% level.

AT's role in diverging from market consensus, thereby potentially facilitating price discovery and enhancing market efficiency (Malceniece, Malcenieks, and Putniņš 2019). These outcomes are in line with Galariotis, Krokida, and Spyrou (2016b) and supply insight into the differing behaviours of AT and non-AT participants across various liquidity conditions.

Our findings extend the discussion on AT and market behaviour, suggesting that anti-herding induced by AT can be a strategic response to different market conditions. The anti-herding effect emphasises the sophisticated nature of AT that is not only reactive but also proactive in navigating market dynamics. The implications for market efficiency and systemic risk are profound, as anti-herding could both mitigate and exacerbate market stability, depending on the prevailing market conditions and the dominant trading strategies of the time.

5 | Conclusions and Policy Implications

In January 2018, MiFID II introduced safeguards and increased market transparency for AT activities in European stock exchanges. These regulations are intended to prevent AT and HFT from causing market disorder and participating in abusive practices. One of the new policies is that trading venues across the European Union must flag and retain all trades executed by algorithmic traders. We utilise the MiFID II regulations concerning AT to investigate its influence on herding behaviour within the stock market.

As far as we know, this is the first study examining AT-induced herding. This is notable given that AT comprises a significant portion of trading volume in developed markets, where herding has critical negative consequences for asset pricing, market efficiency, portfolio diversification, and overall market stability. We report strong evidence of AT-induced herding that is in absolute terms 14 times greater than non-AT herding. Different findings from national and international indicators provide an extra layer of complexity and depth to our understanding of herding behaviour. Our findings emphasise the influence of volatility on herding, while also highlighting the need to consider stock-specific traits when analysing herding. Categorising stocks into aggressive and defensive groups enables a more nuanced understanding of herding behaviour, providing a detailed perspective on how various market segments react to volatility. By shedding light on these different dynamics, our research offers valuable insights for market participants and regulators seeking to navigate and manage the complexities of financial markets. By investigating three channels of AT, our findings underscore the conditional nature of AT-induced herding. The market environment, characterised by liquidity conditions and return co-movement, significantly influences AT behaviour. These results emphasise the necessity of considering the broader market context when analysing AT and the potential implications for asset pricing, market efficiency, and stability. As such, regulatory policies must take into account these intricate dynamics to effectively mitigate potential market disruptions while maximising the benefits of AT.

Herding behaviour, a central concept in behavioural finance, challenges the assumption of rational expectations by proposing that investors are susceptible to a variety of psychological biases. Herding, along with related market microstructure phenomena like price clustering, is predominantly observed in human traders, with machines traditionally presumed exempt from such behavioural tendencies. Our research findings contest the notion of rational expectations for machines. We demonstrate that AT, contrary to expectations, not only engenders herding behaviour but does so more conspicuously than non-AT trading strategies. This observation may appear puzzling at first glance; however, several plausible explanations and theoretical frameworks can elucidate this phenomenon. Trading algorithms are crafted by human operators, who may consciously or inadvertently incorporate traits reflective of the trading behaviours of other market participants, including non-algorithmic traders (non-ATs). For example, Information Cascade Theory posits that individuals may base their decisions on observed actions, even if they possess contradictory private information. Moreover, if stock trading is influenced by social dynamics, exploiting such social information may represent an optimal trading strategy, particularly in environments characterised by imperfect information. By programming machines to emulate human behaviour in these respects, they become susceptible to deviations from rational expectations. In conclusion, our study underscores the intricate relationship between algorithmic trading behaviour and herding tendencies. By integrating insights from behavioural finance and related theoretical frameworks, we advance understanding of the mechanisms driving herding behaviour in financial markets, even within the domain of AT.

Our results carry substantial implications for market participants, as well as for the regulation and oversight of stock exchanges. Although we cannot definitively determine whether herding is intentional or spurious, we uncover a potentially destabilising effect of AT. From a regulatory perspective, our results underscore the need for vigilant monitoring to prevent undue systemic risks associated with algorithmic trading. To this end, it is important to estimate a metrics of AT trading intensity in European markets as current regulations fail to capture the interconnectedness of AT activities and more importantly the effect of AT activities on systemic risk and market efficiency. The latter is particularly important, as our findings suggest that AT-induced herding contributes to market inefficiency, particularly under high volatility condition, liquidity stress and market uncertainty. This type of herding behaviour, which intensifies during times of elevated international volatility or market uncertainty, has the potential to transmit financial shocks globally. For investors, heightened herding suggests a potential impact on market efficiency, influencing stock prices based on collective rather than fundamental factors. This effect is potentially more destabilising for short-term investment strategies. Finally, our results demonstrate that investors should implement risk management strategies that consider the increased interconnectedness of stocks. The above indicate that, given the proliferation of AT in stock markets, investors are potentially better off adopting a more long-term view in the markets.

To this end, future research should also concentrate on the increased interconnectedness of AT activities across European markets and the extent to which such developments increase systemic risk at a European level. An interesting line of research is to examine the interactions between AT and institutional ownership. Our article indicates that institutional ownership potentially moderates the relationship between AT activities and stock herding, however data unavailability restricts us from testing this relationship. Furthermore, considering the advancements in AT methodologies, such as the CR-DQN algorithm proposed by Huang et al. (2023), which combines deep Q-learning with strategies like moving averages and trading range breakouts, future studies might explore how such sophisticated strategies could influence the dynamics of stock herding and return comovement. Previous literature suggests that AT increases return comovement (see Malceniece, Malcenieks, and Putniņš 2019), and the adoption of advanced AT algorithms like CR-DQN could offer new insights into these effects. Finally, future research should also concentrate on the increased interconnectedness of AT activities across European markets and the extent to which such developments increase systemic risk at a European level.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Endnotes

[1] According to Article 4(1)(39) of MiFID II, algorithmic trading is described as ‘trading in financial instruments where a computer algorithm automatically determines individual parameters of orders such as whether to initiate the order, the timing, price or quantity of the order or how to manage the order after its submission, with limited or no human intervention, and does not include any system that is only used for the purpose of routing orders to one or more trading venues or for the processing of orders involving no determination of any trading parameters or for the confirmation of orders or the post-trade processing of executed transactions’. According to algorithmic trading survey, more than 50% of trading is conducted via algorithms (Algorithmic trading survey—the trade, 2022).

[2] For an in-depth discussion of the specifics regarding international participants at the Athens Stock Exchange, please see Section 3.1.1.

[3] In this study, we differentiate between large and small stocks by their market capitalization. To differentiate between stock sizes, we categorise the top 30% of stocks based on their market capitalization as of December 31st each year as large stocks, resulting in a group of 19 stocks. Similarly, the bottom 30% by market capitalization are identified as small stocks, also comprising 19 distinct stocks.

[4] Initially encompassing 77 stocks, our methodical approach involved cross-referencing with Bloomberg's daily data for the most traded stocks on the ASE. This process was vital as the original dataset's ticker symbols (TIC codes) did not explicitly reveal the names of the stocks. By generating and manually comparing price line charts from both our dataset and Bloomberg's records, we identified and matched 62 stocks, subsequently forming our final dataset. This reduction was necessitated due to an inability to match 15 stocks from our raw sample.

[5] It is important to clarify that our empirical analyses do not delve into sector-specific examinations, as the focus of our study is not on industry-level trends or behaviours.

[6] There are in total 4,639,100 algorithmic trades from our final sample with 62 stocks.

[7] Commission Delegated Regulation (EU) 2017/584, issued on July 14, 2016, supplements Directive 2014/65/EU from the European Parliament and Council, outlining the organisational requirements and regulatory technical standards that apply to trading venues under RTS 7.

[8] The ESMA review report on Algorithmic Trading, linked to MiFID II/MiFIR, dated September 28, 2021 | Reference: ESMA70-156-4572.

[9] For robustness test, we first replace $CSAD_t$ with $CSSD_t = \sqrt{\frac{\sum_{i=1}^{n}(R_{i,t}-R_{m,t})^2}{n-1}}$ by Christie and Huang (1995). Results remain unchanged under both *CSAD* and *CSSD* measures. Second, we compute the simple return as $\frac{(R_{i,t}-R_{i,t-1})}{R_{i,t-1}}$ to replace the log return. The results remain consistent with those obtained using the CSAD with log return. Therefore, we are presenting only these findings. Regression results using *CSSD* measures and simple return are available upon request.

[10] Data for the FTSE ASE Index and VIX Index were sourced from Bloomberg, while the Twitter Economic Uncertainty Index (TEU) was obtained from the Economic Policy Uncertainty Database.

[11] To test the robustness of this result, we also employed two different measures: standard deviation of daily open and close price from FTSE/ASE large cap index, and standard deviation across 62 sample stocks. The results are qualitatively the same. In addressing potential concerns, a robustness analysis incorporating a COVID-19 effect into Equation (3) was conducted, with subsequent re-estimation of the regressions for two periods: from the initial COVID-19 case in Greece on February 26, 2020, and throughout the entire year of 2020, deemed a COVID-19 affected period. The analysis confirmed the robustness of our initial findings, indicating no significant herding behaviour associated with the COVID-19 pandemic. For brevity, these additional results are excluded from this article, but are available upon request.

[12] This analysis, conducted on the upper and lower 30% of market capitalization as of 31st December each year, retains robustness when the threshold is adjusted. Repeating the regressions with the top and bottom 20% of market capitalization yields empirically consistent results.

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