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Herding and Anti-Herding Behaviour in the UK, French and German Stock Markets Before and During the Covid Pandemic

Dimitrios Asteriou[1] | Paraskevi Katsiampa[2] | Keith Pilbeam[3] | Alexander Tziamalis[4]

[1]Oxford Brookes Business School, Oxford, UK | [2]Sheffield University Management School, the University of Sheffield, Sheffield, UK | [3]City, University of London, London, UK | [4]Higher Colleges of Technology, Al-Nahda Campus, Dubai., Dubai, United Arab Emirates

Correspondence: Dimitrios Asteriou (dasteriou@brookes.ac.uk)

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ABSTRACT

This paper studies herding and anti-herding behaviour in three European stock markets before and during the Covid-19 pandemic by employing both static and dynamic analysis. We examine four different questions related to herding behaviour: (i) Did herding behaviour increase during the pandemic? (ii) Does herding behaviour respond differently in up and down market conditions? (iii) Is herding behaviour related to the volume of trading activity? and (iv) Does herding behaviour increase in periods of high market volatility? We find that, contrary to much of the existing literature, there is very little evidence of herding activity, and if anything, we find the evidence points to anti-herding behaviour during the Covid-19 pandemic.

JEL Classification: G12, G15, G4

1 | Introduction

The outbreak of Covid-19 at the end of 2019, which started in Wuhan, the capital of Hubei province of the People's Republic of China, rapidly spread to many other countries, resulting in the World Health Organisation (WHO) declaring it to be a public health emergency of international concern on 30th January 2020. By mid-April 2021, the ongoing Covid-19 pandemic has infected over 142 million people and cost over 3 million lives worldwide.[1] In addition to the incalculable loss of human life, the virus and the ensuing lockdowns to contain its spread have led to a major collapse in economic activity, a steep rise in unemployment and underemployment, significant increases in government and company debt, as well as the worsening of educational, health, and gender inequalities in many affected countries (Blake and Wadhwa 2020).

As expected, this sudden and acute worsening of the global economic environment has also significantly impacted equity markets. Stock markets responded to rising numbers of infections from Covid-19 with some of the steepest falls in history (Ashraf 2020). Within only 1 week, in February 2020, the S&P 500 stock market index erased a total of $5 trillion of market capitalisation (Ozili and Arun 2020), and in March 2020, the circuit breaker mechanism was activated four times in 10 days to contain losses (Funakoshi and Hartman 2020). Stock markets in Europe, Africa, and Asia have also plunged, often at unprecedented speed (Ashraf 2020; Ozili and Arun 2020; Zhang et al. 2020).

However, what started as an acute reaction to investors' perceived risk increase soon began transforming into a bullish market aided by further quantitative easing programs initiated by the Federal Reserve, Bank of England, and European Central Bank. Against a background of a deteriorating real economy and acute uncertainty about the course of a deadly pandemic, from late March 2020, stock markets started to rise fast (Krugman 2020). By the end of 2020, main stock market indices in the US, Japan, and China (such as S&P 500, Dow Jones, NASDAQ, Nikkei 225, Topix, Hang Seng and the Shanghai Stock Exchange) were hitting new records (Hodgson and Badkar 2020), while several European stock markets had risen back to nearly their 2019 pre-pandemic levels. With the virus still raging in several countries and against a globally weakened and more indebted economy, investors in various countries seemed to jump on the bandwagon of optimism. By April 2020, continually rising equity markets started giving concern to seasoned professional investors about the possibility of a heavily over-inflated market (Jolly 2021).

The events that have occurred throughout the Covid-19 pandemic provide an extraordinary setting to unveil the way markets process information when a unique global disaster unfolds (Ramelli and Wagner 2020), a period during which there was a significant increase in uncertainty about the direction of the global economy and increased business and economic uncertainty as evidenced from a rise in the IMF economic uncertainty index from 32,801 in 2019Q3 to a record of 55,685 in 2020Q1. In such periods of increased uncertainty, investors often observe others' actions and mimic their behaviour, reducing heterogeneity among them (Schmitt and Westerhoff 2017), known as *herding*. An implication of herding behaviour is that dispersions of asset returns substantially reduce during periods of extreme market conditions compared to normal periods, which contrasts with predictions from rational asset pricing models (Christie and Huang 1995). Such collective investment behaviour tends to be more pronounced during periods of extreme market movements when market volatility and information flows hinder the accuracy of investment forecasts (Mobarek et al. 2014). On the other hand, some studies (e.g., Choe et al. 1999; Hwang and Salmon 2004) have shown that crises constitute turning points in herding behaviour.

Motivated by the above, given the crisis induced by the Covid-19 pandemic and its effects on financial markets, this study aims to explore the existence of both herding and importantly, anti-herding behaviour in three major European stock markets, namely the UK, French and German stock markets by comparing the results both before and during the Covid-19 pandemic. The rationale for selecting these specific countries' stock markets is as follows: First, these were among the first countries to report confirmed cases of Covid-19 in Europe.[2] Second, these stock markets are considered exceptionally mature and situated in highly developed G7 member economies. In these three stock markets, regulatory oversight is more effective and transparent, and there is also a well-developed market for information on equities listed in these markets. As a result, movements in these stock markets are more likely to be attributed to investor behaviour influenced by herding rather than government/institutional and/or managerial failures on a company level. Third, the FTSE 100, CAC 40, and DAX 30 stock indices include some of the biggest companies by market capitalisation in Europe. Many of these companies represent household names for Europeans and thus trigger a familiarity bias for investors (Wang et al. 2011). This fact becomes relevant in a study of herding because existing literature suggests that in times of crises, investors tend to seek safe harbour in equity assets, which are considered less risky (Cardak et al. 2019; Harjoto et al. 2020; Lippi and Rossi 2020; Vu et al. 2021). As investors 'flee to quality' (Bekiros et al. 2017) or to what they *perceive as a quality* based on their familiarity bias, their investing behaviour should better highlight the effect of herding behaviour in a stock market. Third, Germany, the UK and France have the largest populations in Europe—these three countries account for about 30% of the population of the European continent (Clark 2021). This fact becomes particularly important in our study because an unexpected effect of the Covid-19 crisis was to spur unprecedentedly large numbers of amateur and novice investors to enter the world of investing (Pagano et al. 2021; Tokic 2020; Heinemann 2021).[3] In light of this, the effect of large and affluent populations in the UK, Germany and France becomes particularly important for a study of investor herding.

An important consequence of herding is that it can aggravate market volatility and render markets unstable (Furman and Stiglitz 1998; Morris and Shin 1999; Persaud 2001; Schmitt and Westerhoff 2017; Shiller et al. 1991; Wermers 1999), while also increasing the risk for the individual and institutional investor (Banerjee 1992; Furman and Stiglitz 1998; Morris and Shin 1999; Venezia et al. 2011) and potentially cutting off firms from a source of funding (Economou et al. 2011; Furman and Stiglitz 1998).[4] However, herding is not a uniform phenomenon, and its strength may vary in different settings, markets and times. To address this issue, our methodology builds upon Chang et al.'s (2000) cross-sectional absolute deviation (CSAD) measure of herding by employing not only static but also dynamic analysis. Moreover, we further investigate the presence of asymmetries in herding behaviour between up and down markets, between periods of high and low volatility, and between periods of high and low trading activity.

Our contributions to the literature are the following: First, while the literature on the impact of the Covid-19 pandemic on financial markets has rapidly emerged, the literature examining herding behaviour since the outbreak of the Covid-19 pandemic remains rather sparse. Second, the limited research on herding during the Covid-19 pandemic has mostly considered exploring herding behaviour only during the first few months of the pandemic. In contrast, most European—and not only—governments had to impose several new restrictions in the second half of 2020, including a second lockdown, due to the new waves of the pandemic as well as since new, more transmissible variants of the virus were detected. Our study's extended sample period thus provides a better understanding of herding behaviour throughout the different stages of the pandemic. Third, our study examines herding behaviour not only during the Covid-19 period but also during the pre-Covid-19 period, therefore enabling us to compare such effects before and after the outbreak of Covid-19. Finally, unlike several previous studies which have performed static analysis giving average values of the estimated effects, our time-varying analysis enables us to explore how herding behaviour changes throughout our entire sample period. Our study, therefore, contributes to the literature on herding behaviour and efficiency in stock markets, and in particular to the strand of the literature focusing on cross-sectional dispersions of asset returns in extreme market movements, as well as to the growing literature on the impact of Covid-19 on financial markets.

As will be shown, contrary to the common belief that fear and uncertainty over the effects of the pandemic would drive the less informed agents to abandon their beliefs and follow the more informed ones, our results show that the crisis induced by Covid-19 did not lead to herding and, if anything, it led to some evidence of an increase in anti-herding behaviour in stock markets. In particular, our dynamic analysis provides evidence of neither herding nor anti-herding behaviour during the Covid-19 pandemic period for any of the three European stock markets considered.

The remainder of the paper is organised as follows. Section 2 reviews relevant literature on herding. Section 3 details the methodology and data employed in our study, while Section 4 discusses the empirical results. Finally, Section 5 offers concluding remarks and discusses the policy implications stemming from the research.

2 | Literature Review on Herding Behaviour in Financial Markets

Mainstream economic theory on asset valuation and particularly the Efficient Market Hypothesis argues that asset prices are grounded on a rational analysis of their fundamentals, such as macroeconomic trends, earnings, and risk assessment (Fama 1970). Any deviations from these prices are thought to only stem from genuine news, which are mainly unforecastable since they follow a 'random walk' (Fama 1965). Moreover, price changes reflecting either positive or negative news also happen very quickly, usually within a day (Fama et al. 1969). Interestingly, the Efficient Market Hypothesis leads to the conclusion that it is never a good time to enter the stock market and never a good time to leave; investors are always buying and selling at the fair price for a stock—there cannot be any 'deals' in well-functioning markets. In addition, once the incoming information is incorporated into securities' prices, then these prices should remain relatively stable, and even professional traders working in actively managed mutual funds fail, on average, to consistently beat the market (Gruber 1996).

Despite the enduring popularity of the Efficient Market Hypothesis, the high volatility in asset prices cannot be fully explained by using mainstream economic thinking (Akerlof and Shiller 2010). For example, in the 1920s, the value of US stock exchange prices rose by more than 400% before it crashed (Shiller et al. 1991) – a rise that could not be explained by the growth in dividends paid by companies or the growth of the US economy during that decade (Campbell and Shiller 1988). Prices consistently deviated from their fundamentals and the expected discounted cash flow they could generate for their owner (Shiller 2014). The literature has since tried to identify factors explaining such stock market movements, with a strand of the literature having turned to herding (Akerlof and Shiller 2010).

Herding is far from a new concept in financial economics. Banerjee (1992) defines it as 'doing what the others are doing, even though their private information suggests doing something quite different' (Banerjee 1992, 798). Keynes (1936) highlighted the importance of herding behaviour in an attempt to explain price fluctuations in asset markets. For Keynes (1936), the valuation of long-term assets is essentially a matter of convention. Whatever investors consider good value for a security will become a consensus, even if actual returns fail for quite some time to confirm these expectations.

Herding can be intentional or unintentional (Bikhchandani and Sharma 2001). Intentional herding happens when a trader rationally calculates that he can benefit by following the actions of others. An obvious example is when a trader recognises that another party has superior information about an investment (Devenow and Welch 1996; Trueman 1994) or when a trader seeks to protect his reputation in case of failure by copying the actions of other traders (Clement and Tse 2005; Scharfstein and Stein 1990). In particular, this may be the case in developing markets where the availability of statistical data and corporate information is more difficult and costly to obtain (Bikhchandani et al. 1992; Economou et al. 2015). On the other hand, unintentional herding could be more challenging to deal with, as it is supported by cognitive and perceptive biases of our imperfect minds (Akerlof and Shiller 2010). Conformity bias (Hirshleifer 2001), home bias (Feng and Seasholes 2004) and availability bias (Kuran and Sunstein 1999) have been identified by the literature as cognitive biases that are linked to the deep-rooted human tendency to herd.

Scholars do not universally accept the existence of herding; several studies have found no evidence of the herding phenomenon, a finding consistent with rational asset pricing models. For instance, while studying U.S. stock markets, Christie and Huang (1995) found no evidence of herding during extreme down movements, and BenSaïda et al. (2015) found inconclusive results about herding, even though in the latter study, the authors reported a positive relationship between herding and trading volume. Moreover, Demirer and Kutan (2006) reported no herding behaviour in Chinese stock markets.

Nevertheless, the majority of studies have found evidence in support of herding. Evidence of herding by institutional investors in the US market is found by Bekiros et al. (2017), Choi and Sias (2009), Clements et al. (2017), Liao et al. (2011), and Sias (2004), including ADR (foreign) shares purchased in the US stock market (Li and Yung 2004). International evidence of herding has also been found in Asia, in the case of China (Tan et al. 2008; Yao et al. 2014; Zhu et al. 2020), South Korea (Chang et al. 2000; Choe et al. 1999; Kim and Wei 2002a, 2002b; Teh and de Bondt 1997), as well as Taiwan (Chang et al. 2000; Demirer and Kutan 2006; Hung et al. 2010; Lu et al. 2012), in African markets (Aawaar et al. 2020), and in several European countries such as Germany (Kremer and Nautz 2013; Walter and Moritz Weber 2006), Greece (Economou et al. 2016; Messis and Zapranis 2014), Spain (Blasco et al. 2012; Mobarek et al. 2014), and Portugal (Mobarek et al. 2014), among others.

An important and consistent finding in the literature is that herding is more pronounced in times of uncertainty and crises. When fear—let alone panic—is prevalent, investors may opt to follow the market consensus (Economou et al. 2015, 2018; Devenow and Welch 1996; Philippas et al. 2013), that is, *the herd*, which can, on an aggregate level, contribute to market volatility and generate market instability (Akerlof and Shiller 2010; Banerjee 1992; Persaud 2001; Schmitt and Westerhoff 2017). In particular, the literature offers substantial evidence that traders herd when indices are falling (Chang et al. 2000; Chiang and Zheng 2010; Demirer et al. 2010; Mobarek et al. 2014; Philippas et al. 2013). However, there is evidence that herding also occurs in market upswings (Economou et al. 2011, 2015; Tan et al. 2008). The literature further reveals a positive correlation between increased market volatility and herding (Bekiros et al. 2017; Blasco et al. 2012; Tan et al. 2008). In addition, the volume of shares traded (or the *liquidity* of a share) has been identified as a factor with the potential to negatively or positively affect herding (Economou et al. 2011; Galariotis et al. 2016; Mobarek et al. 2014; Tan et al. 2008).

As for literature on herding during the Covid-19 pandemic, the number of studies investigating herding behaviour during the crisis induced by the pandemic remains rather limited. Specifically, Kizys et al. (2021) examined whether the government response to the Covid-19 pandemic can mitigate investor herding behaviour and found evidence of investor herding in international stock markets. However, the authors' sample covered only the period from 1st January 2020 to 31st March 2020. Espinosa-Méndez and Arias (2021) investigated whether the Covid-19 pandemic had an effect on herding behaviour in Europe using a sample from the stock exchanges of France, Germany, Italy, United Kingdom, and Spain over the period from 3rd January 2000 to 19th June 2020. They found that the Covid-19 pandemic increased herding behaviour in the European markets under investigation. Ferreruela and Mallor (2021) studied herding behaviour in the markets of Spain and Portugal and found evidence of herding during high volatility days during the Covid-19 period in both countries. Ghorbel et al. (2023) investigated the presence of herding behaviour in developed and BRICS stock markets and found evidence of herding in all considered stock markets except for the American and British stock indices. Nguyen et al. (2023) found herding behaviour in the Vietnamese stock market. In contrast, Jiang et al. (2022) found evidence of herding behaviour in six Asian stock markets (specifically those of Japan, South Korea, Chinese Mainland, Hong Kong, Singapore and Taiwan). They captured a sharp rise in the magnitude of herding during the market crash in March 2020. In contrast, Wu et al. (2020) found that herding behaviour was significantly lower than usual in Chinese stock markets during the Covid-19 period. On the other hand, Yarovaya et al. (2021) studied herding behaviour in cryptocurrency markets during the Covid-19 pandemic and found that the outbreak of Covid-19 did not amplify herding in cryptocurrency markets.

Nevertheless, most of the aforementioned studies have explored herding behaviour during the first few months of the pandemic, omitting a long period during which financial markets would still respond to negative news related to Covid-19, such as new restrictions and lockdowns. While similar in spirit to the study of Espinosa-Méndez and Arias (2021), our study is distinctively different in that not only does it employ an extended sample period enabling us to better comprehend herding behaviour during the different stages of the pandemic, but it also compares herding behaviour before and after the outbreak of Covid-19. Most importantly, our study employs not only a static but also a dynamic analysis, which allows us to explore how herding behaviour changes throughout our entire sample period, unlike previous studies, which have only performed static analyses, obtaining a single estimated value for such effects.

3 | Methodology and Data

3.1 | Methodology

In order to test for herding behaviour, similar to the literature (e.g., Economou et al. 2011; Espinosa-Méndez and Arias 2021; Mobarek et al. 2014; Tan et al. 2008), our methodology is based on cross-sectional correlations of the entire stock market. Two pioneering studies to detect herding behaviour are those of Christie and Huang (1995) and Chang et al. (2000), which introduced the cross-sectional standard deviation (CSSD) and cross-sectional absolute deviation (CSAD), respectively, of stock returns in relation to the market return as herding measures. Both of these measures are based on the intuition that low dispersion of returns around their cross-sectional mean implies that market participants disregard their prior information or beliefs in order to adhere to the market consensus as shown through correlated trading patterns (Economou et al. 2011). More specifically, Christie and Huang's (1995) CSSD measure is defined as:

$$\mathrm{CSSD}_t = \sqrt{\frac{\sum_{i=1}^{N} (r_{i,t} - r_{m,t})^2}{(n-1)}} \tag{1}$$

where $r_{i,t}$ denotes stock i's return on day t, $r_{m,t}$ represents the market's return on day t calculated as the cross-sectional average of the returns of all stocks on day t, and n denotes the number of stocks in the market portfolio. Nevertheless, Christie and Huang's (1995) CSSD measure can be affected by outliers (Economou et al. 2011). As a result, Chang et al. (2000) used the CSAD measure of dispersion, defined as follows:

$$\mathrm{CSAD}_t = \frac{\sum_{i=1}^{n} \left| r_{i,t} - r_{m,t} \right|}{n} \tag{2}$$

where $r_{i,t}$, $r_{m,t}$ and n are defined as above. We employ Chang et al.'s (2000) herding measure in this study due to its better handling of outliers.

Chang et al. (2000) further argued that in periods of large average price swings, the relationship between dispersion and market returns, which is predicted by standard asset pricing models to be linear and increasing, becomes nonlinear, and thus extended Christie and Huang's (1995) methodology by using a nonlinear regression model to study the relationship between CSAD and market returns to test for herding behaviour. To capture such nonlinearities, the following nonlinear model is therefore implemented in our study:

$$\mathrm{CSAD}_t = \gamma_0 + \gamma_1 \left| r_{m,t} \right| + \gamma_2 r_{m,t}^2 + \varepsilon_t \tag{3}$$

Chang et al. (2000) highlighted that under the assumption that the CAPM is valid, CSAD_t is entirely explained by the expected value of the absolute market return, and this relationship should be linear. Thus, in the absence of herding effects, it is expected that $\gamma_1 > 0$ and $\gamma_2 = 0$. In contrast, if γ_2 differs from 0, then the linearity assumption is violated, and

$r_{m,t}^2$ proxies the market return variance.[5] If in periods of high volatility investors herd towards the market, this should be reflected by significantly negative values of γ_2, in which case the dispersion of returns decreases during periods of market distress. On the other hand, a significant positive value γ_2 suggests that large market movements increase investors' mistrust of the market consensus, therefore indicating anti-herding behaviour. In such a case, investors tend to rely strongly on their stock price valuations and hold on to their portfolios. Given that the existence of herding behaviour has been confirmed for several European markets in the literature (see, e.g., Blasco et al. 2012; Economou et al. 2016; Espinosa-Méndez and Arias 2021; Kremer and Nautz 2013; Mobarek et al. 2014; Walter and Moritz Weber 2006), our first hypothesis conjectures:

H1. *There is herding behaviour in European stock markets.*

In addition, as herding behaviour may be more prevalent in periods of market distress in particular (Christie and Huang 1995), we also investigate whether the dispersion of returns has a different behaviour in up and down markets, and thus whether herding behaviour is asymmetric between up and down markets, by employing the following model:

$$\begin{aligned} \text{CSAD}_t = {} & \gamma_0 + \gamma_1 D^{\text{up}} |r_{m,t}| + \gamma_2 (1 - D^{\text{up}}) |r_{m,t}| \\ & + \gamma_3 D^{\text{up}} r_{m,t}^2 + \gamma_4 (1 - D^{\text{up}}) r_{m,t}^2 + \varepsilon_t \end{aligned} \tag{4}$$

where D^{up} denotes a dummy variable taking the value one on days with positive market returns and the value zero on days with negative market returns. Negative values of coefficients γ_3 and γ_4 suggest herding behaviour. Following Christie and Huang's (1995) rationale, the literature generally expects herding to be more likely observed during down market periods, when fear and uncertainty among investors are likely to be more prevalent. This expectation is largely supported by a number of subsequent studies on herding (see, e.g., Chen 2013; Chiang and Zheng 2010; Demirer et al. 2010; Mobarek et al. 2014; Philippas et al. 2013). It should be noted, though, that a number of studies have supported the claim that herding can also be detected in up-market periods (see, e.g., Economou et al. 2015; Economou et al. 2011; Hwang and Salmon 2004; Tan et al. 2008). In light of the foregoing, our second hypothesis contends:

H2. *Herding behaviour responds differently in up and down market conditions.*

Similarly, we are interested in examining whether herding behaves differently in periods of high or low trading activity. Therefore, we estimate the model below:

$$\begin{aligned} \text{CSAD}_t = {} & \gamma_0 + \gamma_1 D^{\text{HVolume}} |r_{m,t}| + \gamma_2 \left(1 - D^{\text{HVolume}}\right) |r_{m,t}| \\ & + \gamma_3 D^{\text{HVolume}} r_{m,t}^2 + \gamma_4 \left(1 - D^{\text{HVolume}}\right) r_{m,t}^2 + \varepsilon_t \end{aligned} \tag{5}$$

where $D^{HVolume}$ is a dummy variable taking the value one on days with high trading volume and the value zero otherwise. We calculated the monthly moving average trading volume for each asset over the study period to distinguish between high and low trading volumes. Then, a trading volume is classified as *high* if the actual observed volume in a given period is higher than the calculated monthly moving average and vice versa. This approach allows us to account for variations in trading activity over time while ensuring that the classification is consistent and data-driven. Using the monthly moving average, we normalise trading volumes relative to recent trends, which provides a more accurate measure of what constitutes 'high' or 'low' activity. We believe this method offers a robust and transparent means of distinguishing between high and low trading volumes while avoiding the arbitrariness of fixed thresholds. Again, negative values for coefficients γ_3 and γ_4 imply the presence of herding behaviour. The literature has long identified a relationship between the volume, or liquidity, of shares traded and investor sentiment (Baker and Stein 2004), investors' clustering (Devenow and Welch 1996; Gelos and Wei 2002) as well the existence of asymmetric information (Taylor 2002). However, the studies that explore specifically the relationship between volume and herding offer mixed results. BenSaïda et al. (2015) report a bidirectional link between herding and trading volume. Interestingly, their study further found that during the subprime crisis period herding was actually inhibited. In line with BenSaïda et al. (2015), Economou et al. (2011) and Tan et al. (2008) also report herding as more prevalent during up-volume periods. Similarly, Galariotis et al. (2016) examined data for a number of major stock markets and detected herding in high *liquidity* shares—a metric largely based on the volume of shares traded. The notable exception in Galariotis et al.'s (2016) study for Germany, where no association between liquidity and herding was detected. Other studies have produced contrasting results, though. For instance, Economou et al. (2015) and Mobarek et al. (2014) found herding to be more prevalent during down-volume days, while Ukpong et al. (2021), who report anti-herding behaviour for the period 2010–20 and found no significant relationship of trading volumes with herding. Thus, our third hypothesis posits:

H3. *Herding behaviour responds differently in periods of high and low trading activity.*

Finally, we explore whether herding behaviour is different between periods of high or low market volatility by estimating the model below accordingly:

$$\begin{aligned} \text{CSAD}_t = {} & \gamma_0 + \gamma_1 D^{\text{HVolatility}} |r_{m,t}| + \gamma_2 \left(1 - D^{\text{HVolatility}}\right) |r_{m,t}| \\ & + \gamma_3 D^{\text{HVolatility}} r_{m,t}^2 + \gamma_4 \left(1 - D^{\text{HVolatility}}\right) r_{m,t}^2 + \varepsilon_t \end{aligned} \tag{6}$$

where $D^{\text{HVolatility}}$ is a dummy variable taking the value one on days with high market volatility and zero otherwise. Similarly, in the presence of herding behaviour it is expected that coefficients γ_3 and γ_4 will be negative. Early studies on herding have proposed a theoretical link between periods of extreme market movements and herding (Bikhchandani et al. 1992; Christie and Huang 1995; Morris and Shin 1999; Shiller et al. 1991). The main argument is that during a period of high volatility, investors may be even more likely to ignore their own information and beliefs and herd towards the market consensus, resulting in a reduction of the cross-sectional dispersion of their investment decisions. However, the empirical literature has offered mixed support for the link between herding and increased market volatility. For instance, the study by Gleason et al. (2004) fails to confirm a relationship between herding and volatility.

On the other hand, Balcilar et al. (2014) used a smooth transition regression model and found evidence of herding in all Gulf Arab stock markets, with volatility being identified as the paramount factor causing switches between the states of herding/no herding. In addition, Blasco et al. (2012) documented a strong linear relationship between intraday herding and volatility in the Madrid Stock Exchange. While Tan et al. (2008) detected herding for the A-share Shanghai market in periods with high volatility, but not for the B-share market. Further, Bekiros et al. (2017) used the CSAD model with implied volatility and found evidence of herding being reduced during the 2008 financial crisis, eventually becoming insignificant. Thus, our fourth hypothesis asserts:

H4. *Herding behaviour responds differently in periods of high and low market volatility.*

It is worth pointing out that in the case of asymmetric herding being found, the effect will be more pronounced on days with negative market returns if $\gamma_4 < \gamma_3$ in the model presented in Equation (4), on days with high trading volume if $\gamma_3 < \gamma_4$ in the model presented in Equation (5), and on days with high volatility if $\gamma_3 < \gamma_4$ in the model presented in Equation (6) (Economou et al. 2011).

In the second part of our analysis, we study the time-varying herding behaviour by considering dynamic estimations of Equations (3–6) presented earlier. All previous models were based on static specifications where the estimated parameters of the models are assumed to remain constant over time. Nevertheless, this means that these models fail to address the fact that herding may be a dynamic market feature that changes based on changes in investors' behaviour and market characteristics. Static models also fail to consider the occurrence of structural breaks and regime changes (such as the pandemic outbreak), which justifies the sample split in our static analysis, as explained in the next subsection. As such, to capture the evolving nature of herding behaviour in stock markets, we also employ a state-space model combined with a Kalman filter. State-space modelling is increasingly used in finance (e.g., Arjoon and Bhatnagar 2017; Chen 2013; Hwang and Salmon 2004). The dynamic version of our static benchmark model represented by Equation (3) is as follows:

$$\mathrm{CSAD}_{j,t} = \gamma_{j,0} + \gamma_{j,1}\left|r_{j,m,t}\right| + \gamma_{j,2} r_{j,m,t}^2 + \varepsilon_t \tag{7}$$

$$\gamma_{j,i,t} = \gamma_{j,i,t-1} + v_t, v_t \sim N\left(0, \sigma^2\right) \tag{8}$$

where i represents the coefficient, $i = 0$, 1 and 2, and j denotes the stock market, where $j = 1$, 2 and 3. Equation (7) represents a transition equation showing the evolution of the unobserved state variables over time, whereas Equation (8) constitutes a measurement equation expressing the observed variables in terms of unobserved state variables (Arjoon and Bhatnagar 2017), with the vector $[\gamma_{0,t}, \gamma_{1,t}, \gamma_{2,t}]$ being a vector of state variables, and the state variables are assumed to follow a random walk process. The model presented in Equations (6) and (7) is estimated by the Kalman-filter in a state-space form. The Kalman filter procedure is employed to produce smooth estimates of the state variables, $\gamma_{j,i,t}$. The estimation of the model is achieved by the Berndt et al. (1974) algorithm by maximising the likelihood function.

Specifications of the state-space Kalman-filter form for the models presented in Equations (4–6) are also used in a similar manner, allowing for dynamic estimations through time of the respected φ_i coefficients.

3.2 | Data

This study aims to investigate the existence of herding in European stock markets and compare the results before and during the Covid-19 pandemic. To this end, we focus on the three major European stock markets, namely the UK, France, and Germany. Consequently, our dataset is based on all listed stocks in the FTSE 100 (UK), CAC 40 (France), and DAX 30 (Germany) stock indices during the period from 1st July 2016 to 31st December 2020. The sample start date has been selected so that potential periods during which the global financial crisis, the European sovereign debt crisis, and the UK referendum, among other important economic and political events, are excluded. In contrast, the sample end date allows us to better understand herding behaviour during different stages of the pandemic. For the purposes of this study, we examine the relationships shown in the previous sub-section not only for the entire sample period of our study but also for two sub-periods enabling us to assess changes in herding behaviour before and during the Covid-19 outbreak. In the sub-period analysis, we use the first date of the first lockdown for the UK (23rd March 2020) and France (16th March) and the start of the *protection stage* for Germany (13th of March) as a breakpoint to split our sample period.[6] The selection of this breakpoint when splitting our sample period is based on the increased CSAD and stock market return levels as shown in Figures A1–A3 (in the Appendix) and as discussed below.[7] Apart from choosing the breakpoint as the date of the first lockdown, we also used the Bai and Perron (1998, 2003) method to identify multiple possible breaks. After setting a maximum of five possible breakpoints, the results suggested three breakpoints for Germany and the UK, and two for France. However, interestingly, for all three countries, the first (and most important) breakpoint was identified as being very close to our chosen date. For Germany, it was suggested to split the sample on the 10th of March (3 days before the first lockdown date), for the UK on the 15th of March (1 day before the first lockdown date), and for France, it coincided on the date of the first lockdown (16th of March). So, the test picks up clearly the best date for splitting the sample to be very close to the one chosen based on the dates of lockdowns. The results (not shown here for economy of space) with adding a few more days were not significantly affected.

To compute CSAD, we calculate daily price returns as the first logarithmic close price difference on two consecutive days, as follows $r_{i,t} = \ln\left(p_{i,t}\right) - \ln\left(p_{i,t-1}\right)$, whereas the average market portfolio return, $r_{m,t}$, is calculated in our study using both the equally weighted average of stock returns[8] and the value-weighted market return. As we also study the asymmetric effects of herding in response to trading volume, we further collect data on the trading volume for each stock market, which is calculated as the aggregate trading volume for all the active shares on a given trading day. In addition, we compute the daily volatility series as the conditional variance series of a GARCH(1,1) estimated model of both the equally weighted and value-weighted return series.[9] The stock price and trading volume data are derived from the Thomson Reuters Eikon database.

The computed market returns and CSAD measures are illustrated in Figures A1–A3 (Appendix), clearly showing increased levels for the CSAD and, therefore, increased dispersion of returns around their cross-sectional mean around the first announcement in all three stock markets. The figures of the market returns further illustrate increased volatility levels. Table 1 reports summary statistics for each stock market's CSAD and return series, calculated using both equal weights and market value weights, over the entire sample period as well as for the two sub-periods (before and during the first Covid-19 lockdown) separately. It is shown that for all three stock markets both the average values and standard deviations of CSAD are higher during the Covid-19 sub-period compared with those for the first sub-period, as consistent with Figures A1–A3 (Appendix). This finding is in accordance with the results in the study of Espinosa-Méndez and Arias (2021). As pointed out by Chiang and Zheng (2010), a high mean value for CSAD indicates significantly increased market variations across stock returns, whereas a high standard deviation could denote that the market has unexpected cross-sectional variations as a result of unanticipated news or shocks.

Table 2 presents the correlation matrices of the CSAD measures and market portfolio returns, calculated again using both equal weights and market value weights for each of the three considered markets. For calculating these correlations, we use only observations on the days that all three markets were open for trading, resulting in a total of 1121 daily observations. All the reported correlations are exceptionally high, indicating the high market integration among the considered stock markets in our study.

4 | Empirical Results

4.1 | Static Analysis

We first present the estimation results from our static analysis. Tables 3–6 report the estimation results for the models presented in Equations (3–6), respectively, using Newey and West (1987) consistent standard errors. More specifically, Table 3 presents the estimation results of our benchmark model shown in Equation (3) for each country. Panel A reports the results for the entire sample period from July 2016 to December 2020, whereas Panels B and C show the results for the sub-periods before and after the lockdown announcement, respectively, in each country. When investigating the presence of herding effects during the entire sample period (Panel A), we find that for all the three countries considered in our study cross-sectional returns' dispersion increases with the market return, as revealed by the positive and significant γ_1 coefficient, when either equally weighted or value-weighted returns are used. This result is in line with standard asset pricing models.

Nevertheless, when examining the effect of the squared market return, which enables us to investigate further whether the cross-sectional dispersion increases at a decreasing rate during extreme market conditions (Economou et al. 2011; Mobarek et al. 2014), we find no evidence of a significant reduction in the cross-sectional dispersion around the market portfolio, and therefore no evidence of herding behaviour, as revealed by the insignificant γ_2 coefficient. This result holds using both equally weighted and value-weighted market returns and for all three European stock markets. We therefore find no support for the assertion in Hypothesis 1.

When dividing our sample into two sub-periods, we find again that for all three countries, cross-sectional returns' dispersion has a positive association with the market return in both sub-periods for both equally weighted and value-weighted market returns. Interestingly, most estimated γ_2 coefficients are now positive, indicating anti-herding behaviour, but again mostly insignificant. In particular, the UK stock market appears to maintain a consistent lack of significant herding or anti-herding behaviour both before and after the lockdown announcement. In contrast, the results for France and Germany paint a different picture. Specifically, although when using equally weighted market returns the two countries do not exhibit any significant anti-herding behaviour, when using value-weighted market returns France is found to exhibit significant anti-herding behaviour in both sub-periods, with its magnitude becoming even more intense in the Covid-19 sub-period. On the other hand, under value-weighted market returns, Germany displays significant anti-herding behaviour in the first sub-period, which becomes insignificant during the Covid-19 sub-period. These results are, therefore in contrast with the assertion in our first hypothesis and will be revisited in the following analyses.

Table 4 reports the estimation results for the model presented by Equation (4), which enables us to examine whether there exists an asymmetric response of CSAD to market returns in rising and falling markets, as captured by the corresponding dummy variables. When studying the entire sample period, we find no significant evidence of either herding or anti-herding behaviour for the UK and Germany again when either equally weighted or value-weighted portfolio returns are used. However, we find that France exhibits significant anti-herding behaviour under both equally weighted and value-weighted portfolio returns, with the evidence in favour of anti-herding behaviour for the French market being much stronger on days with positive returns. We further test the null hypothesis that the (anti-)herding coefficients are equal on days with rising and falling market prices using a Wald test. The test statistic results suggest the rejection of the null hypothesis in the case of CAC 40, therefore confirming the asymmetry for the French stock market. We thus find some support for the contention in Hypothesis 2.

When analysing the two sub-periods separately, not only do we find evidence of anti-herding behaviour in all three European stock markets, but also asymmetries between the up and down markets as well as between the two sub-periods. However, the results are mixed across the three stock markets during the first sub-period, clearly depending on both the stock market and the proxy of market return. More specifically, for the first sub-period, when using equally weighted portfolio returns, the

TABLE 1 | Summary statistics.

	UK		France		Germany	
	CSAD	r_m	CSAD	r_m	CSAD	r_m
Panel A: Entire period						
Equally weighted market returns						
Mean	0.01094	0.00038	0.00928	0.00046	0.00893	0.00040
Median	0.00954	0.00078	0.00814	0.00058	0.00807	0.00055
Max	0.07043	0.09913	0.05603	0.09489	0.04177	0.10406
Min	0.00415	−0.10974	0.00296	−0.13329	0.00259	−0.12085
St dev	0.00550	0.01137	0.00499	0.01263	0.00414	0.01181
Observations	1139		1151		1136	
Value weighted market returns						
Mean	0.01117	0.00004	0.00935	0.00029	0.00902	0.00037
Median	0.00977	0.00050	0.00822	0.00044	0.00816	0.00062
Max	0.06985	0.09050	0.05535	0.08389	0.04173	0.10976
Min	0.00419	−0.10870	0.00296	−0.12277	0.00257	−0.12239
St dev	0.00559	0.01066	0.00498	0.01192	0.00419	0.01239
Observations	1139		1151		1136	
Panel B: Pre-Covid-19 period						
Equally weighted market returns						
Mean	0.00965	0.00009	0.00811	0.00013	0.00810	−0.00004
Median	0.00905	0.00073	0.00765	0.00054	0.00762	0.00047
Max	0.03068	0.02701	0.03355	0.04058	0.03090	0.03310
Min	0.00415	−0.10974	0.00296	−0.13329	0.00259	−0.12085
St dev	0.00294	0.00877	0.00289	0.00980	0.00285	0.00955
Observations	937		946		933	
Value weighted market returns						
Mean	0.00986	−0.00017	0.00819	0.000008	0.00819	−0.00008
Median	0.00925	0.00040	0.00772	0.00042	0.00778	0.00059
Max	0.03184	0.02460	0.03508	0.04144	0.03099	0.03373
Min	0.00419	−0.10870	0.00296	−0.12277	0.00257	−0.12239
St dev	0.00303	0.00864	0.00289	0.00972	0.00289	0.01015
Observations	937		946		934	
Panel C: Covid-19 period						
Equally weighted market returns						
Mean	0.01695	0.00174	0.01465	0.00199	0.01280	0.00233
Median	0.01404	0.00119	0.01227	0.00080	0.01068	0.00106
Max	0.07043	0.09913	0.05603	0.09489	0.04177	0.10406
Min	0.00679	−0.05450	0.00439	−0.07512	0.00530	−0.05997
St dev	0.01695	0.01925	0.00816	0.02125	0.00639	0.01894

(Continues)

TABLE 1 | (Continued)

	UK		France		Germany	
	CSAD	r_m	CSAD	r_m	CSAD	r_m
Observations	202		205		203	
Value weighted market returns						
Mean	0.017257	0.001064	0.01469	0.00163	0.01289	0.00218
Median	0.014271	0.000750	0.01233	0.00090	0.01086	0.00072
Max	0.069853	0.090500	0.05535	0.08389	0.04173	0.10976
Min	0.007036	−0.052500	0.00432	−0.05936	0.00526	−0.05564
St dev	0.009437	0.017158	0.00814	0.01903	0.00648	0.01956
Observations	202		205		203	

Note: This table reports descriptive statistics for the measure of daily cross-sectional absolute deviation (CSAD) of individual stock returns with respect to the market portfolio return and the market return (r_m) for the UK, French and German markets during the three periods under consideration. The table reports the descriptive statistics both when equal weights and market value weights are employed for the calculation of the market return.

results indicate significant anti-herding behaviour for the UK and French stock markets on days with rising market prices. It is worth noting, though, that for France we also find significant anti-herding behaviour in down markets, although in this case, the effect is less pronounced. For the first sub-period, the Wald test results confirm the asymmetry only for the UK. On the other hand, when using value-weighted market returns, we find evidence of anti-herding in the case of France and Germany, which is significant only in down markets, although no such asymmetry is confirmed by means of a Wald test. Interestingly, the results for the second sub-period show significant anti-herding behaviour only on days with falling market prices. The Wald test results mostly confirm the asymmetry between rising and falling markets in the second sub-period. Our results for the second sub-period therefore offer support for the contention in Hypothesis 2. Yet, the magnitude of the anti-herding effects is overall higher in the second sub-period than those observed in the first sub-period.

Accordingly, the estimation results for the model presented by Equation (5), which allows us to explore potential asymmetries in herding behaviour between days with high and low trading volumes, are reported in Table 5. When studying the entire sample period, we find consistent results across all three markets and across both proxies of market returns, providing robust evidence that trading activity asymmetrically influences the cross-sectional dispersion of returns in all three European stock markets. In particular, we find evidence of anti-herding once again, which is significant only on days with high volume. The result is confirmed by the Wald test, supporting Hypothesis 3. Similar results are found for the first sub-period, with the anti-herding behaviour being significant only on days with increased trading activity. The only exception to this is in the case of France, for which we now also find significant anti-herding behaviour on days with low trading volume when using the value-weighted proxy for market returns, with the effect being less pronounced in the latter case. The asymmetry is further confirmed by the Wald test results for all three markets again. As for the estimation results for the second sub-period, we find significant anti-herding behaviour on days with high volume for Germany under both proxies of market return as well as for the UK when using equally weighted market returns. The opposite result holds for France, for which the evidence in favour of anti-herding behaviour is now found stronger on days with low trading volume. The Wald test now confirms the asymmetry only for the UK when using equally weighted market returns.

Finally, we investigate potential asymmetric behaviour of CSAD between days with high volatility and days with low volatility, as shown in the model presented in Equation (6). We distinguish between days with high and low volatility relative to a 30-day moving average, as is standard practice in the relevant literature (see Tan et al. 2008; Economou et al. 2011 among others). The estimation results are presented in Table 6. According to the results for the entire sample period, we find significant anti-herding behaviour only for Germany, for which anti-herding behaviour is more likely to be encountered on days with high volatility, and for which the asymmetry is confirmed by the Wald test. In the first sub-period, we find significant evidence of anti-herding behaviour only for France on days with low volatility when value-weighted returns are used, whereas in the second sub-period we find no significant evidence of either herding or anti-herding behaviour. We therefore find very limited support for the contention in Hypothesis 4.

4.2 | Dynamic Analysis

To further our understanding of herding behaviour, we have also chosen to discuss our estimation results using our dynamic analysis. Figure 1[10] illustrates the estimated time-varying γ_1 and γ_2 coefficients from the benchmark model of Equation (3) – presented in dynamic forms in Equations (7) and (8)—for both the equally weighted and value-weighted market returns for each country. Again, we find that for all the three countries considered in our study, and with either equally weighted or value-weighted returns, the market return is positively associated with cross-sectional returns' dispersion, consistent with standard asset pricing models, as revealed by the positive γ_1 coefficient, although its value changes over time and differs across the three countries considered. Similarly, the effect of the squared market return, as captured by the estimated

TABLE 2 | Pairwise cross-market correlations.

	UK	France	Germany
Panel A: Cross-market correlations of CSAD measures (equally weighted returns)			
UK	1.000		
France	0.870	1.000	
Germany	0.811	0.830	1.000
Panel B: Cross-market correlations of CSAD measures (value weighted returns)			
UK	1.000		
France	0.866	1.000	
Germany	0.801	0.827	1.000
Panel C: Cross-market correlations of market portfolio returns (equally weighted returns)			
UK	1.000		
France	0.893	1.000	
Germany	0.872	0.938	1.000
Panel D: Cross-market correlations of market portfolio returns (value weighted returns)			
UK	1.000		
France	0.875	1.000	
Germany	0.837	0.935	1.000

Note: This table reports the pairwise correlation coefficients of the cross-sectional absolute deviation (CSAD) measures and market portfolio returns for the UK, French, and German markets over the entire sample period. For the calculation of these correlations, we use only observations on the days that all three markets were open for trading, resulting in a total of 1121 daily observations. Panels A and B contain the correlations for the CSAD measures using equal and value weights for the market portfolio, respectively. Panels C and D present the correlations of market portfolio returns using equal and value weights, accordingly.

γ_2 coefficient, changes over time. In this regard in particular, Figure 1 reveals several interesting findings. First, for the UK and Germany we find evidence of herding in the beginning of our sample period which is consistent with past studies that have found herding behaviour in Europe (see, e.g., Kremer and Nautz 2013, and Walter and Moritz Weber 2006, for Germany), which however disappears during the pandemic. More specifically, for the UK, when equally weighted returns are used, the herding behaviour is followed by anti-herding and then some fluctuations, before the γ_2 coefficient approximates the zero line during the pandemic period. When value-weighted returns are used for the UK, the herding behaviour before the pandemic is even clearer, with the γ_2 coefficient stabilising again close to zero during the Covid-19 period. Similarly, for Germany, when equally weighted returns are used, the herding behaviour is strong up to 2018 but then the γ_2 coefficient approaches zero and remains zero even throughout the pandemic period, whereas when value-weighted returns are used, the time-varying estimation results suggest some anti-herding behaviour before the γ_2 coefficient becomes zero. These results might suggest a decrease in investors' irrational imitative trading behaviour (Bekiros et al. 2017). Second, the results for France reveal anti-herding behaviour in the beginning of our sample period, which however disappears during the Covid-19 pandemic. Our results therefore consistently provide no evidence of either herding or anti-herding behaviour during the Covid-19 pandemic period for all the three countries stock markets considered using both equally weighted and value-weighted market returns. We thus find no support for the contention in Hypothesis 1 during the pandemic period.

Figure 2 shows the evolution of the estimated coefficients from the dynamic version of the model presented in Equation (4), which allows us to explore the behaviour of CSAD in rising and falling markets for each country. Although the values of the coefficients change over time and differ across the three countries considered and across the two methods for calculating returns, we notice that the estimated γ_3 and γ_4 coefficients are nearly zero throughout the crisis induced by Covid-19 in all cases. The only exception to this constitutes the estimated γ_3 coefficient for France, which remains positive even during the pandemic, thus indicating anti-herding behaviour in up-markets. Our results, therefore, provide limited support to the assertion in Hypothesis 2 for the period covering the Covid-19 pandemic.

Accordingly, Figure 3 plots the estimated coefficients from the dynamic version of the model presented in Equation (5), which allows us to investigate the behaviour of CSAD on days with high and low trading volumes for each country. The estimated γ_3 and γ_4 coefficients for the UK and France when either equally weighted or value-weighted returns are used and for Germany when equally weighted returns are used reveal herding during days with low trading volumes but anti-herding behaviour during days with high volumes, with the anti-herding behaviour being overall stronger. On the other hand, when value-weighted returns are used for Germany, we also find some evidence of anti-herding on days with low trading volume throughout 2017. We further find anti-herding behaviour on days with low volumes during 2018 and 2019 for France. Nevertheless, we notice that in all cases during the Covid-19 pandemic period the values of both the γ_3 and γ_4 coefficients substantially reduce, with the γ_4 coefficient, in particular, approaching zero. These results thus indicate anti-herding behaviour on days with high trading volume but provide no evidence of either herding or anti-herding on days with low volume during the pandemic, therefore providing some support to the contention in Hypothesis 3 for the period covering the Covid-19 pandemic.

Finally, Figure 4 depicts the evolution of the estimated coefficients from the dynamic version of the model presented in Equation (6), which enables us to examine whether there exists an asymmetric response of CSAD to days with high volatility and days with low volatility for each country. It is shown that the γ_3 coefficient is mostly positive throughout our entire sample period, including the pandemic period, for all the three countries considered in our study. In contrast, the γ_4 coefficient is very close to zero during the Covid-19 period in all cases. These results suggest anti-herding behaviour on days with high volatility but provide no evidence of either herding or anti-herding on days with low volatility during the pandemic, therefore providing support to the assertion in Hypothesis 4 during the pandemic.

TABLE 3 | Estimates of herding behaviour.

	UK		France		Germany	
	Equally weighted	**Value weighted**	**Equally weighted**	**Value weighted**	**Equally weighted**	**Value weighted**
Panel A: Entire period						
a	0.007 (25.46)***	0.008 (21.21)***	0.006 (18.85)***	0.006 (17.58)***	0.006 (29.09)***	0.006 (29.33)***
γ_1	0.412 (5.20)***	0.413 (4.21)***	0.337 (4.70)***	0.313 (3.90)***	0.277 (5.87)***	0.251 (5.55)***
γ_2	−0.260 (−0.18)	−0.550 (−0.35)	−0.075 (−0.07)	0.411 (0.35)	−0.027 (−0.04)	0.192 (0.31)
Adj R^2	0.403	0.315	0.436	0.388	0.367	0.353
Panel B: Pre-covid-19 period						
a	0.008 (48.21)***	0.088 (48.47)***	0.007 (44.63)***	0.007 (45.45)***	0.006 (43.99)***	0.007 (43.10)***
γ_1	0.234 (6.05)***	1.641 (4.75)***	0.168 (6.90)***	0.139 (6.27)***	0.172 (8.13)***	0.147 (7.89)***
γ_2	−0.193 (−0.464)	4.551 (1.14)	0.331 (1.54)	0.796 (3.89)***	0.173 (0.932)	0.378 (2.37)***
Adj R^2	0.244	0.164	0.243	0.234	0.210	0.196
Panel C: Covid-19 period						
a	0.011 (16.75)***	0.011 (15.06)***	0.009 (12.29)***	0.010 (11.71)***	0.009 (17.36)***	0.009 (17.82)***
γ_1	0.347 (3.31)***	0.392 (2.87)***	0.260 (2.43)***	0.222 (1.81)*	0.269 (3.36)***	0.278 (3.60)***
γ_2	1.544 (0.90)	1.537 (0.78)	1.904 (1.44)	3.401 (1.99)**	0.640 (0.68)	0.497 (0.57)
Adj R^2	0.429	0.353	0.512	0.479	0.450	0.452

Note: This table reports the estimation results for the benchmark model: $\mathrm{CSAD}_t = a + \gamma_1 |r_{m,t}| + \gamma_2 (r_{m,t})^2 + e_t$, where $r_{m,t}$ is measured both as the equally weighted portfolio and the value weighted portfolio return at time t. CSAD_t is also measured as both the equally weighted and value weighted cross-sectional absolute deviation. Numbers in parentheses denote the corresponding values of the t-statistics based on Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

4.3 | Further Analysis

In this sub-section, we assess the robustness of our results obtained from the dynamic analysis of the state-space models. In particular, we concentrate on the dynamic estimates of the benchmark model and, similar to Arjoon and Bhatnagar (2017), we regress the herding coefficient ($\gamma_{j,2,t}$) on various variables in order to identify the factors that affected the herding behaviour during the period under examination. The regression model for stock market j, $j = 1,2$ and 3, is as follows:

$$\mathrm{Herd}_{j,t} = \delta_0 + \delta_1 r_{mj,t} + \delta_2 \mathrm{Liq}_{j,t} + \delta_3 \mathrm{Var}_{j,t} + \delta_4 \mathrm{Herd}_{j,t-1} + \delta_5 \mathrm{Covid}_{j,t} + \varepsilon_t \quad (9)$$

where $\mathrm{Herd}_{j,t}$ is the indicator of daily herding behaviour obtained from the state-space model, that is, $\gamma_{j,2,t}$, when using either equally weighted returns or value-weighted returns. The independent variables include the market return ($r_{mj,t}$), market liquidity measured by the daily volume traded ($\mathrm{Liq}_{j,t}$) and market variance measured by the estimated daily GARCH(1,1) conditional variance series ($\mathrm{Var}_{j,t}$). The idea is similar to the static analysis, namely, to examine whether positive market returns (or up markets) affect herding positively and whether increased market liquidity (proxied by the market volume), as well as increased market uncertainty (proxied by the market variance), are associated with increased herding. Additionally, we include a Covid-19 related dummy variable, taking the value one from the first date of the first lockdown for the UK and France and from the start of the *protection stage* for Germany, and zero otherwise, to examine how the Covid-19 period affected the herding coefficient, as well as a lagged dependent variable to ensure that our results are not affected by potential autocorrelation in the dependent variable.

The estimation results are reported in Table 7. It is important to discuss these results in conjunction with the plots illustrated in Figure 1 that depict the dynamic herding estimates of $\gamma_{j,2,t}$ for each country. When the dependent variable is negative (as herding suggests), then a negative (positive) coefficient for one of the determinants suggests that herding is reinforced as this variable increases (decreases). Our results reveal no clear pattern of association between the herding behaviour indicator and the main determinants considered. Specifically, the market return has a positive and significant impact on herding behaviour, thus suggesting anti-herding effects, only in the case of the UK when the results are based on equally weighted market returns and of Germany when the results are based on value-weighted market returns. In all other cases, the market return's coefficient is statistically insignificant. Higher liquidity is also associated with anti-herding in the case of Germany under both methods and in the case of the UK when the results are based on value-weighted market returns. Finally, while the coefficient of market variance is negative in all cases, indicating higher herding during periods of stress, it is statistically significant only in the case of the UK

TABLE 4 | Estimates of herding behaviour in rising and declining markets.

	UK		France		Germany	
	Equally weighted	**Value weighted**	**Equally weighted**	**Value weighted**	**Equally weighted**	**Value weighted**
Panel A: Entire period						
a	0.008 (25.84)***	0.008 (21.88)***	0.006 (20.33)***	0.007 (19.51)***	0.006 (27.89)***	0.006 (28.21)***
γ_1	0.408 (4.27)***	0.422 (3.60)***	0.317 (4.07)***	0.283 (3.40)***	0.297 (4.86)***	0.273 (4.76)***
γ_2	0.385 (5.66)***	0.358 (4.326)***	0.287 (4.68)***	0.254 (3.78)***	0.238 (5.73)***	0.217 (5.26)***
γ_3	1.712 (0.87)	2.077 (0.91)	1.835 (1.72)*	3.091 (2.79)***	0.777 (0.89)	0.798 (1.00)
γ_4	−1.109 (−1.40)	−0.995 (−1.12)	−0.231 (−0.42)	0.299 (0.45)	−0.137 (−0.363)	0.050 (0.12)
Adj R^2	0.430	0.346	0.646	0.420	0.387	0.370
$\gamma_1 - \gamma_2$ Wald-χ^2	0.023 [0.147]	0.064 [1.105]	0.029 [0.490]	0.029 [0.432]	0.588 [2.598]	0.056 [2.632]
$\gamma_3 - \gamma_4$ Wald-χ^2	2.822 [2.246]	3.072 [2.345]	2.067 [5.26]***	2.792 [7.795]***	0.914 [1.521]	0.747 [1.523]
Panel B: Pre-covid-19 period						
a	0.008 (58.25)***	0.008 (48.11)	0.007 (44.27)***	0.007 (44.68)***	0.006 (40.84)***	0.007 (40.91)***
γ_1	−0.034 (−0.482)	0.110 (1.27)	0.151 (4.50)***	0.139 (4.11)***	0.171 (3.79)***	0.134 (3.39)***
γ_2	0.192 (5.54)***	0.167 (5.25)***	0.147 (5.12)***	0.115 (4.53)***	0.164 (6.43)***	0.131 (5.73)***
γ_3	17.209 (3.02)***	3.388 (0.511)	2.367 (1.88)*	2.098 (1.54)	0.743 (0.30)	1.858 (0.944)
γ_4	0.096 (0.28)	0.400 (1.19)	0.488 (2.04)**	1.006 (4.45)***	0.245 (1.08)	0.514 (2.61)***
Adj R^2	0.280	0.165	0.246	0.238	0.211	0.198
$\gamma_1 - \gamma_2$ Wald-χ^2	−0.227 [0.065]***	−0.057 [0.502]	0.003 [0.012]	0.024 [0.597]	0.006 [0.028]	0.003 [0.009]
$\gamma_3 - \gamma_4$ Wald-χ^2	17.112 [9.138]***	2.988 [0.201]	1.878 [2.308]	1.091 [0.655]	0.497 [0.043]	1.344 [0.485]
Panel C: Covid-19 period						
a	0.012 (13.96)***	0.012 (15.89)***	0.010 (13.84)***	0.010 (13.95)***	0.009 (18.42)***	0.009 (18.58)***
γ_1	0.417 (3.56)***	0.514 (3.45)***	0.332 (2.81)***	0.302 (2.25)**	0.323 (3.73)***	0.306 (3.77)***
γ_2	0.071 (0.46)	−0.010 (−0.06)	0.100 (1.32)	−0.074 (−0.70)	0.026 (0.308)	−0.012 (−0.129)
γ_3	0.602 (0.36)	−0.110 (−0.05)	0.959 (0.663)	1.933 (1.12)	0.007 (0.007)	0.033 (0.040)
γ_4	6.913 (1.66)*	10.59 (1.89)**	4.576 (3.53)***	9.756 (3.50)***	5.369 (2.87)***	6.579 (2.84)***
Adj R^2	0.452	0.401	0.538	0.530	0.484	0.485
$\gamma_1 - \gamma_2$ Wald-χ^2	0.346 [4.636]***	0.525 [10.68]***	0.231 [7.325]***	0.376 [7.153]***	0.296 [10.886]***	0.319 [9.213]***
$\gamma_3 - \gamma_4$ Wald-χ^2	−6.311 [2.093]	−10.706 [3.389]**	−3.616 [4.845]***	−7.823 [5.865]***	−5.361 [7.507]***	−6.545 [7.561]***

Note: This table reports the estimation results for the model: $\mathrm{CSAD}_t = a + \gamma_1 D^{\mathrm{Up}}|r_{m,t}| + \gamma_2(1-D^{\mathrm{Up}})|r_{m,t}| + \gamma_3 D^{\mathrm{Up}}(r_{m,t})^2 + \gamma_4(1-D^{\mathrm{Up}})(r_{m,t})^2 + e_t$, where $r_{m,t}$ is measured both as the equally weighted portfolio and the value weighted portfolio return at time t. CSAD_t is also measured as both the equally weighted and value weighted cross-sectional absolute deviation. D^{Up} is a dummy variable that takes the value 1 on days with positive market returns and the value 0 otherwise. Numbers in parentheses denote the corresponding values of the t-statistics based on Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors. Values in brackets report the Chi-square (χ^2) statistics corresponding to the null hypotheses $\gamma_1 - \gamma_2$ and $\gamma_3 - \gamma_4$ in the estimated model. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

TABLE 5 | Estimates of herding behavior during periods of high or low volume trading.

	UK		France		Germany	
	Equally weighted	**Value weighted**	**Equally weighted**	**Value weighted**	**Equally weighted**	**Value weighted**
Panel A: Entire period						
a	0.008 (30.77)***	0.008 (24.51)***	0.006 (20.95)***	0.007 (20.38)***	0.007 (33.57)***	0.007 (33.63)***
γ_1	0.124 (2.01)***	0.146 (1.644)	0.230 (2.97)**	0.167 (2.01)**	0.064 (1.36)	0.048 (0.955)
γ_2	0.444 (4.60)***	0.457 (3.77)***	0.359 (4.46)***	0.332 (3.81)***	0.290 (5.09)***	0.263 (4.98)***
γ_3	7.004 (4.17)***	6.420 (2.51)***	2.076 (1.75)*	4.017 (2.68)***	6.451 (5.75)***	6.336 (5.52)***
γ_4	−0.834 (−0.589)	−1.191 (−0.74)	−0.498 (−0.55)	−0.117 (−0.120)	−0.301 (−0.49)	−0.070 (−0.120)
Adj R^2	0.418	0.330	0.442	0.401	0.391	0.376
$\gamma_1 - \gamma_2$ Wald-χ^2	−0.319 [17.15]***	−0.310 [11.33]***	−0.129 [3.573]*	−0.165 [5.771]**	−0.225 [20.933]***	−0.251 [17.594]***
$\gamma_3 - \gamma_4$ Wald-χ^2	7.839 [18.37]***	7.611 [9.54]***	2.574 [4.375]**	4.134 [8.024]***	6.752 [36.748]***	6.406 [31.523]***
Panel B: Pre-covid-19 period						
a	0.008 (37.90)***	0.009 (39.46)***	0.007 (41.87)***	0.007 (43.18)***	0.007 (45.63)***	0.007 (43.45)***
γ_1	−0.113 (−1.62)	−0.189 (−2.84)***	−0.311 (−4.77)***	−0.284 (−4.67)***	−0.107 (−2.37)***	−0.137 (−2.88)***
γ_2	0.238 (4.93)***	0.177 (4.10)***	0.161 (5.60)***	0.141 (5.52)***	0.184 (7.51)***	0.157 (7.47)***
γ_3	12.953 (3.14)***	14.890 (3.72)***	26.290 (5.67)***	22.052 (4.93)***	11.67 (4.80)***	11.63 (4.42)***
γ_4	−0.347 (−0.727)	0.220 (0.494)	0.292 (1.27)	0.672 (3.161)***	−0.013 (−0.05)	0.195 (1.04)
Adj R^2	0.269	0.206	0.303	0.294	0.253	0.242
$\gamma_1 - \gamma_2$ Wald-χ^2	−0.351 [40.78]***	−0.366 [42.05]***	−0.473 [66.038]***	−0.426 [58.639]***	−0.249 [48.14]***	−0.295 [46.082]***
$\gamma_3 - \gamma_4$ Wald-χ^2	13.30 [11.54]***	14.674 [14.46]***	25.997 [32.505]***	21.379 [23.408]***	11.692 [28.875]***	11.436 [19.504]***
Panel C: Covid-19 period						
a	0.012 (18.08)***	0.012 (16.92)***	0.010 (16.82)***	0.010 (15.57)***	0.009 (19.85)***	0.009 (19.52)***
γ_1	0.071 (0.740)	0.224 (1.66)*	0.213 (2.47)**	0.161 (1.63)	0.020 (0.25)	0.060 (0.69)
γ_2	0.504 (3.75)***	0.589 (3.20)***	0.275 (2.44)**	0.242 (2.05)**	0.333 (3.12)***	0.331 (3.37)***
γ_3	6.064 (2.58)***	2.037 (0.75)	1.442 (1.38)	2.968 (2.18)**	5.832 (3.35)***	4.586 (2.27)***
γ_4	−0.389 (−0.218)	−0.664 (−0.27)	2.598 (1.90)*	4.185 (2.39)**	−0.276 (−0.25)	−0.284 (−0.296)
Adj R^2	0.479	0.412	0.543	0.521	0.490	0.485
$\gamma_1 - \gamma_2$ Wald-χ^2	−0.433 [6.99]***	−0.364 [3.37]***	−0.061 [0.290]	−0.081 [0.498]	−0.313 [7.848]***	−0.271 [5.860]**
$\gamma_3 - \gamma_4$ Wald-χ^2	6.454 [4.72]***	2.701 [0.630]	−1.156 [0.498]	−1.217 [0.332]	−0.610 [0.266]	0.615 [0.341]

Note: This table reports the estimation results for the model: $\text{CSAD}_t = a + \gamma_1 D^{\text{HVolume}} |r_{m,t}| + \gamma_2 (1 - D^{\text{HVolume}}) |r_{m,t}| + \gamma_3 D^{\text{HVolume}} (r_{m,t})^2 + \gamma_4 (1 - D^{\text{HVolume}}) (r_{m,t})^2 + e_t$, where $r_{m,t}$ is measured both as the equally weighted portfolio and the value weighted portfolio return at time t. CSAD_t is also measured as both the equally weighted and value weighted cross-sectional absolute deviation. D^{HVolume} is a dummy variable that takes the value 1 on days characterised by high trading volume, as compared to a 30-day moving average, and the value 0 otherwise. Numbers in parentheses denote the corresponding values of the t-statistics based on Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors. Values in brackets report the Chi-square (χ^2) statistics corresponding to the null hypotheses $\gamma_1 - \gamma_2$ and $\gamma_3 - \gamma_4$ in the estimated model. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

TABLE 6 | Estimates of herding behaviour during periods of high or low volatility.

	UK		France		Germany	
	Equally weighted	**Value weighted**	**Equally weighted**	**Value weighted**	**Equally weighted**	**Value weighted**
Panel A: Entire period						
a	0.008 (28.74)***	0.008 (22.10)***	0.006 (20.15)***	0.007 (18.68)***	0.007 (28.82)***	0.007 (29.82)***
γ_1	0.251 (4.25)***	0.268 (3.153)***	0.271 (4.53)***	0.247 (3.35)***	0.189 (4.21)***	0.153 (3.49)***
γ_2	0.480 (4.18)***	0.471 (3.14)***	0.371 (3.30)***	0.337 (2.86)***	0.323 (4.13)***	0.285 (3.94)***
γ_3	2.832 (1.64)	2.810 (0.95)	1.132 (0.88)	1.870 (0.96)	2.102 (1.83)*	2.792 (2.65)***
γ_4	−1.037 (−0.63)	−1.220 (−0.64)	−0.422 (−0.36)	0.136 (0.101)	−0.515 (−0.67)	−0.197 (−0.278)
Adj R^2	0.408	0.317	0.437	0.389	0.378	0.363
$\gamma_1 - \gamma_2$ Wald-χ^2	−0.228 [6.14]***	−0.203 [3.19]*	−0.099 [1.378]	−0.090 [1.091]	−0.133 [4.085]**	−0.131 [4.449]**
$\gamma_3 - \gamma_4$ Wald-χ^2	3.870 [4.44]**	4.031 [2.15]	1.555 [1.514]	1.734 [0.926]	2.617 [5.065]**	2.989 [7.462]***
Panel B: Pre-covid-19 period						
a	0.008 (36.59)***	0.002 (37.86)***	0.007 (40.37)***	0.007 (41.80)***	0.007 (44.44)***	0.007 (43.26)***
γ_1	0.098 (1.65)*	0.0546 (0.99)	0.148 (3.66)***	0.122 (3.03)***	0.157 (4.15)***	0.107 (2.79)***
γ_2	0.247 (4.64)***	0.177 (3.45)***	0.185 (3.53)***	0.152 (5.00)***	0.198 (6.79)***	0.166 (6.57)***
γ_3	1.558 (0.57)	2.455 (0.92)	−1.470 (−0.84)	−0.794 (−0.50)	−0.844 (−0.53)	0.911 (0.57)
γ_4	−0.335 (−0.59)	0.3139 (0.56)	0.188 (0.64)	0.684 (2.41)**	−0.047 (−0.179)	0.209 (0.93)
Adj R^2	0.228	0.160	0.236	0.230	0.218	0.196
$\gamma_1 - \gamma_2$ Wald-χ^2	−0.149 [7.53]***	−0.122 [5.16]**	−0.037 [0.672]	−0.030 [0.453]	−0.041 [0.872]	−0.058 [1.828]
$\gamma_3 - \gamma_4$ Wald-χ^2	1.894 [0.558]	2.141 [0.706]	−1.658 [0.938]	−1.478 [0.091]	−0.796 [0.244]	0.701 [0.189]
Panel C: Covid-19 period						
a	0.011 (15.11)***	0.011 (14.11)***	0.009 (13.66)***	0.010 (11.88)***	0.009 (17.11)***	0.009 (18.10)***
γ_1	0.190 (1.66)*	0.3475 (2.44)***	0.248 (2.72)***	0.242 (1.98)**	0.126 (1.48)	0.138 (1.65)
γ_2	0.659 (4.59)***	0.7370 (3.55)***	0.533 (2.64)***	0.466 (2.14)***	0.529 (3.86)***	0.459 (3.56)***
γ_3	2.351 (0.81)	−1.365 (−0.33)	0.494 (0.27)	0.651 (0.23)	2.588 (1.35)	2.389 (1.32)
γ_4	−2.238 (−1.27)	−2.618 (−0.94)	−0.170 (−0.45)	0.491 (0.17)	−2.086 (−1.46)	−1.358 (−1.06)
Adj R^2	0.511	0.429	0.577	0.544	0.549	0.520
$\gamma_1 - \gamma_2$ Wald-χ^2	−0.468 [5.67]**	−0.389 [2.817]*	−0.285 [2.528]	−0.223 [1.492]	−0.403 [8.553]***	−0.320 [5.554]**
$\gamma_3 - \gamma_4$ Wald-χ^2	4.635 [1.471]	1.253 [0.066]	1.564 [0.413]	0.160 [0.002]	4.675 [5.040]**	3.748 [3.508]*

Note: This table reports the estimation results for the model: $\text{CSAD}_t = a + \gamma_1 D^{\text{HVolatility}}|r_{m,t}| + \gamma_2 (1 - D^{\text{HVolatility}})|r_{m,t}| + \gamma_3 D^{\text{HVolatility}} (r_{m,t})^2 + \gamma_4 (1 - D^{\text{HVolatility}}) (r_{m,t})^2 + e_t$, where $r_{m,t}$ is measured both as the equally weighted portfolio and the value weighted portfolio return at time t. CSAD_t is also measured as both the equally weighted and value weighted cross-sectional absolute deviation. $D^{\text{HVolatility}}$ is a dummy variable that takes the value 1 on days characterised by high volatility, as compared to a 30-day moving average, and the value 0 otherwise. Numbers in parentheses denote the corresponding values of the t-statistics based on Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors. Values in brackets report the Chi-square (χ^2) statistics corresponding to the null hypotheses $\gamma_1 - \gamma_2$ and $\gamma_3 - \gamma_4$ in the estimated model. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

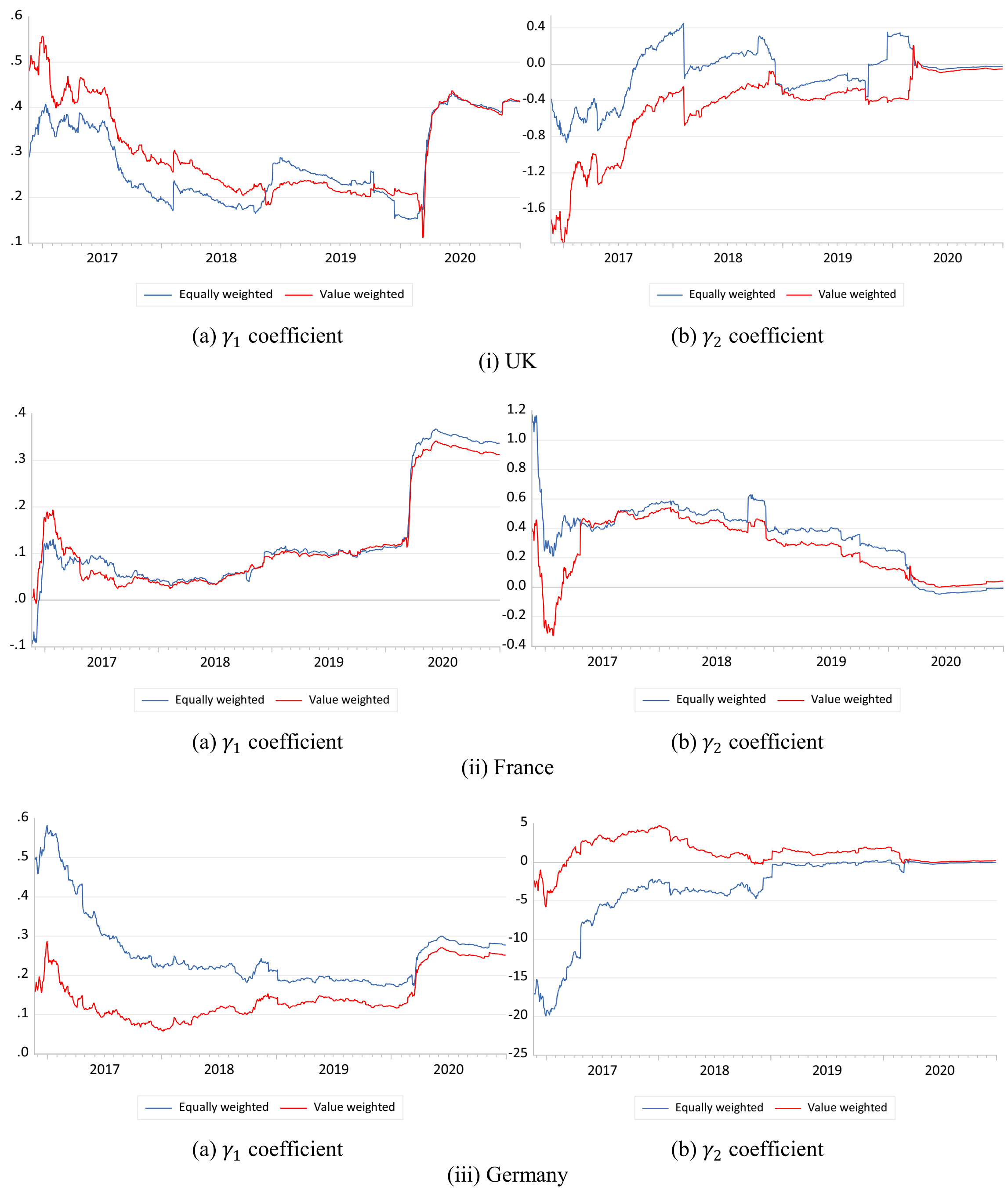

FIGURE 1 | State space kalman filter herding coefficient estimates. [Colour figure can be viewed at wileyonlinelibrary.com]

when the results are based on value-weighted market returns. Interestingly, the Covid-19 related dummy variable is found to have a statistically significant impact on herding behaviour in all cases (with the sole exception of Germany's equally weighted returns), which is positive in the case of the UK but negative for France and Germany.

Analysing these estimation results in conjunction with the plots in Figure 1 enables us to understand the impact of each variable better. The results for the dummy variable in particular show that, since the dynamic herding coefficient is mostly negative for the UK (Figure 1i), the positive effect of the dummy variable contributes to reducing herding behaviour to nearly zero during the Covid-19 period. The opposite is true in the case of France, where the dynamic herding coefficient is mostly positive (Figure 1ii). Thus, the negative coefficient of the Covid-19 dummy variable reduces the anti-herding behaviour that was previously observed in the market to nearly zero. Similar results are observed for Germany when the results are based on value-weighted market returns. On the other hand, Germany's dynamic herding coefficient (Figure 1iii), when the results are based on value-weighted market returns, is nearly zero for a prolonged period prior to the Covid-19 pandemic, which explains the insignificance of the reported coefficient.

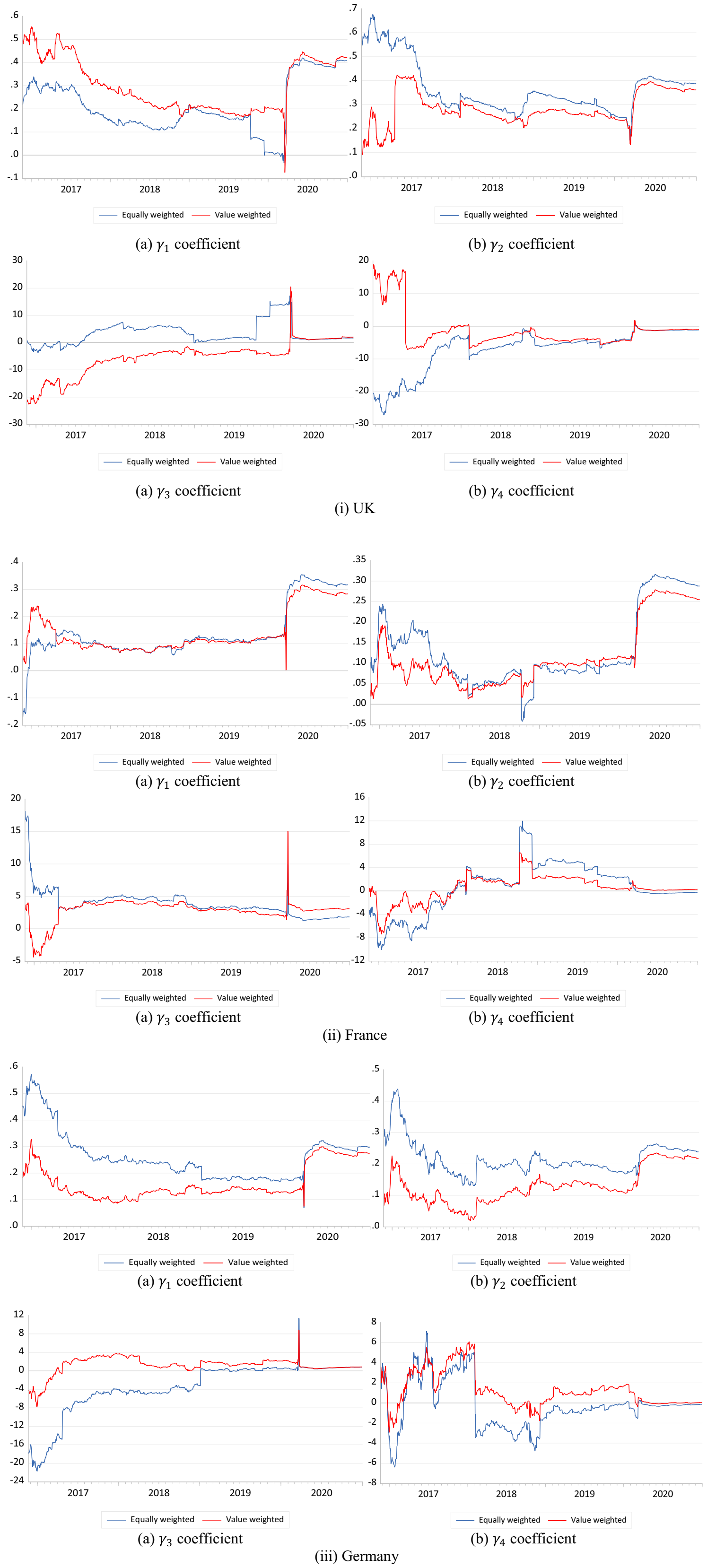

FIGURE 2 | State space kalman filter herding coefficient estimates in rising and declining markets. [Colour figure can be viewed at wileyonlinelibrary.com]

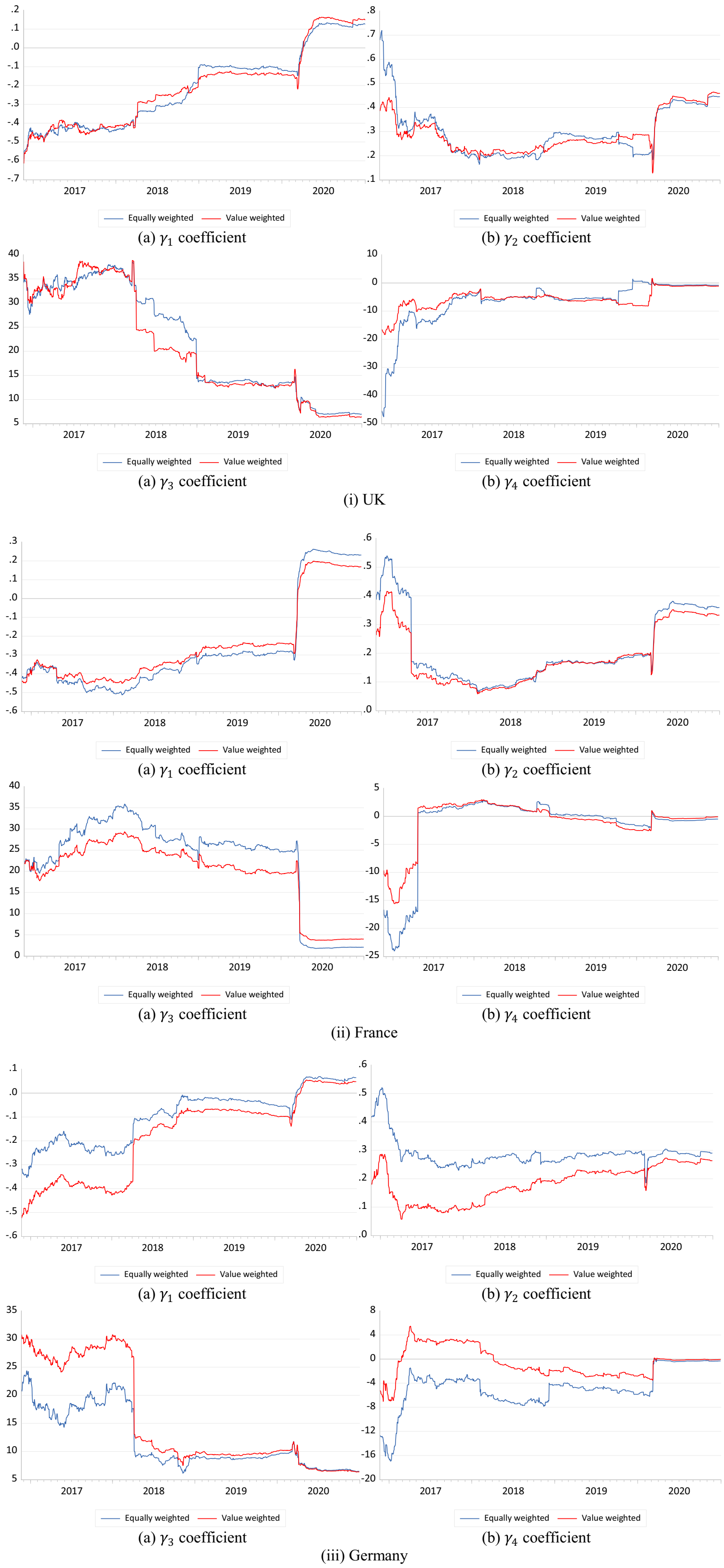

FIGURE 3 | State space kalman filter herding coefficient estimates during periods of high or low volume trading. [Colour figure can be viewed at wileyonlinelibrary.com]

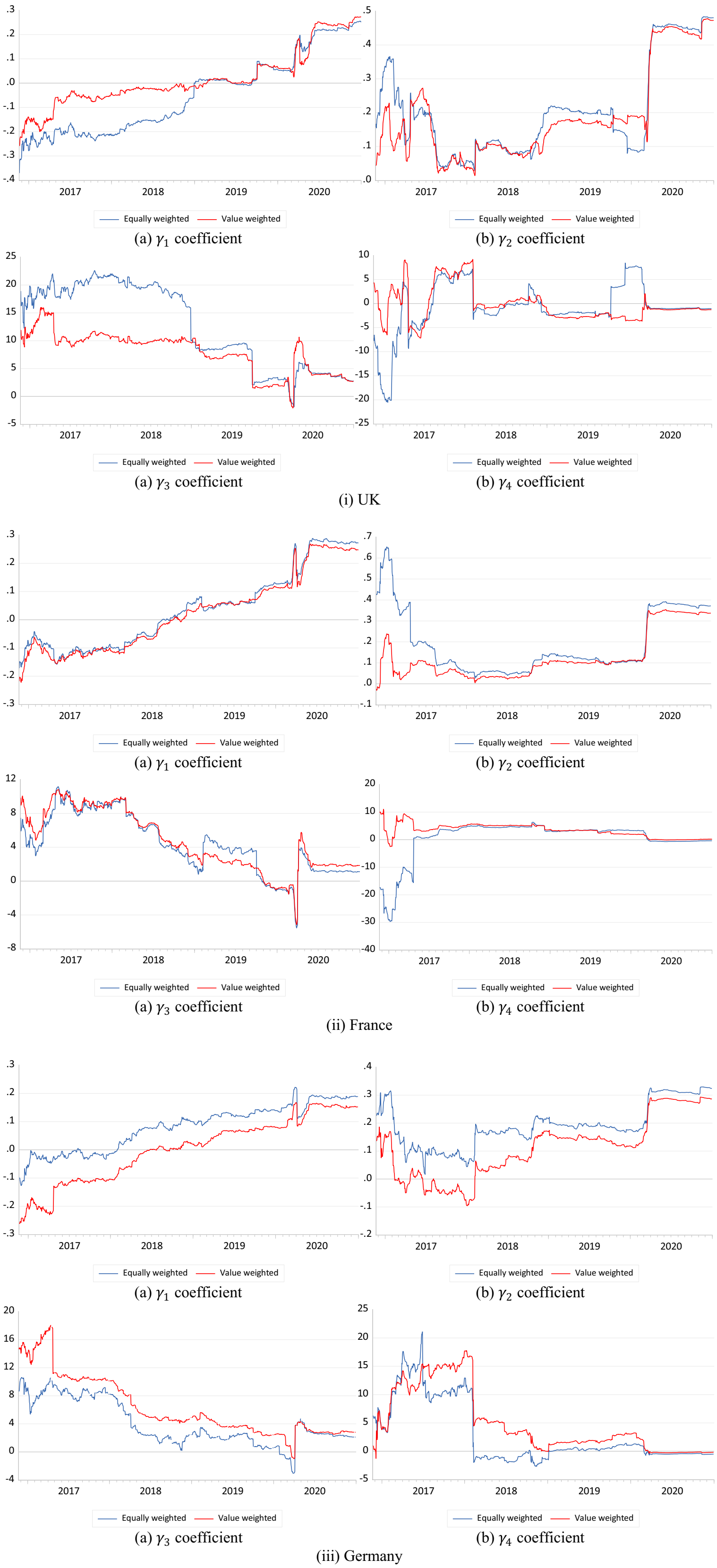

FIGURE 4 | State space kalman filter herding coefficient estimates during periods of high or low volatility. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 7 | Determinants of herding dynamics.

	UK		France		Germany	
	Equally weighted	Value weighted	Equally weighted	Value weighted	Equally weighted	Value weighted
constant	−0.206 (−0.29)	−1.44 (−2.30)**	0.051 (1.68)*	−0.451 (−1.55)	−0.93 (−2.19)**	−0.56 (−1.82)*
$R_{m,t}$	4.933 (6.13)***	−0.039 (−0.051)	0.44 (1.19)	−0.12 (−0.33)	0.52 (0.95)	0.91 (2.37)**
Liq_t	0.01 (0.29)	0.07 (2.27)**	−0.02 (−1.35)	0.025 (1.58)	0.05 (2.19)**	0.03 (1.87)*
Var_t	−33.76 (−0.82)	−95.8 (−2.04)**	−4.51 (−0.34)	−18.27 (−1.03)	−50.13 (−1.39)	−37.4 (−1.45)
Herd_{t-1}	0.994 (28.9)***	0.99 (44.1)***	0.97 (25.6)***	0.99 (34.9)***	0.99 (68.1)***	0.99 (33.2)***
Covid_t	0.004 (2.15)**	0.03 (2.32)**	−0.101 (−4.50)***	−0.014 (−1.87)*	−0.023 (1.09)	−0.004 (−1.97)*
Adj R^2	0.988	0.996	0.995	0.994	0.998	0.991

Note: This table presents the estimation results for the model: $\text{Herd}_{j,t} = a + \delta_1 r_{mj,t} + \delta_2 \text{Liq}_{j,t} + \delta_3 \text{Var}_{j,t} + \delta_4 \text{Herd}_{j,t-1} + \delta_5 \text{Covid}_{j,t} + \epsilon_t$, for stock market j, $j = 1$, 2 and 3. The dependent variable, $\text{Herd}_{j,t}$, denotes the dynamic daily herding indicator derived from the state-space Kalman filter model, presented in Equations (7) and (8). $r_{mj,t}$ denotes the stock market return, $\text{Liq}_{j,t}$ represents market liquidity measured by the daily volume traded, $\text{Var}_{j,t}$ denotes the estimated daily GARCH(1,1) conditional variance series, $\text{Herd}_{j,t-1}$ is the lagged dependent variable, and $\text{Covid}_{j,t}$ is a dummy variable taking the value one from the first date of the first lockdown for the UK (23rd March 2020) and France (16th March) and from the start of the *protection stage* for Germany (13th of March), and zero otherwise. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

5 | Conclusions and Discussion

Herding is widely believed to be an important element of behaviour in financial markets and particularly at times when the market is exhibiting stress. Humans feel safer when they find themselves as part of a crowd (Devenow and Welch 1996), and this particularly applies in contexts of uncertainty, high volatility, and perceived danger. In such a context, investors may be inclined to ignore their private information and join the herd in an effort to feel safer and reduce their perception of exposure to risk. This study aimed to investigate the existence of herding or anti-herding behaviour in three major European stock markets, namely the UK, French, and German stock markets, and to compare the results before and during the Covid-19 pandemic. As well as employing static analysis, we use a dynamic analysis, which allows us to investigate changes in herding behaviour over the entire sample period. We further studied asymmetric effects of herding in response to market conditions, trading volume, and return volatility.

Our static analysis provided no evidence of significant herding behaviour for the UK. In contrast, it provided some evidence of anti-herding for France and Germany, especially before the onset of the Covid-19 crisis. Our dynamic analysis confirmed that the effect of the squared market return in cross-sectional returns' dispersion, and thus the herding behaviour, is time-varying and differs across the three countries considered and across the two methods for calculating returns. Consistent with our static analysis, our dynamic analysis shows evidence of either herding or anti-herding behaviour—depending on the market, period, and method for calculating returns—but only up until the onset of the Covid-19 crisis.

An interesting finding of our study is related to investor behaviour after the onset of the Covid-19 crisis. According to the time-varying estimation results, we found no evidence of either herding or anti-herding behaviour during the Covid-19 pandemic period for any of the three countries considered. These findings are in contrast with the study of Espinosa-Méndez and Arias (2021), which concluded that the Covid-19 pandemic increased herding behaviour in European capital markets. Our findings are also in contrast with past studies that found evidence of herding behaviour in European stock markets (see, e.g., Kremer and Nautz 2013; Walter and Moritz Weber 2006). On the other hand, our findings are in line with Wu et al. (2020) who found that herding behaviour was significantly lower than usual in Chinese stock markets during the Covid-19 period, as well as with Yarovaya et al. (2021) who found a decreasing trend in herding in cryptocurrency markets during the beginning of the Covid-19 outbreak. Our results are also in accordance with Bekiros et al. (2017) who found that herding appeared to be insignificant during the global financial crisis, and with Choe et al. (1999) who showed that during the period of Korea's economic crisis herding behaviour fell. Similarly, Hwang and Salmon (2004) showed that the Asian crisis and in particular the Russian crisis reduced herding as identified.

An important implication of our results is that they point to stock markets returning to 'rationality'. Such a rational behaviour, contrast to earlier studies that find herding behaviour in stock markets (e.g., Blasco et al. 2012; Choi and Sias 2009; Clements et al. 2017; Kremer and Nautz 2013; Mobarek et al. 2014; Walter and Moritz Weber 2006), arguing that if herding exists, it should be at its highest in contexts of uncertainty, high volatility and perceived danger. In such contexts, investors may be inclined to ignore their private information and join the herd in an effort to feel safer (Devenow and Welch 1996). Nevertheless, our findings for European stock markets during the Covid-19 outbreak contradict the common belief that herding is stronger during heightened uncertainty. Our results suggest that investors acted rather independently and traded on fundamentals during the Covid-19 crisis period. Our results, therefore, indicate that crises are more likely to urge investors to forgo herding/anti-herding behaviour and attempt to invest in a more 'rational' way. Such a proposition is in accordance with Hwang and Salmon's (2004) findings concerning the Asian financial crisis and the Russian crisis, as well as to Bekiros et al.'s (2017) results during the global financial crisis. Instead of making irrational decisions and following the herd in times of fear and uncertainty, investors have an additional incentive to examine investments against the information available to them. Indeed, given that the availability and cost of information have been identified by theory as potential generating mechanisms of herding (Bikhchandani et al. 1992; Economou et al. 2015), in a context where critical pieces of information are widely available, agents could more confidently form their own decisions without relying on information cascades from their peers. In such scenarios, the Efficient Market Hypothesis (Fama 1965; Fama et al. 1969) according to our results is more likely to hold that is widely given credit. Such a view of investor behaviour is in accordance with the literature suggesting that rationality is context-dependent (Stewart 1992).

A possible side effect of the Covid-19 crisis has been the millions of investors who entered the stock-market, lured by the promise of substantial profits through equities which were considerably lower and probably undervalued compared to their highs in February/March 2020 (Pagano et al. 2021). Academics (Tokic 2020), seasoned investors (Mackenzie 2021) as well as policymakers have drawn attention to the funds as well as the large appetite for risk that these retail investors brought into the global stock markets. The entry of millions of new retail investors, along with the availability of information and the general optimism that the shares of companies mostly hit by Covid-19 lockdowns would quickly rise to somewhere close to their previous highs once an effective vaccine/therapy was discovered, might help explain the reduced effect of herding/anti-herding reported in our results.

Overall, our findings improve our understanding of investor sentiment during financial crises. One possible suggestion for further research is to incorporate measures of market randomness (e.g., volatility clustering, regime-switching models, or randomness proxies) alongside herding behaviour in order to provide deeper insights into how investors behaved under extreme uncertainty during COVID-19. Additionally, it would be interesting in the future to investigate the behavioural mechanisms which generate herding/anti-herding, or which even cause its absence. To this end, in addition to robust quantitative methodologies, a qualitative investigation of the retail/institutional investor behaviour could potentially make important contributions to the debate about the contexts and mechanisms which may trigger or reduce herding/anti-herding behaviour.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available in GDrive at https://drive.google.com/drive/folders/1IP8VxTVJV4xpNYFJH-X1INzv69hgaDgC.

Endnotes

[1] The data are publicly available by the John Hopkins Coronavirus Resource Center at https://coronavirus.jhu.edu/map.html.

[2] Notably, the first confirmed Covid-19 case in Europe was detected in France on 24th January 2020, whereas the first confirmed case in Germany and in the UK was detected shortly after, on 27th January 2020 and 31st January 2020, respectively.

[3] The assertion that a significant number of new retails investors entered the stock market during the COVID-19 pandemic is asserted by various studies and reports, such as the FINRA (2021), the JPMorgan Chase Insitute Study (2024) and the RMIT (2020) study, among others.

[4] The importance of studying herding behaviour in financial markets has been further detailed in Economou et al. (2011), among others.

[5] It holds that $Var\left(r_{m,t}\right) = E\left(r_{m,t}^2\right) - E\left(r_{m,t}\right)^2 \approx E\left(r_{m,t}^2\right)$.

[6] Information on these dates has been derived from the Covid-19 pandemic entries of Wikipedia for each country. For the UK visit: https://en.wikipedia.org/wiki/COVID-19_pandemic_in_the_United_Kingdom or https://www.gov.uk/government/speeches/pm-address-to-the-nation-on-coronavirus-23-march-2020. For France visit: https://en.wikipedia.org/wiki/COVID-19_pandemic_in_France. For Germany visit: https://en.wikipedia.org/wiki/COVID-19_pandemic_in_Germany.

[7] It is worth noting that an alternative breakpoint has also been considered and results were obtained for splitting the sample period on the date of the first Covid-19 related reported death (i.e., 6th March for the UK; 15th Feb for France; and 9th March for Germany). Results are not presented here in interest of brevity but are available from the authors upon request.

[8] In our equally weighted return calculation, we considered changes in the firms that constitute the stock market index by including joiners and excluding leavers, correspondingly.

[9] In the interest of brevity, the estimation results of the GARCH(1,1) models are not presented here but are available from the authors upon request.

[10] To improve the visual clarity of the figures, standard errors are not shown in all graphs. While this helps highlight the patterns in the EV and VW dynamic estimates, we acknowledge that in several cases (particularly for Germany and the UK prior to March 2020) these estimates are not statistically significant. As such, any apparent differences should be interpreted with caution. For France, the estimates are generally significant. Complete results including standard errors are available upon request.

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Appendix A

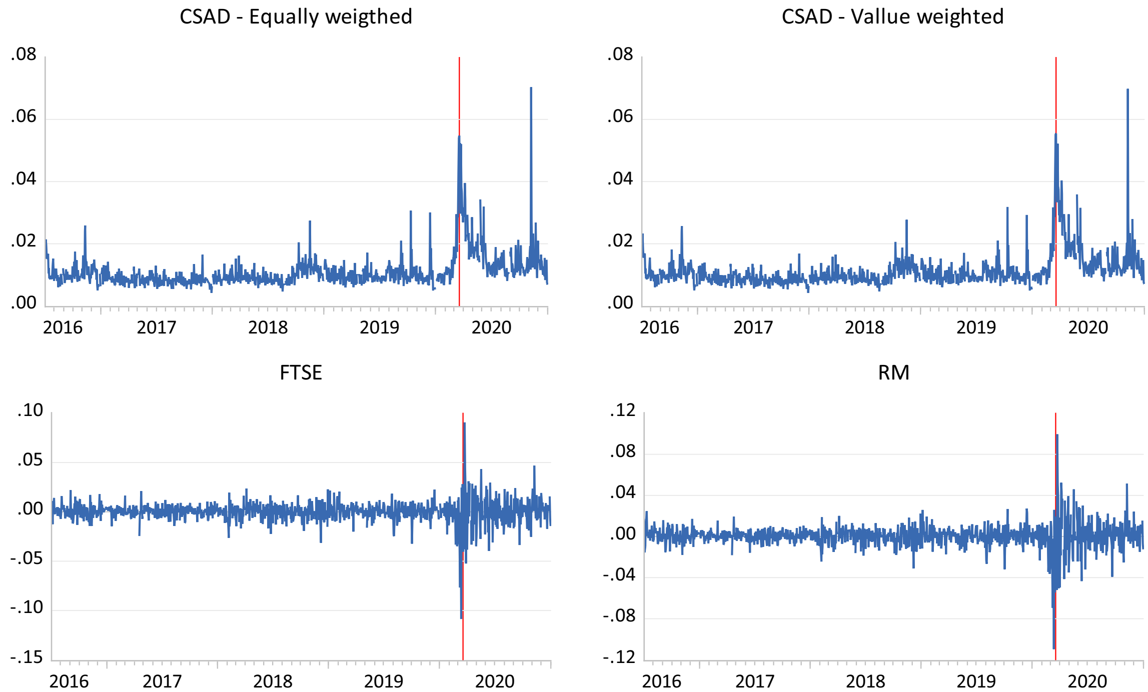

FIGURE A1 | CSAD measures and stock market returns for the UK. [Colour figure can be viewed at wileyonlinelibrary.com]

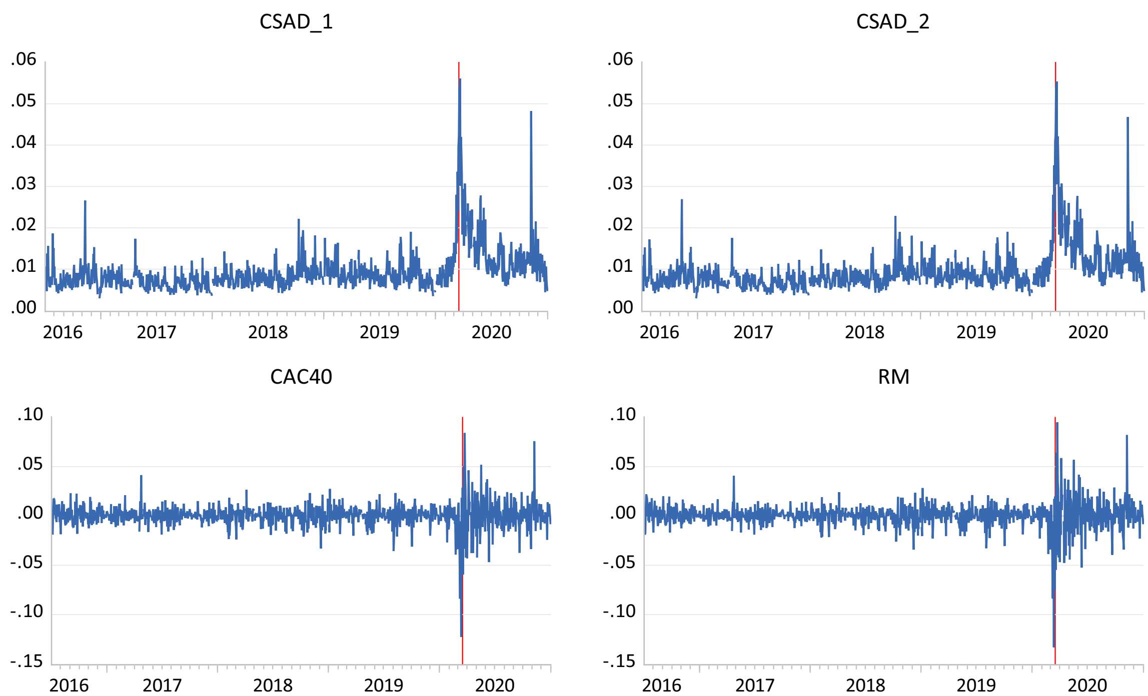

FIGURE A2 | CSAD measures and stock market returns for France. [Colour figure can be viewed at wileyonlinelibrary.com]

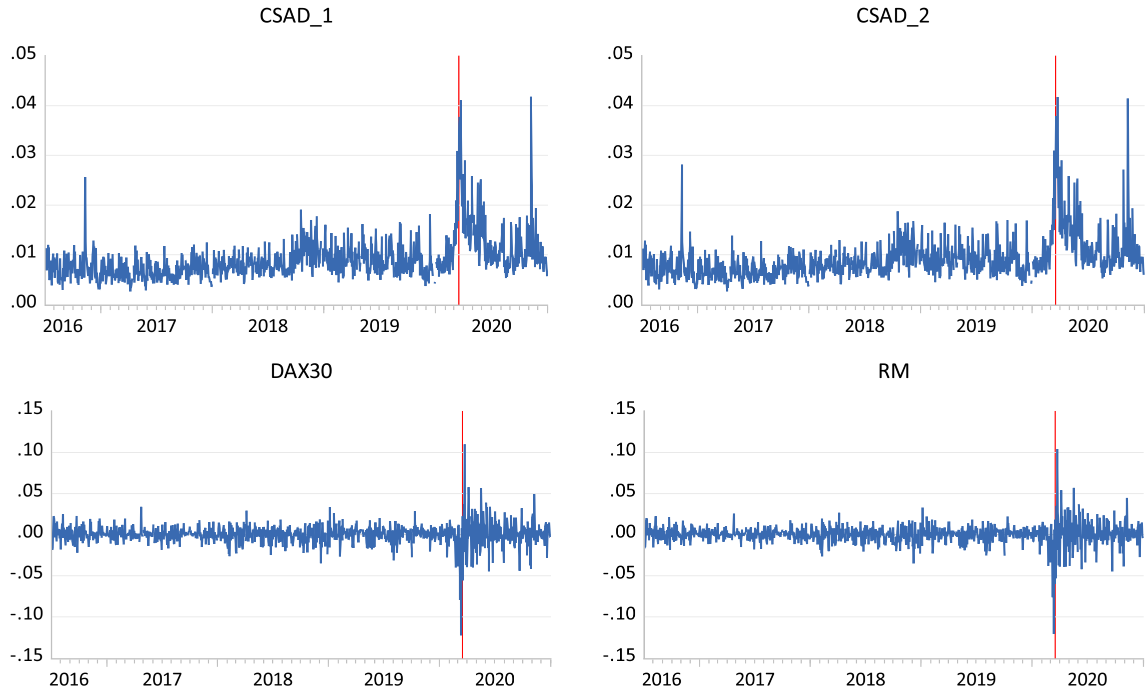

FIGURE A3 | CSAD measures and stock market returns for Germany. [Colour figure can be viewed at wileyonlinelibrary.com]