Investors' herd effect in stock markets: An empirical investigation during the outbreak of the Covid-19 pandemic

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Abstract: This paper investigates the impact of the COVID-19 pandemic on investors' herding behaviour in major international stock markets categorized into three geographical regions (American, European, and Asian-Pacific). We examine the presence of herding by measuring the cross-sectional absolute deviation of stock returns around the market portfolio return, and it also considers whether returns' dispersion differs on up and down-market days. The results reveal a herding effect due to COVID-19 in all three regions, with higher levels of herding observed only on up-market days in the American region and on both positive and negative market days in the European and Asia-Pacific regions, although the level of herding is lower in the latter.

Keywords. Asset Pricing; Behavioural Finance; Herding behaviour; International Financial Market; Cross Sectional Dispersion of Returns

JEL CLASSIFICATION: G12; G14; G15; G41

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1. Introduction

The outbreak of the Covid-19 pandemic has had a significant impact on individual investment behavior, leading to turmoil in global financial markets. In uncertain situations, people tend to imitate others' decisions, and this behavioral bias is known as herd behavior. It has been identified as a contributing factor to the contagion of financial crises, and researchers have focused on clarifying its role in recent years. Luu and Luong (2020) studied herd behavior during the periods of H1N1 and Covid-19 and found strong evidence for its presence in investors due to anxiety and psychological instability caused by the disease.

Several studies have investigated the global presence of herding bias. For instance, Chang et al. (2000) reported limited evidence of herding in Japan and no effect in the USA and Hong Kong markets, while South Korea and Taiwan showed evidence of herding. Hwang and Salmon (2004) found the persistence of herding in the USA and South Korean equity markets but noted that market crises reduce its behavior. Chiang and Zheng (2010) suggested that herding behavior leads to deviation in asset prices across 18 advanced and developing economies.

Recent studies have examined the impact of the pandemic on financial markets. Ali et al. (2020) investigated the effect of the Coronavirus epicenter moving from China to Europe and then the US, while Kizys et al. (2021) studied if the government can reduce herding behavior's influence on international stock markets during Covid-19. Espinosa-Méndez and Arias (2021) examined whether the pandemic affected herding behavior in Europe. However, there is still a research gap regarding the pandemic's effect on investors' herding behavior in global stock markets during the outbreak of the pandemic and how returns' dispersion behaves in rising and declining market days when herding behavior is present.

This study aims to fill this relative research gap by investigating the role of the pandemic in the herding behavior of investors from July 10, 2019, to July 15, 2020. This research also aims to examine whether the dispersion of returns behaves differently on up and down-market days when herding behavior prevails, making it the first thorough empirical investigation of herding behavior in global stock markets, including extreme market conditions.

Our study employs Chang et al. (2000) model to investigate the existence of rational asset pricing and the herding effect in 30 major global stock indices. We observe the relationship between cross-sectional (CSAD) and squared market returns ($R_{m,t}^2$) and report evidence of herding behavior in the European and American regions, but not in the Asia-Pacific region using the classic Newey and West (1987). However, these findings are not definitive, as they need to be validated using static and time-varying extensions because nonlinear regression does not reflect extreme values.

In addition, inspired by Cui et al. (2019), we examine whether the dispersion of returns behaves differently on up and down-market days when herding behavior prevails. Our findings reveal the significant impact of the pandemic on the geographical areas of America only on upmarket days, and we reveal significant herding both on positive and negative market days in European region. We notice a significant anti-herding effect on rising market days.in the Asia-Pacific region.

To further analyze our results, we proceed with a series of regression methods. First, we follow Yarovaya et al. (2020) to investigate the presence of herding behavior in different regimes through Markov-switching regressions using the EM algorithm. Our evidence suggests stronger herding behavior in the American region.

We used quantile regressions, building upon the work of Kizys et al. (2021) and Gębka and Wohar (2013), to investigate how the coefficients varied across different quantiles. Our analysis showed unconditional herding in the American region, except for extreme quantiles (5% and 95%). In the European region, we found unconditional herding in all quantiles of return variation, but at a decreasing rate. Conversely, the Asia-Pacific region exhibited lower herding effects at higher quantiles. These findings suggest that herding behavior increased during the Covid-19 pandemic.

We also examined the impact of the pandemic on market returns, and our results indicated conditional herding in the American region during positive average market performance, except for the extreme quantiles. However, during negative average market performance, there was a herding effect in the lower quantiles, indicating higher levels of herding behavior. In the European and Asia-Pacific regions, we observe a decreasing trend in the higher quantiles for both positive and negative average market performance. Finally, we found that in the Asian-Pacific region, herding behavior was observed for both positive and negative average market performance, but only in higher quantiles displaying lower levels of herding.

To assess the evolution of herding behavior over time, we conducted Time-Varying Regressions following the approaches of Yarovaya et al. (2020) and Bollerslev et al. (2016).

Our analysis revealed that the American region demonstrated stable herding behavior throughout the examined period, before and during the COVID-19 pandemic, without any volatility. However, herding occurred only from February 25th to March 13th in the European region, coinciding with a period of increased investor uncertainty. In contrast, the Asia-Pacific region exhibited negative herding behavior throughout the study period. Additionally, we found that higher levels of herding behavior prevailed on upmarket days in the US region without any volatility, whereas no herding was observed on down-market days. In Europe, herding behavior was present on up and down-market days without any volatility. In the Asia-Pacific region, herding behavior was observed only on negative market days throughout the examined period.

The remainder of this paper is organized as follows. Section 2 presents the conceptual framework and the formulated hypotheses. Section 3 outlines the data and variables used in the analysis. In Section 4, we describe the econometric methodology used to examine herding behavior throughout the examined period and investigate whether the dispersion of returns differs on up and down-market days. In Section 5, our findings are presented and discussed, and in Section 6, the conclusions are presented, and implications for financial decision-makers are discussed.

2. Conceptual Framework and Hypotheses Development

There are two different approaches to investigating investors' herding behavior, as identified by Lakonishok et al. (1992), and Christie and Huang (1995), and Chang et al. (2000) respectively. The former collects and processes trading data and orders executed within a given period, whereas the latter group financial asset returns based on similar characteristics.

Herding behavior has been widely examined in various global financial market contexts with mixed results. Christie and Huang (1995) initially concluded that neither daily nor monthly returns indicate the presence of herding behavior during periods of market stress, suggesting instead that they align with rational asset pricing. However, Chang et al. (2000) modified the prior model and reported evidence of herding behavior in South Korea and Taiwan, with limited evidence of bias in Japan and no herding effect in the USA and Hong Kong markets. Hwang and Salmon (2004) find that herding behavior persists in the direction of the market in the USA and South Korean equity markets and that market crises reduce such behavior. Moreover, Chiang and Zheng (2010) examine 18 advanced and developing economies and suggest that herding behavior causes deviation in asset prices. Conversely, Economou et al. (2011) investigated the impact of the global financial crisis on the Portuguese, Italian, Spanish, and Greek markets, revealing that it did not cause intense herding behavior.

Several studies have examined herd behavior in individuals or up to two markets during a pandemic. Wu et al. (2020) study herding behavior in the Chinese stock market during extreme market conditions caused by COVID-19 and report that herding behavior is more pronounced during upside market movement. Additionally, Luu and Luong (2020) investigate herding behavior in Vietnam and Taiwan stock markets during the H1N1 and COVID-19 pandemics, using the Return Dispersion Model and the State Space Model of Christie and Huang (1995) and Chang et al. (2000) and Hwang and Salmon (2004) to calculate CSAD. Dhall and Singh (2020) apply Chang et al. (2000) model and find evidence of herding behavior at the industry level in the Indian stock market during the COVID-19 pandemic. Finally, Espinosa-Méndez and Arias (2021) detected an increase in herding behavior in the Australian stock market during the COVID-19 pandemic.

The literature is limited on how the Covid-19 pandemic has affected international stock markets. Ali et al. (2020) investigate that even if China shows stability, global financial markets (United States of America, United Kingdom, Italy, Spain, France, Germany, Switzerland, and South Korea) show strong recession, especially during the later phase of the epidemic spread. Kizys et al. (2021) claim that there is evidence of herding behavior examining 72 countries. Espinosa-Méndez and Arias (2021) explore that in France (Paris), Germany (Frankfurt), Italy (Milan), the United Kingdom (London), and Spain (Madrid) the herding behavior increased in the capital markets of Europe through COVID-19 period. The authors expect that the Covid-19 pandemic will highlight the presence of herding behavior among investors in their study. They tested two hypotheses using Chang et al. (2000) model to determine the presence of herding behavior in stock markets due to the uncertainty caused by the pandemic.

Hypothesis 1 predicts a negative relation between squared market ($\beta_2 < 0$) and cross-sectional absolute deviation (CSAD) in $CSAD_{m,t} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + e_t$ if herding behavior is pronounced. A positive relation occurs ($\beta_2 > 0$) if anti-herding behavior prevails and if $\beta_1 > 0$ and $\beta_2 = 0$ indicates that there is no herding behavior.

Hypothesis 2 predicts a negative relation between positive values of the squared market ($\beta_3 < 0$), and cross-sectional absolute deviation, and/or negative relation between negative values of the squared market ($\beta_4 < 0$) and cross-sectional absolute deviation (CSAD) in $CSAD_{m,t} = \beta_0 + \beta_1 D_{up}|R_{m,t}| + \beta_2(1 - D_{up})|R_{m,t}| + \beta_3 D_{up} R_{m,t}^2 + \beta_4(1 - D_{up}) R_{m,t}^2 + e_t$, if there are no herding effects. Notably, if coefficient $\beta_4 < \beta_3$, then herding effects are more pronounced during days with declining market returns. There are no herding effects if $\beta_1 > 0$ and $\beta_2 > 0$.

3. Data, Sample Formation, and Variable Measurement

3.1 Data

Our sample consists of 30 major international stock indices, which are categorized based on their geographical area. Our aim is to investigate whether the COVID-19 pandemic has influenced the herding behavior of stock investors globally. We have created three geographical regions: the American, European, and Asia-Pacific. Figure 1 displays the stock indices used in our analysis, and the corresponding stock markets are indicated in parentheses.

[Insert Figure 1 here]

We have gathered our data from Thomson Reuters DataStream, specifically the hourly closing prices of the stock indices. The European region's data covers the period from 11:00 am on July 10, 2019, to 6:00 pm on July 15, 2020. The American region's data is from 5:00 pm on July 10, 2019, to 11:00 pm on July 15, 2020, while the Asia-Pacific region's data is from 02:00 am on July 10, 2019, to 1:00 pm on July 15, 2020. Furthermore, we have collected the hourly closing prices of the general stock index of each region, which represents the market return for that particular region. The American general stock index is the SXA1, the European index is the STOXX, and the Asia-Pacific index is the SXP1.

To analyze the data, we converted all closing prices of the stock indices from their respective local currency to the landmark currency of each geographical area. For this purpose, we defined the US geographical area as the landmark currency of the US, the euro for the European area, and the US dollar for the Asia-Pacific region. It's important to note that the currencies used do not affect the empirical results, as we work with logarithmic values of the closing prices.

Descriptive statistics for all indices of the American, European, and Asia-Pacific regions are presented in Tables A1, A3, and A5, respectively, while Tables A2, A4, and A6 show descriptive statistics for the general stock index of each region. These general stock indices represent the market return of each region, which we will further analyze to examine the herding behavior of stock investors.

3.2 Measuring herding behavior

Even if there are several approaches that could be adopted to examine herding in stock markets during the COVID-19 pandemic, we estimate herding behavior by means of Chang et al. (2000) due to its widespread and efficient use according to the numerous studies that base on this study and we present them in Section 2. So, low dispersion of returns around their cross-sectional average indicates that market participants ignore their prior heterogeneous beliefs and information to follow correlated trading patterns around the “market consensus”. Chang et al. (2000) proposed the cross-sectional absolute deviation (CSAD) of stock returns around the market portfolio return as a more appropriate measure. This measure is given by:

$$CSAD_{m,t} = \frac{\sum_{t=1}^{N} |\mathrm{R_{i,t}} - \mathrm{R_{m,t}}|}{N} \qquad \textbf{(1)}$$

where $\mathrm{R_{i,t}}$ is the observed stock return of index i on hour t and it is the first logarithmic difference of closing prices for stock index i at time t, as given below:

$$R_{i,t} = \ ln\, P_t - ln\, P_{t-1} \qquad \textbf{(2)}$$

We have converted the closing prices of all stock indices belonging to the Americas region to be denominated in the same currency, i.e., dollars, as well as Asia-Pacific in dollars and Europe in euros. N is the number of stocks in the market portfolio and $R_{m,t}$ is the average absolute market return of each geographical region, which is the general stock index i.e., SXA1 for American region, STOXX for European region and SXP1 for Asian – Pacific region. $R_{m,t}$ is the first logarithmic difference of closing prices for general stock index m at time t:

$$R_{m,t} = \ ln\, P_t - ln\, P_{t-1} \qquad \textbf{(3)}$$

Concretely, Chang et al. (2000) defined that the model below is what occurs by market stress.

$$CSSD = \beta_0 + \beta_1 D_t^U + \beta_2 D_t^L + e_t \qquad \textbf{(4)}$$

where D_t^U=1 if return lies in the extreme upper tail of the return's distribution or $D_t^L = 1$ if return lies in the extreme lower tail of the return's distribution. Asset pricing models, like the conditional CAPM expect a linear relationship between returns' dispersion and market returns. With this assumption in mind, if herding behavior takes place during period of market stress, this can be displayed by a nonlinear relationship to test for herding behavior, so we run the following regression model for each market i:

$$CSAD_{m,t} = \beta_0 + \beta_1 \left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + e_t \qquad \textbf{(5)}$$

If there were no herding effects one would expect a positive value of coefficient β_2. However, even if linear asset pricing models would assume that when herding behavior shows up in days of extreme market movements, the change of cross-sectional dispersion of stock returns will be proportional with market return, we notice the exact opposite. So, we use the squared market return to the previous model to notice this nonlinear relationship through a negative estimate of the coefficient β_1. To sum up, we examine irrationality and herding behavior in stock markets testing the *Hypothesis 1* (H1)

Furthermore, we examine whether the returns' dispersion behaves differently in up and down-market days. It is reasonable to investigate whether herding is impacted by periods with market distress, as it is a common indicator of such periods. More specifically, we would expect that the cross-sectional dispersion of stock returns would be reduced during days with negative market returns. So, we examine irrationality and herding behavior in stock markets testing *Hypothesis 2 (H2)*.

Taking into consideration other studies in the literature Christie and Huang (1995), Chang et al. (2000), Demirer et al. (2010) and Chiang and Zheng (2010) and the asymmetric impact of market return sign, they have pointed out that herding effects prevail during periods of abnormal information flows and market downturn, as investors follow public opinion to feel more secure, but there is no common confession regarding the findings, as it depends on the examined market and the sample period. Furthermore, we follow the Cui et al. (2019) approach to discover herding in up and down market days (conditional herding). More specifically, to examine the asymmetric effect of market return sign, we estimate the following model for each market i:

$$CSAD_{m,t} = \beta_0 + \beta_1 D_{up}\left|R_{m,t}\right| + \beta_2\left(1 - D_{up}\right)\left|R_{m,t}\right| + \beta_3 D_{up} R_{m,t}^2 + \beta_4\left(1 - D_{up}\right) R_{m,t}^2 + e_t$$

(6)

where D_{up} is a dummy variable equal to one (zero) on days with positive (negative) values of $R_{m,t}$. Significantly negative values of β_3 (β_4) would indicate the presence of herding on days of positive (negative) average general stock index market performance.

4. Econometric Methodology

The aforementioned hypotheses in Section 2 and therefore model (5) and model (6) are examined using different quantitative methods. Firstly, we estimate the classic Newey and West (1987) Heteroscedasticity and Autocorrelation consistent (HAC) estimators to estimate linear regressions using Bartlett kernel weights as described in Newey and West (1994, 1987) so as to test if there is herding behavior in the three examined geographical regions. The classic linear Newey-West regression allows estimating the average relationship between the dependent and the explanatory variables. Hence, we can draw wrong conclusions, as abrupt changes are a common phenomenon in the herding behavior of investors during extreme conditions like the COVID-19 pandemic.

On the other side, quantile regression estimates the average relationship between the dependent and the explanatory variables at specific quantiles of the distribution of the dependent variable reflecting extreme values in a fat-tailed or asymmetric distribution of the dependent variable. Thus, we apply some static and time-varying extensions of the Chang et al. (2000) analysis to verify the herding effect of the examined geographical regions. We look at the presence of herding given different regimes through Markov-Switching regressions using the Expectation-Maximization.(EM) algorithm as in Yarovaya et al (2020), Hamilton (1994, 1989), Goldfeld and Quandt (1973), and Chiang and Zheng (2010):

$$CSAD_{m,t} = \beta_{0,s_t} + \beta_{1,s_t}|R_{m,t}| + \beta_{2,s_t}R^2_{m,t} + e_t \cdot e_t \sim \text{ii}d(0\,,\sigma^2_{s_t}) \qquad \textbf{(7)}$$

where s_t is a discrete regime variable taking values of 1 and 2, follows a two-regime Markov process and $e_t \sim iid(0\,,\sigma^2_{s_t})$, thus s_t is described as a two-state first-order Markov chain. In addition, we run quantile regressions as in Kizys et al. (2021) and Gębka and Wohar (2013) with the purpose to test the behavior of the coefficients across quantiles. So, we run the following regression model for each market i:

$$CSAD_{m,t} = Q[\tau|r_{m,t}] = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R^2_{m,t} + e_t \qquad \textbf{(8)}$$

where $CSAD_{m,t} = Q[\tau|r_{m,t}]$ stands for cross-sectional absolute deviation of stock returns with respect to the market portfolio return R_m for each period t and market i and τ is the τ th quantile (0.05, 0.25, 0.5, 0.75, 0.95) of the conditional distribution of the average absolute market return of the geographical region, e_t is the error term with a zero τ -quantile. Moreover, we examine herding in up and down markets across quantiles in each market i:

$$CSAD_{m,t} = Q[\tau|r_{m,t}] = \beta_0 + \beta_1 D_{up}|R_{m,t}| + \beta_2(1 - D_{up})|R_{m,t}| + \beta_3 D_{up}R^2_{m,t} + \beta_4\,(1 - \mathrm{D_{up}})R^2_{m,t} + e_t$$

(9)

where D_{up} is a dummy variable that takes the value 1 on days with positive values of $R_{m,t}$ and the value 0 otherwise.

Last but not least, the coefficients in the model of Chang et al. (2000) are subject to change if the time interval changes, as they are sensitive to the examined period. When a crisis prevails, like the COVID-19 pandemic, then the OLS regression will examine an average relationship, without taking into account the size of the crisis, and without providing any information for the dynamics before or after the crisis. We run Time-Varying Regressions as in Yarovaya et al. (2020) and Bollerslev et al. (2016) to assess the evolution of (unconditional, conditional) herding over time. Thus, if the coefficients can vary over time, we run the following time-varying coefficient model (TV-LM) for each market i:

$$y_t = x_t^T \beta(z_t) + u_t \, , t = 1 \ldots T \qquad \textbf{(10)}$$

where y_t is the dependent variable $CSAD_{m,t}$, $x_t = (x_{1t}, x_{2t}, \ldots, x_{dt})T$ is a vector of repressors at time t, $\beta = (\beta_0, \beta_1, \ldots, \beta_d)\ T$ is a vector of coefficients and u_t is the error term. z_t is the smoothing variable, transforming coefficients to be a function of z_t: $\beta(z_t) = (\beta_0(z_t), \beta_1(z_t), \ldots, \beta_d(z_t))T$ and it is estimated by combining OLS and the local polynomial kernel estimator Fan and Gijbels (1996).

5. Empirical Results

5.1 Analyzing the movements of closing prices

To provide context to our regression results, we present Figure 2, which depicts the price dynamics of the general stock indices of the three geographical regions during the sample period.

[Insert Figure 2 here]

As observed in the figure, the price movements of the American, European, and Asian-Pacific regions were similar. Examining the price behavior of the general stock indices of the American and European regions, we note an increase from July 2019 to February 2020, reaching their maximum levels, followed by a significant decline from February 20th, as the first recorded deaths due to the COVID-19 outbreak were reported. This decline was most severe on March 23, 2020, when the Senate failed to vote through the coronavirus economic relief package, and European governments imposed sudden economic stops to contain the virus. Despite a slight increase in the indices after April 7, the indices did not recover to their January price levels.

Similarly, for the Asian-Pacific region, there was a small increase in prices from July 2019 to January 2020, reaching their highest level during the sample period. However, prices started to decline from January 20, 2020, as the first recorded death in Asia was detected in Wuhan. The prices of the general index experienced an enormous decline from February 20 to April 7, with the biggest drop observed on March 23, 2020, due to the rise of national business locks that overshadowed the efforts of nations to avoid an economic crisis. Nonetheless, the prices of the general index recovered slightly from April 7 until the end of the sample period, although they did not return to the January price levels.

5.2 Estimating herding behavior

[Insert Table 1 here]

Table 1 presents the results of our study on unconditional herding behavior across three geographical regions, covering the period from July 2019 to July 2020, using Newey-West consistent estimators. We investigate whether cross-sectional dispersion increases at a decreasing rate during extreme market movements by introducing the squared market return to the model.

Our findings reveal positive β_1 coefficients with a significant level of 1% for all regions, indicating that cross-sectional returns' dispersion increases with the magnitude of the market return, consistent with standard asset pricing models. However, this does not directly assess herding behavior. In contrast, a negative and statistically significant β_2 coefficient signifies strong herding behavior, where cross-sectional dispersion increases at a decreasing rate during extreme market movements. Our results reveal the presence of unconditional herding only in the European and American geographical regions.

In the Asian-Pacific region, we observe a positive and statistically significant β_2 coefficient, indicating that investors not only fail to inhibit their own opinions but also overstate their own perspectives, neglecting market information. As a result, cross-sectional dispersion of returns across assets rises significantly, which could be due to localized herding during market anxiety and investor overconfidence. However, we cannot draw definitive conclusions for the Asia-Pacific region until we confirm our findings from other methods of regressions. Non-linear regression, as mentioned earlier, does not reflect extreme values.

Our findings contradict those of Christie and Huang (1995), and Chang et al. (2000) and Chiang and Zheng (2010) who found no evidence of herding behavior in the US markets. Conversely, our evidence for the Asian-Pacific region is consistent with Dhall and Singh (2020), who found no evidence of herding behavior during the examined period (1st January 2015 until 1st June 2020) in the Indian stock market.

Bernales et al. (2020) suggest that herding would be even stronger if the relationship between the CSAD of assets' returns and the market returns were negative, which implies that β_1 would be negative. However, we do not find a negative β_1 coefficient in our study, indicating that stronger herding is not observed in our sample.

5.3 Results of Markov – Switching regressions

[Insert Table 2 here]

The results of the Markov-Switching (MS) regressions in Table 2 reveal statistically significant herding behavior in the selected geographical regions except for the Asian-Pacific region. The two-regime MS CSAD model is used to examine the existence of herding behavior among regions. The model assumes a positive relationship between the squared market return and the CSAD in an expansionary period with lower volatility, $\beta_{2,1} > 0$, and a negative relationship in a recessionary period with higher volatility, $\beta_{2,2} < 0$. The transition probability p_{ij} satisfies $\Sigma_{i=0}^{2} p_{ij} = 1$, where i and j take values of 1 and 2.

The findings show that herding behavior is stronger in Regime 2 for the American and European regions. In the American region, Regime 2 has a higher probability of switching to another regime (89%) compared to Regime 1 (52%). In the European region, the opposite is observed, with Regime 1 having a higher probability of switching (91%) compared to Regime 2 (69%). In the Asia-Pacific region, Regime 1 not only shows stronger herding behavior but is also more persistent with a higher probability of switching (87%) compared to Regime 2 (69%). Overall, the MS CSAD model suggests that herding behavior is present in the examined regions, with differences in the strength and persistence of the effect across regions and regimes.

5.4 Results of Quantile regressions

[Insert Table 3 here]

The use of quantile regressions in this study allowed for a better understanding of the dynamics of herding behavior during the COVID-19 crisis. The results presented in Table 3 show that the impact of various quantiles of return variation on herding behavior differs across the three examined geographical regions. For the American region, there is evidence of unconditional herding, but no herding effect is observed in the extreme quantiles (5% and 95%). In contrast, for the European region, herding behavior is observed in all quantiles, and with a decreasing rate. As for the Asian-Pacific region, herding evidence is only present in higher quantiles of return variation, indicating lower levels of herding behavior.

These findings suggest that herding behavior increases during the COVID-19 crisis in all examined regions. This contradicts the hypothesis put forward by Krokida et al. (2020), which suggests that herding behavior can be attributed to shocks in conventional expansionary policy and non-standard policy support. Furthermore, the results are consistent with previous studies that have found evidence of herding behavior during times of financial crises Gębka and Wohar (2013). Overall, the use of quantile regressions provides a more nuanced understanding of the relationship between return variation and herding behavior across different quantiles, highlighting the importance of examining herding behavior under extreme conditions.

5.5 Estimating Time-Varying Coefficients

Figure 3 below displays unconditional herding behavior using time-varying coefficients for the period 07/15/2019 - 07/10/2020 using hourly data.

[Insert Figure 3 here]

The aim of the study is to identify trends in herding behavior during and pre-COVID-19 period in three geographical regions. The American region displays stable herding behavior throughout the examined period without any volatility. In the European region, herding behavior is absent in the pre-COVID-19 period but increases for some days post-COVID-19 period, and then becomes absent again until the end of the sample period. The squared market is stable and positive throughout the examined period in the Asian-Pacific region, indicating no trend in herding behavior. The results contradict those of Stavroyiannis and Babalos (2017), who find an anti-herding effect in the turbulent period from 2007 until 2014 using stocks of the U.S Dow Jones Islamic Index.

The study confirms that herding behavior is present on stock markets during the examined period that contains the COVID-19 crisis. Although there is no evidence of herding behavior using the classic Newey and West (1987) in the Asian-Pacific region, herding behavior prevails using quantile regressions. The study will now test the herding behavior on positive and negative market days for all examined geographical regions.

5.6 Estimating herding behavior on up and down market days

The results of model (6) presented in Table 4 showing the conditional herding behavior across the three geographical regions during the sample period from July 2019 to July 2020.

[Insert Table 4 here]

The results indicate significant herding behavior on up-market days in the American and European regions, as evidenced by the significantly negative value of β_3, except for the Asian-Pacific region where it is positive and statistically significant at the 10% level. On down-market days, herding behavior is observed only in the European region, as indicated by the negative and statistically significant coefficient β_4 at the 5% level.

These findings are consistent with the research of Espinosa-Méndez and Arias (2021), which suggests that the COVID-19 pandemic increases herding behavior in the capital markets of Europe. However, they differ from the results of Wu et al. (2020), who found that herding behavior is more significant in upside market movement in the Chinese stock market.

The presence of negative values of β_3 (β_4) and statistical significance implies the presence of herding on days of positive (negative) average performance for the examined regions. In the European region, both β_3 and β_4 are negative and statistically significant, indicating herding behavior on both positive and negative average market performance, but stronger on positive days.

5.7 Results of quantile regressions on up and down market days

The table provides insights into the relationship between market performance and herding behavior in different regions.

[Insert Table 5 here]

In the American region, there is evidence of herding behavior during both positive and negative market performance, with higher levels of herding in lower quantiles during negative performance. In contrast, herding behavior in the European region is more pervasive during positive market performance, with a decreasing trend in higher quantiles during both positive and negative market performance. The Asian-Pacific region shows lower levels of herding, with evidence of herding behavior in higher quantiles during both positive and negative market performance.

These findings suggest that market conditions and regional factors play a significant role in shaping herding behavior. Furthermore, the study provides valuable insights into how the COVID-19 pandemic may have impacted herding behavior in global markets.

5.8 Results of time varying coefficients on up and down-market days

[Insert Figure 4 here]

Figure 4 shows the results of the study's analysis of conditional herding using time-varying coefficients during the period from July 10, 2019, to July 15, 2020, based on hourly data.

In the American region, the results reveal higher levels of herding on up-market days without volatility, while no herding was observed on down-market days. Conversely, the European region exhibited herding behavior on both up and down-market days throughout the study period, without regard to volatility. Notably, the herding levels on positive market days were higher in the European region compared to other regions, as evident from the absolute values in the figure. In the Asian-Pacific region, the study observed herding behavior on negative market days throughout the examined period.

6. Conclusions

Herding behavior, which can result in stock price bubbles and reduce the benefits of portfolio diversification, has been identified as a key factor in the global financial crisis (Galariotis et al. (2016); Devenow and Welch (1996); Hott (2009); Economou et al. (2011). Thus, understanding herding behavior in financial markets is crucial to mitigating the risk of financial crises and optimizing portfolio diversification strategies.

In this study, we investigate the impact of investor herding behavior in major international stock markets during the COVID-19 pandemic. This is the first study to examine whether the pandemic affected global stock markets and to analyze whether returns and dispersion differed on up and down-market days during the outbreak of the Covid-19 pandemic using static and time-varying regression methods to validate the results of the cross-sectional dispersion approach.

Our dataset includes hourly returns for 30 stocks listed in major global markets from July 2019 to July 2020. We classify these stocks into three geographical regions (America, Europe, and Asia-Pacific) to draw global conclusions and use the cross-sectional dispersion approach and regression methods (Markov-Switching Regressions, Quantile Regressions, and Time-Varying Regressions) to identify potential herding effects.

In our study, we aimed to investigate the presence of herding behavior in major international stock markets during the COVID-19 pandemic. Our results support the first hypothesis, indicating that herding behavior is present in all three regions, including the Asian-Pacific region, where lower levels of herding are observed using Quantile Regressions. Our findings contrast those of Our results contradict those of Christie and Huang (1995), Chang et al. (2000), and Chiang et al. (2010) who didn't document any herding effect in the US markets.

Regarding the second hypothesis, we aimed to explore whether returns and dispersion behave differently on up and down-market days. We find that herding behavior is observed in the American region on up-market days, in the European region on both positive and negative market days, and in the Asian-Pacific region on up and down-market days in higher quantiles. Our findings are similar to those of Espinosa-Méndez and Arias (2021) that the COVID-19 pandemic increases herding behavior in capital markets of Europe (France, Germany, Italy, United Kingdom, and Spain). However, our evidence is on the opposite side of those of Wu et al. (2020) who support that herding behavior is more significant in upside market movement in the Chinese stock market, as we find that β_3 is positive and significant, which means that there is an anti-herding effect in positive days in the Asian-Pacific region.

Our results highlight the role of herding in market turbulence phases and have relevant implications for investors and market regulators to maintain financial stability. Our empirical results have relevant implications for investors and market regulators in a market turbulence phase like the COVID-19 pandemic. Investors should be informed about the role of herding in the selection of assets to be avoided market volatility and market regulators should issue guidelines to listed entities for disclosure of the associated risk that they concur. In a broader context, our study is of interest to the financial community to maintain financial stability.

Future research can explore the impact of pandemics on financial markets by examining the first year of the COVID-19 pandemic compared to other past pandemics. Further research can also investigate the lack of knowledge about investor herding behavior in other markets, such as bond markets, and examine the stability and motivation of herding behavior. Additionally, the volume of trading can be explored to assess the tension of the herding effect. The current study contributes to the existing literature by presenting evidence of herding behavior in financial markets and highlighting significant issues that warrant further research.

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APPENDIX

Table A1: Descriptive Statistics of all European stock market indices

	Mean	**Median**	**Maximum**	**Minimum**	**Std. Dev.**	**Observations**
_FCHI	5.08E-05	-7.80E-05	0.0887	-0.0481	0.0065	2288
_GDAXI	-8.12E-06	-9.55E-05	0.0778	-0.0518	0.0066	2246
_BFX	2.21E-05	-0.0002	0.0820	-0.0690	0.0068	2288
_AEX	-7.13E-07	-0.0001	0.0748	-0.0475	0.0061	2287
_SSMI	-2.04E-05	-0.0002	0.0739	-0.0405	0.0053	2231
_IBEX	0.0001	-8.64E-05	0.0847	-0.0440	0.0064	2278
_FTITLMS	5.18E-05	-7.81E-05	0.0980	-0.0523	0.0065	2256
_FTMIB	5.24E-05	-0.0001	0.1074	-0.0528	0.0068	2258
_PSI20	7.17E-05	-5.15E-05	0.0639	-0.0603	0.0054	2288
_ATX	0.0001	4.02E-05	0.0903	-0.1050	0.0075	2247
_ATG	0.0002	0.0000	0.1068	-0.0640	0.0076	2011
_FTSE	8.93E-05	-5.47E-05	0.0853	-0.0595	0.0065	2259
_IRTS	0.0001	-0.0001	0.2477	-0.1258	0.0105	2084
_OMXS30	-2.72E-05	-0.0001	0.0785	-0.0520	0.0064	2226
_OMXC25CAP	-0.0001	-5.40E-05	0.0707	-0.0424	0.0052	2105
_XU100	1.79E-05	-6.61E-05	0.0833	-0.0513	0.0063	2083

Notes: Table A1 reports univariate statistics on number of mean, median, maximum, minimum, standard deviation and observations for all stock indices that included in the geographical area of Europe during the examined period of July 2019 – July 2020.

Table A2: Descriptive statistics of STOXX (General Stock Market Index of Europe)

	Mean	**Median**	**Maximum**	**Minimum**	**Std. Dev.**	**Observations**
R_m (STOXX)	2.40E-05	-9.84E-05	0.0801	-0.0425	0.0057	2297

Notes: Table A2 displays the univariate statistics on number of mean, median, maximum, minimum, standard deviation and observations for the general stock index of Europe (STOXX), which is the market return ($R_{m,t}$) for the geographical area of Europe during the period July 2019 – July 2020.

Table A3: Descriptive Statistics of all American stock market indices

	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
_DJI	2.35E-05	-5.01E-05	0.1078	-0.0616	0.0071	1999
_SPX	-2.79E-05	-5.79E-05	0.1003	-0.0550	0.0067	1999
_NDX	-0.0002	-0.0001	0.0967	-0.0639	0.0068	2008
_GSPTSE	4.60E-05	-5.72E-06	0.1088	-0.0586	0.0069	1939
_BVSP	0.0002	6.75E-06	0.1550	-0.0835	0.0110	1891
_SPCLXIGPA	0.0002	5.76E-05	0.0972	-0.0915	0.0087	1671
_MERV	0.0003	0.0000	0.4832	-0.1307	0.0180	1647

Notes: Table A3 demonstrates the univariate statistics on number of mean, median, maximum, minimum, standard deviation and observations for all stock indices that included in the geographical area of America during the period July 2019 – July 2020.

Table A4: Descriptive statistics of SXA1(General Stock Market Index of America)

	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
R_m (SXA1)	-3.31E-05	-5.23E-05	0.0989	-0.0556	0.0066	2042

Notes: Table A4 reports the univariate statistics on number of mean, median, maximum, minimum, standard deviation and observations for the general stock index of America (SXA1), which is the market return ($R_{m,t}$) for the geographical area of America during the period July 2019 – July 2020.

Table A5: Descriptive Statistics of all Asian-Pacific stock market indices

	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
NKC1	-1.32E-05	0.0000	0.0681	-0.0502	0.0048	3310
_HSI	4.24E-05	0.0000	0.0588	-0.0445	0.0051	1962
_SSEC	-6.64E-05	0.0000	0.0746	-0.0291	0.0041	1895
_TWII	-0.0001	-0.0002	0.0641	-0.0578	0.0060	1184
_KS11	-4.73E-06	0.0000	0.0806	-0.0632	0.0065	1941
_KLSE	4.64E-05	0.0000	0.0678	-0.0478	0.0044	1822
_AXJO	6.24E-05	0.0000	0.0780	-0.0517	0.0070	2023

Notes: Table A5 presents the univariate statistics on number of mean, median, maximum, minimum, standard deviation and observations for all stock indices that included in the geographical area of Asia-Pacific during the period July 2019 – July 2020.

Table A6: Descriptive statistics of SXP1(General Stock Market Index of Asia-Pacific)

	Mean	**Median**	**Maximum**	**Minimum**	**Std. Dev.**	**Observations**
R_m (SXP1)	1.44E-05	0.0000	0.0631	-0.0350	0.0033	3310

Notes: Table A6 displays the univariate statistics on number of mean, median, maximum, minimum, standard deviation and observations for the general stock index of Asia-Pacific (SXA1), which is the market return ($R_{m,t}$) for the geographical area of Asia-Pacific during the period July 2019 – July 2020.

Table 1

Herding behavior estimates

	Constant	β_1	β_2	R^2 adj.
America	0.0021 (18.76) ***	0.2349 (8.76) ***	-1.8592 (-5.48) ***	10.6%
Europe	0.0011 (20.50) ***	0.3053 (10.20) ***	-2.790 (−5.21) ***	46.43%
Asia-Pacific	0.0022 (24.22) ***	0.7045 (14.06)***	2.3345 (2.22) **	26.81%

Notes: Table 1 presents the estimated coefficients for the benchmark model: $CSAD_{m,t} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + e_t$ *where* $CSAD_{m,t}$ *stands for cross-sectional absolute deviation of stock returns with respect to the market portfolio return* $R_{m,t}$ *for each period t and market i. The sample period is July 2019 to July 2020. t-Statistics are given in parentheses, calculated using Newey–West heteroscedasticity and autocorrelation consistent standard errors. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.*

Table 2

Markov-Switching estimates and constant transition matrices

Panel A	**Constant**	β_1	β_2	**log(sigma)**
America				
Regime 1	0.0057 (7.67) ***	0.1821 (3.21) ***	-1.6388 (-2.67) ***	-5.2748 (-18.54) ***
Regime 2	0.0015 (26.96) ***	0.2050 (13.27) ***	-3.1391 (-4.25) ***	-7.0036 (-110.36) ***
Europe				
Regime 1	0.0010 (50.56) ***	0.2055 (12.48) ***	-2.7638 (-2.09) **	-7.7649 (-122.75) ***
Regime 2	0.0025 (12.40) ***	0.2572 (9.20) ***	-2.3418 (-4.59) ***	-6.3229 (-62.27) ***
Asia-Pacific				
Regime 1	0.0053 (17.58) ***	0.6557 (8.47) ***	2.2463 (1.60)	-5.2548 (-59.02) ***
Regime 2	0.0013 (26.59) ***	0.3271 (11.28) ***	0.1654 (0.07)	-7.066 (-117.13) ***

Panel B		Regime 1	Regime 2
America	Regime 1	0.5185	0.4815
	Regime 2	0.1119	0.8889
Europe	Regime 1	0.9153	0.0847
	Regime 2	0.3048	0.6952
Asia-Pacific	Regime 1	0.6872	0.3128
	Regime 2	0.1347	0.8653

Notes: Table 2 reports the estimated coefficients for the benchmark model: $CSAD_{m,t} = \beta_{0,s_t} + \beta_{1,s_t}|R_{m,t}| + \beta_{2,s_t}R_{m,t}^2 + e_t \cdot e_t \sim iid(0, \sigma_{s_t}^2)$ *where* $CSAD_{m,t}$ *represents cross-sectional absolute deviation of stock returns with respect to the market portfolio return* R_m *for each period t and market i. The sample period is July 2019 to July 2020. Panel A includes the estimated coefficients and the adjusted* R^2*.* s_t *is a discrete regime variable taking values of 1 and 2, follows a two-regime Markov process and* $e_t \sim iid(0, \sigma_{s_t}^2)$ *, so* s_t *is described as a two-state first-order Markov chain. Panel B contains the transition probabilities of the Markov chain are specified as* $p_{ij} = P(S_{t+1}|S_t = j)$*,* p_{ij} *is the probability of regime i at time* $t+1$*, given that the market was in regime j at time t. t-Statistics are given in parentheses, calculated using Huber-White robust standard errors & covariance. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.*

Table 3

Unconditional Quantile regressions

Panel A: America	**5th Quantile**	**25th Quantile**	**50th Quantile**	**75th Quantile**	**95th Quantile**
$\boldsymbol{C}$	0.0004(4.81)***	0.0009(24.04)***	0.0015(36.50)***	0.0025(30.71)***	0.0061(23.06)***
$\lvert \boldsymbol{R_{m,t}} \rvert$	0.1434(1.95)**	0.1967(9.44)***	0.2161(17.03)***	0.2854(10.37)***	0.2666(3.09)***
$\boldsymbol{R_{m,t}^2}$	-1.9167(-0.52)	-2.1327(-3.45)***	-1.7258(-12.63)***	-2.5187(-9.33)***	0.7238(0.68)
Pseudo R^2	8.7%	9.4%	10.35%	9.6%	9.2%

Panel B: Europe	**5th Quantile**	**25th Quantile**	**50th Quantile**	**75th Quantile**	**95th Quantile**
$\boldsymbol{C}$	0.0006(38.18)***	0.0007(42.02)***	0.0009(44.30)***	0.0013(41.50)***	0.0023(15.27)***
$\lvert \boldsymbol{R_{m,t}} \rvert$	0.1339(18.02)***	0.2083(20.42)***	0.2886(22.94)***	0.3303(17.28)***	0.5813(10.24)***
$\boldsymbol{R_{m,t}^2}$	-0.8679(-7.21)***	-1.6242(-13.38)***	-2.6556(-17.63)***	-2.2133(-4.28)***	-6.1981(-7.40)***
Pseudo R^2	13.55%	20.51%	26.93%	32.71%	34.95%

Panel C: Asia-Pacific	**5th Quantile**	**25th Quantile**	**50th Quantile**	**75th Quantile**	**95th Quantile**
$\boldsymbol{C}$	0.0004(11.12)***	0.0008(26.97)***	0.0013(28.77)***	0.0025(28.28)***	0.0063(21.78)***
$\lvert \boldsymbol{R_{m,t}} \rvert$	0.1708(3.06)***	0.3233(9.99)***	0.5780(11.03)***	0.9465(20.42)***	2.2265(8.26)***
$\boldsymbol{R_{m,t}^2}$	5.8809(1.39)	8.6499(17.55)***	4.4839(5.58)***	-1.6495(-2.24)***	-22.8590(-5.44)***
Pseudo R^2	4.9%	9.4%	12.26%	15.78%	22.91%

Notes: Table 3 reports the results for quantile regression equivalents of model: $CSAD_{m,t} = Q[\tau|r_{m,t}] = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + e_t$ *where* $CSAD_{m,t}$ *stands for cross-sectional absolute deviation of stock returns with respect to the market portfolio return* R_m *for each period t and market i and* τ *is the* τ^{th} *quantile (0.05, 0.25, 0.5, 0.75, 0.95) of the conditional distribution of the average absolute market return of the geographical region,* e_t *is the error term with a zero* τ *-quantile. The sample period is July 2019 to July 2020. t-Statistics are given in parentheses, calculated using Huber Sandwich Standard Errors & Covariance. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.*

Table 4

Conditional on up/down market days Herding behavior estimates.

	Constant	β_1	β_2	β_3	β_4	R^2 adj.
America	0.0022 (18.37)***	0.1952 (7.77) ***	0.2342 (4.68) ***	-1.6159 (-6.39) ***	-0.4446 (-0.19)	11.07%
Europe	0.0011 (22.38)***	0.3034 (10.42) ***	0.2923 (9.93) ***	-2.8128 (5.34) ***	-2.0572 (-2.45) **	46.34%
Asia-Pacific	0.0022 (27.74)***	0.7227 (11.11) ***	0.6630(6.91) ***	1.8877(1.70) *	4.3731(0.59)	26.79%

Notes: This table reports the estimated coefficients for the model: $CSAD_{m,t} = \beta_0 + \beta_1 D_{up}|R_{m,t}| + \beta_2(1 - D_{up})|R_{m,t}| + \beta_3 D_{up} R^2_{m,t} + \beta_4(1 - D_{up})R^2_{m,t} + e_t$ *, where* $CSAD_{m,t}$ *represents the cross-sectional absolute deviation of stock returns with respect to the market portfolio return* $R_{m,t}$ *for each market i.* D_{up} *is a dummy variable that takes the value 1 on days with positive values of* $R_{m,t}$ *and the value 0 otherwise. The sample period is July 2019 – July 2020. t-statistics are given in parentheses, calculated using Newey–West heteroscedasticity and autocorrelation consistent standard errors. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.*

Table 5

Conditional Quantile Regressions.

Panel A: America	**5th Quantile**	**25th Quantile**	**50th Quantile**	**75th Quantile**	**95th Quantile**
$\boldsymbol{C}$	0.0003(6.03)***	0.0009(29.47)***	0.0015(15.84)***	0.0025(31.69)***	0.0062(18.56)***
$\boldsymbol{D_{up}\lvert R_{m,t}\rvert}$	0.1417(1.46)	0.1694(11.38)***	0.1921(10.47)***	0.2267(9.38)***	0.1177(1.00)
$\boldsymbol{(1-D_{up})\lvert R_{m,t}\rvert}$	0.1599(4.17)***	0.2104(11.12)***	0.2445(1.53)	0.2384(7.38)***	0.0947(0.35)
$\boldsymbol{D_{up}R^2_{m,t}}$	-1.6722(-0.36)	-1.2035(-7.99)***	-1.4828(-8.08)***	-1.9329(-8.13)***	4.1780(1.28)
$\boldsymbol{(1-D_{up})R^2_{m,t}}$	-3.1071(-1.67)*	-2.3833(-7.05)***	-1.8620(-0.13)	2.4984(3.91)***	12.1701(1.33)
Pseudo R^2	8.81%	9.5%	10.55%	10.52%	9.90%

Panel B: Europe	**5th Quantile**	**25th Quantile**	**50th Quantile**	**75th Quantile**	**95th Quantile**
$\boldsymbol{C}$	0.0006(30.20)***	0.0007(36.91)***	0.0010(49.09)***	0.0013(37.40)***	0.0023(15.74)***
$\boldsymbol{D_{up}\lvert R_{m,t}\rvert}$	0.1338(13.32)***	0.2117(17.19)***	0.2782(20.18)***	0.3431(10.71)***	0.6842(6.66)***
$\boldsymbol{(1-D_{up})\lvert R_{m,t}\rvert}$	0.1473(9.47)***	0.2039(10.83)***	0.2581(18.44)***	0.3185(11.66)***	0.4883(10.52)***
$\boldsymbol{D_{up}R^2_{m,t}}$	-0.8636(-5.55)***	-2.0969(-10.60)***	-2.5291(-15.14)***	-2.4792(-3.28)***	-7.7586(-5.04)***
$\boldsymbol{(1-D_{up})R^2_{m,t}}$	-1.2306(-2.01)**	-0.8781(-0.71)	-0.3958(-1.05)	-1.8978(-1.47)	-4.5277(-3.97)***
Pseudo R^2	13.63%	20.77%	27.17%	32.75%	35.41%

Panel C: Asia-Pacific	**5th Quantile**	**25th Quantile**	**50th Quantile**	**75th Quantile**	**95th Quantile**
$\boldsymbol{C}$	0.0004(10.58)***	0.0008(10.65)***	0.0014(30.22)***	0.0026(27.11)***	0.0062(22.38)***
$\boldsymbol{D_{up}\lvert R_{m,t}\rvert}$	0.1742(2.13)**	0.3452(6.78)***	0.5884(12.01)***	0.9440(11.04)***	1.9379(5.82)***
$\boldsymbol{(1-D_{up})\lvert R_{m,t}\rvert}$	0.2541(6.68)***	0.3008(1.24)	0.4266(5.19)***	0.8133(9.98)***	2.4792(8.99)***
$\boldsymbol{D_{up}R^2_{m,t}}$	5.7997(1.14)	8.3015(10.58)***	4.3104(5.61)***	-1.6185(-1.20)	-18.2804(-3.49)***
$\boldsymbol{(1-D_{up})R^2_{m,t}}$	-4.0390(-1.43)	10.1814(0.21)	19.7826(3.23)***	8.4631(3.55)***	-42.1468(-5.51)***
Pseudo R^2	6.51%	9.11%	11.77%	15.49%	22.37%

Notes: Table 5 reports the results for quantile regression equivalents of model: $CSAD_{m,t} = Q[\tau|r_{m,t}] = \beta_0 + \beta_1 D_{up}|R_{m,t}| + \beta_2(1-D_{up})|R_{m,t}| + \beta_3 D_{up}R^2_{m,t} + \beta_4(1-D_{up})R^2_{m,t} + e_t$ *where* $CSAD_{m,t}$ *stands for cross-sectional absolute deviation of stock returns with respect to the market portfolio return* R_m *for each period t and market i and* τ *is the* τ^{th} *quantile (0.05, 0.25, 0.5, 0.75, 0.95) of the conditional distribution of the average absolute market return of the geographical region,* e_t *is the error term with a zero* τ *-quantile.* D_{up} *is a dummy variable that takes the value 1 on days with positive values of* $R_{m,t}$ *and the value 0 otherwise. The sample period is July 2019 to July 2020. t-Statistics are given in parentheses, calculated using Huber Sandwich Standard Errors & Covariance. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively.*

Figure 1

Stocks market indices used.

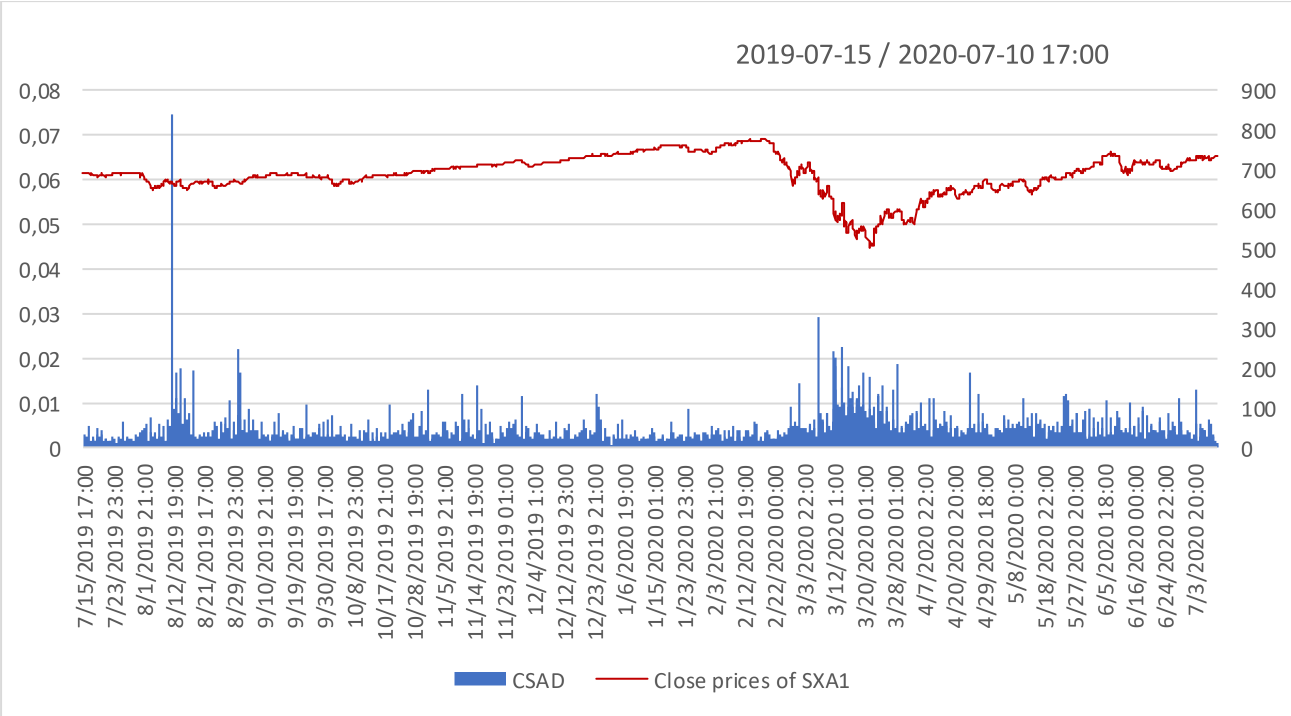
Figure 1 below visualizes the stock indices that are used in our study and the respective stock markets to which they belong are given in parentheses.

Figure 2

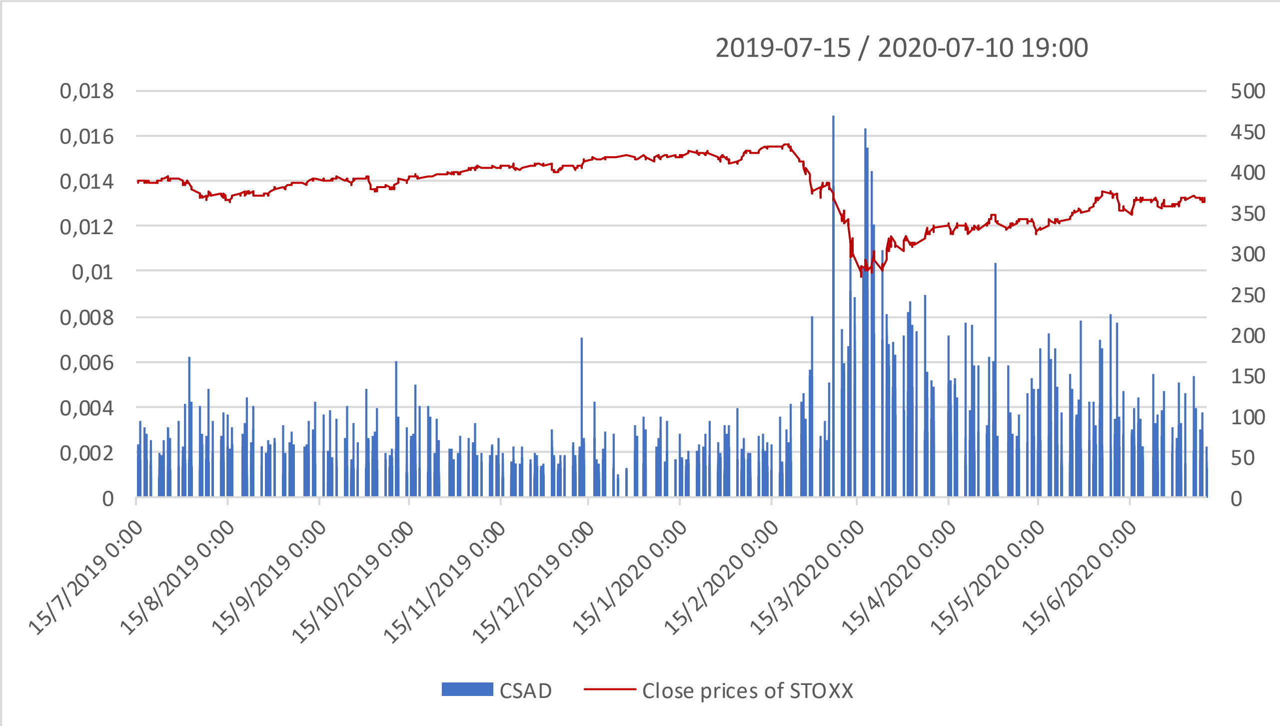
Price dynamics of selected geographical regions

This figure (A, B and C) displays the close prices of the general stock index of American, European, and Asian-Pacific geographical regions and the corresponding values for the cross - sectional absolute deviation (CSAD) for each region. The left axis depicts the values of the general stock index, and the right axis indicates the values for the CSAD. The sample period is July 2019 – July 2020 using hourly data.

A. Close prices of SXA1 index (America) and American herding behavior



B. Close prices of STOXX index (Europe) and European herding behavior



C. Close prices of SPX1 index (Asia-Pacific) and Asian-Pacific herding behavior

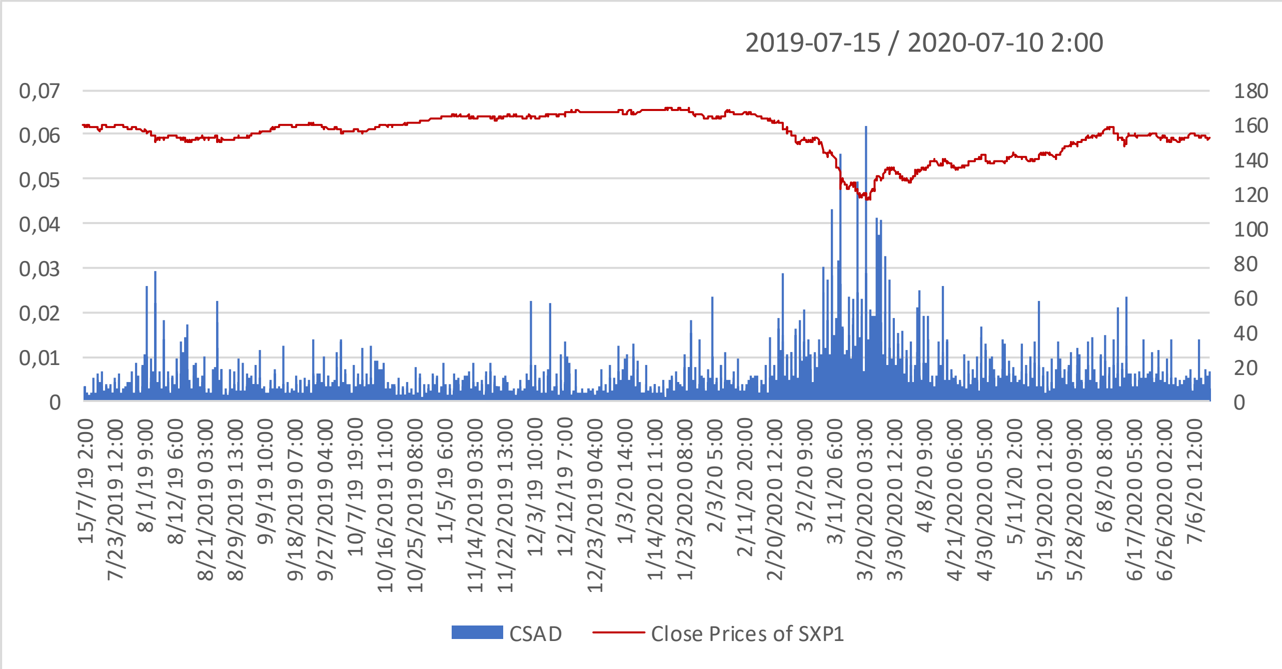
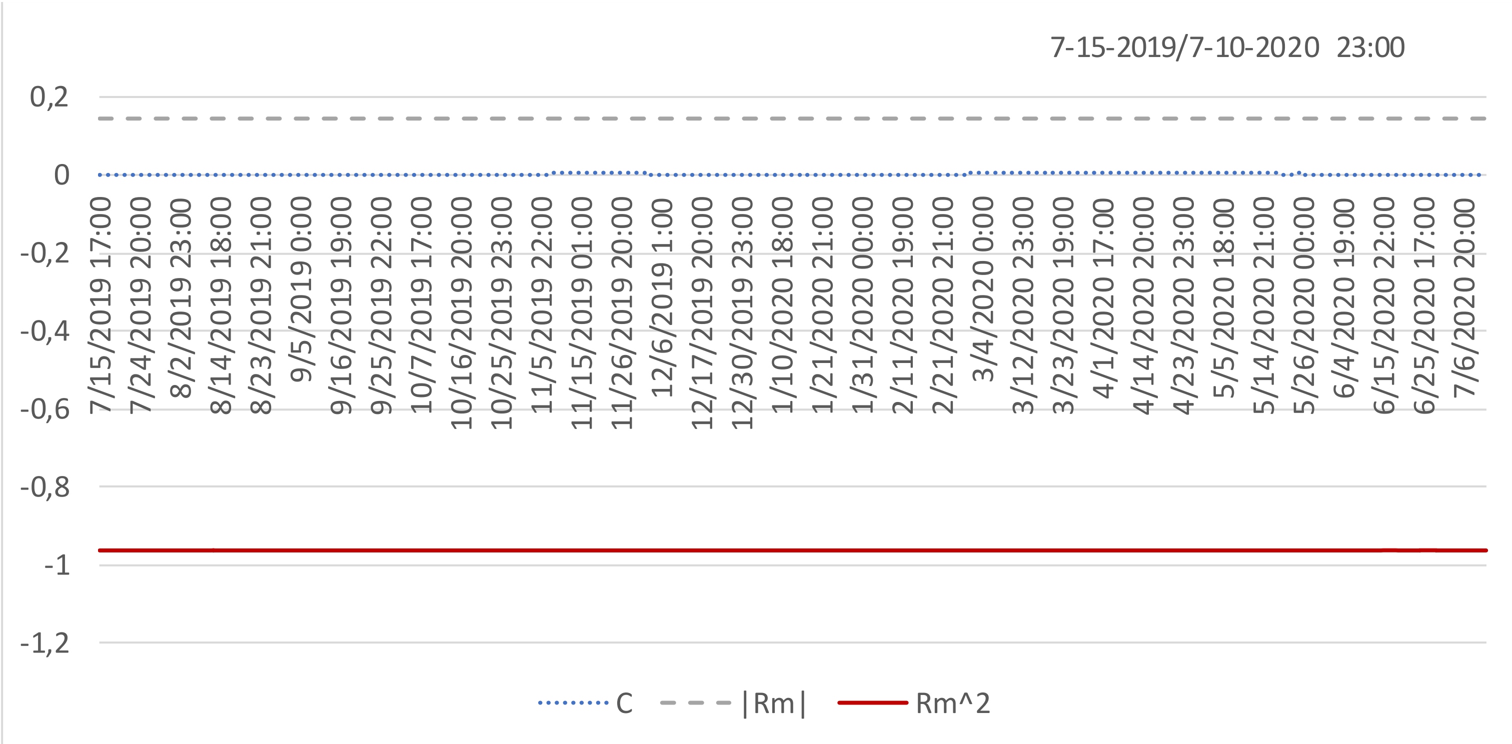


Figure 3

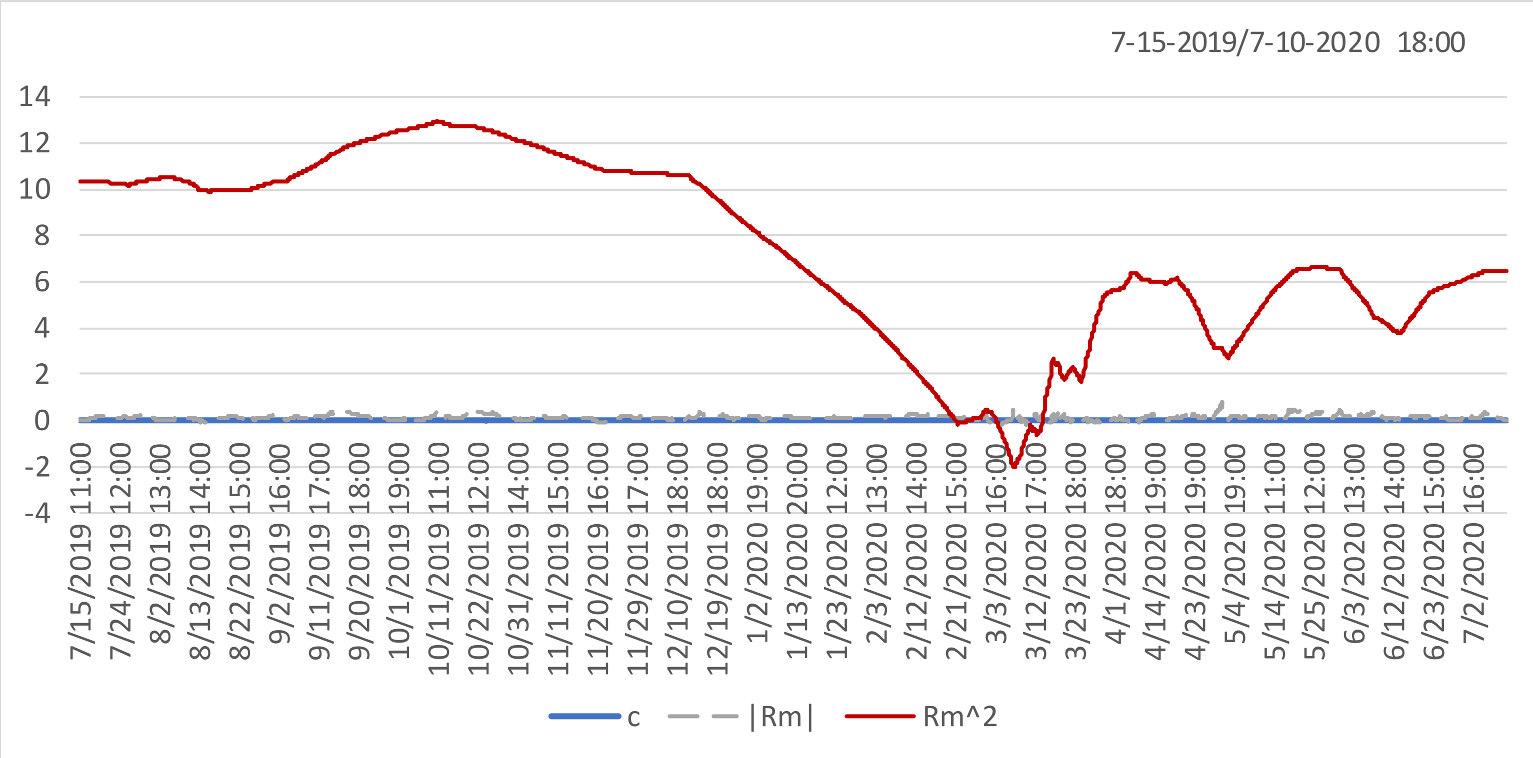
Unconditional Herding in geographical regions, time-varying regressions

Figure 3 (A, B and C) depicts the unconditional herding behavior in the American, European, and Asian-Pacific geographical regions using time – varying coefficients. The left axis depicts the values of the coefficients for the corresponding dates and hours. The sample period is July 2019 – July 2020 using hourly data.

A. Time-varying regression (unconditional) America



B. Time-varying regression (unconditional) Europe



C. Time-varying regression (unconditional) Asia-Pacific

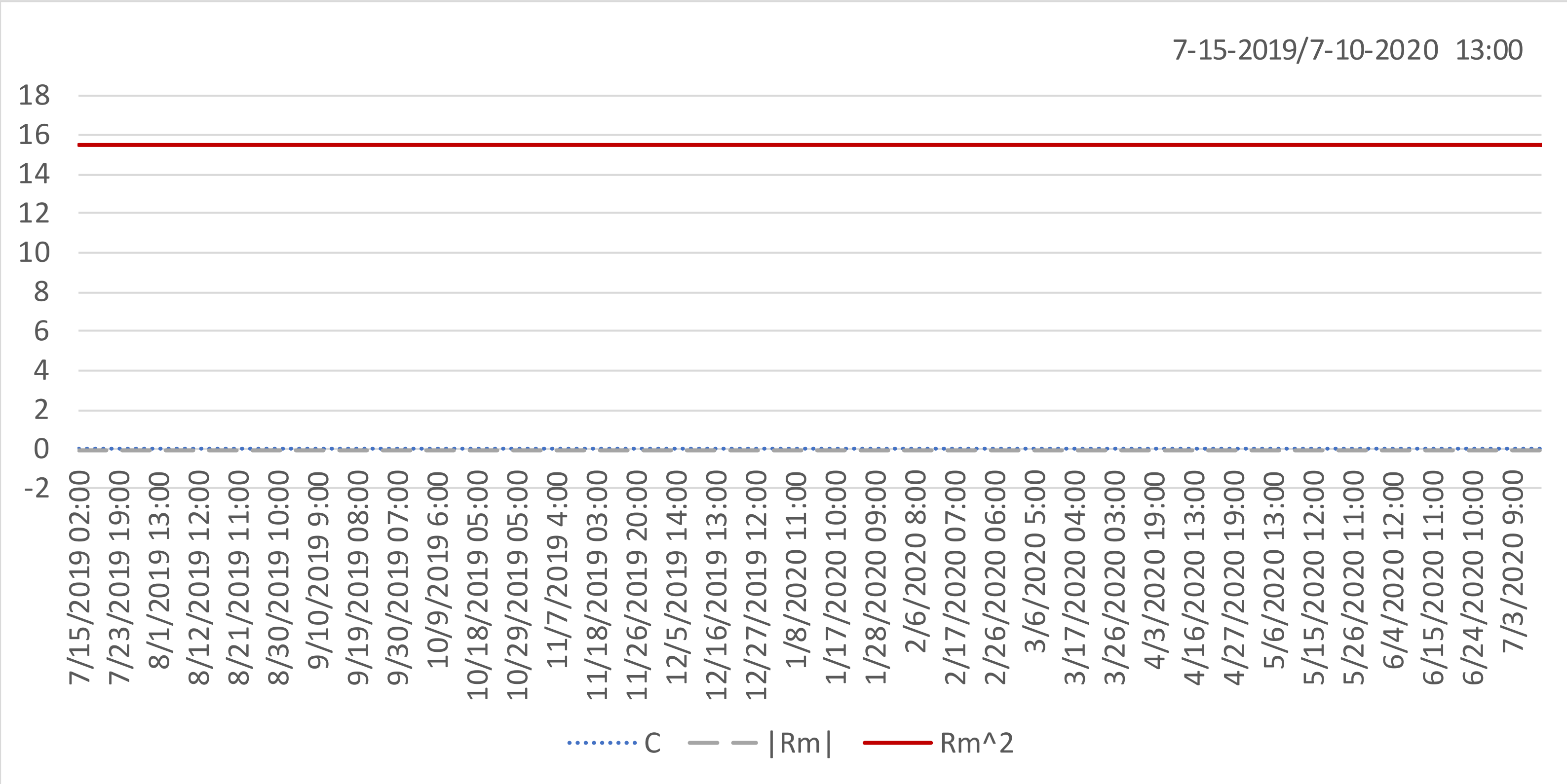
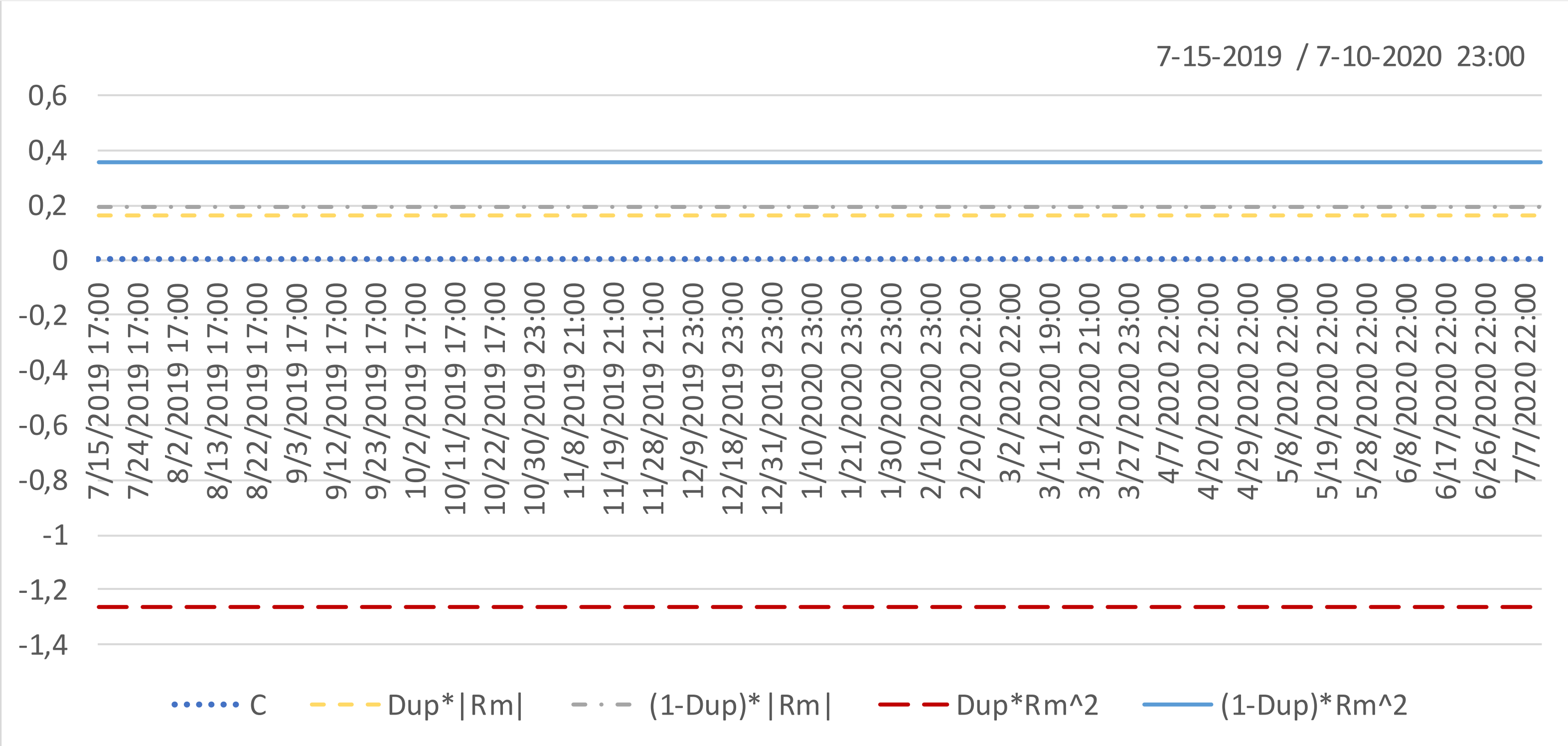


Figure 4

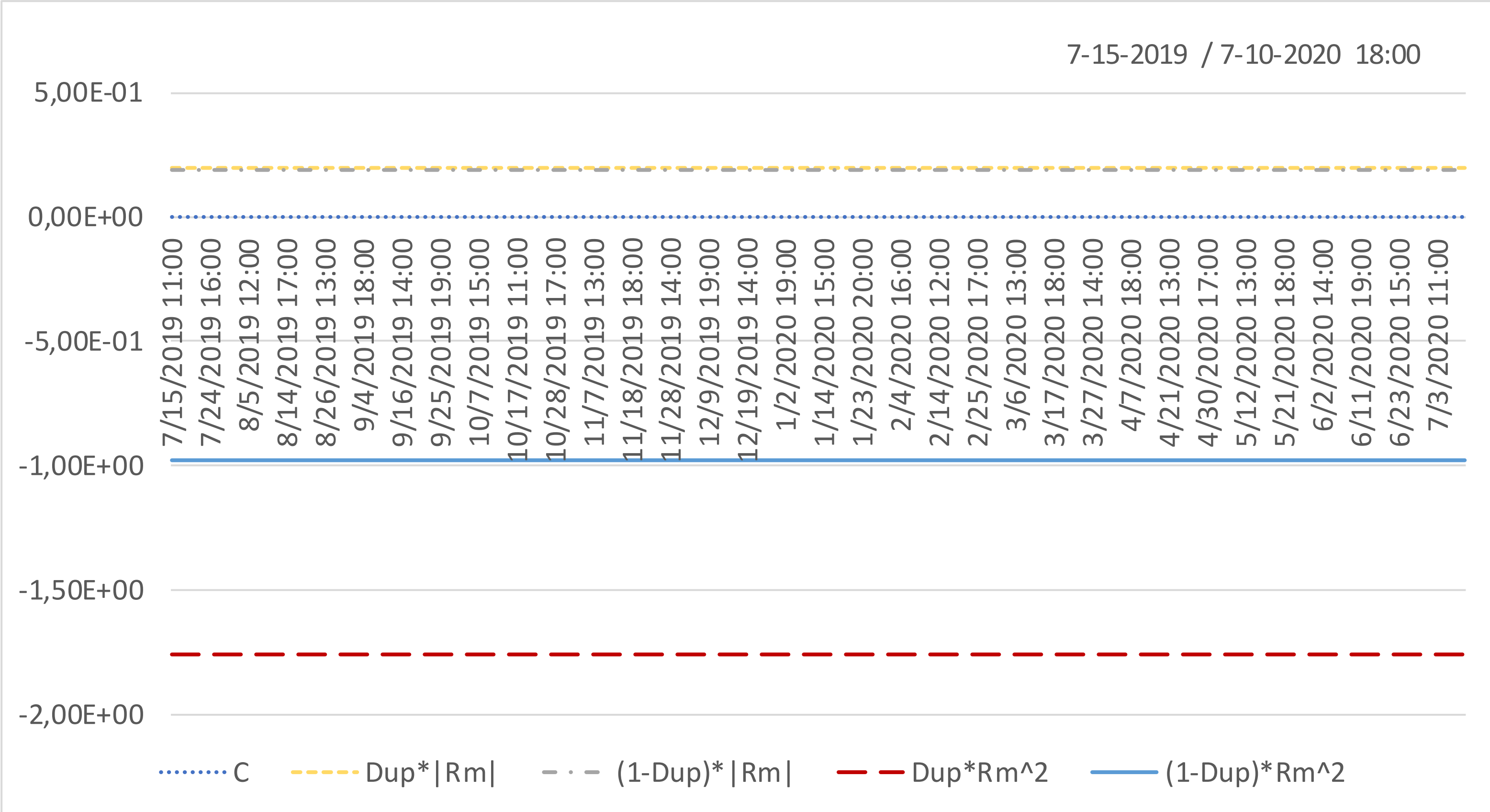
Conditional Herding on up/down market days, geographical regions (time-varying regression)

Figure 3 (A, B and C) displays herding behavior o up and down market days in the American, European, and Asian-Pacific geographical regions correspondently using time – varying coefficients. The left axis depicts the values of the coefficients for the corresponding dates and hours. The sample period is July 2019 – July 2020 using hourly data.

A. Time-varying regression (conditional) America



B. Time-varying regression (conditional) Europe



C. Time-varying regression (conditional) Asia-Pacific