# The effect of the war in Ukraine on herding behaviour in European stock markets

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**ABSTRACT**

***This research paper investigates the effects of the war in Ukraine on herding behaviour in the European stock market, by using raw data from Yahoo Finance, sorting it into three samples, based on three different time periods, and performing a series of statistical tests with each of them. It aims to study and explain the reasons behind an increase, or decrease, in the acuity of this behaviour among investors, from the moment the war started, by comparing the results of the statistical analyses performed on the three samples among themselves.***

***An empirical approach will be preferred to a purely theoretical one due to the fact that the issue discussed is a very recent one and no substantial research was done on this specific topic yet. Therefore, two theoretical frameworks were selected to support the research process, while the process itself was solely mathematical, economic, statistical, and observational (statistical output analysis).***

***Overall, the goal of this study is to add to the body of existing knowledge, by presenting a thorough understanding of the relationship between economic and social factors, like market shocks and limited human rationality, and their impact on the common phenomenon of herding among investors in the European market.***

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*Laura Spierdijk, Lingbo Shen*

**Keywords**
Stock market, herding, investors, market shocks, war, statistical analysis.

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## 1. Situation and argumentation

On the 24th of February 2022, an invasion and occupancy was initiated by Russia on parts of Ukraine in a major escalation of the Russo-Ukrainian war, which began back in 2014. The current form of the war has resulted in tens of thousands of deaths on both sides and caused Europe's largest refugee crisis since World War 2.

Besides, the heavy toll on human life, the war also caused major economic problems both domestically and globally, that are still persisting today. The global economy continues to be weakened, through significant disturbances in trade, food, and fuel prices, which are having a big contribution to high inflation rates and the tightening of monetary policies. Despite the fact that the whole world is experiencing a crisis, the Euro Area has been particularly vulnerable to the economic consequences of the invasion, when compared to other economic regions.

The higher vulnerability has to do with the high dependency on energy imports from Russia and the fact that both countries were key players in the import of food and fertilisers before the war. In more general terms, due to the Euro zone being a highly open economy, its market is more vulnerable to disruptions in global markets and value chains.

Besides the broad economic effects, the war also had multiple negative effects on the European stock markets, which, based on existing literature, are limited to stock price drops occurring on, pre- and post-event days (Ahmed et al., 2022) and lowered stock returns over time (Boungou & Yatié, 2022). In this context, an aspect not investigated so far is whether the invasion also has an effect on herding behaviour in European stock markets.

Herding is the process where investors converge in behaviour in deciding whether to participate in the market, what securities to trade, and whether to buy or sell (Bikhchandani & Sharma, 2000). As the definition of herding behaviour accentuates, the investors, who tend to herd, would avoid sharing their private information, consequently placing the prices in a position that is away from the intrinsic values of the stocks. This could cause the market to be volatile, which, during an already volatile economic climate, could lead to rather bad consequences, thus making it important to determine current herding (Balcilar et al., 2013).

Moreover, during a more volatile state of the market, investor's herding behaviour is also changing, creating a non-linear relationship between herding and market returns (Chang et al., 2000). Furthermore, herding could create a pricing bubble beneficent for the most informed investors, who can carry out strategies to benefit from the unawareness of other investors, that just follow the flock.

## 2. Research objective & question

Based on the information above, this research explores how the war in Ukraine affects the European stock markets and the investment behaviour of market partakers during the crisis. To narrow down the objective into one research question, that the paper explores, the following research question was formulated: 'Does the war in Ukraine have a significant impact on the degree of herding behaviour in the European stock markets?'. It will be answered by taking a closer look into the general market reactions on the war first and then determining the general pretext of how herding behaviour is affected by global shocks.

## 3. Theoretical framework/literature review

In the research paper, we use two base theories to determine herding during the Ukraine war, starting with the first being the work of Christie & Huang (1995), which focuses on the price implications of herding by investigating whether equity returns reveal the presence of herd behaviour. To measure the potential influence of herding on prices, dispersion was determined as an intuitive measure for market impact, further defined as the cross-sectional standard deviation of returns (CSSD regression) (Christie & Huang, 1995). One of the important notes to make regarding using CSSD regression is the fact that it mostly captures extreme movement.

The second base theory, proposed by the works of Chang et al. (2000), extends the work of the prior theory. Firstly, it's proposing a more powerful approach to detect herding based on equity return behaviour. Using a non-linear regression specification, the relationship between the level of equity returns dispersions, as measured by the cross-sectional absolute deviation of returns (CSAD), and overall market return can be examined. This shows that when equity return dispersion is measured by the CSAD, rational asset pricing models predict not only that dispersion is an increasing function of the market return, but also that the relation is linear.

The rational asset pricing model being defined as models typically relating individual returns to some common factors, in this case being market returns. Furthermore, if there is an increased tendency on the part of market participants to herd around the market consensus during volatile pricing periods, it's sufficient to convert the by CSSD deemed linear relation into a non-linear one.

However, these two base theories are solely focused on the identifying the emergence of herding behaviour in the financial stock market, meaning that for more precise insights one needs to consider additional theories. To gain more precise insights on the specific timing, cause and magnitude of herding one could consider Markov's switching and the herding measurement model, but for this research paper we will solely identify the herd behaviour in European stock markets (Hwang & Salmon, 2001; Jiang et al., 2022).

Based on the basic outline of these theories and the situation visualised in the introduction above, one can assume that based on the fact that currently stock prices are volatile, herding behaviour is expected to be increased within the stock markets in the current war. To be more specific the following null hypotheses arise that need to be tested, one of main importance to estimate the one answering this paper:

- *Q1: There is herding behaviour measurable based on the two methods proposed by the works of Christie & Huang (1995) and Chang et al.(2000). (base for main hypothesis)*
- *Q2: There is an increase in herding behaviour in the European stock markets since the start of the Ukraine war. (main hypothesis)*

## 4. Academic & practical relevance

Investigating the effect of the Ukrainian war on herding behaviour in European stock markets can be academically relevant in multiple ways. Firstly, it would further extend the base works of Christie & Huang (1995) and Chang et al. (2000) to measuring herding behaviour during wars alike. Furthermore, it also expands the works of Jiang et al. (2022) and others alike, investigating herding behaviour in stock market during the COVID-19 crisis, as the methods used in this paper cover strong resemblance to the investigatory methods in these previous works on the corona crisis.

In addition, to the academic relevance, the work could also have practical implications for investors as the research could contribute to creating a wider understanding of herding behaviour in general, as it examines the impact of a geopolitical event such as a war on investor behaviour in the stock markets and allows to further understand the underlying mechanisms driving herding behaviour.

Besides the better understanding of herding behaviour, it could also grant an insight into the impact of a war on financial markets. Furthermore, the work could help investors to anticipate investment behaviour in future crises, thus forcing for adjustments in investment strategies to account for these changes.

Lastly, the study could have implications for policymakers and regulators who are responsible for ensuring the stability of financial markets. If found that the war has significant impacts on the herding behaviour in European capital markets, policymakers might need to make adjustments to mitigate the potential risks associated with such behaviour.

## 5. Research design

The data needed for further analysis based on the methods established, is gathered through the Yahoo! Finance historical database. It will be daily data on the closing stock prices of firms listed on the AEX 25 Index (Netherlands), CAC 40 Index (France), DAX 30 Index (Germany), Ibex 35 Index (Spain) and OMXS 30 Index (Sweden) over three different periods ranging from the 20th of February 2014 to the 20th of February 2023. The first period being from the 20th of February 2014 to the 20th of February 2018, this period serving as the benchmark period. The second period covers the global Covid-19 crisis, with data starting from the 20th of February 2020 to the 20th of February 2022, where the pandemic started normalising and the world fell into a new crisis, the Ukraine war. Therefore, the data from the 20th of February 2022 to the 20th of February 2023 will be covering the current war. However, it is important to beforehand mention that the last data set might be less accurate, due to persisting after shocks from the previous crisis. Furthermore, the longer period of data is chosen, to ensure a noticeable difference in herd behaviour, through economical events, like standard state and global shock adjustment of the market.

In the following section, we develop an empirical methodology to detect the presence of herd behaviour in European capital markets. Firstly, Christie & Huang (1995) suggests the use of CSSD to detect herd behaviour in the market, where the CSSD measure is defined as:

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

Where $R_{i,t}$ is the observed stock return of firm i at time t and $R_{m,t}$ is the cross-sectional average of the N returns in the aggregate market portfolio at time t. This dispersion measure quantifies the average proximity of individual returns to the realized average. The theory argues that rational asset pricing models predict that the dispersion will increase with the absolute value of the market return, due to the separate stocks differing in their sensitivity to market return. However, in the presence of herding, stock returns will of course not deviate too much from the portfolio return. This might lead to contradicting predictions by both stances.

Therefore, the theory assumes that during periods of extreme market movement, like a war, investors most likely supress their own beliefs, based on this assumption there is the need for empirically examining whether return dispersions are significantly lower than normal during these extreme circumstances. This is estimated through the following multivariate regression equation:

$$(2)\quad CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t,$$

$D_t^L = 1$, if the market return on day *t* lies in the extreme *lower* tail of the market distribution; and equal to zero otherwise, and $D_t^U = 1$, if the market return on day *t* lies in the extreme *upper* tail of the market distribution; and equal to zero otherwise. The extreme lower tail or left tail of the distribution being defined as the area of great negative market movements and the extreme upper tail or right tail being defined as the area of grate positive market movements. The presence of negative and statistically significant beta coefficients would be the indicator for the presence of herding in the market (Herding hypothesis = $HA: \beta^L < 0$ & $\beta^U < 0$) (Chang et al., 2000).

Besides, the use of CSSD to detect herding, one could also use CSAD for identifying herding behaviour in the European capital market. The works of Chang et al. (2000) proposes the alternate test of herding, requiring an additional regression parameter to capture any possible non-linear relation between stock return dispersions and general market returns. The presence of herding is tested through the average relationship between $CSAD_t$ and $R_{m,t}$, so solely CSAD is not the measure. To allow for the possibility that the degree of herding would be different in a rising and decreasing market, the following empirical specifications were first established:

$$(3)\quad CSAD_t^{UP} = \alpha + \gamma_1^{UP} R_{m,t}^{UP} + \gamma_2^{UP} (R_{m,t}^{UP})^2 + \varepsilon_t,$$

$$(4)\quad CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN} R_{m,t}^{DOWN} + \gamma_2^{DOWN} (R_{m,t}^{DOWN})^2 + \varepsilon_t,$$

where $CSAD_t$is the average $AVD_t$ of each stock relative to the return of the equally-weighted market portfolio ($CSAD_t = \frac{1}{N}\sum_{i=1}^{N} |R_{i,t} - R_{m,t}|$), $R_{m,t}$ in period t, and $|R_{m,t}^{UP}|$ ($|R_{m,t}^{DOWN}|$) is the absolute value of an equally-weighted realized return of all available securities on day t when the market is up (down). (Herding hypothesis = $HA$: $\gamma_2^{UP} < 0$ & $\gamma_2^{DOWN} < 0$)

However, it turned out that the two methods ((3) & (4)) might provide contradicting results regarding the presence of herd behaviour, thus resulting in the combined specification, where a quadratic relationship is assumed between $CSAD_t$ and $R_{m,t}$:

$$(5)\quad CSAD_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 {R_{m,t}}^2 + \varepsilon_t,$$

where the presence of a negative $\gamma_2$ parameter is an indication of herd behaviour in the model (Herding hypothesis = $HA$: $\gamma_3 < 0$) (Chang et al., 2000).

Lastly, besides these theoretical specifications on how to determine herding behaviour through two different theories ((2) & (5)) , we should also be able to fully analyse the outcomes, which can be done by first exporting the stock data into excel, then importing it into R-studio and performing hypothesis tests on the multivariate regression models to determine whether herding behaviour is apparent and increasing during the current economical shocks caused by the Russian invasion into Ukraine. The increase can be researched based on difference between the outcome coefficients of the different data periods.

First of all, the one-sample left-sided t-test we will be using for the CSAD-regression is a hypothesis test that can help during the process of statistical decision-making and clarify whether one of the proposed hypotheses is correct based on the sample data. To do a t-test or any hypothesis test for that matter, one needs to state a null and an alternative hypothesis, which are eventually compared, making only one of them appropriate.

In the case of this test the null hypothesis is: 'The beta-coefficient of the squared market return is equal or greater than zero.' and the alternative hypothesis (the one determining herding) is: 'The beta-coefficient of the squared market return is (significantly) smaller than zero.' The value of the t-test can be calculated through the following formula:

$$(6)\quad t = \frac{\gamma_3}{SE(\gamma_3)}, with\ a\ t_{(1-\alpha,df)} distribution,$$

where the t-value is compared with its 5% critical value of the t-distribution to determine whether to reject or keep the null hypothesis. The null hypothesis would be rejected if the t-value computed is equal or smaller than the appropriate critical t-value($t \le t^*$).

Furthermore, as for the hypothesis testing appropriate for the CSSD regression function, we will be using the Wald test, where the null hypothesis would be: 'The beta coefficients of the extreme lower and upper tail are equal or greater than zero.' and the alternative hypothesis would be: 'The beta coefficients of the extreme lower and upper tail are smaller than zero.' The Wald test is computed through the following test statistic:

$$(7)\quad Q = (C\hat{\beta})'(CVC')^{-1}(C\hat{\beta}),$$

where $\hat{\beta}$ is the estimated regression coefficient vector and $V$ is the variance-covariance matrix. The resulting p-value computed is compared with the standard alpha of 0.05 to determine whether the reject or keep the null hypothesis. The null hypothesis would be rejected if the p-value is equal to or smaller than the alpha.

In addition, for the successful implementation of the tests there are some preliminary assumptions that need be made and tested, with the normal distribution of the data being the first assumption tested. This can be tested through making a QQ-plot and seeing whether the data points collected follow the fixed linear line. In addition, the goodness of fit can be tested by researching the value of the $R^2$ and the constant variance, also known as homoscedasticity, through performing a White test ($LM = nR^2, with\ H0{:}\ homoskedasticity\ and\ rejected\ if\ the\ LM - value > chi - square\ value$) or investigating the uniformity of residual plots on both the CSAD and CSSD regressions.

However, it might be concluded that the basic model assumptions don't hold based on the residual analysis of the CSSD and CSAD regressions, which would result in a need of adjusting the sample data. In both models the data would be normalised through transformation and resolving outliers. In addition, robust standard errors need to be fitted to the models for solving the homoskedasticity violation.

Lastly, these adjusted regressions will be tested through the same hypothesis tests as proposed above (Wald $= H0{:}\ \beta^L \le 0$ & $\beta^U \le 0,\ HA;\ \beta^L < 0$ & $\beta^U < 0$) (t-test $= H0{:}\ \gamma_3 = 0$ , $HA{:}\ \gamma_3 < 0$), but now adjusted to resolve for the basic model assumptions violations. In the case of the one sample t-test resulting in the usage of robust standard errors and for the Wald test resulting in $V^{HC}$ is the HAC (robust) standard error variance matrix.

## 6. Descriptive data

The daily data employed in this study consist of closing stock prices of five selected European indexes, covering different economic levels. As mentioned before, the indexes chosen are those of the Netherlands, France, Germany, Spain and Sweden over three periods, ranging from the 20th of February 2014 to the 2nd of June 2023. The stock return per index is calculated as $R_t = \frac{P_t}{P_{t-1}} - 1$, where $P_t$ denotes the closing price in period t and $P_{t-1}$ denotes the closing price in period $t-1$.

Table 1.1 and 1.2. provide descriptive statistics of CSSD and CSAD in stock returns for different indexes. By checking the mean values and comparing it between the different indexes, we find that some have higher mean values compared to others, taking for example the significantly higher mean in CSSD-period 2 as opposed to the one in CSSD-period 1. This higher mean value suggesting significant higher market variations across the market of the period-specific sample.

Besides the mean value, one could also compare the differences in standard deviations between two periods of the same model, taking here for example the significant higher standard deviation value of CSAD in period 2 as opposed to the one in period 3. In this case a higher standard deviation potentially suggests that the index has an unusual cross-sectional variation due to unexpected shocks, like the COVID-19 crisis in period 2.

| | CSSD - period 1 | CSSD - period 2 | CSSD - period 3 |
|---|---|---|---|
| **Min.** | 0.000563 | 0.001338 | 0.001128 |
| **Mean** | 0.008787 | 0.012045 | 0.010966 |
| **Max.** | 0.078103 | 0.071318 | 0.055262 |
| **Std. Dev.** | 0.006031 | 0.009545 | 0.005990 |
| **Var.** | 0.000036 | 0.000091 | 0.000036 |

**Table 1.1. Descriptive statistic of CSSD**

| | CSAD - period 1 | CSAD - period 2 | CSAD - period 3 |
|---|---|---|---|
| **Min.** | 0.000425 | 0.000916 | 0.000932 |
| **Mean** | 0.006629 | 0.009185 | 0.008379 |
| **Max.** | 0.055845 | 0.060786 | 0.040328 |
| **Std. Dev.** | 0.004618 | 0.007498 | 0.004704 |
| **Var.** | 0.000021 | 0.000056 | 0.000022 |

**Table 1.2. Descriptive statistics of CSAD**

# 7. Results

## 7.1 Estimating basic model assumptions

Prior to determining the estimates of herding behaviour for both the CSSD and CSAD methods, we needed to do some preliminary tests for checking whether the basic model assumptions are kept or violated. The selection of assumptions checked in this are the normal, equal variance(homoscedasticity) and goodness-of-fit assumptions. These conditions were checked through multiple alterations of residual analysis.

The normality condition was checked through plotting the residuals in a QQ-plot, which for every separate model and period can be found in figures 1.1 up and until 1.6. The plots overall exhibit that the residuals in the middle follow the set linear straight line, but towards the tails really curve off into the extremities. These extremities are explained through the existence of outliers in data samples and results that we need to conclude that in the instances of these samples, we have samples without normality that are heavily skewed to the right.

This can be interpreted as the fact that this shows us that based on the significant positive skewness the market returns are more often above the mean than underneath, which is of course good news, but does not allow us to assume normality in the samples.

Next up, through the residual analysis we also checked whether the samples are homoscedastic or heteroskedastic. This was tested through comparing the computed White test value and Chi-square value, the estimated values of both can be found in Table 2. As explained before, the sample would be homoscedastic if the White test value is smaller than the Chi-square value computed (null hypothesis is kept not rejected).

In the case of these analysed samples, we can conclude that most White test values are greater than the Chi-square values. This implying that there is heteroskedasticity present in the samples, which happens when the standard deviations of a predicted variable, monitored over the different values of the independent variables, are non-constant.

However, there is one sample that does fulfil the equal variance assumption and thus is homoscedastic, this is the sample of the CSSD model in period 3, which could be explained due to its smaller range of values in the sample as opposed to the rest. This does beg the question why based on this it shouldn't also result for CSAD in period 3 to be homoscedastic, but this is explained through the model having a greater number of independent variables with a wider value range.

Furthermore, the goodness-of-fit condition for all the period specific regression models was checked, which tests the relationship strength between the variables determining the model. In this case rather unexpected r-squared values are estimated in Table 2, as all of the values are rather close to zero, which means that there is no significant relationship between the model and the dependent variable (CSSD or CSAD). As the value range is set between zero and one, with zero being the lowest and one being the most optimal.

However, a lower r-squared value is not per se being a problem, as some fields of study have an inherently greater amount of unexplainable variation. When taking for example studies that try to explain human behaviour, like this paper, they generally have r-squared values less than 0.5 (Frost, 2022). Thus, implying that in the case of the lower r-squared values found, they might still imply a good fit of the model in relation to the dependent variable.

So, assuming that the goodness-of-fit was still explained through the lower r-squared values, based on it in this instance being a human behavioural study, the other two violated assumptions needed to be resolved. Therefore, the data samples were normalized through the standardization of values and resolving the problematic outliers, resulting in new residual QQ-plots now proving normality in the samples. As proof for fixing the normality violation, two examples of the new residual QQ-plots are shown in figures 2.1 and 2.2, in which it's clearly exhibits that the residuals now tend to more equally distributed follow the set linear straight line, with still in the tails slight curve off into the lower extremities focused on the left. This now implying that the market returns are more equally distributed at the mean.

Lastly, when resolving the non-equal variance (heteroskedasticity) problem we need to use robust standard errors (HAC errors) for estimating the regression models, naturally keeping in mind that this wasn't needed for the CSAD regression in period 3. The resulting homoscedastic robust standard error models suggests a level of consistency in the dependent value of the model, thus making it easier to work with the data.

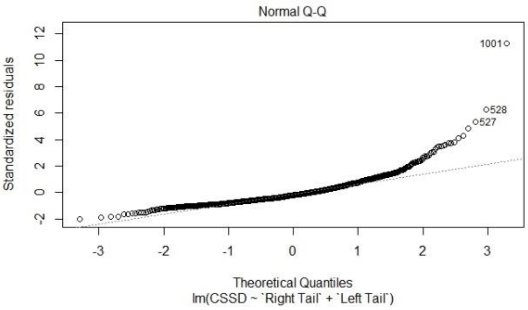


**Figure 1.1. Residual Q-Q plot for testing normality of CSSD regression – period 1.**

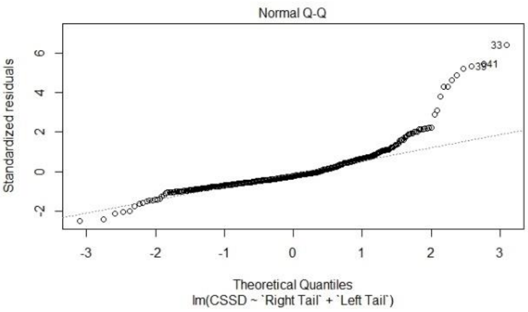


**Figure 1.2. Residual Q-Q plot for testing normality of CSSD regression – period 2.**

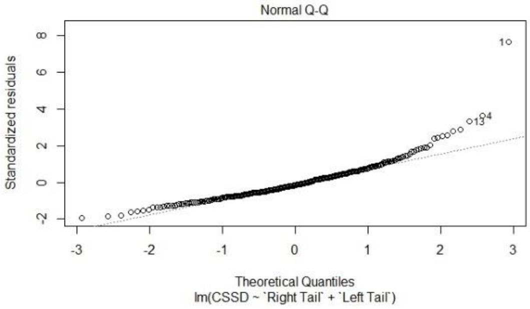


**Figure 1.3. Residual Q-Q plot for testing normality of CSSD regression – period 3**.

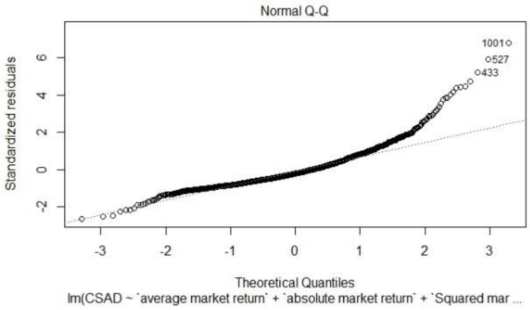


**Figure 1.4. Residual Q-Q plot for testing normality of CSAD regression – period 1.**

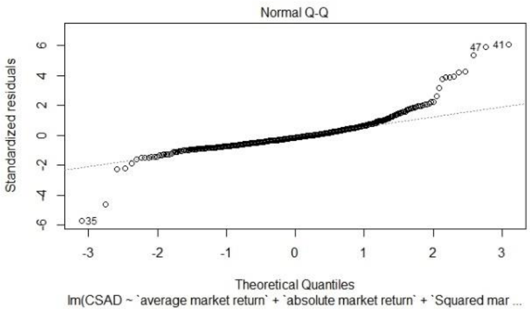


**Figure 1.5. Residual Q-Q plot for testing normality of CSAD regression – period 2**.

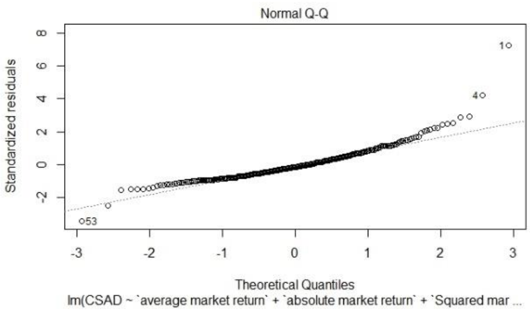


**Figure 1.6. Residual Q-Q plot for testing normality of CSAD regression – period 3.**

| Method | Period | Adj. R^2 | LM = nR^2 | Chi-Square |
|---|---|---|---|---|
| **CSSD** | 1 | 0.023 | 25.70282 | 5.991465 |
| **CSSD** | 2 | 0.067 | 36.26751 | 5.991465 |
| **CSSD** | 3 | 0.003 | 0.9319959 | 5.991465 |
| **CSAD** | 1 | 0.170 | 178.1461 | 7.814728 |
| **CSAD** | 2 | 0.235 | 126.2373 | 7.814728 |
| **CSAD** | 3 | 0.018 | 12.38976 | 7.814728 |

**Table 2. Basic assumption testing statistics.**

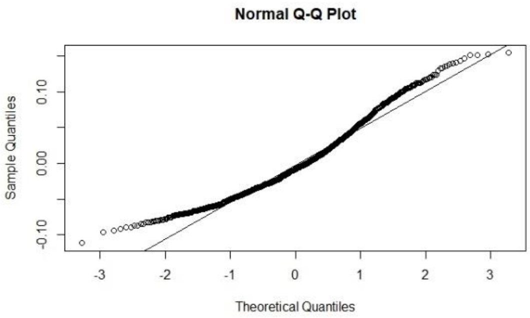


**Figure 2.1. Residual Q-Q plot after data transformation of CSSD regression – period 1.**

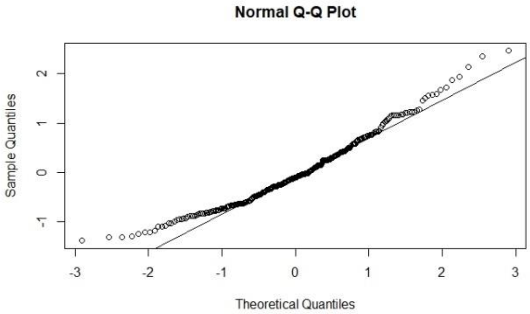


**Figure 2.2. Residual Q-Q plot after data transformation of CSAD regression – period 3.**

## 7.2 Estimates of herding behaviour

The CSSD regression function (Eq. (2)) is estimated through the fitting of the linear model in r-studio and separating it in three periods, to emphasize the difference between the degree of herding in the different periods. As stated earlier a negative beta coefficient on the lower and upper tail market distribution is consistent with herding behaviour.

The presence of herding behaviour in the case of CSSD, is tested through the standard and robust Wald test, due to the need of testing a combined hypothesis ($H0: \beta^L \leq 0 \,\&\, \beta^U \leq 0 \,\&\, HA: \beta^L < 0 \,\&\, B^U < 0$). As beforehand determined, the samples didn't follow the basic assumptions set for regression models. This leading to the need of performing a robust Wald-test, where the null hypothesis is rejected if the computed P-value is smaller than the traditional alpha of 5%.

The estimates in Table 3.2 prove that during all three periods, the estimated p-values were smaller than 0.001. Based on rejection rule of the robust Wald test we therefor rejected the null hypothesis and kept the alternative hypothesis. This means that in the proposed periods there is a presence of herding behaviour based on the CSSD model.

Next up, the CSAD regression function (Eq. (5)) was also estimated through linearly fitting it in r-studio and separating it based on the same three periods of different economic state as with the CSSD model. In the case of testing the CSAD regression, a robust one-sided t-test was performed as we seek to test a simple hypothesis with one variable ($H0: \gamma_3 = 0 \,\&\, HA: \gamma_3 < 0$). The null hypothesis is rejected if the computed t-value is equal or smaller than the critical t-value($t \leq t^*$).

In the case of the three researched periods of the CSAD model, the evidence in Table 3.4 suggests that all estimated t-values are not smaller than the computed critical t-value, thus resulting in the keeping of the null hypothesis and concluding that there is no presence of herding behaviour in the different periods based on the CSAD model.

| | CSSD – period 1 | CSSD – period 2 | CSSD – period 3 |
|---|---|---|---|
| $\beta^L$ | -0.005*** (0.001) | -0.011*** (0.002) | -0.007*** (0.002) |
| $\beta^U$ | 0.006*** (0.001) | 0.017*** (0.002) | 0.003*** (0.002) |
| **Adj. R^2** | 0.079 | 0.211 | 0.048 |
| **No. of Obs.** | 1,014 | 515 | 298 |
| **P-value(Wald)** | < 0.001 | < 0.001 | < 0.001 |
| **Alpha** | 0.05 | 0.05 | 0.05 |

**Table 3.1. Herding estimators CSSD regression before adjusting data for fulfilling model assumptions.**

| | CSSD – period 1 | CSSD – period 2 | CSSD – period 3 |
|---|---|---|---|
| $\beta^L$ | -0.045*** (0.009) | -0.057*** (0.016) | -0.079*** (0.030) |
| $\beta^U$ | 0.035*** (0.008) | 0.124*** (0.018) | 0.046* (0.023) |
| **Adj. R^2** | 0.046 | 0.106 | 0.029 |
| **No. of Obs.** | 970 | 485 | 288 |
| **P-value(Wald)** | < 0.001 | < 0.001 | < 0.001 |
| **Alpha** | 0.05 | 0.05 | 0.05 |

**Table 3.2. Herding estimators CSSD regression after adjusting data for fulfilling model assumptions.**

| | CSAD – period 1 | CSAD – period 2 | CSAD – period 3 |
|---|---|---|---|
| $\gamma_1$ | -0.018 (0.018) | -0.090*** (0.033) | -0.038 (0.041) |
| $\gamma_2$ | 0.059 (0.059) | 0.611*** (0.099) | -0.252 (0.190) |
| $\gamma_3$ | 17.778*** (2.598) | 3.867 (3.030) | 38.647*** (11.979) |
| **Adj. R^2** | 0.234 | 0.357 | 0.096 |
| **No. of Obs.** | 1,014 | 515 | 298 |

| | | | |
|---|---|---|---|
| **Std. error ($\gamma_3$)** | 2.598*** | 3.030 | 11.979 |
| **t-value** | 6.843 | 1.276 | 3.226 |
| **Critical t-value** | -1.647 | -1.647 | -1.650 |

**Table 3.3. Herding estimators CSAD regression before adjusting data for fulfilling model assumptions.**

| | CSAD – period 1 | CSAD – period 2 | CSAD – period 3 |
|---|---|---|---|
| $\gamma_1$ | -0.076** (0.037) | -0121*** (0.046) | -0.148*** (0.057) |
| $\gamma_2$ | 0.200 (0.137) | 0.222 (0.184) | -0.148 (0.226) |
| $\gamma_3$ | 0.188 (0.354 | 0.370 (0.637) | 0.477 (0.342) |
| **Adj. R^2** | 0.053 | 0.088 | 0.041 |
| **No. of Obs.** | 881 | 442 | 273 |
| **Robust std. error ($\gamma_3$)** | 0.354 | 0.629 | 0.342 |
| **t-value** | 0.531 | 0.588 | 1.395 |
| **Critical t-value** | -1.647 | -1.648 | -1.651 |

**Table 3.4. Herding estimators CSAD regression after adjusting data for fulfilling model assumptions.**

## 8. Conclusion

This study examines investors' herding activity for five different European stock indexes. By applying daily data from the 20th of February, 2014 and 2nd of June, 2023, for stock returns, divided in three separate periods for comparison. Furthermore the herding behaviour over three periods is testing through two different models, one more appropriate for extreme market movements (CSSD) and the other one adjusted to fit all the market circumstances (CSAD).

This study finds significant evidence of herding behaviour during all three periods based on the CSSD model, however these estimates do seem to be abnormal due to the estimates being comparable without there being a noticeable difference in herding behaviour between the periods. This abnormality is important to mention as the first period was meant to be a base period without extreme market movements to have as comparison for the other two periods. Furthermore, due to this abnormality we weren't in the position to answer the predetermined hypothesis that stated that the Ukraine war (period 3) should have had an increase on herding behaviour in comparison to the other periods.

However, this study also found that there is no significant herding behaviour on the basis of the CSAD model, during all three periods. In the case of the herding estimations based on this model there also seems to be a problem with the data, as the herding determining beta coefficient didn't portray any negative values over the course of all periods, this might be due to some problems in calculating the squared market return values in the excel workbook.

Besides that, there is a noticeable increase of the calculated robust t-values over the course of the three periods, which should have been inverse based on the expectations that due to market circumstance during the Ukraine war and the previous COVID-crisis, the t-value would move closer to fulfilling the rejection rule and proving herding behaviour in the periods.

This paper tried to extend the investigation of herding behaviour based on market shocks, but due to some abnormalities in data we were not able to fully understand the relationship between the degree of herding behaviour and extreme market shocks like a war, in this case the Ukraine war. The reason for the data problems might be explained through noting that there could be some issues that might have been omitted during the research, due to the fact that the data on the Ukraine war can be considered as not complete as the war is still ongoing, thus comprehensive future research being advisable.

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