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Reverse herding behavior in the Malaysian stock market: a wavelet multiple cross-correlation analysis

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Abstract

This study uses wavelet multiple cross correlations (WMCC) analysis to identify the reverse herding behaviour in equities market using a dataset from October 2009 to September 2023. WMCC is an enhances traditional cross-correlation analysis by integrating wavelet transform methods, enabling the simultaneous examination of interdependencies between multiple time series across various time scales. The empirical result shows that local retail investors lead other investors stock trading followed by local institutional in term of trading volume. This pattern occurs for both buy and sell activities thus supporting the existence of reverse herding in Malaysian stock market. Policymakers should explore implementing or enhancing mechanisms such as circuit breakers to address the potential rise in market volatility caused by retail investor sentiment and trading behaviours.

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1. Introduction

According to Hwang and Salmon (2004) and Madaan and Shrivastava (2022), herding behaviour is the act of mimicking other investors behaviour of investing. Optimism or pessimism among the investors causes them to make the decision of herding behaviour during the investment. According to Bikhchandani et al. (1992), such behaviour was coming from information cascade model. The model explains how the individual observes other individual behaviours before make investment decision based on limited information and observed actions towards other individuals. This model is aligned with the model of investor sentiment (Barberis et al., 1998) and overconfidence (Daniel et al, 1998) that explain how the individual tends to be overconfidence on the private information received. Herding behaviour consists of leader and followers. The investors who are dominant in stock market trend considered as leader while the investors that are following leader's investment trends can be called as followers. Herding behaviour considers rational to the followers because they think that others have certain information that they do not have.

From the market microstructure perspective, trading volume reflects the transmission of information and order flow (Easley & O'Hara, 1987) and leadership in trading behaviour through information can discover the adjustment of price (O'Hara, 1995). In Malaysia, there are four categories of investors in stock market. They are foreign institutions, foreign retail, local institutions and local retail in Malaysian stock market.

Previous studies before 2020 such as Tan et al. (2008), Galariotis et al. (2015), Pochea et al. (2017) and Akbar et al. (2019) found the existence of herding behaviour trends in the stock market regardless of developed and developing countries. However, Hann (2021) states that the opposite situation occurs in 2020 where there is a situation where retail investors dominate the stock market in Malaysia. When investors intentionally behave contrary to the dominant market pattern, this is referred to as reverse herding behaviour. In this behaviour, irrational investors ignore market movements and trade in the market by taking inaccurate information while ignoring fundamental values to get high rates of return (Choi & Yoon, 2020). The motivation is the investors are overconfidence and lack of private knowledge information where they are noisy and irrational traders (Daniel et al, 1998 and Choi & Yoon, 2020). Our paper covers broad term of reverse herding which identify the leader of investors in trading volume across time horizon.

According to Akbar et al. (2019), sophisticated investor behaviour in developed markets is based on better information and the use of high-quality analytical tools. In addition, retail investors do more searches with the Google search engine to obtain various information before making investment decisions (Hsieh et a, 2020). Thus, it has the possibility to increase the risk for retail investors in developing countries because some of them analyse without referring to those who are more experts. Apart from that, retail investors do seek financial information from analysts' reports, online forums, family and friends, traders in the markets, online search, newspaper, magazines and journals (Jaiyeoba et al., 2018).

This paper aims to explore in detail the pattern of leader and followers among investors categories in buy and sell of Malaysian stock market. Thus, it helps the policymakers to develop the tools to mitigate the influence of dominant investors in stock market trading activity. At initial, the cross-sectional standard deviation been used to measure herding behaviour. Since CSSD cannot capture the herding behaviour in extreme outlier, Chang et al. (2000) introduced CSAD. Past research found that herding behaviour occurred by using CSAD method (Akbar et al., 2019; Ukpong et al., 2021 & Zhou et al., 2022). CSAD measure the difference of individual stock returns compared to average market return. Although CSAD is widely used, it cannot measure the co-movement in terms of time and frequency domain. While wavelet analysis tools capable in doing depth analysis regarding the time and frequency domain. Furthermore, according to Wadi et al. (2010), wavelet analysis can be used to analysed nonlinear and nonstationary time series signals that are usually found in economy and financial variables.

Previous studies have shown the importance of wavelet tools in analysing co-movement and the market dynamics. For example, Rua & Nunes (2009) used the wavelet coherence to study time-frequency co-movement of international stock market returns which are Germany, Japan, UK and US. While Vacha & Barunik (2012) studied the dynamic of time-frequency domain on energy market co-movement using the wavelet coherence.

This paper helps to fill the gap of methodology. The previous studies only analyse the time aspects whereas WMCC method also give the understanding how the investor categories correlated over time and frequencies. This paper employs the trading volume data of buy and sell since it is more accurate predicts herding behaviour than stock returns (Akbar et al, 2019). By using wavelet multiple cross correlation, it helps to identify leader and follower in stock market using trading volume. Regarding the concept of leader and followers, Kumar (2017) stated that the market that maximizes the wavelet multiple correlations against the linear combination of other market at each scale is selected as a potential leader or follower in the group, and is shown in the upper left corner of figure. Thus, in our study the potential leader is the investor that maximize the wavelet multiple correlations against the linear combination of other investor categories.

2. Data and Methodology

This study uses monthly data covering the period from October 2009 to September 2023[1]. The selection of October 2009 is due to the availability of stock trading data (buy and sell) during that period. Data on the buy and sell equities of four types of investors were obtained from Bursa Malaysia. The buy and sell trading of investors are foreign institutions (BFI & SFI), foreign retail (BFR & SFR), local institutions (BLI &SLI), and local retail (BLR &SLR). We used trading volume data as it is more representing the trading activity among investor categories (Pak & Choi, 2022). Table 1 summarize each variables used.

Table 1: Summary of variables

Abbreviation	Description	Unit	Source
BFI	Buy trading volume of foreign institutional	Million	Bursa Malaysia
BFR	Buy trading volume of foreign retail		
BLI	Buy trading volume of local institutional		
BLR	Buy trading volume of local retail		
SFI	Sell trading volume of foreign institutional		
SFR	Sell trading volume of foreign retail		
SLI	Sell trading volume of local institutional		
SLR	Sell trading volume of local retail		

This research uses the wavelet multiple cross-correlation (WMCC) which decomposed from Maximum Overlap Discrete Wavelet Transform (MODWT). The WMCC is chosen

[1] Weekly and daily data not available.

because the model can detect the leader and followers across the wavelet scales. We proceed the WMCC by allowing a lag τ between the observed and fitted values of the criterion variable at each scale λ_j as follow (Azam et al. 2020):

$$\varphi_x,\ \tau\ (\lambda_j) = \text{Corr}\ (W_{ijt}, \widehat{W}_{ijt}) = \frac{Cov\ (W_{ijt}, \widehat{W}_{ijt+\tau})}{\sqrt{Var\ (W_{ijt})\ Var\ (\widehat{W}_{ijt} + \tau)}} \quad (1)$$

Then, let X = [X_1, X_2... X_T] be a multivariate Gaussian stochastic process to developed the confidence intervals in the above equation. The wavelet coefficient vectors is obtained by using the *j*th order MODWT for individual univariate time series [x_{i1}, x_{i2},..., x_{iT}] for *i* = 1, 2,... n as following:

$$\widehat{W}_j = [\widehat{W}_{j0} \ldots W_{j,T-1}] = [W_{1j0}, \ldots, W_{nj0}], \ldots, \left(W_{1j, \frac{T}{2^j}-1}\right)] \ldots \text{J} \quad (2)$$

The confidence interval (CI) for the coefficient of sample wavelet correlation can be obtained as follow:

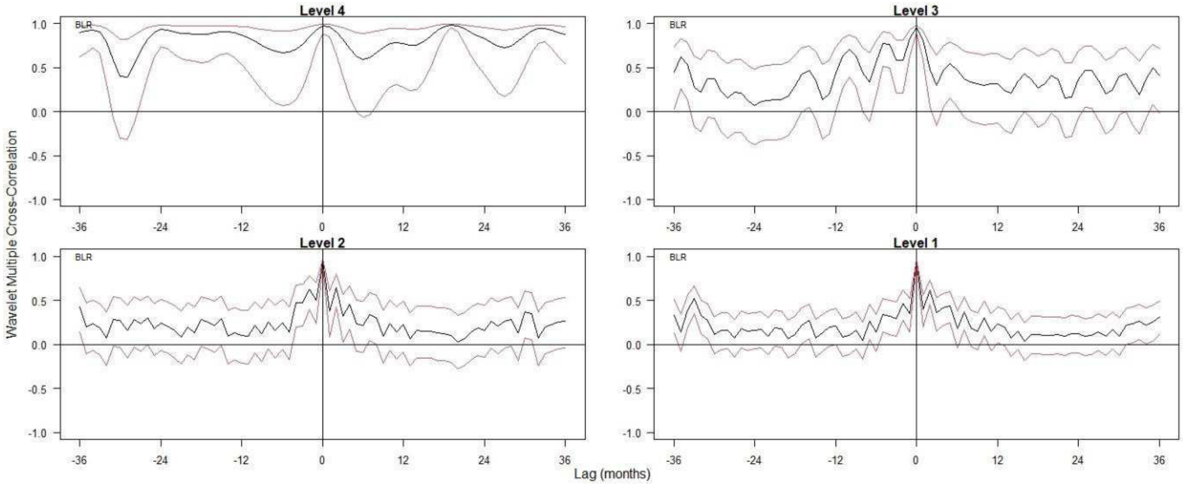
$$CI_{1-\alpha}\ (\varphi\text{x}\ (\lambda\text{j})) = \tanh \left[\hat{z}_j \pm \theta^{-1}_{1-\alpha/2} \,/\, \sqrt{\frac{T}{2^j} - 3} \right] \quad (3)$$

There are four wavelet scales that indicates investment horizons; 2-4 months, 4-8 months, 8-16 months and 16-32 months. These wavelet scales are ranging from short term to long-term dominance. We applied lag range of ±36 months in order to detect the lead-lag relationships. To get significance testing, we constructed 95% confidence intervals using Monte Carlo simulations with 1,000 replications.

We used the least asymmetric wavelet filter of length L=8 or denoted as LA (8) which was introduced by Daubechies (1992), based on eight nonzero coefficients. There are several reasons to choose this wavelet filter. First, this filter is adequate for the characteristics of time series data. Second, using this filter can generates more smooth wavelet coefficients compared to other filters (Najeeb et al., 2015).

3. Results and Discussion

Figure 1: Wavelet Multiple Cross-Correlation among local retail, local institutional, foreign retail and foreign institutional for buy activity.



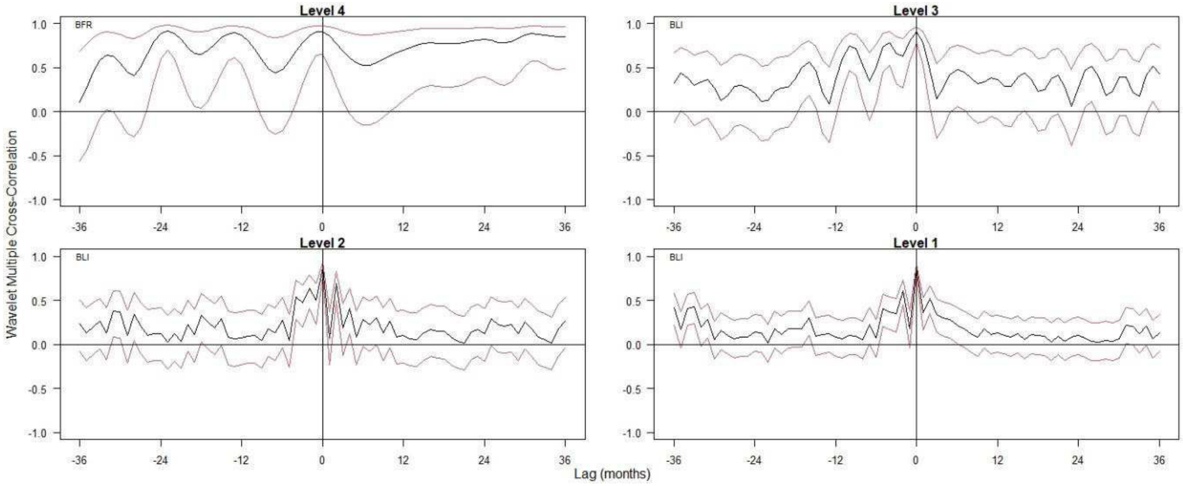
Notes: Upper left corner shows the potential leader, and the red line corresponds to the upper and lower bound of 95% confidence interval.

Figure 1 shows the result of wavelet multiple cross-correlation for different wavelet scale with lead and lag up to 3 years (36 months). The overall graph indicates that multiple correlations tend to increase with longer horizons, aligning with the wavelet cross coherency results. Wavelet level 1 corresponds to a 2–4-month horizon. In this level, local retail seems to be a potential leader for investor's category trading in stock market for the horizon of 2-4 months. These investors often steer market dynamics within a short-term timeframe, likely influenced by swift reactions to market conditions and global news, which in turn affects the local market.

Meanwhile, level 2 shows the horizon for 4-8 months where local retail investor also as a potential leader in stock market. In addition, wavelet level 3 and level 4 shows that cross-correlation are much higher compared to level 1 and level 2. Both wavelet in level 3 and 4 shows that local retail investor still becoming the potential leader in stock market for the horizon of 8-32 months. According to Sobol & Szmelter (2020), retail investors in the foreign exchange market has increased significantly because of the liberalisation processes occurring in the world economy and the development of new technologies. This indicates a shift where local retail investors start to have a greater influence over the long term. This could be due to their deeper insight into local market conditions and trends, which gradually become evident, thus proves the existence of reverse herding in Malaysian stock market.

We further the analysis by eliminating the local retail from the WMCC analysis to confirm who is the leader in different time scales after local retail. Figure 2 shows the result of WMCC using three investor categories namely foreign institutional, foreign retail and local institutional. Based on the upper left corner of each figure, local institutional leads other investor for the wavelet 1 until 3 while foreign retail lead other investor in level 4.

Figure 2: Wavelet Multiple Cross-Correlation among local institutional, foreign retail and foreign institutional for buy activity

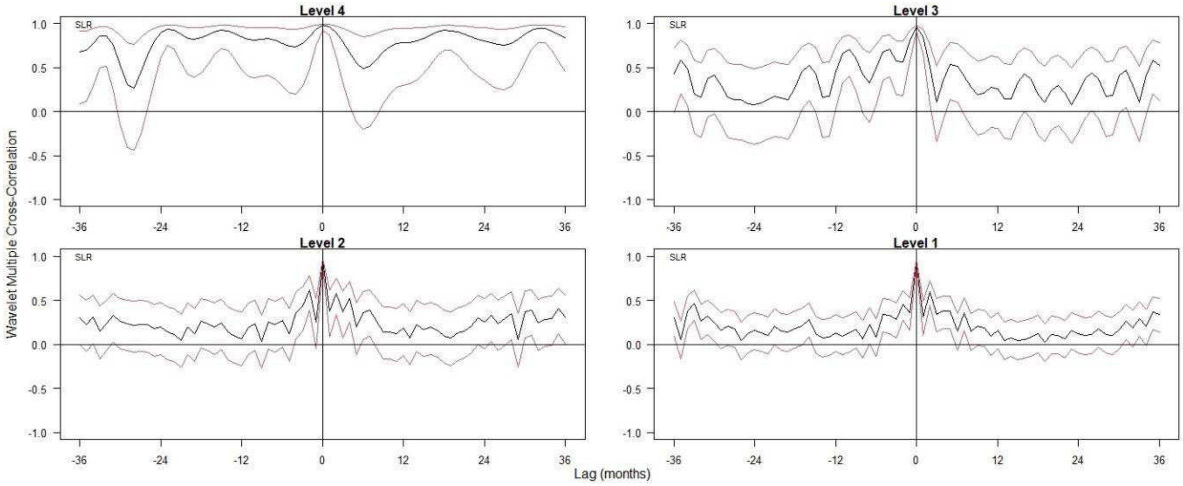


Notes: Upper left corner shows the potential leader, and the red line corresponds to the upper and lower bound of 95% confidence interval.

Figure 3 explains the wavelet multiple cross-correlation for sell trading among investors categories. The overall graph shows that multiple correlation tends to increase as the horizon increasing. In this level, local retail seems to be a potential leader for stock market for the horizon of 2-4 months. Similarly, local retail investors are seen leading in sell activities over a 4–32-month period, reinforcing the idea that their market decisions begin to play a more significant role in the longer term, thus proves the existence of reverse herding behaviour.

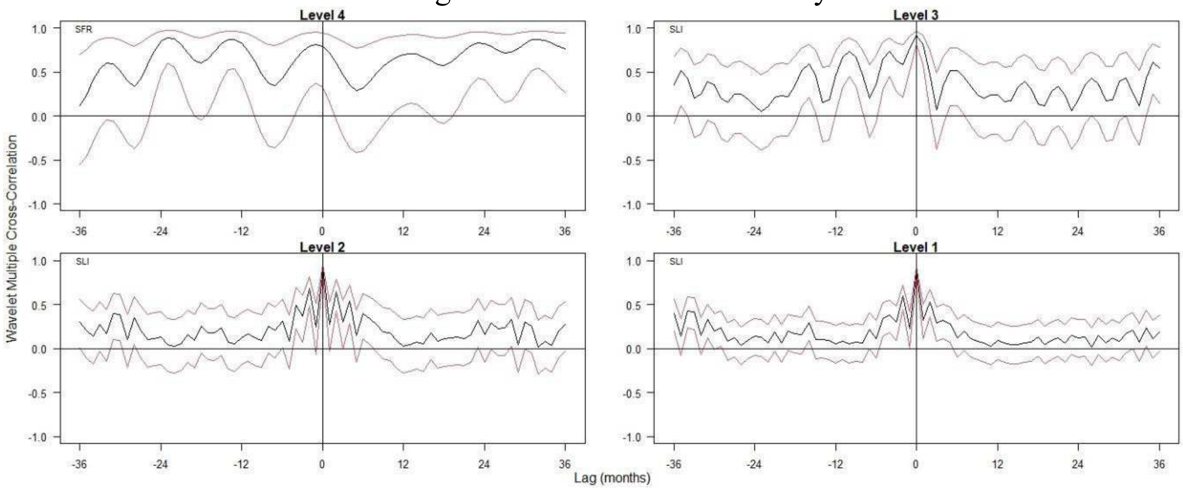
We further the analysis by eliminating the local retail from the WMCC analysis to confirm who is the next leader after local retail. Figure 4 shows the result of the WMCC using three categories of investors namely local institutional, foreign retail and foreign institutional. Based on the upper left corner of each figure, local institutional leads other investors for the wavelet 1 to 3 while foreign retail lead other investor for wavelet level 4. This outcome aligns with Nguyen et al. (2023), who determined that domestic retail investors lead among investor categories using the Vector Error Correction Model (VECM). However, their study concentrates solely on the time domain, neglecting the frequency domain. Therefore, focusing exclusively on the time domain might lead to a misleading conclusion.

Figure 3: Wavelet Multiple Cross-Correlation among local retail, local institutional, foreign retail, and foreign institutional for sell activity.



Notes: Upper left corner shows the potential leader, and the red line corresponds to the upper and lower bound of 95% confidence interval.

Figure 4: Wavelet Multiple Cross-Correlation among local institutional, foreign retail, and foreign institutional for sell activity.



Notes: Upper left corner shows the potential leader, and the red line corresponds to the upper and lower bound of 95% confidence interval.

4. Conclusion

Retail investors leading the market could change the behaviour of traditional market where it can be seen as a type of "reverse herding behaviour". There are many factors likely influence this behaviour such as influence of social media trends, sentiment, or short-term perspectives, unlike institutional investors who usually depend on expert analysis and long-term investment strategies.

With retail investors steering market trends, policymaker can implement a circuit breaker in response to retail excessive buying or selling activity. The circuit breaker halting trading activity temporarily during the information is disseminated to all market participants. This gives investors to make well-considered investment decisions. This approach helps market stability from overreaction and retain investor confidence. For investors, the WMCC framework can help them analyse the market trends, find the right timing of the entry and exit point, thus giving the opportunity to make wise decisions regarding asset allocation.

Future research can be done by focus what other factors instead of investor sentiment that influence herding and reverse herding behaviour such as technology improvement in decision making.

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