“Investigation of the fractal footprint in selected EURIBOR panel banks”

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INVESTIGATION OF THE FRACTAL FOOTPRINT IN SELECTED EURIBOR PANEL BANKS

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Abstract

EURIBOR emerged as a conventional proxy for a risk-free rate for a reasonably long period of time after the creation of the Eurozone. However, the joy was short-lived, as the global credit crisis shook the markets in mid-2008. Significant counterparty risk embedded in a derivative transaction cannot be left out. EURIBOR reflects the credit spread on borrowing. Hence, risk and uncertainty are inextricably linked here. This study investigates five banks out of 19 panel banks that manage EURIBOR in various Eurozone countries. These banks, HSBC, ING, Deutsche Bank, the National Bank of Greece and Barclays, are tested from January 2009 to December 2017 on a daily basis. Bank specific EURIBOR can be predicted in all five cases with different degrees. The trace of a profound herd is observed in the case of the National Bank of Greece, others were relatively mild in nature. The customer base and their risk grade were recognized as the main factor. Their information asymmetry and derived information entropy suggest embedded chaos and uncertainty.

Keywords herding, entropy, EURIBOR, forward rate agreement (FRA), multifractal detrended fluctuation analysis

JEL Classification C53, C58, C88

INTRODUCTION

Historically, swap rates were based entirely upon interbank lending rates (e.g., LIBOR, EURIBOR, etc.). This indicates that they were essentially risk-free in nature. The global credit fiasco in 2008 proved that interbank lending rates were not risk-free, as it was earlier perceived. Besides, a significant counterparty risk in derivative transactions was identified. However, they were not subject to collateral or margin calls. This was most evident when Lehman Brothers failed at a time when it was a counterparty to more than 930,000 derivative transactions. Interestingly, these figures accounted for approximately 5% of global transactions (Summe, 2011). The apparent panic-stricken herd behavior during the financial crisis and the resultant bubble in the stock market created a crash possibility. These, in turn, became one of the main reasons for financial distress. The price-discovery mechanism had a negative impact due to herding behavior. Herd behavior caused a bubble in the market, which led to a market crash due to the downside effect almost instantly (Filip, Pochea & Pece, 2015).

Price discovery will not be possible if herding prevails in the stock market due to the distortion it creates. In psychology terms, herding is an act of mindlessly following actions of another. In finance terms, herding means mindlessly following the decisions and actions of other market participants. If one follows the actions of others mindlessly, and everyone in the market demonstrates this behavior, then rationality is lost, and if any of the upper or lower circuit breaks, a bubble forms (H. Wang, X. Wang, Bu, G. Wang, & Pan, 2018).

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A bubble is formed due to two reasons: 1) the divergence between real valuation and perceived valuation, and 2) a short-time period. These two reasons are the need for and the rationale of the study. Heuristics in investment decision-making plays a significant role in governing the investor's behavior and the study of this domain is important to detect and avoid market fear and crash possibility.

The behavioral finance studies are gaining more importance, as the investors' and other financial market participants' decision-making and judgements are driven by the information available and the information leaked in the market. As a result, the information, which is floated in the market, results in an impulsive buy and sell behavior and can impair the process of fair price discovery and cause a downturn in the event of downside herding. Downside herding then leads to a financial market crash, which causes great damage to the economy and affects its financial health (Bekiros, Jlassi, Lucey, Naoui, & Uddin, 2017).

The purpose of this study is to examine the presence of herding phenomenon with respect to the EURIBOR of five top European banks. The nature of the study is to build a mathematical construct based on behavioral philosophy. The major part of the credit is behavioral, and, in that regard, this study is quite significant as it aims to identify any herding possibility and subsequent bubble information by using the measures of Hurst Exponent and Shannon's Entropy to understand the mind-set of the market participants and their behaviors and actions for effective market functioning.

This study is based on analyzing the results obtained by calculating the Hurst Exponent and Shannon's Entropy in order to comprehend the momentum of the market. This study is useful for various banks of the European region, and the same model design can be used to detect embedded herding and bubble possibility for banks in other regions applying the interbank offered rates in the European context. The study itself is one of a kind in the sense that for the first time, herding and bubble possibilities are traced using EURIBOR or FRA data. Previously, all studies considered stock prices, volatility and log return for the same purpose, but not EURIBOR.

1. LITERATURE REVIEW

Tracing the presence of herd behavior and the likelihood of bubble in the stock market is of interest to researchers around the world who have used stock prices, volatility and log returns to detect herd behavior and bubble possibility in a set of parameters. Satish and Padmasree (2018) investigated the herding phenomenon in the Indian stock market using the cross sectional absolute deviation method of daily and weekly data of stocks listed on the Indian stock market (NSE) for the period from January 2003 to December 2017, and probed the fluctuations in the daily and weekly figures for three different time states – before the crisis, during the crisis and after the crisis. The results showed that herd behavior did not exist in the Indian stock market in all three periods evaluated. Bouri, Gupta, and Roubaud (2018) examined the cryptocurrency market from the behavioral finance viewpoint to examine the presence of the investor herding pattern. Due to structural breaks and non-linearity in the time series, the use of a static model was not suitable, as there was no significant herding.

A Logistic regression technique, using a rolling window approach, was applied. The findings suggest noteworthy herd behavior, which takes place with the rise in the dispersion and uncertainty due to information asymmetry and information entropy in the market.

BenSaida (2017), a researcher of repute, conducted a study on a sectoral level, focusing on the herd behavior effects on the excessive market's idiosyncratic volatility in the US stock market. The analysis adjusted the cross-sectional absolute deviation model by incorporating additional dimensions of trading volume and sentiments of the investors as the herding signals. The results indicate herd behavior in almost all sectors of the US stock market during the crisis, using data from registered American companies for four major crisis peri-

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ods of black Monday 1987, dot com bubble, the stock market downturn of 2002, and the global financial crisis. Similarly, two separate research groups – Litimi (2017) and Litimi, BenSaida, and Bouraoui (2016) – investigated herd behavior in the French and American stock markets using the same technique and approach. Litimi, BenSaida, and Bouraoui (2016) furthered and conducted a sectoral analysis examining whether the investor herd behavior is a strong determinant of excessive risk and the formation of a bubble in the US stock market during four main periods of turmoil. Daily closing prices of all listed firms were included and analyzed using the Granger causality test. The analysis showed that herding was a major component that drove an increase in the bubbles in the US stock market. The results also showed that herd behavior was present during certain times thought out in the studies, similar to BenSaïda (2017). Indārs, Savin, and Lublóy (2019) examined the relationship between market returns of the Moscow Exchange and the dispersion of individual asset returns for a period from April 2008 to December 2015 and concluded that herding phenomenon was present during the days when the market returns were negative.

Akinsomi, Coskun, and Gupta (2017) applied the technique of cross-sectional absolute deviation as a measure of dispersion to examine any sort of herding occurrence in Turkish Real Estate Investment trusts. The authors used daily closing prices over the period from January 2007 to May 2016 and concluded there was herd behavior, which increased during the period of turmoil.

Investigating further evidence of herding pattern in the Vietnam stock exchange, Phan and Vo (2017) used data from 299 companies listed on the Ho Chi Minh Stock Exchange for the period 2005–2015. The authors used the cross-sectional absolute deviation of stock returns with respect to market returns. The results of the study showed the presence of herding during the entire period; the periods were also divided into three sub-periods, which included the pre-crisis period, the period during the 2007–2008 financial crisis, and the post-crisis period.

A study of herd behavior in the Indian IT sector, by observing the herding pattern of the sectoral index with the multi-sectoral benchmark index for a developing country, was conducted by Kumar and Bharti (2017). The authors used daily closing data of the Indian Bellwether bourse and CNX Nifty IT Index for a period from April 2009 to October 2015. The study applied cross sectional absolute deviation and concluded that there was no herding in the IT sector stocks in the Indian capital market.

Balcılar, Demirer, and Ulussever (2017) explored the herding phenomenon to determine if time fluctuations in the stock markets of the largest oil exporting countries correspond to speculation and volatility in the global oil market. Daily data of all companies listed on five Gulf Corporation Council (GCC) exchanges – Abu Dhabi, Dubai, Kuwait, Qatar and Saudi Arabia – were included in the study. The time period from April 2004 and January 2014 was used for the study and a Markov switching time-varying parameter herding model was applied. The results indicated that herd behavior was present during periods of market volatility. Like Balcılar, Demirer, and Ulussever (2017), Balcılar and Demirer (2015) also used a Markov switching time-varying parameter herding model to investigate the relationship between global factors and the herding pattern in the emerging market of Borsa Istanbul. Three different market regimes were included, using daily closing prices of all listed firms for a period from January 2000 to March 2012. Borsa Istanbul is a market led by a large portion of foreign investors, so the risk of global factors contributes to the herding phenomenon. The results found that herd behavior exists during the high volatility and in the extreme volatility regimes.

Braga (2016) investigated the presence of herding in the Portuguese stock market using cross sectional standard deviation and absolute deviation. These two measures were used as dispersion measures. Daily data of stock returns for a period from 2000 to 2016 was included in the study. The results of the study showed that there was herd behavior during periods that exhibit positive returns, but not during periods of negative returns. It is a conclusion that herd behavior was present in asymmetric market conditions. In addition, evidence is found that after the sovereign debt crisis broke out, increased herding behavior was observed.

Cakan and Balagyozyan (2016) examined investor herd behavior using cross-sectional absolute deviation as a measure of dispersion of return. Borsa Istanbul was included in daily sectoral stock prices for a period from 2002 to 2014, across all industrial sectors of the Turkish bourse. Conclusive evidence of asymmetric herding has been found in all sectors covered by the study.

Ghosh (2016) analyzed the stock market bubble and herd behavior in the Indian capital market. To achieve that, the author explored daily closing data of CNX Nifty for the period from September 2007 to April 2016. Using upgraded forms of Augmented Dickey Fuller Test, the findings indicated there was evidence of an asset price bubble.

Galariotis, Krokida, and Spyrou (2016a) explored herd behavior in the equity price data for G5 markets in light of 2007–2009 financial crisis. The cross-sectional deviation approach (similar to Chang, Cheng and Khorana (2000)) and the illiquidity measure (Amihud, 2002) were used to capture relevant equity liquidity in data. G5 markets are France, Germany, Japan, United Kingdom, and the Unites States of America. A period from 2000 to 2015 was included in the study and further divided into three periods (before, during and after the financial crisis). In the full data period, no evidence of herding was found in these five markets; however, during sub-periods, herding was present in four of the markets in high liquidity stocks. Germany showed weaker herd behavior for the high liquidity stocks. Galariotis, Krokida, and Spyrou (2016b) analyzed the presence of investor herd behavior in European market in the backdrop of the European Debt Crisis and found no conclusive evidence of herd behavior in both the pre-crisis and post-crisis periods. The results of the study did show that during the crisis in the EU from 2007 to 2013, macroeconomic information affected the bond market and caused herding in it. This was a contribution to the bond market literature, which is solid evidence of herding during the crisis period due to the dissemination of information about certain macroeconomic factors.

Vieira and Pereira (2015) explored the herding pattern in the Portuguese Stock PSI-20 Index using two different techniques – the first technique proposed by Patterson and Sharma (2007) and a cross-sectional standard deviation. 2003–2011 data for the Portuguese stock market was included in the study. The two techniques led to conflicting results, which indicated that different methods used in the analysis had an impact on the results of the study. An opportunity for further study was identified in the approaches used to explore herding behavior.

Huang, Lin, and Yang (2015) assessed the effect of idiosyncratic volatility on the investor's herding behavior. They explored the Taiwanese equity market using data on individual stocks and index levels covering daily stock prices, index values, industry sectors and risk-free rates. The data was analyzed using a single-factor model to estimate idiosyncratic volatility. Cross-Sectional Absolute Deviation and Cross-Sectional Standard Deviation were used as measures of stock return dispersion to understand the herding phenomenon. The findings showed that there were distinctive herding patterns under different portfolios in accordance with idiosyncratic volatility.

BenSaïda, Jlassi, and Litimi (2015) investigated herd behavior for a developed stock market of the USA using dispersion measures of Cross-Sectional Absolute Deviation and Cross-Sectional Standard Deviation. A daily dataset of stocks listed on Dow Jones Industrial Average and the S&P 100 markets for 2000–2014 was included in the study. The Cross-Sectional Absolute Deviation and Cross-Sectional Standard Deviation models provided inconclusive results regarding the presence of herding behavior.

A further analysis, using VAR and Granger causality tests, showed that there was a bidirectional strong link between trading volume and herding in the US stock market. Filip, Pochea, and Pece (2015) examined the presence of herding in Central and Eastern European stock markets using cross sectional absolute deviation measure applied on logarithmic stock returns. The stock returns of the stock markets of Czech Republic, Poland, Hungary, Romania and Bulgaria from January 2008 to December 2010 were included in the study. The results indicated there was herding behavior in upward and downward trending markets, except for the Polish market.

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A herding pattern detection test was conducted by Xie, Xu, and Zhang (2015) with regard to the Chinese A-share market; the authors used a new propounded method based on Arbitrage Pricing Theory with the advanced weighted cross-sectional variance (WCSV) model. The method can identify strong herding patterns, removing the weaker ones, which shows the better distinguishing strength than other methods, like the univariate CAPM model, as well as the ability to reveal time points that condition the overall herding phenomenon. The results of this experiment show that the multivariate Fama-French Three-Factor model fits well and concludes that global 2007–2008 financial crisis created enduring herding situation with a declining trend in China.

BenMabrouk and Litimi (2018) conducted a study on cross-market correlation with regard to investor herding behavior on the American stock market and oil market, encompassing volatility in these two markets. To study the herding pattern at the sectoral level in the light of extreme oil market movements, US stock prices on a daily basis for the period 2000 to 2017 were taken into account, and the technique of cross-section absolute deviation was used to obtain results. The results indicated no industry herding, but, given the extreme oil market movements, the results showed that sector herding was more noticeable in the downward state of the market than in the upward one. The results also provide conclusive evidence of herding due to oil market information which affects investor behavior.

Ghosh, Krishna, Rao, Kozarević, and Pandey (2018) invented the Financial Reynolds number and conducted an econophysics study to discover the level of predictability and herding pattern in the CNX Nifty Regular, as well as CNX Nifty high-frequency trading section. Strong evidence was found related to the predictability and herd behavior in the CNX Nifty Regular, as well as the CNX Nifty high-frequency trading section. Using the generalized method of moments (GMM) coupled with artificial neural networks (ANN), Ghosh (2017a) evaluated availability heuristics to identify any evidence of herding in case of Indian public sector banks. The study included the 2004–2015 time period, focusing on three Indian public sector banks. The results revealed availability heuristics; besides, timid choice, bold forecast and herding biases were also present.

In addition, Ghosh (2017b) conducted a study to find behavioral heuristics using ANN algorithms on S&P BSE 100 bourse to create a predictability model for examining the presence of biases in the market participant behavior. The results of the study revealed Heuristic Simplification, Familiarity Bias and Cognitive Error. Ghosh, Le Roux, and Ianole (2017) developed a fear index using the BRICS and UK markets. The fear index elicits any asset transfer to gold on account of fear among the investors using GMM under the panel data regression. The study identifies that the transfer of assets to a safer type of assets occurs during high volatility periods in the market, which indicates herding behavior at these times.

2. METHODOLOGY

The purpose of the study is to examine the presence of herding phenomenon with respect to EURIBOR of Top five European banks. FRA in the Eurozone is linked to the interbank credit exchange index, which is EURIBOR. Hence, FRAs are directly related to EURIBOR, so its value is based on the former. In any case, EURIBOR reflects the true credit spread on borrowing. FRA takes into account the perspective of both parties involved. Thus, there is always a component of indirect fear embedded in FRA.

Certain facts are quite likely with regard to fear. As we know, ignorance, lack of knowledge, application and understanding inspire fear. There are two types of fear in this context – direct and indirect fear.

Direct fear is a case when a person cannot interpret the information available. In the case of indirect fear, everyone can interpret the information available, but that market participant is under the influence of someone else who cannot understand and interpret and, therefore, indirectly, he/she is subject to fear. In an FRA, the perspective of both parties involved represents and signifies the presence of a market fear component. Hence, FRA is a measure of indirect fear.

There is an idea or rationale for using EURIBOR data for the period from January 1, 2009 to December, 31 2017 on a daily basis to trace any herding and the appearance of bubbles in the future. The nature of the study is to build a mathematical model based on behavioral philosophy. The main part of credit is behavioral, and in that regard, this study is quite significant aiming to identify any herding possibility and subsequent bubble information by using Hurst exponent and Shannon's Entropy to understand the mindset of market participants and their behaviors and actions for effective market functioning.

Hurst exponent is a measure to quantify a behavioral pattern, and its value ranges from 0 to 1. The higher the value of Hurst exponent, the higher the level of herding and bubble in the market and therefore the risk component is very high, which can jeopardize the whole market and result in financial crisis.

The level of information available to any market participant at a point in time varies. The Efficient Market Hypothesis does not work in most cases. In other words, different market participants receive different information at different point of time. Also, the level of financial literacy varies from individual to individual. They decipher the same information differently because of different behavior, perspectives, investing needs and background. Therefore, there will always be an element of uncertainty in the market.

2.1. Shannon's entropy (SE)

For a given probability distribution $Pi = P(xi)$, where $i = 1, 2, 3, 4 \ldots n$, there is a given random variable. The formula is:

$$S\left(X_i\right) = -\sum_{i=1}^{n} P_i \log\left(P_i\right). \tag{1}$$

Shannon's entropy is proved to be quite successful for processing stock markets or similar stochastic time-series based systems, where random series will have the same average behavior in the space and in time (this concept is known as "ergodicity").

Shannon's entropy is a measure used to quantify the level of information uncertainty. If the measure of Shannon's entropy is higher than 3.5, the uncertainty is beyond control, indicating that crisis is eminent. If this measure is below 3.5, it means that there is low uncertainty of information, which is within control. The study is based on analyzing the results obtained by calculating the Hurst Exponent and Shannon's Entropy to comprehend the momentum of the market.

This study is useful for different banks in the European region, and the same model can be used to detect embedded herding and bubble possibility for banks of other regions using interbank offered rates. The study itself is one of a kind in the sense that for the first time, herding and bubble possibilities are traced using EURIBOR or FRA data. All past studies considered stock prices, volatility and log return for the same purpose, but not EURIBOR. Although it is believed that the risk-free rate is apparent, EURIBOR was ignored in such studies.

2.2. Multifractal detrended fluctuation analysis (MFDFA)

A group of prominent researchers (Kantelhardt et al., 2002) gave a plausible shape to the entire process of identifying the impact of multifractality in a noisy time series; after Mandelbrot's discovery of 'Fractals', multifractals are used almost everywhere today: from the helm of bio-medical series to stochastic financial series. The transformation in this analysis takes the following steps:

Firstly, the time series in question is converted to a true random series. Each observation was subtracted from the mean value. According to a famous research work, the series was integrated (Ihlen, 2012). RMS, or the root mean square variation calculation, was conducted. RMS values are calculated from the area of the series exhibiting clear trend. Then it was further summarized. RMS clearly demonstrates 'power law' connection here. This is referred to as the famous "monofractal detrended fluctuation analysis", or DFA. Besides, the coefficient of this DFA is the Hurst exponent (Hurst, 1951; Graves, Gramacy, Watkins & Franzke, 2017). Once the study is done to the qth (5^{th} order is usually used for stock markets) order, it becomes "multifractal detrended fluctuation analysis", or MFDFA (Ihlen, 2012). Researchers find MFDFA more accurate than DFA.

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Table 1. Hurst exponent values and interpretation

Value range	Interpretation
0 < H < 0.5	Anti-persistent, no herding, no bubble, high risk
H = 0.5	Random walk, no predictability
0.5 < H < 0.64	Mild herding, mild bubble, high predictability
0.65 < H < 0.71	High herding, high bubble, heading crisis
0.72 < H < 1	Higher herding, higher bubble, danger zone, the crisis period

2.3. Hurst exponent (H) value and interpretation

Fractal dimension (FD) corresponds to the Hurst exponent, both being two-dimensional. The formula to calculate it is as follows:

$$FD = 2 - \text{Hurst Exponent}.$$

2.4. Shannon's entropy (SE) value and interpretation

Shannon's entropy (SE) is a metric used to measure the dispersion and information uncertainty in the stock market.

Table 2. Shannon's entropy values and interpretation

Value range	Interpretation
SE < 3.5	Information uncertainty is within the control
SE > 3.5	Information uncertainty is beyond the control

3. RESULTS

This section gives the results of the study of five banks from different Eurozone countries that manage EURIBOR. The measures of Hurst exponent and Shannon's entropy are used individually for each of the panel banks.

3.1. Barclays Bank

Table 3. Depicting Hurst, Fractal Dimension and Shannon's Entropy for Barclays Bank

Hurst exponent	0.63102
Fractal dimension	1.36898
Shannon's entropy	3.38253

Figure 1 depicts the 5th order Hurst Exponent of Barclays Bank. According to Hausdorff topology, Douady rabbit is represented (see Figure 2).

3.2. ING Bank

Table 4. Depicting Hurst, Fractal Dimension and Shannon's Entropy for ING Bank

Hurst exponent	0.55089
Fractal dimension	1.44911
Shannon's entropy	3.38551

Figure 3 depicts the 5th order Hurst Exponent for ING Bank. According to Hausdorff topology, Vicsek fractal is represented (see Figure 4).

3.3. Deutsche Bank

Table 5. Depicting Hurst, Fractal Dimension and Shannon's Entropy for Deutsche Bank

Hurst exponent	0.57622
Fractal dimension	1.42378
Shannon's entropy	3.35765

Figure 5 depicts the 5th order Hurst Exponent for Deutsche Bank. According to Hausdorff topology, Vicsek fractal is represented (see Figure 6).

3.4. Hong Kong Shanghai Banking Corp (HSBC)

Table 6. Depicting Hurst, Fractal Dimension and Shannon's Entropy for HSBC

Hurst exponent	0.54798
Fractal dimension	1.45202
Shannon's entropy	3.37055

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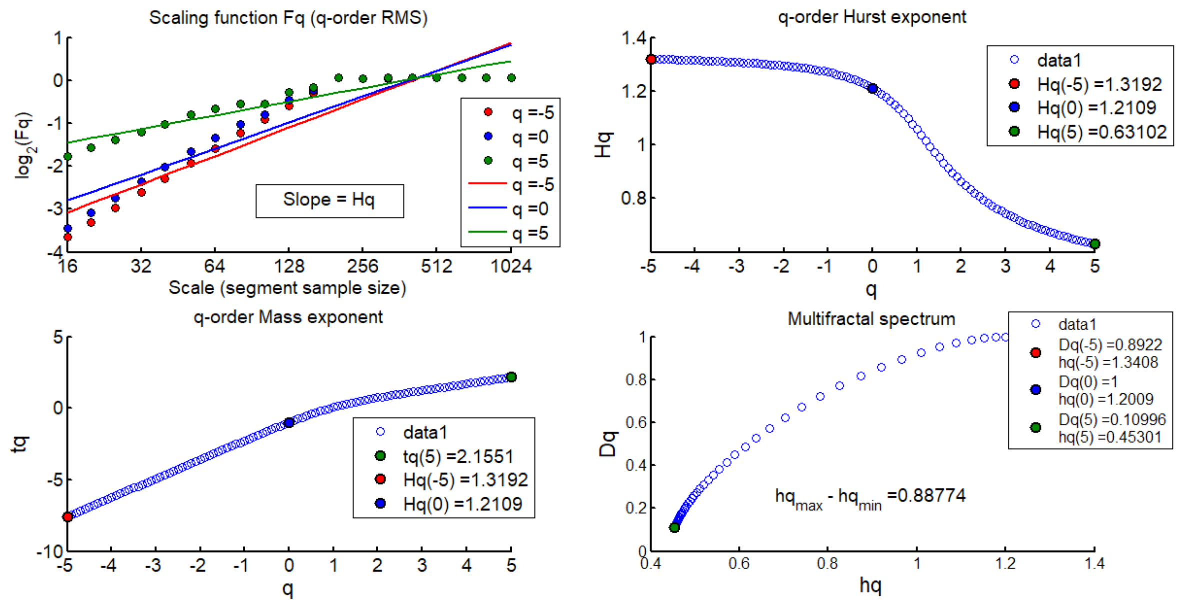

Figure 1. The 5th order Hurst Exponent of Barclays Bank

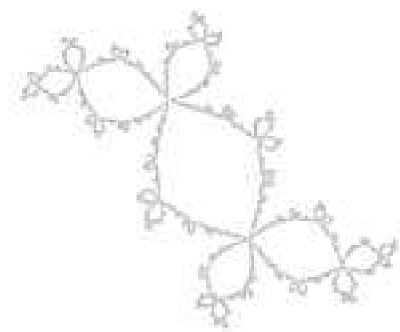

Figure 2. Depicting the Fractal Dimension of Barclays Bank as Douady Rabbit

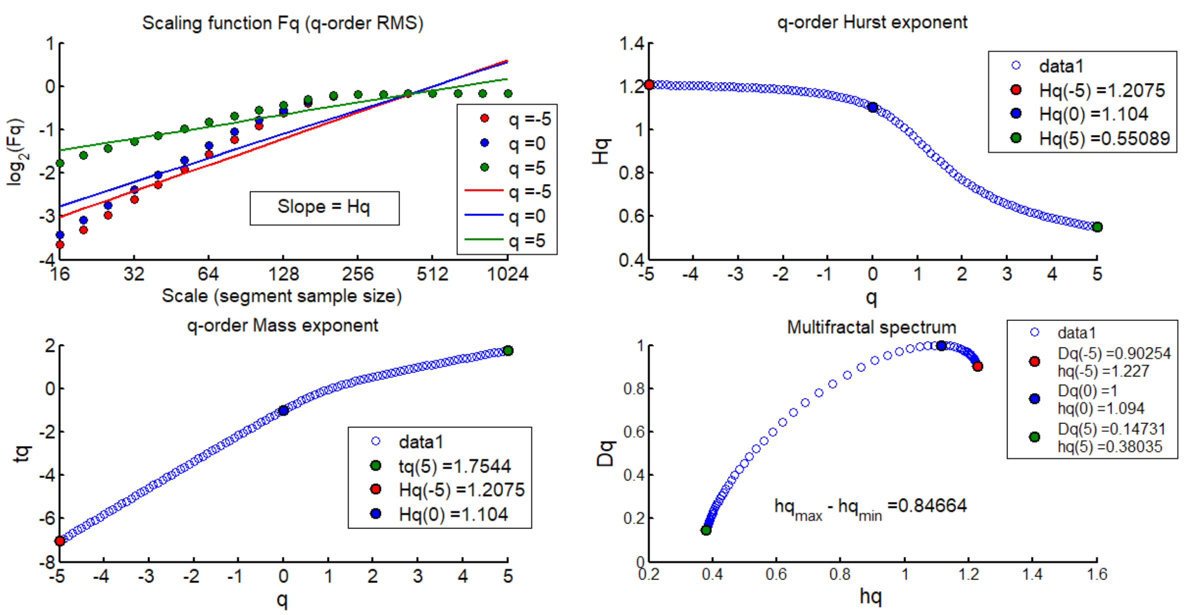

Figure 3. The 5th order Hurst Exponent for ING Bank

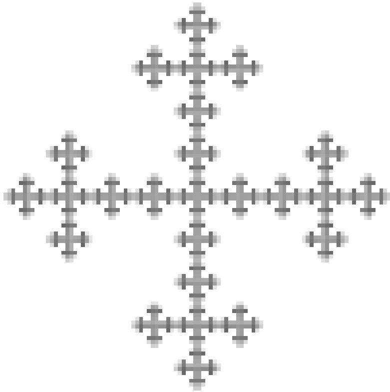

Figure 4. Depicting the Fractal Dimension of ING Bank as Vicsek Fractal

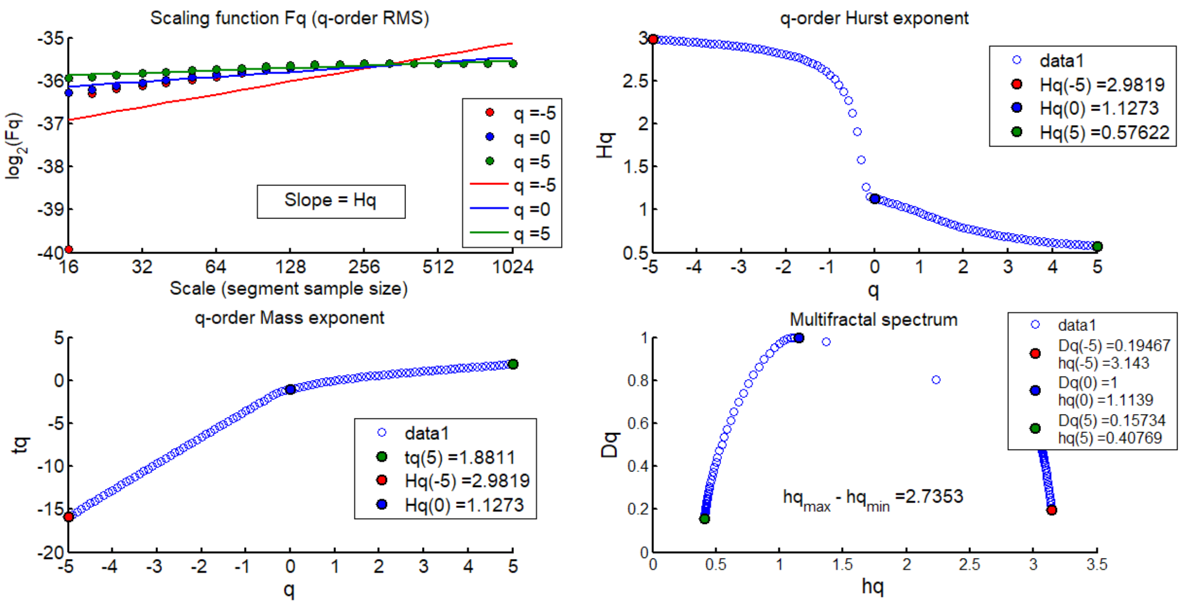

Figure 5. The 5th order Hurst Exponent for Deutsche Bank

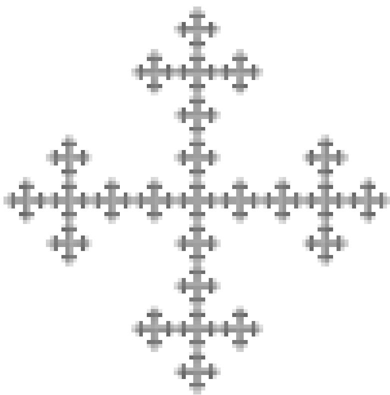

Figure 6. Depicting the Fractal Dimension of Deutsche Bank as Vicsek Fractal

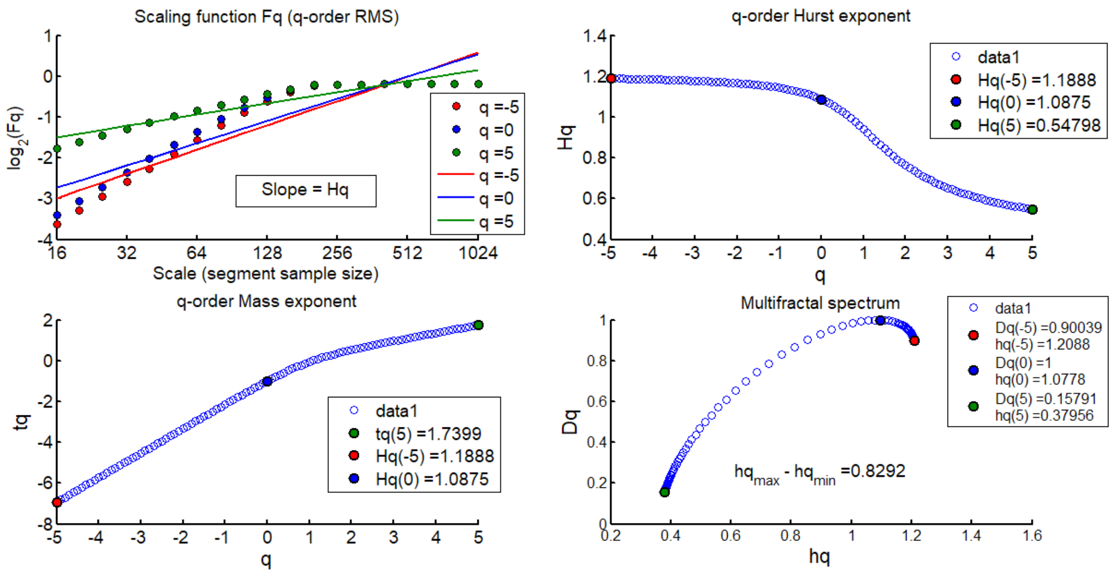

Figure 7. The 5th order Hurst Exponent for HSBC

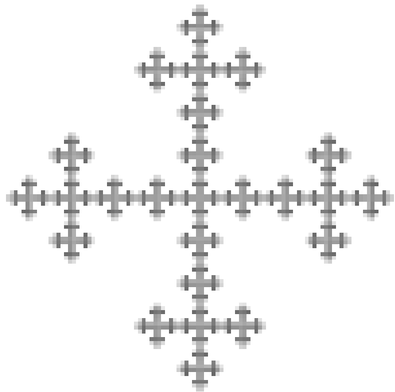

Figure 8. Depicting the Fractal Dimension of HSBC as Vicsek Fractal

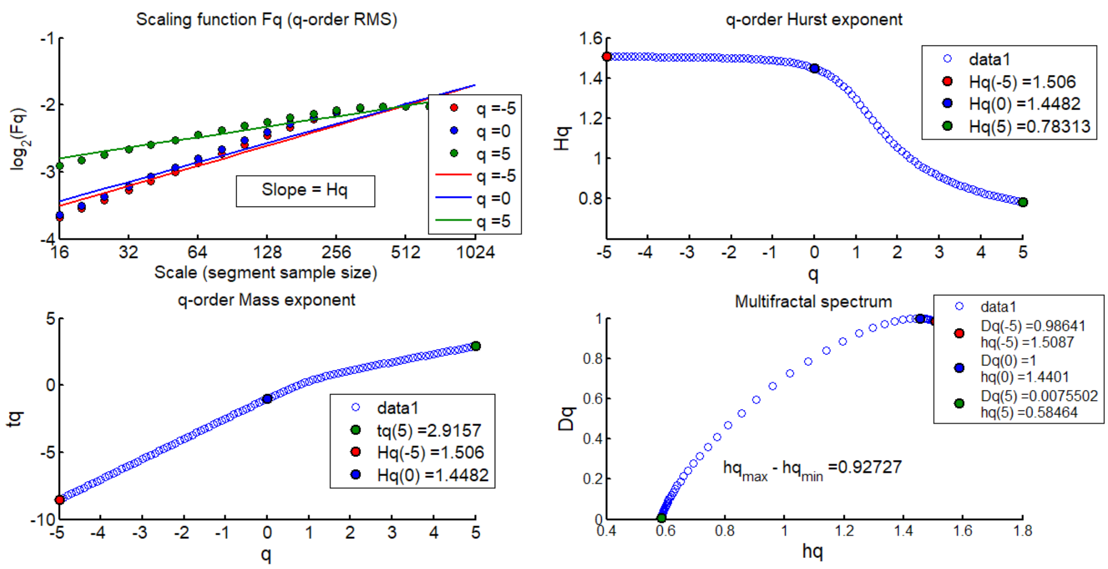

Figure 9. The 5th order Hurst Exponent for NBG

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Figure 10. Depicting the Fractal Dimension of NBG as Tame Twin Dragon

Figure 7 depicts the 5th order Hurst Exponent for HSBC. According to Hausdorff topology, Vicsek fractal is represented (see Figure 8).

3.5. National Bank of Greece (NBG)

Table 7. Depicting Hurst, Fractal Dimension and Shannon's Entropy for NBG

Hurst exponent	0.78313
Fractal dimension	1.21687
Shannon's entropy	3.41018

Figure 9 depicts the 5th order Hurst Exponent for NBG. According to Hausdorff topology, a tame twin dragon is represented (see Figure 10).

In the case of Barclays Bank (UK), the Hurst exponent is 0.63102, which shows that there is mild herding phenomenon in the market, which leads to the formation of a bubble. This is still in a healthy zone. This herding and the bubble formation are eminent, but this is a counter-intuitive result, because the adult financial literacy rate is around 67%, which is pretty good globally. However, the Hurst exponent is the highest for Barclays among the five banks studied. This can be due to high perceived uncertainty in the UK market. Besides, the news suggests that Barclays Bank is one of the UK banks that have been fearful of lending to countries such as Greece, Portugal and Spain that have not fulfilled their default obligations (Greece debt crisis, European debt crisis). This exposure of default from the borrowing entities in crisis-stricken nations enhanced the perceived uncertainty in the UK debt market and contributed to herding possibility and bubble formation. The spill-over effects of this phenomenon continued for a significant time, as evidenced by Shannon's entropy of 3.38, stretched over the period of study.

Moving on to the case of HSBC bank (UK), it was found that the Hurst exponent was 0.54798, which indicates little herding and bubble formation. This also indicates situation under control, since it is still in a healthy zone as robust solution points do exist in this case. This is confirmed by the adult literacy rate of 67% and by Shannon's entropy of 3.37 clearly indicating a healthy and safe zone.

In the case of Deutsche Bank of Germany, it has been found that herding is present to some extent, and bubble formation also occurs, which is well confirmed by the Hurst exponent of 0.57622 showing some traces of herding and bubble formation. This is also accompanied by low information uncertainty denoted by Shannon's entropy of 3.35765, which shows that it is in a healthy zone. This can be attributed to the adult financial literacy rate of Germany of 66%.

In the case of ING Bank (Netherlands), the results show a healthy zone, which is characterized by the Hurst exponent of 0.55089, showing a very low level of herding and bubble phenomenon. The information uncertainty is also low due to Shannon's entropy of 3.38 and seems to be in a safe zone. In addition, this is due to the adult financial literacy rate of 66%, which is a good sign compared to other companies.

Last but not the least, is the National Bank of Greece. The output for this bank shows that herding phenomenon is prominent and a bubble forms. This indicates that the crisis is eminent and beleaguered by the danger zone due to high Hurst exponent value of 0.78313, indicating that the risk component is very high. Also, this is characterized by a relatively high uncertainty indicated by Shannon's entropy of 3.41, which is the lowest among the five banks. The risk component is high doe to the blazing up of the Greek crisis in 2010, which had spill-over effects over the next 5-6 years, and the Greek debt market had a bleak future. The study shows that among the top five European banks involved in the study, the National Bank of Greece and Barclays Bank show quite interesting results.

CONCLUSION

The origin of a bank does not matter much in the era of globalization. Barclays' prices show mild to semi-strong herding due to its exposure in Greece, Portugal and Spain (as a part of its sub-prime asset base). HSBC, on the other hand, did not expose a significant portion of its asset base to sub-prime assets, which makes it relatively robust.

ING (Netherlands) and Deutsche (Germany) somewhat strengthened their positions amidst high volatility. Another interesting chapter is revealed when one looks at this analysis. It has been found that most banks in the EURIBOR domain (under consideration) face a dilemma. Sub-prime offers better profit with less security, while prime offers have lesser returns with more security. Prudent decision-making and balanced decisions regarding mix and match of the risk and return ratio remain the key.

The results obtained from the National Bank of Greece are quite logical, since their major exposure is skewed more towards home grown businesses. Entropy (Shannon's) sheds light on the information availability. It depicts a clear picture of whether information is changed or deformed during cascading or the interpretation of information is questionable. As for the uncertainty (i.e. SE > 3.5), all banks analyzed are fairly certain. However, interpretation of information should ideally be good, since financial literacy indicators are quite sound. Obviously, the reason is something completely different. Information is present (confirmed by Shannon's entropy) and can be easily interpreted (confirmed by % of financial literacy); however, banks (40% or two out of five panel banks under consideration) are running behind sub-prime assets. This is both strange and uncanny. Since it is based on EURIBOR, which is a kind of FRA, i.e. an indirect indicator for risk, therefore, it can be an underestimation of 'greed and fear'. Further research in this domain may prove the motivation for such movements. Last but not least, Hausdorff topology can again be used to generate clear heuristics for investors (to decipher the financial health of the panel banks in EURIBOR).

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