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Fintech market efficiency: A multifractal detrended fluctuation analysis

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A B S T R A C T

The efficiency of the Fintech market is still an unverified issue. We aim to investigate the Fintech market efficiency for four S&P Kensho Fintech indices using the multifractal detrended fluctuation analysis (MF-DFA) method. All indices except one are found to be inefficient based on the joint hypothesis tests. We also find combinations of autocorrelation and/or extreme values as the main causes of the inefficiencies.

1. Introduction

Innovation within the Financial Technology industry (known as Fintech) has revolutionized the financial services market in recent years. With growing general mistrust towards banks, especially amongst millennials (Deloitte, 2016), Fintech firms are growing rapidly ($238.9 billion global investment in 2021) (KPMG, 2023), with apparent advantages such as P2P lending, crowdfunding, Cryptocurrencies, expansion of blockchain technology, Robo-advisors and overall, more cost-effective products (Buchak et al., 2017). Although still relatively small in size, they are believed to have the potential to disrupt the banking and finance industry, particularly with regard to the generation of new business models (Vives, 2017), which pose a systemic risk to the financial industry (Omarova, 2018). While extant literature provides evidence for the significant role of Fintech in the overall financial system, the results on the direction of this impact are contradictory. For instance, Daud et al. (2022) assert that there is a positive correlation between technologically enabled financial innovation (which provides decentralization and diversification of products and improve financial inclusion) and financial stability, while Nguyen and Dang (2022) found that potential threats are posed by Fintech to financial stability in term of micro and macroeconomic risks. The mixed results on the implication of fintech can also be found in Fung et al. (2020), Cantú and Chui (2020), and Vučinić (2020). Therefore, it is crucial to focus on the underlying mechanism of the Fintech market.

One of the most important and widely used theories to evaluate and model financial markets is the efficient market hypothesis (Fama, 1970). However, its application in the Fintech market is still extremely under-researched. Most of the related studies focus on the cryptocurrency market. For instance, Kristoufek and Vosvrda (2019) constructed an index using long-range dependence, fractal dimension, and approximate entropy and reported that the pioneering currencies (Bitcoin, DASH, Ripple, etc.) are unanimously inefficient. Wei (2018) used autocorrelation and automatic variance test (AVR) and provided evidence for market efficiency for liquid markets such as Bitcoin, while in the case of lower turnover (illiquid) currencies, the market was found to be inefficient. Similarly, Noda (2021) utilized a GLS-based time-varying AR model and reiterated that the market efficiency is higher for established and

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high-liquidity cryptocurrencies.

One of the shortcomings of the dominant methodologies employed in related literature is that these methods do not allow for quantifying the multiple scaling components within a time series. To overcome this, we used multifractal detrended fluctuation analysis (MF-DFA), which can precisely detect the multifractal properties of non-stationary time series. This method has been recently successfully used by Shrestha (2021) to evaluate the Bitcoin market efficiency. Our analysis is based on the daily price data of four S&P Kensho Fintech indices[1]: distributed ledger index, Alternative Finance Index, Future Payments Index, and Democratized Banking Index extracted from the Thomson Reuters Datastream database. Our study makes the following contributions: (i) it is amongst the first, if any, studies to measure the efficiency of the fintech index markets, (ii) it further investigates the sources of multifractality and (iii) it generates confidence intervals used to test the hypothesis in market efficiency using a Monte Carlo simulation.

2. Literature review

This section briefly describes some of the most recent studies that use MF-DFA to analyze market efficiency. For example, Arshad et al. (2016) use MF-DFA to empirically analyze the MSCI indices from 11 Organization of Islamic Conference (OIC) countries (e.g., Malaysia, Indonesia, Pakistan, Turkey, Jordan, Egypt, Nigeria, Kuwait, UAE, Saudi Arabia, and Qatar). They find, among other things, improving efficiency over the past decade. Similarly, Bouoiyour et al. (2018) study the efficiency of emerging and developed Islamic stock market indices using MF-DFA. They find the presence of multifractality. They also find emerging Islamic stock markets to be less efficient than developed Islamic markets. Ning et al. (2018) apply MF-DFA to the Euro and British Pound exchange rates and find the series to be multifractal. According to their findings, the efficiencies vary over sub-samples. The efficiencies of these two exchange rates are affected differently by major global economic events. Five GCC MSCI stock market indexes (e.g., Bahrain, Kuwait, Oman, Qatar, and UAE), MSCI world index, MSCI GCC, MSCI emerging market, MSCI emerging Asia, MSCI Europe, and MSCI North America, as well as Dow Jones Islamic stock market index, are analyzed by Mensi et al. (2018) using MF-DFA. Results show that the stock market returns exhibit multifractal features. Additionally, GCC stock markets are less efficient than the global, regional, and Islamic markets. In another study, Al-Yahyaee et al. (2018) analyzed Bitcoin, gold, the Morgan Stanley Capital International (MSCI) world stock index, and the U.S. dollar index. They find multifractality in all series and that Bitcoin is the most inefficient.

Similarly, Mensi et al. (2019) analyze the stock market index from Greece, Ireland, Portugal, Spain, Italy, and US as well as the World stock market index using MF-DFA. They find evidence of long memory. They also find Greece to be the most inefficient and Ireland and Portugal to be the least inefficient among GIPSI (Greece, Ireland, Portugal, Spain, and Italy) indices. Tiwari et al. (2019) investigate the multifractality and efficiency of stock markets in eight developed (Canada, France, Germany, Italy, Japan, Switzerland, the UK, and the USA) and two emerging countries (India and South Africa). They show that stock markets are multifractal and are more efficient in the long-term than in the short-term. Similarly, four cryptocurrencies (Bitcoin, Ethereum, Ripple, and EOS) are analyzed by Cheng et al. (2019). They find a strong momentum effect (persistent) in Bitcoin and Ethereum and a reversion (anti-persistent) effect in Ripple and EOS for large fluctuations.

Furthermore, Milos et al. (2020) apply MF-DFA to seven Central and Easter European stocks markets (Poland, Czech Republic, Romania, Croatia, Hungary, Bulgaria and Slovenia) and find multifractality and inefficiency in these markets. Aslam et al. (2020) use MF-DFA to analyze nine MSCI frontier markets (Croatia, Kenya, Mauritius, Morocco, Nigeria, Romania, Serbia, Slovenia and Tunisia). They find markets of Kenya, Morocco, Romania and Servia to exhibit mean reversion (anti-persistent) behavior while the remaining frontier markets show persistent behavior. Similarly, Al-Yahyaee et al. (2020) empirically analyzed six major cryptocurrencies (Bitcoin, Ethereum, Monero, Dash, Litecoin, and Ripple) using MF-DFA and find these series to be multifractal. They also find Dash to be the least inefficient and Litecoin to be the most inefficient. Shrestha (2021) analyze Bitcoin using MF-DFA. He finds that Bitcoin is multifractal instead of mono-fractal. He also finds Bitcoin to be inefficient, where the inefficiency is caused by autocorrelated and extreme returns.

In another study, Yin and Wang (2021) apply MF-DFA to CBOT soybean futures. They find multifractality and market inefficiency. The inefficiency is attributed to both fat-tail distribution and long-range correlation. Ftiti et al. (2021) use the data on WTI crude oil and natural gas futures prices to analyze the multifractality using MF-DFA. They find, that multifractality in lower frequency might be more biased than in the intraday data. Furthermore, forecasting results show that the proposed multifractal approach outperforms conventional methodologies. In another study, Diniz-Maganini et al. (2021) empirically analyzed 20 exchange rates using MF-DFA. They find that the currencies of countries following a free float regime show greater price efficiency than the currencies of countries following a managed float regime.

More recently, Diniz-Maganini et al. (2022) analyzed the American depositary receipts (ADRs) of foreign firms and the shares listed in their home markets using MF-DFA. They find that ADRs, in general, show greater price efficiency than their corresponding home market shares.

3. Methodology

The generalized Hurst exponent $h(q)$ can be estimated using MF-DFA.[2] In general, $h(q)$ depends on q, i.e., $h(q)$ will be different for

[1] Considering the theme of present study, we have chosen these indices from S&P Kensho New Economies series since these are the only available indices under 'Fintech' category.

[2] The description of MF-DFA can be found in Kantelhardt et al. (2002) a brief description of which is also provided in the online appendix.

different values of q. However, if $h(q)$ is the same for different values of q, i.e., $h(q) = H$, then the return series is said to be *mono-fractal* instead of *the multifractal* process. If $H = 0.5$, the process is a standard Brownian motion with an independent increment that is consistent with the market efficiency. If, $H \neq 0.5$, then the process is a fractional Brownian motion. If $0.5 < H < 1$, the autocorrelations for the process decay too slowly so that the sum of the autocorrelations overall lags will be infinite. Such processes are said to be long memory processes, which means that the successive nonoverlapping increments in the process are more likely to have the same sign. These processes are also called persistent processes. Such behavior is inconsistent with market efficiency. On the other hand, if $0 \leq H < 0.5$, the process is said to be a short-memory process or anti-persistent process where a positive increment is more likely to be followed by negative increments. This behavior is also inconsistent with market efficiency. In the case of mono-fractal returns, $H = 0.5$ represents market efficiency (Urquhart (2016); Nadarajah and Chu (2017); Bariviera (2017); Tiwari et al., (2018) and Shrestha (2021)).

However, in the case of the multifractal process, the process could be persistent for some $q's$ (i.e., $h(q) > 0.5$) and anti-persistent for others $q's$. For some other $q's$ it could even be independent (i.e., $h(q) = 0.5$), in which case the returns are consistent with the market efficiency. Finally, it is important to note that the positive $q's$ represent large fluctuations and negative $q's$ represents small fluctuations. Therefore, if the returns are inefficient, MF-DFA can allow us to identify whether the large or small fluctuations or both violate the market efficiency.[3]

Following Shrestha (2021), we generate the empirical distribution for $h(q)$ using a Monte Carlo simulation of size 10,000 with the length of the generated returns being equal to the length of the return series considered in this study.

Using MF-DFA, we can also measure the so-called market inefficiency (*MI*) as follows[4]

$$MI = \sqrt{\frac{\sum_{i \in S}[h(q_i) - 0.5]^2}{7}} \tag{1}$$

If the market is efficient, in theory, *MI* will be 0. A value away from 0 indicates a higher level of inefficiency. However, even if the market is efficient, the estimated value of *MI* can deviate from 0 due to sampling error. In order to test the inefficiency as a statistical test, we generate the critical values using the simulation of size 10,000. The critical values are 0.09459, 0.10937, and 0.14098 at the 10, 5, and 1 percent levels, respectively.

4. Empirical results and discussions

We use the daily prices (P_t) for all four S&P Kensho Fintech indices, (i) *Alternative Finance, (ii) Democratized Banking, (iii) Distributed Ledger,* and *(iv) Future Payments* from May 31, 2018 to November 30, 2022, leading to the sample size of 1175. The distribution of firms and index weights by country is given in Table 1. Alternative finance is the smallest among 4 indices in terms of market capitalization ($334.59 billion). It is designed to measure the performance of companies focused on providing alternative financing and wealth management capabilities. Distributed Ledger ranks third with a market capitalization of $370.32 billion. It is designed to measure the performance of companies involved in the advancement of distributed ledger technology and those enabling services, such as miners. The future payments index is the second largest, with a market capitalization of $4 trillion. It is designed to measure the performance of companies involved in providing products or services related to general-purpose platforms that allow consumers to transact using a digital balance. Finally, democratized banking is the largest index with a market capitalization of $5.04 trillion. It is designed to measure the performance of companies focused on innovations within financial services, including direct lending, crowdfunding, automated wealth management, usage/on-demand insurance services, and digital currencies and related capabilities.[5]

Following previous studies, we compute logarithmic return as follows:

$$r_t = [\ln(P_t) - \ln(P_{t-1})] \times 100 \tag{2}$$

We estimate the generalized Hurst exponent for seven moment orders, $q = -6, -4, -2, 0, 2, 4, 6$. The time scales are generated as 2^p where p is a series starting from 4 to 24 with step 1/3 with the restriction that the maximum value of the scale is less than $N/4$ where N is the length of the series. This results in the following values for the scales (s)

$$s = 16,\ 20,\ 25,\ 32,\ 40,\ 50,\ 64,\ 80,\ 128,\ 161,\ 203\ \&\ 256$$

The summary statistics in Table 2 show that the Future Payments Index has the highest mean and median returns. The Jarque-Bera test statistics are highly significant, indicating non-normal distribution and that MF-DFA is the correct method to use.[6]

Table 3 presents the correlation between the four fintech indices where all the correlation coefficients are highly significant at the 1 percent level.

Table 4 presents the estimated generalized Hurst, $h(q)$, exponents for $q = -6, -4, -2, 0, 2, 4 and 6$. The generalized Hurst exponents for the original series are presented in Column 2, which indicates that all the series considered are multifractal. Looking at the number of significant $h(q)'$s in the original series (column 2), the first index (Alternative Finance) seems to be the least inefficient, and the

[3] The traditional detrended fluctuation analysis (DFA) considers only the case where $q = 2$. Therefore, DFA is a special case of MF-DFA.

[4] Here we estimate $h(q)$ for q=-6,-4,-2, 0, 2, 4, 6.

[5] These figures are obtained from Bloomberg as of February 6, 2023.

[6] Jarque-Bera test statistics have a Chi-squared distribution with 2 degrees of freedom with 9.21 as the right-hand side critical value at the 1 percent level of significance.

Table 1
Number of firms and index weights by country.

	Alternative finance		Democratized banking		Distributed ledger		Future payments	
Country	No. of firms	Index weight	No. of firms	Index weight	No. of firms	Index weight	No. of firms	Index weight
Argentina	1	3.0	3	3.9			3	8.0
Brazil	2	4.4	6	7.0			5	9.8
Canada	1	2.5	7	11.0	3	23.1	3	7.5
China	3	8.7	6	5.8	2	15.1	2	3.0
Germany			1	1.5			1	2.1
India			1	0.9			1	1.4
Netherlands	1	3.0	1	1.2	1	9.9		
Peru			1	0.4			1	1.1
Singapore			2	2.9			2	4.4
Spain			1	1.1	1	10.4		
Turkey			1	0.5	1	1.7	1	1.9
Uruguay			1	2.0			1	2.9
USA	21	73.6	44	59.4	4	39.8	24	53.9
UK	1	4.7	2	2.5			2	4.1
Total	30	100	77	100	12	100	46	100

Table 2
Summary statistics.

	Alternative finance	Democratized banking	Distributed ledger	Future payments
Min	-14.691	-63.290	-14.440	-15.271
Q1	-1.180	-0.816	-1.450	-0.878
Q2	0.000	0.031	0.017	0.053
Mean	-0.065	-0.052	-0.053	0.016
Q3	1.084	0.976	1.433	1.031
Max	9.698	10.313	13.947	9.534
Std. Dev	2.140	2.656	3.059	1.955
Skewness	-0.362	-11.729	-0.046	-0.759
Kurtosis	6.847	276.646	5.770	9.618
Jarque-Bera	749.531	3689,892.000	375.653	2255.199

Table 3
Correlation.

	Alternative finance	Democratized banking	Distributed ledger	Future payments
Alternative Finance	1.0000			
Democratized Banking	0.4606***	1.0000		
Distributed Ledger	0.5157***	0.6957***	1.0000	
Future Payments	0.2819***	0.6479***	0.9175***	1.0000

second index (Democratized Banking) seems to be the most inefficient. However, it is better to test the inefficiency based on the joint hypothesis using *MI* index (Eq. (1)) instead of looking at the significance of the individual $h(q)'s$. The estimated *MI's* for Alternative Finance, Democratized Banking, Distributed Ledger, and Future Payments are 0.0990*, 0.2152***, 0.1848***, and 0.1132** respectively.[7] If we use the conventional level of 5 percent, then we find the Alternative Finance to be efficient and the rest of the series to be inefficient. The highest inefficiency associated with the Democratized Banking index could be because this index includes the highest number of firms and firms from diverse countries compared to other indices (Table 1). This makes the elimination of arbitrage opportunities more difficult and costly.

Finally, we analyze the causes of inefficiency related to individual $h(q)'s$ by reshuffling the original series to eliminate the impact of autocorrelation. We also winsorize the original series at the top and bottom 1% to the eliminate the impact of extreme values. Finally, we both reshuffle and winsorize the original series to eliminate the impact of autocorrelation and extreme values. The generalized Hurst exponents for the shuffled and winsorized series are presented in Columns 3 and 4 respectively. Column 5 represents the results for the winsorized and shuffled series. It is clear that for the first (Alternate Finance) and fourth (Future Payments) series, the efficiency is violated due to extreme values. Whereas for the third (Distributed Ledger) series, the inefficiency is caused by autocorrelated returns. Finally, both the autocorrelation and extreme values are responsible for the violation of the market efficiency for the second (Democratized Banking) series.

[7] *, ** and *** indicates the *MI* to be significantly different from 0 at the 10, 5 and 1 percent level respectively based on the simulated critical values mentioned at the end of Section 3.

Table 4
Generalized hurst exponent.

Moment	Original	Shuffled	Winsorized	Shuffled & winsorized
q	Alternative Finance			
-6	0.6541*	0.6716**	0.6214	0.6182
-4	0.6279*	0.6553**	0.5961	0.6062
-2	0.5935	0.6375**	0.5633	0.5925
0	0.5534	0.6152**	0.5270	0.5741
2	0.5036	0.5852	0.4937	0.5504
4	0.4396	0.5514	0.4660	0.5246
6	0.3847	0.5209	0.4437	0.5013
	Democratized Banking			
-6	0.7444***	0.7076***	0.6746**	0.6048
-4	0.7065***	0.6947***	0.6275*	0.5995
-2	0.6616***	0.6870***	0.5658	0.5939
0	0.6318**	0.6863***	0.5109	0.5847
2	0.4819	0.5719	0.4804	0.5703
4	0.2553***	0.3428**	0.4640	0.5529
6	0.1562***	0.2423***	0.4495	0.5359
	Distributed Ledger			
-6	0.7986***	0.6168	0.7423***	0.5273
-4	0.7593***	0.5950	0.7035***	0.5288
-2	0.6960***	0.5705	0.6405**	0.5318
0	0.5984*	0.5419	0.5631	0.5312
2	0.4899	0.5087	0.5032	0.5242
4	0.4023	0.4737	0.4622	0.5131
6	0.3419*	0.4422	0.4322	0.5006
	Future Payments			
-6	0.6598**	0.6400*	0.6099	0.5637
-4	0.6300*	0.6298*	0.5781	0.5606
-2	0.5837	0.6218**	0.5330	0.5640
0	0.5222	0.6107**	0.4786	0.5685
2	0.4632	0.5863	0.4324	0.5678
4	0.3941	0.5465	0.4000	0.5617
6	0.3349*	0.5051	0.3754	0.5527

Note: *,** and *** indicate the generalized Hurst exponent to be significantly different from 0.5 at the 10, 5, and 1 percent levels respectively based on the simulated confidence intervals given in Table 5.

Table 5 presents the 99, 95, and 90% confidence intervals for individual $h(q)'s$. Consistent with Shrestha (2021), the results show that the generalized Hurst exponent estimators are generally biased upwards (downwards) for negative (positive) values of q. This indicates the importance of testing the Hurst exponent.

Our mixed result on inefficiency is similar to the ones found by other studies with other financial time series as mentioned in the Literature Review Section. It is important to note that with the exception of Shrestha (2021), most existing studies do not perform a hypothesis test. These studies draw their conclusions based on the estimated values of the generalized Hurst exponent instead of testing how significantly different these values are from 0.5 implied by market efficiency.

5. Conclusion

This paper aims to shed light on Fintech market efficiency using four S&P Kensho Fintech indices. Following the analytical technique recently used by Shrestha (2021) in the context of the Bitcoin market, we employed MF-DFA due to its reported advantages over the other methodologies in testing market efficiency, including mono-fractal methods. Based on the number of generalized Hurst exponents significantly different from 0.5 implied by the market efficiency, our findings identify the Alternative finance Index market to be the least inefficient, while the Democratized Banking Index market appeared to be the most inefficient among the four indices. The joint hypothesis tests based on the estimated Market Inefficiency index show the Alternative Finance index market to be efficient at the standard 5 percent level. All other markets are found to be inefficient.

In order to find the causes of inefficiency, we shuffled the original series to eliminate the impact of autocorrelation. We also winsorized the original series to eliminate the impact of extreme values. We find that extreme values are the cause of inefficiency for the Alternative Finance Index and Future Payments Index markets, and autocorrelation is the cause of the inefficiencies for Distributed Ledger Index market. Finally, both extreme values and autocorrelation are the causes of inefficiency for the remaining Democratized Banking Index market.

CRediT authorship contribution statement

Keshab Shrestha: Conceptualization, Data curation, Methodology, Supervision, Software, Investigation, Validation, Writing – original draft, Writing – review & editing. **Babak Naysary:** Conceptualization, Writing – original draft, Writing – review & editing.

Table 5
Simulated confidence intervals.

	99% confidence interval		95% confidence interval		90% confidence interval	
q	Lower	Upper	Lower	Upper	Lower	Upper
-6	0.3723	0.6913	0.4185	0.6548	0.4370	0.6351
-4	0.3827	0.6677	0.4188	0.6312	0.4351	0.6154
-2	0.3893	0.6497	0.4170	0.6147	0.4314	0.5981
0	0.3785	0.6419	0.4084	0.6082	0.4223	0.5910
2	0.3565	0.6467	0.3900	0.6122	0.4066	0.5932
4	0.3250	0.6682	0.3627	0.6213	0.3824	0.6015
6	0.2935	0.6879	0.3318	0.6307	0.3555	0.6047

Sheena Sara Suresh Philip: Data curation, Methodology, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

Authors have no competing interests to declare.

Data availability

Data will be made available on request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2023.103775.

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