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Effect of COVID-19 on ETF and index efficiency: evidence from an entropy-based analysis

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Abstract
We examine the informational efficiency of domestic equity ETFs vis-a-vis their underlying market indices during the COVID-19 pandemic. To do so, we employ a multiscale entropy-based methodology. Our findings indicate that the informational efficiency of all ETFs as well as the indices fall sharply during the COVID induced market crash in February-March 2020. Having said so, we find disproportionate deterioration in market efficiency of ETFs and indices pertaining to USA and Canada as compared to those of China, Hong Kong and Taiwan. Interestingly, ETFs and indices pertaining to certain developed markets were found to be less efficient than their emerging market counterparts even during the pre-covid timeline. Lastly, there is a discernible difference between the efficiency of ETFs vis-a-vis their underlying indices. These findings should nudge investors to exercise caution while dealing with ETFs, for domestic ETFs do not exactly mimic the dynamics of their underlying indices.

Keywords COVID-19 · Entropy · Exchange traded funds · Adaptive market hypothesis

JEL classification: G01 · G14 · G15

1 Background

The dynamics of market efficiency during financial crises has been one of the primary focus areas of financial research. The discourse on market efficiency is heavily influenced by the Efficient Market Hypothesis, which postulates that asset prices

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should follow a random walk (Fama 1965). The rise in popularity of index based Exchange Traded Funds (ETFs) over the last decade, may be attributed to the belief that markets are indeed efficient and hence active investments strategies cannot consistently beat the market. ETFs also offer additional benefits over mutual funds which include lower expense ratio and reduced tax incidence.

Studies that examine ETF efficiency in the context of Efficient Market Hypothesis usually employ traditional econometric methodologies such as regression and cointegration (Xu et al. 2017, 2019; Huang et al. 2021). However, irregularities such as long memory, self-similarity and other non-linear phenomenon have also been reported in financial time series data of ETFs and equity indices (Zhu and Bao 2019; Saha et al. 2020; Caporale et al. 2020).

The current COVID-19 pandemic adversely affected markets across the globe. It has been earlier observed that financial crises can affect different markets to varying degrees (Lim et al. 2008). This study contributes to the literature on market efficiency in the following ways. First, we examine the level of informational efficiency of domestic ETFs and their respective underlying equity indices using an entropy based methodology. In doing so, we compare the degree of efficiency of developed vis-a-vis emerging market ETFs and underlying indices. Second, we examine the impact of covid-19 crisis on the informational efficiency of ETFs and underlying indices. While prior studies have used entropy based measures to examine efficiency across different assets (Alvarez-Ramirez et al. 2012; Ortiz-Cruz et al. 2012), we employ a recently proposed "refined composite multiscale fuzzy entropy" (RCMFE) algorithm that is more accurate and stable, especially for shorter temporal scales (Azami et al. 2017).

2 Methodology

Entropy measures the extent of disorder in a system. In the context of information theory, higher values of entropy for a time series process corresponds to higher levels of efficiency (Gulko 1999). A drop in market prices induced by a market crash creates a trend, that reduces entropy and thereby, informational efficiency. The first step in this analysis is to calculate the entropy of the dataset using the RCMFE method (Azami et al. 2017). Next, we use the informational efficiency index as proposed by Wang and Wang (2021). A brief description is provided here.

2.1 Refined composite multiscale fuzzy entropy

From a time series $y = y_1, y_2, \ldots, y_N$, a de-meaned vector is created as

$$U_t^m = y_t, y_{t+1}, \ldots, y_{t+m-1} - y_{0t}, \text{ where}$$
$$y_{0t} = \sum_{j=0}^{m-1} \frac{y_{t+j}}{m} \text{ for } t = 1, 2, \ldots, N - (m-1)$$

Here, m denotes the embedding dimensions which define the count of samples in every vector. The separation between two vectors is given by:

$$d_{t_1 t_2} = d\left[U_{t_1}^m, U_{t_2}^m\right] = max\left\{ |U_{t_1+k}^m - U_{t_2+k}^m| \, : \, k \in [0, m-1] \,\&\, t_1 \neq t_2 \right\} \quad (1)$$

When this distance is lesser than a given tolerance r, a match occurs. This degree of similarity is measured by the

$$D_{t_1 t_2} = exp(-(d_{t_1 t_2})^n / r)$$

for the level r and entropy power n. Next, the fuzzy entropy of the time series (y) is estimated as:

$$\mathrm{FE}(y, m, n, r) = -\ln\left(\frac{\phi^{m+1}}{\phi^m}\right) \quad (2)$$

where the function ϕ^m is given by

$$\phi^m(y, n, r) = \frac{1}{N-m} \sum_{t_1=1}^{N-m} \frac{1}{N-m-1} \sum_{t_1=1, t_1 \neq t_2}^{N-m} D_{t_1 t_2}$$

Further, the RCMFE measures the entropy at various time scales that are used to arrive at the multi-scale market efficiency. These can be understood as being daily, weekly or monthly. For these, a coarse-graining procedure is employed to extract variations at all scales.

For every time scale factor τ, separate coarse-grained series are created as $z_u^{(\tau)} | (u = 1, \dots, \tau) = \{y_{u,1}^{(\tau)}, y_{u,1}^{(\tau)}, \dots\}$, with mean as

$$\mu_{y_{u,j}^{(\tau)}} = \frac{\sum_{b=u+\tau(j-1)}^{u+\tau j-1} y_b}{\tau}$$

RCMFE improves upon previous measures of entropy by extracting more information from the data since it allows for overlapping windows at every τ. This is implemented by calculating fuzzy entropy for all time scales and then averaged over $u = 1, \dots, \tau$ to get average $\bar{\phi}_\tau^m$ and $\bar{\phi}_\tau^{m+1}$. Subsequently, the RCMFE is calculated as:

$$\mathrm{RCMFE}(y, \tau, m, n, r) = -\ln\left(\frac{\bar{\phi}_\tau^{m+1}}{\bar{\phi}_\tau^m}\right) \quad (3)$$

2.2 Index of informational market efficiency

Asset returns should follow Gaussian white noise in a completely efficient market. Hence, the index of informational market efficiency $[I_{IME}(\tau)]$ is calculated for all time scales τ as:

Table 1 List of ETFs and Equity Indices considered for this study

Region	Domestic ETF	Equity Index	Inception Date (ETF)
Australia	Vanguard Australian Shares Index ETF	S&P ASX 300 Index	May 08, 2009
Brazil	iShares Ibovespa ETF	IBOV Index	Dec 02, 2008
Canada	iShares S&P/TSX 60 Index ETF	S&P/TSX 60 Index	Sep 28, 1999
China	China 50 ETF	SSE 50 A Share Index	Feb 23, 2005
Eurozone	Xtrackers Euro Stoxx 50 UCITS ETF	Euro Stoxx 50 Index	Aug 27, 2008
France	Lyxor CAC40 DR-D-EUR ETF	CAC40 Index	Jan 22, 2001
Germany	iShares Core DAX UCITS ETF	DAX Index	Jan 03, 2001
Hong Kong	Tracker Fund of Hong Kong Ltd	Hang Seng Index	Nov 12, 1999
India	SBI NIFTY50 ETF	NIFTY Index	Jul 27, 2015
Japan	Next TOPIX ETF	TOPIX Index	Jul 13, 2001
New Zealand	Smartshares NZ Top 50 ETF	NZSX 50 Index	Dec 10, 2004
South Korea	Samsung Kodex 200 Securities ETF	KOSPI200 Index	Oct 14, 2002
Taiwan	Yuanta/P-shares Taiwan Top 50 ETF	TW50 Index	Jun 25, 2003
UK	iShares Core FTSE 100 UCITS ETF	FTSE100 Index	Apr 27, 2000
United States	SPDR S&P 500 ETF Trust	S&P 500 Index	Jan 22, 1993

$$I_{IME}(\tau) = \frac{\mathrm{RCMFE}(y, \tau, m, n, r)}{\beta(\tau)} \times 100\% \tag{4}$$

with $\beta(\tau)$ depicting the upper bound entropy of 5000 Monte Carlo simulations of Gaussian white noise samples. For $I_{IME}(\tau) < 100\%$, the asset can be interpreted as partially or fractionally efficient.

3 Data

Table 1 provides the names of the domestic equity ETFs and their respective underlying indices that are considered for this study. We retrieve log returns of daily closing prices of each ETF and its index from January 2018 to April 2021 from Bloomberg. For this study, we chose the largest (by assets under management) domestic ETFs from various markets which fully replicate their indices without derivatives or leverage. This is done to prevent confounding factors at the time of interpreting results.

At the outset, we check the descriptive statistics of the log returns time series data of ETFs and their indices. We use the descriptive statistics data to compare the change from the pre-crash period (Jan 2018 to Jan 2020) to post-crash period (Apr 2020 to Apr 2021). We exclude the period of the crash from February to March 2020 since the volatility was very high during this period. However, even after removing these months of date, we can see that the descriptive statistics, especially the skewness and kurtosis changed markedly in the post crash period compared to the pre-crash period. The following Table 2 shows the details.

Table 2 Descriptive Statistics of log returns of ETFs and their Indices (Pre and post crash)

Region	Instrument	Prior to Feb-March 2020 crash				Post Feb-March 2020 crash			
		Mean	Std. Dev	Skewness	Kurtosis	Mean	Std. Dev	Skewness	Kurtosis
Australia	ETF	0.000	0.007	−0.981	2.705	0.001	0.011	0.037	1.941
	Index	0.000	0.007	−0.964	2.960	0.001	0.012	−0.125	2.148
Brazil	ETF	0.001	0.013	−0.114	1.237	0.002	0.016	−0.168	1.509
	Index	0.001	0.012	−0.154	0.912	0.002	0.016	−0.103	1.198
Canada	ETF	0.000	0.006	−0.641	1.762	0.001	0.010	−0.208	3.689
	Index	0.000	0.006	−0.513	2.737	0.001	0.010	−0.298	3.876
China	ETF	0.000	0.013	0.071	3.582	0.001	0.013	0.707	6.803
	Index	0.000	0.012	−0.046	2.492	0.001	0.012	0.162	3.519
Eurozone	ETF	0.000	0.008	−0.618	1.474	0.001	0.014	0.241	3.932
	Index	0.000	0.008	−0.513	1.523	0.001	0.014	0.080	2.947
France	ETF	0.000	0.009	−0.744	2.196	0.001	0.014	0.210	3.672
	Index	0.000	0.008	−0.557	1.683	0.001	0.014	0.195	3.887
Germany	ETF	0.000	0.009	−0.506	1.192	0.002	0.014	0.099	3.884
	Index	0.000	0.009	−0.407	1.117	0.001	0.015	0.010	2.576
Hong Kong	ETF	0.000	0.011	−0.296	1.356	0.001	0.013	−0.592	2.045
	Index	0.000	0.011	−0.345	1.512	0.001	0.013	−0.496	1.860
India	ETF	0.000	0.008	0.494	3.816	0.002	0.012	−0.193	4.210
	Index	0.000	0.008	0.464	3.791	0.002	0.014	0.157	6.068
Japan	ETF	0.000	0.010	−0.497	3.693	0.001	0.011	−0.147	1.217
	Index	0.000	0.010	−0.475	3.988	0.001	0.011	−0.046	1.275
New Zealand	ETF	0.000	0.006	−0.521	1.735	0.001	0.009	0.377	1.054
	Index	0.000	0.005	−0.619	3.125	0.001	0.008	0.200	1.002
South Korea	ETF	0.000	0.009	−0.547	2.023	0.002	0.014	−0.119	2.069
	Index	0.000	0.009	−0.580	2.113	0.002	0.014	−0.160	1.860
Taiwan	ETF	0.000	0.009	−1.518	10.212	0.002	0.011	0.051	2.100
	Index	0.000	0.010	−1.177	7.296	0.002	0.012	−0.019	1.270
UK	ETF	0.000	0.008	−0.352	1.560	0.001	0.013	−0.136	1.536
	Index	0.000	0.008	−0.404	1.653	0.001	0.013	−0.088	1.386
USA	ETF	0.000	0.009	−0.616	3.965	0.002	0.013	−0.396	4.410
	Index	0.000	0.009	−0.630	3.928	0.002	0.013	−0.352	4.755

4 Results

The entropy based efficiency estimation results are presented and discussed at two levels. First, a full sample (static) analysis of the informational efficiency of each ETF and its underlying index is undertaken. Next, COVID-19 outbreak's impact on the dynamic informational efficiency is estimated using a rolling window approach.

4.1 Full sample informational efficiency

Figure 1 shows informational efficiency estimates for the static sample across all the chosen time scales ($\tau = 1, \ldots, 30$). The drop in $I_{IME}(\tau)$ for increasing values of τ across all markets is due to decline in underlying entropy as time scale (τ) increases. This is due to the reduction of "pattern richness" after filtering the time series using the coarse-graining procedure. These findings are in line with prior studies using entropy methods on various markets (Ortiz-Cruz et al. 2012; Wang and Wang 2021).

A comparison of various panels lead to novel findings. We see that the efficiency index of ETFs and indices from USA and Canada are consistently lower than other markets. On the other hand, ETFs and indices from China, Hong Kong, Taiwan and Japan are seen to be more efficient than remaining markets. We also see that in many cases, the efficiency levels of ETFs do not exactly mimic the level of efficiency of the underlying indices.

4.2 Dynamic informational efficiency

A rolling window methodology is used to measure the time-varying efficiency for both the ETFs and their underlying indices. Here, we relax the implicit assumption that the efficiency level is constant over time. As the economic environment evolves over time and as unforeseen shocks like covid-19 pandemic unfold, a rolling window analysis helps us examine the time varying nature of efficiency. Should the efficiency levels be stable over time, then the rolling window estimates would not vary much. On the other hand, any instability or change in the efficiency level over time will be captured by the dynamic rolling window estimates (Zivot and Wang 2003). In line with precedence in literature, we use the rolling window length of 252 days (Wang and Wang 2021). The rolling window analysis begins with the estimation of efficiency index, $I_{IME}(\tau)$ for the first window period of 252 daily log return values. Then the window is moved forward based on the chosen value of τ. For $\tau = 1$, the rolling windows moves forward a day. Figure 2 shows the daily ($\tau = 1$) informational efficiency plots of all ETFs and their underlying indices.

Quite a few observations stand out. First, as expected, the efficiency drops during Feb-March 2020 when COVID-19 spread rapidly across the world. In addition, more interesting findings can also be gleaned. The fall in informational efficiency was the most for ETFs and indices from Canada and USA, while the ETFs and indices from China, Hong Kong, Japan, South Korea and Taiwan saw the least drop. Another notable observation is that the level of informational efficiency of several developed markets are lower than other cases even in the pre-covid days. Moreover, we see that in several cases, the efficiency plots of the ETFs and their indices do not coincide, especially after the march 2020 crash (Australia, Germany, New Zealand and Taiwan). An encouraging observation is that the level of informational efficiency is seen to increase towards the end of the plots, suggesting that market imperfections have reduced over time.

Table 3 ETF pre-crash efficiency

ETF	pre-crash I_{IME}
Brazil	0.894
Hong Kong	0.883
South Korea	0.881
UK	0.867
New Zealand	0.856
China	0.847
Australia	0.846
Canada	0.841
India	0.832
Germany	0.823
Taiwan	0.794
France	0.782
Japan	0.769
Eurozone	0.768
USA	0.702

Average of rolling I_{IME} values from January 01, 2018 to January 31, 2020

4.3 Comparison

We compare the relative efficiency of ETFs and the Indices based on the average of rolling efficiency index values before and after the Covid-induced market crash (Feb-Mar 2020). While the covid-induced market crash impacted all ETFs and their underlying indices, the magnitude of impact was different for different countries. Tables 3 and 4 show the average efficiency index values for all the ETFs. Of all the ETFs considered for this study, the ETFs of Brazil and Canada appear to be the most affected by the covid induced market crash. Also, the USA based ETF was among the relatively least efficient ones in both the timelines.

Similarly, Tables 5 and 6 show the average efficiency index values for all the underlying indices. While the results for the indices are qualitatively similar to their ETFs, a few notable exceptions stand out. The Indian equity Index shows a higher level of relative efficiency than its ETF, especially in the pre-crash timeline. For the post-crash timelines, indices of Germany, Eurozone and New Zealand were relatively more efficient than their ETFs.

A visual illustration of the findings pertaining to Tables 3 to 6 is made available in Fig. 2, which shows the dynamic nature of informational efficiency of all the ETFs and indices.

A potential factor behind the relative efficiency of ETFs in the pre-crash timeline could be the differential taxation rules in various geographies.[1] It may be noted that ETFs generate capital gains during rebalancing or creation / redemption process.

[1] We thank the anonymous reviewer for highlighting this aspect.

Table 4 ETF post-crash efficiency

ETF	post-crash I_{IME}
Hong Kong	0.794
China	0.714
Taiwan	0.690
South Korea	0.681
Japan	0.671
UK	0.587
Australia	0.578
Brazil	0.540
India	0.532
New Zealand	0.528
France	0.523
Germany	0.484
Eurozone	0.451
USA	0.417
Canada	0.310

Average of rolling I_{IME} values from April 01, 2020 to April 30, 2021

Table 5 Index pre-crash efficiency

Equity Index	pre-crash I_{IME}
Brazil	0.922
Hong Kong	0.895
China	0.876
India	0.871
South Korea	0.870
New Zealand	0.864
UK	0.850
Australia	0.847
Taiwan	0.834
Canada	0.829
Germany	0.814
France	0.796
Eurozone	0.780
Japan	0.762
USA	0.706

Average of rolling I_{IME} values from January 01, 2018 to January 31, 2020

While ETF sponsors in developed economies are liable to pay capital gains taxes, such capital gains are not taxed in many emerging economies such as India and China (Shadforth et al. 2020; Ramachandran and Saha 2020). Further, emerging markets across the globe offer tax friendly policies towards non-resident institutional investors (Blitz et al. 2012). On the other hand, investors in developed markets resort

Table 6 Index post-crash efficiency

Equity Index	post-crash I_{IME}
Hong Kong	0.803
Taiwan	0.745
China	0.726
South Korea	0.675
Japan	0.661
UK	0.586
New Zealand	0.570
Germany	0.552
Australia	0.539
Brazil	0.533
Eurozone	0.521
India	0.517
France	0.517
USA	0.402
Canada	0.311

Average of rolling I_{IME} values from April 01, 2020 to April 30, 2021

to trading ETFs so as to take advantage of various taxation loopholes such as tax loss harvesting and redemption in kind (Bouchey et al. 2016; Mider et al. 2019). Consequently, it is very likely that the relative ranking of ETFs is a function of differential taxation and regulatory environment across geographies. The findings of this study in-connection with relative efficiency levels are, to some extent, in alignment with Morningstar's recent Regulation and Taxation Scorecard for various economies (Pettit et al. 2020).

5 Conclusion

This study analyses the informational efficiency of domestic ETFs and their underlying indices across various markets during the COVID-19 outbreak. We estimate informational efficiency using a refined multiscale entropy-based efficiency index. This methodology is used to measure static and dynamic efficiency of the ETFs and their underlying indices. The takeaways from this study are as follows. First, COVID-19 led to a decline in efficiency of all ETFs and their indices. This inference is based on the rolling window estimations that capture the relative efficiency of ETFs and their underlying indices over time. These findings are in line with literature that have examined the impact of crises on financial markets (Lim et al. 2008; Ortiz-Cruz et al. 2012). Further, the efficiency of ETFs and their indices revert to pre-crash levels since Jan-Feb 2021. This transient deterioration in efficiency levels followed by subsequent reversion of the same is in alignment with Adaptive Market Hypothesis (Lo 2012) and is indicative of agents exhibiting lower rationality during market turbulence. The drop in efficiency during COVID may be attributed to increased fear among investors (Subramaniam and Chakraborty 2021).

Fig. 1 Static Efficiency plots (I_{IME} across Time Scales, τ)

Second, developed markets exhibit relatively lower levels of efficiency than most other emerging markets during the covid-19 induced market crash. Put differently, not all domestic ETFs were equally impacted by the covid-19 crisis. The magnitude

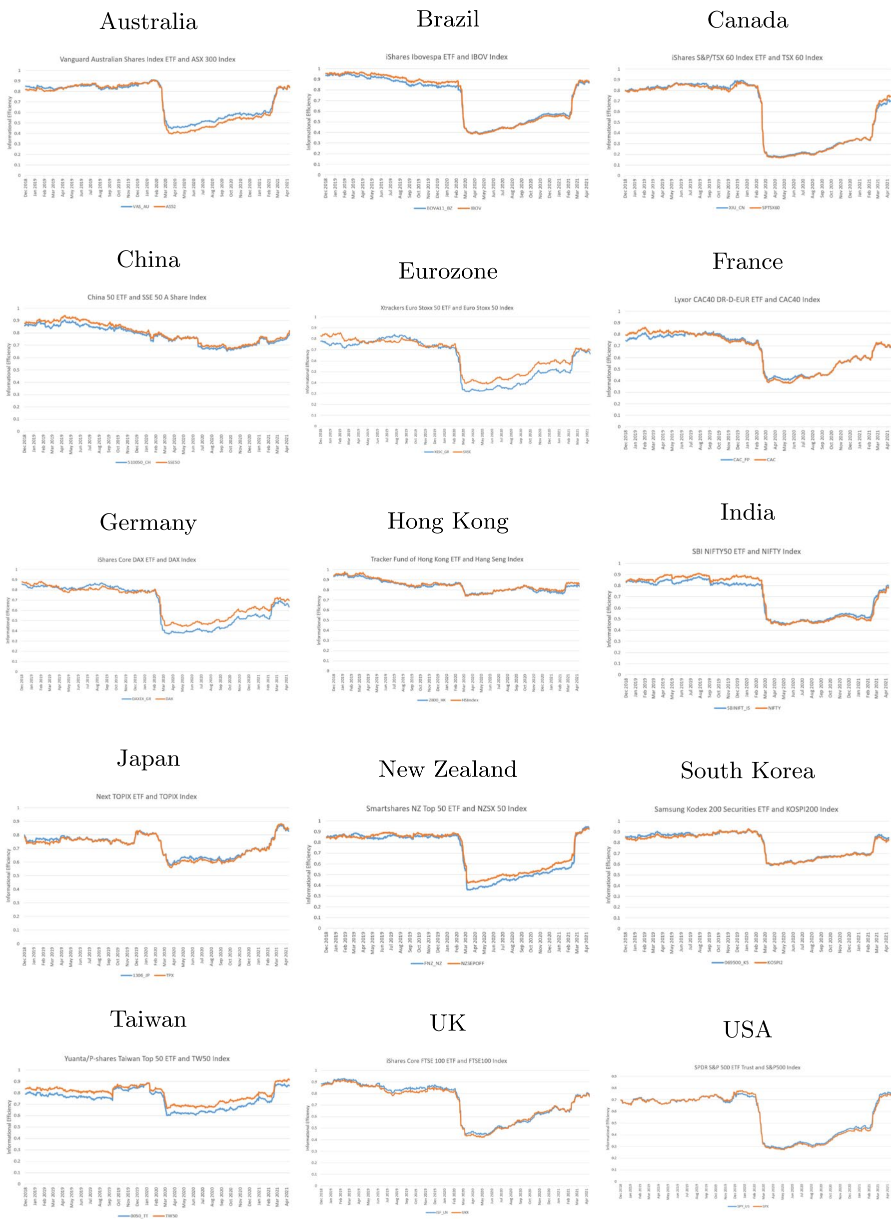

Fig. 2 Dynamic Efficiency plots [$I_{IME}(\tau = 1)$] from January 2018 to April 2021

of drop in efficiency could be due to the degree of distrust in governments. For instance, Engelhardt et al. (2021) reported that volatility of equity markets in high-trust countries was significantly lower than low-trust countries during covid. Third, ETFs and indices pertaining to several developed markets were found to be less efficient than their emerging market counterparts even during the pre-covid timeline. As stated earlier, we believe that differential taxation on ETFs across the globe may be a contributory factor in this regard. Fourth, our findings indicate that not all domestic ETFs considered for this study exactly mimic the dynamics of the underlying indices. In conclusion, these findings should nudge investors to deal with domestic ETFs on a case-to-case basis.

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Data and Code availability The data that support the findings of this study are available from Bloomberg but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of Bloomberg and the source code for analysis associated with the current submission is available at https://doi.org/10.1007/s11517-017-1647-5.

Declarations

Conflicts of interest The authors declare that they have no conflict of interest.

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