High Short Interest Stocks Performance during the Covid-19 Crisis:
An Informational Efficacy measure based on Permutation- Entropy Approach

Abstract

Purpose

We examine the performance of a number of High Short Interest stocks along with the prices of the GameStop stock and three major stock exchange indices, particularly for the period after the eruption of the Covid-19 crisis.

Design

With the employment of the complexity-entropy causality plane approach we categorize the stock prices in terms of the level of informational efficiency.

Findings

We reported that the efficiency level for the index of the High Short Interest stocks falls considerably, not only at the onset of the Covid-19 crisis but during the health crisis period at hand. This is translated into proof of less uncertainty in predicting the stock prices of these specific stocks. On the other hand, the GameStop prices exhibit the same behavior as those with the high short interest firms, but change considerably in the middle of the crisis. The reversal of the behavior, by obtaining higher informational efficiency levels, is attributed to the short squeeze frenzy that increased the price of the stock many times over. Among the stock market indices, the Dow Jones Industrial Average and the S&P 500 decreased their efficiency levels marginally, after the surge of the crisis, while the Russell 2000 index kept the level intact. The high and stable degree of randomness could be attributed to the measures taken concurrently by the Federal Reserve and the government immediately after the outbreak of the crisis.

Originality/value

This is one of the few studies that examine the impact of short selling behavior on the efficiency level of certain stocks' prices, particularly during the health public crisis. It provides an alternative approach in measuring quantitatively the degree of inefficiency and randomness.

Keywords: Efficient Market Hypothesis, Stock Exchange Markets, Public Health Crisis, Short Selling, Permutation Entropy, Information Efficiency

1. Introduction

Global pandemic events have caused major economic fallout and had seismic effects on financial markets. The Covid-19 pandemic belongs to this category and is considered the most perilous pandemic in the last century. The effects of the pandemic were immediate and devastating, causing a paralysis in economic activity, while financial market functioning was severely disrupted. The Federal Reserve (FED) responded rapidly and boldly by increasing liquidity and aiming to ease the vast turbulence in the stock exchange market, where at the outbreak of the pandemic security prices plunged extraordinarily. Major stock market indices declined by more than 35% of their value, from the higher point on February 20th to March 23rd of 2020.

The meltdown in prices was likely further exacerbated, among other things, by the bearish strategy of the investors who went short in an attempt to increase their profits from the position of selling high and buying low (Miller, 1977, Curtis and Foster, 2014). The view that in downward price trend "predatory" short selling could bring down solvent companies is substantiated, apart from the 1929 incident of stock manipulation and the imposition of the Security Exchange Act in 1934, by the ban of short selling imposed by the SEC during the 2007-2008 crisis. The temporary ban initially issued for the so-called "naked" short selling and later, in September 2008, the prohibition of short selling increased to around 1,000 financial stocks.

Nowadays, short selling as an investment strategy is used much more often than twenty years ago. A plethora of researchers argue that short selling enhances price efficiency, since short sellers have the ability to identify overvalued stock prices (price discovery) and utilize all possible information better (Desai *et al.*, 2002; Boehmer *et al.*, 2008; Diether *et al.*, 2009). When it comes to imposing short selling constraints during normal times, the prices no longer include all available information (positive and negative) and consequently, information efficiency decreases as well as the prices, while price volatility increases (Curtis and Foster, 2014; Duffie *et al.,* 2002; Bai *et al.,* 2006).

On the other hand, a subset of papers argue that the activities of short sellers, informed or uniformed, especially when stock markets are under stress, are highly controversial and that they use predatory techniques that may lead to stock manipulation, to artificially force prices down, inducing price volatility and constraining information efficiency (Allen and Gale, 1992). Brunnermeier *et al.* (2014) argued that although short selling during normal times could be beneficial, in times of distress predatory short selling technique could further depress the stock prices of financial institutions even for solvent ones. Apart from the above argument, it is by now recognized as Asquith *et al.* (2005) put it, “stocks with high short interest ratios underperform the market and that the higher the short interest ratio, the lower is the subsequent performance”.

In this paper, we examine the performance of a number of highly shorted firms and we calculate the fluctuation of the informational efficiency level, especially during extremely anxious times, such as the recent Public Health Crisis. We proceed with the construction of an index comprising a number of High Short Interest stocks, with a short interest ratio (e.g. short interest / shares outstanding) of over 20%. Although there is no hard rule of what percentage is regarded as high short interest, generally the 20% threshold is used in many market reports, given that the average short interest of the S&P 1500 index was around 4.4%[1]. The High Short Interest Index is calculated as an arithmetic mean, with a base of 100[2]. In addition, we separately examine the prices of the GameStop stock, which for a long period of time was on the radar of considerable institutional short interest. However, in the middle of the recent Public Health Crisis, and, specifically in January 2021, an unanticipated short squeeze frenzy occurred,

[1] There are numerous market reports referring to high short interest stocks with more than 20%, like the marketwatch https://www.marketwatch.com/story/these-20-stocks-have-short-interest-of-19-or-more-and-amc-and-gamestop-are-not-even-in-the-top-half-11663262098. Also S&P Global Market Intelligence, https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/short-selling-of-consumer-discretionary-stocks-hits-highest-point-in-a-year-68898461

[2] Based on the S&P Global Market Intelligence, we’ve included the following firms that constitute the high short interest index: Blink Charging, Workhorse Group, B&G Foods, Beam Global, PetMed Express, BlackBerry, and Bed, Bath & Beyond. An important factor in including a high shorted stock in the index (besides the 20% shorting interest) is that the time series should start from January 2011.

trapping hedge funds and short selling investors. Lastly, as "typical control variables", we measured the information efficiency of three major stock exchange indices: the Dow Jones Industrial Average Index (DJIA), the S&P 500 and the Russell 2000 as the representative of small firms defined by their capitalization. Data were collected from Bloomberg.

The sample spans from January 2011 to the end of December 2021 and is divided into two uneven subsamples. The first subsample starts from January 3th, 2011 until February 20th, 2020, and the second – the public health crisis – from February 21st, 2020 to December 28th, 2021. By doing this we hope to shed light concerning the changing characteristics of the data and the evolution of the informational efficiency especially for the Covid-19 period. The uneven samples could not influence the reliability of the results since we measure efficiency, with quite enough data points, aiming in highlighting the evolution of the informational efficiency changes through time. The motivation of examining the behavior of the short interest stock during the health crisis comes from the notion that complex systems such as the exchange stock markets unveil clearly their characteristics when they're in distress. We expect to improve our understanding of the mechanism behind such dynamics, and consequently to develop early warning systems in predicting periods of financial distress. In doing so, we utilize a novel concept named permutation entropy (PE), along with the entropy-complexity causality plane (ECCP) in an effort to measure the degree of informational efficiency of the specified financial instruments.

The remainder of the study is organized as follows. Section 2 reviews the existing literature, section 3 describes the information-permutation theory along with the permutation entropy causality plane. In section 4 we provide the descriptive statistics for the financial indices, and discuss the empirical results obtained by using the permutation entropy and the causality plane. In section 5 we present our conclusions.

2. Literature Review

Informational efficiency is closely related to the so-called Efficient Market Hypothesis (EMH). Although the EMH concept goes back to 1900, when Bachelier (1900) stated the difficulty of predicting the financial market returns, it was not until 1965 and 1970 that Samuelson (1965) and Fama (1970, 1991) demonstrated that stock prices are described by a random walk, as all available public information are absorbed and incorporated immediately in the stock prices. In such an environment, investors have no ability to predict prices and gain in a systematic way. But following the dot.com crisis of 1999-2000, researchers scrutinized the EMH and were convinced that price irregularities could exist in stock returns at least for a short period of time[3], while others point out that because information is costly, stock prices do not absorb all information (Grossman and Stiglitz , 1980)[4].

A large strand of literature investigated the validity of EMH and has found mixed evidence. Some researchers concluded that there is no supporting evidence of the hypothesis, nor that the stock prices evolve according to a random walk (Barkoulas and Baum, 1996; Lo and MacKinlay, 1999). Expanding this literature, Ito & Sugiyama (2009) showed that in the case of US stock exchanges, the efficiency level varies substantially through time. In the international sphere, some literature has introduced the Hurst exponent concept and, by examining 60 various stock exchange markets, documented a strong positive correlation between market efficiency and predictability, which is a clear contradiction of the random walk theory (Eom *et al.*, 2008). In addition, investigation of the bond market within the EU reveals different memory dynamics among the various bonds just after the outbreak of the 2008 crisis (Bariviera *et al.,* 2012). With the Hurst exponent measuring long range memory, they show that the information efficiency for corporate bonds deteriorates during the financial crisis in contrast to the enhanced efficiency of the sovereign bond markets. Wang *et al.* (2020) reported that the market slow

[3] Please see Robert Shiller (2000).

[4] For a thorough analysis of the EMH please see B.G. Malkiel (2003).

incorporated public shorting information into prices, an outcome which is inconsistent with the semi-strong form of market efficiency. On the same vein, with the employment of simple statistical analysis Vasileiou *et. al.* (2020) reported that during the Covid-19 period, stock markets do not include all available information on time and in some periods markets exhibit irrational and inefficient behavior. Recently, Vasileiou (2022b) examined the impact of the Russo-Ukrainian War on oil, wheat, and natural gas with the use of the exponential and the threshold asymmetry GARCH models and documented abnormal conditions of the above markets. Scherf *et. al.* (2022) found that stocks markets- during the Covid-19 period and especially at the announcement of the lockdown- showed signs of underreaction with a significant post-announcement drift. This delayed response by the stocks to absorb all available information is considered by the authors a rejection of the EMH.

The entropy concept, among other applications, was utilized to measure stock exchange efficiency and to characterize the complexity of financial markets. In light of the recently growing literature on the entropy concept, Zhang (1999) proposed the conditional entropy method to measure stock exchange efficiency, while Zunino *et al.* (2010) attempted to differentiate the degree of market progress among mature and emerging financial markets[5]. They reported that emerging markets display much less informational efficiency based on the PE and ECCP technique. Hou *et al.* (2017) examined the level of Permutation entropy (PE) variation in the Chinese stock markets. They concluded that efficiency decreases significantly especially in two instances, one when the market exhibited an increased trend and the other when there was a market crash. On the same vein, Siokis (2018) investigated the level of the informational efficiency for specific financial instruments of the U.S. financial markets, before and just after the outbreak of the Great Recession. He revealed that after the certain events and namely the credit crunch and Lehman Brothers' collapse, the efficiency level of short term

[5] Also Zunino et al. (2012) investigated the bonds market and, by using daily values, revealed strong correlations between developed and emerging markets.

instruments' yield deteriorated. Among others, Lahmiri and Bekiros (2020) explored the advancement of the informational efficiency for a number of cryptocurrency markets and stock exchanges, prior and during the Covid-19 public health crisis. By using the approximate entropy method, they concluded that the stability degree along with the regularity was dramatically affected during the Covid-19 period. They also concluded that the cryptocurrency fluctuations affected more than the equity markets. Parietti *et al.* (2021) considered the Cross-sample entropy (CSE) estimation under a nonparametric approach and gave a general estimation framework. The authors applied the CSE to two foreign exchange rates namely the CAD/USD and SGD/USD in order to study the synchrony of the exchange rates namely the Canadian to USD dollar (CAD/USD) and the Singapore to USD dollar (SGD/USD), before and after the 1999 Asian financial crisis. Based on the bootstrap-type method, the authors obtained a more realistic estimation of the cross-sample entropy (CSE) statistics and reported that the synchrony level for the exchange rates was higher after the 1999 Asian financial crisis. Other researchers (Bariviera *et al.,* 2015) studied the fluctuation of the Libor rate during the 2007-2008 timeframe and revealed an anomalous behavior. Lastly, entropy based applications measuring the efficiency level can be found in other financial markets such as in foreign exchange, in energy markets or in real estate markets (Zunino *et al.,* 2016; Oh *et al.*, 2008; Risso, 2008; Alvarez-Ramirez *et al.,* 2012; Martin *et al.,* 2011; Ortiz-Cruz *et al.,* 2012; Argyroudis and Siokis, 2019).

3. Methodology

3.1. Permutation entropy

The concept of entropy originated from the study of thermodynamics, but it has been utilized in numerous research fields. When it comes to the information theory, entropy is a general measure investigating the information content of a probability distribution. One procedure of estimating the probability distribution, which is based on Shannon's entropy is the Bandt and Pompe (B&P) (2002) method, mapping the continuous time series onto an ordinal encoding. This procedure is called permutation entropy (PE) and it measures the complexity of a time series. It has been applied to different disciplines, other than in geophysics, from the financial markets, as discussed before, to astrophysical plasmas (Weck *et al.,* 2015) to epileptic seizures, (Cao et al., 2004; Li *et al.,* 2007 Bruzzo et al., 2008), heartbeat dynamics (Frank et al., 2006; Bian *et al.,* 2012) and the effects of anesthetic drugs (Olofsen *et al.*, 2008; Li *et al.*, 2008). The PE approach can be applied to both the non-stationary and nonlinear signals and the main advantages are the simplicity of the process, the high computational speed and the fact that there is need for fewer input-parameters, leading to no assumptions about the underlying stochastic process.

In view of the fact that measures of entropy do not adequately quantify the degree of structure in a dynamic process, a statistical complexity measure was used by Lamberti *et al.* (2004)[6]. The complexity measure assists in detecting essential details of the dynamics, while differentiating various degrees of periodicity and chaos[7]. This arbitrary time series is defined in terms of a window length called the embedding dimension d. The embedding dimension determines the size of patterns investigated in calculating the entropy and complexity of the series. The instances of each ordinal patterns of that size are counted in order to associate an ordinal pattern probability distribution with the time series, after which the calculation of entropy and complexity is straightforward.

Given a one-dimensional time series $\{x_i: i = 1,2, ..., N\}$, where N is the length of the sample, we can generate a vector $X_t = (x_t, x_{t+1},...,x(_{t+(d-1)\ \tau}))$ with d is the dimension and the length of each vector, where $t=1, 2, ..., N-(d-1)\tau$ and τ is the time delay. Each vector can be sorted in an ascending order and for d different numbers there will be $d!$. the embedding dimension $D > 1$, and a lag (time delay) τ, consider the ordinal pattern which is defined for a segment $s = (x_t, x_{t+1},...,x_{t+(d-1)})$ of the time series as the permutation π of the index set $\{0,1,...,d - 1\}$ corresponding

[6] The measure of complexity was first advanced by R. López-Ruiz et al. (1995).
[7] Please see Zanin et al. (2012).

to the ranking of the x_i in ascending order, namely $x_{\pi t} < x_{\pi t+1} < \ldots < x_{\pi t+(d-1)}$. In order to have a unique result, if $x_i = x_j$ where $i < j$, then the ranking is $x_i < x_j$. Given a time series of length N, the corresponding ordinal pattern probability distribution $P = \{p(\pi)\}$ is defined in terms of all $N - d + 1$ length d segments s in the series and all $d!$ permutations π of order d by

$$p(\pi) = \frac{\#\{s \mid s \leq N - d + 1; (s)\, has\ type\ \pi\}}{\mathrm{N} - d + 1} \qquad (1)$$

Where # stands for frequency of occurrence of π. $p(\pi) = |\{s : s \text{ has ordinal pattern } \pi\}|\ N - d + 1$. The permutation entropy (PE) is based on Shannon's information entropy which measures the uncertainty of a process and is described as:

$$PE(d) = -\sum_{i=1}^{N} p_i(\pi) \log_2 p_i(\pi) \qquad (2)$$

The permutation entropy value lies between 0 and log(d!) when the probability $P_i = 1/d!$ and the Shannon's entropy index takes the highest value, which is $\log_2(d!)$. In other words, a completely increasing or decreasing time series takes a value of 0 and a completely random system where all d!

3.2. Complexity entropy causality plane

For convenience we normalize equation (2) dividing it by $\log_2(d)!$, which is the maximum entropy. The outcome is the normalized Shannon entropy ($H[P]$) given as.

$$H_s[P] = [-\frac{\sum_{i=1}^{D!} p_i(\pi) \log_2 p_i(\pi)}{\log_2 d!}] \qquad (3)$$

The value range of $H_s[P]$ is between 0 and 1 and it measures the randomness of the time series. When $H_s[P] \to 0$ the time series is defined regular and could be considered predictable with greater certainty. If $H_s[P] \to 1$ the time series is considered random, with no memory in the series, so last period's price change does not dictate today's period price change.

The calculations of permutation entropy depend crucially on the selection of *d*. If *d* takes a small number (mainly less than 3), the procedure loses effectiveness and it will work inaccurately, given the existence of only a few distinct states. Further, a large *d* causes memory restrictions. B&P proposed the embedding dimension to be set between 3 and 7, conditional to the length of the time series. Usually, based on the criterion N>>d!, the chosen pattern length of d is equal to four with a time delay τ of one. [8]

In order to take into account the degree of correlation structure, along with the randomness of a time series, a relation called statistical complexity measure (SCM) is utilized. This is based on the Jensen-Shannon complexity (C_{JS}) defined as[9] [10].

$$C_{JS}[P] = Q_J\,[P, P_e]\,H[P] \tag{4}$$

P_e is the uniform probability, Q_J is the disequilibrium of the Jensen-Shannon divergence, quantifying the difference between at least two probability distributions. Note that in the case of more states, like the accessible ones, the quantity Q_J takes values other than zero. By normalizing the disequilibrium, i.e. $0 \leq C_{JS} \leq 1$ then

$$C_{JS}[P] = -2\frac{S[\frac{P+P_e}{2}] - \frac{1}{2}S[P] - \frac{1}{2}S[P_e]}{\frac{N+1}{N}\log(N+1) - 2\log(2N) + \log(N)}H[P] \tag{5}$$

[8] Also, pattern length of d=3 and d=5 were estimated in order to ensure behavioral similarity.

[9] Lopez-Ruiz *et al.* (1995) introduced the statistical complexity measure and further advanced by Rosso *et al.* (2007) by introducing the CH-plane.
[10] Another approach for calculating the complexity-entropy causality plane introduced recently based on Tsallis q entropy (Ribeiro *et al.*, 2017).

It is worth noting that the SCM depends on two different probability distributions: the one associated with the system under analysis P and the uniform distribution P_e [11][12].

4. Descriptive statistics and empirical results

4.1 Descriptive statistics

We analyzed daily stock price levels of a High Short Interest Index, the GameStop stock prices and three major stock market indices, the Dow Jones Industrial, the S&P 500 and the Russell 2000. Table 1 illustrates the summary statistics of the indices, for the Covid-19 period, the pre-period of Covid-19, as well as for the whole sample. Along with the mean, median and minimax statistics, we present the standard deviations showing the changes between the two sub-periods. In terms of the mean, the statistics reveal than among all indices the stock of GameStop has the highest annualized return for the Covid-19 period, followed by the High Short Interest index. The main stock market indices, the DJIA, S&P 500 and Russell 2000, are all exhibiting very similar annualized average returns, between 0.14% and 0.19%. Please note that the GameStop and High Short Interest indices, for the pre-Covid 19 period exhibit negative annualized returns compared with the positive returns of the main Market Indices. The higher annualized average return is associated with a higher volatility as well, based on the standard deviation. The GameStop exhibits by far the highest volatility, while the main Stock Indices consistently are very close to each other. In comparison with the pre-Covid-19 period, the standard deviation of the High Short Interest Index is much higher – more than doubled – during the Covid-19 period, while for the GameStop prices, the increase is remarkably higher,

[11] Soriano *et al.* (2011).

[12] Vignat and Bercher (2003) have shown alternatively that the Fisher-Shannon information plane can be used in a context on non-stationary detection.

almost fivefold, increasing from 0.028 to 0.134[13]. In addition, all series show platykurtosis with the GameStop to exhibit a higher change from pre-period to Covid-19 period.

Fig. 1 illustrates the actual performance of the High Short Interest Index, GameStop prices, the Dow Jones, the S&P 500 and the Russell 2000 indices over the full sample period. This figure clearly indicates that there is an abrupt nosedive at the onset of the Public Health Crisis, which is more noticeable in the three major stock exchange indices. The High Short Interest Index and the GameStop were not impacted as much, since the downtrend established at the pre-Covid-19 period continued as we moved into the Public Health Crisis. In particular, the downtrend for the high shorting interest index continued for about 10 days after the breakout of Covid-19, when the index changed trend until September 2020 and high volatility started to emerge. On the other hand, GameStop prices were trending downwards until September 2020, and the trend reversed, with prices sharply increased in January 2021, when the short squeeze was initiated.

4.2 Empirical results

This section computes the quantifiers of the stock exchange indices and information efficiency, for PE and statistical complexity, with embedding dimension $d=4$ and delay $\tau=1$.
We define as a fully efficient index, when the quantifier for PE takes the maximum value of 1 and for the JC statistical complexity the value of 0. In this setting, the times series is defined as random, prices follow a perfect random walk, and all available information is taken into account. But in the opposite case, when there is a significant departure from the two points above, with lower level of information efficiency, then one could predict prices with greater certainty[14].

[13] For the GameStop prices Vasileiou (2022a) found that the GME returns were not randomly distributed and the volatility increased when the GME prices increased.
[14] See Zunino *et al.* (2010)

Fig. 2 presents the localization for the stock market indices for the pre-Covid-19 period and the Covid-19 period. For the pre-period, the quantifiers of the indices are located between the 0.93 and 0.95 level, while the statistical complexity is low and between 0.07 and 0.09, dictating thus that there is a random behavior and no memory in the indices. In contrast, the Covid-19 period exhibits some interesting outcomes. Although, the stock exchange indices, namely the DJIA and the S&P 500 display a marginal decrease in terms of permutation entropy and increase in statistical complexity, the High Sort Interest Index displays much lower permutation entropy (0.89) and higher statistical complexity (0.15). In comparison with the quantifiers of the pre-Covid-19 period (0.935 and 0.098, respectively), this is translated into a diminishing efficiency level during the health crisis. For the GameStop prices one would expect the same behavior as with the High Short Interest Index. However, instead of a drop in information efficiency, the GameStop quantifiers of the Covid-19 period exhibit a much higher level compared with the pre-Covid-19 period. The divergence and the increase in information efficiency, during the health crisis is attributed to short squeeze frenzy initiated in the middle of the health crisis. In fig.2 we also include the quantifiers of the shuffled time series, after randomly shuffling the data, for the purpose of removing any temporal correlations. Both entropy and complexity are located in the corner of the right hand of the phase plane and their values are very close to unity and zero respectively, confirming the random walk theory.

Additionally, table 2 presents the quantifiers for both periods along with the inefficiency level which is calculated by taking the Euclidian distance, such as

$$D = \sqrt{(H_s - 1)^2 + (C_{js})^2} \tag{6}$$

In this setting, a higher level (or longer distance) is interpreted as an increase in inefficiency, taking into account the entropic measure, where Hs =1 and statistical complexity, Cjs=0. Evidently, for the Covid-19 period, the calculated higher inefficient value obtained for the high short interest index (0.180) compared with (0.112) of the pre-Covid-19 period and the lower value for the GameStop (0.097) compared with (0.109) support our previous findings.

For the next step we present the dynamic time advancement of the quantifiers as a robustness check of our previous findings and we draw the inefficiency level. Utilizing one- and-a-half-year window, which is equal to about 350 business days, and shifting the series through time with a step of 1 day, we calculate the changes of the PE and JS statistical complexity quantifiers for the total time series[15]. Figure 3 depicts the changes taking place and the locations of the various indices, within the entropy-complexity causality plane. At this point, we also include a separate diagram for Bed, Bath & Beyond (BB&B) quantifiers, as a prominent example of a meme stock (a stock that gained popularity during the Covid-19 period, through the social media, like the GameStop). BB&B is still subsumed in the calculations of the High Short Interest Index.

In contrast to the pre-Covid-19 period, almost all data points of the High Short Interest Index, for the Covid-19 period are located in the left and higher part of the diagram, depicting lower entropy and higher complexity. It signifies an increase of inefficiency during the health crisis and sketches a more predictable pattern. The same outcome is depicted for the BB&B prices with lower entropy and higher statistical complexity, during the crisis. With regards to GameStop, the data points – for the Covid-19 period – are overspread from a low entropy level of 0.89 and high complexity level of 0.16 to a level of 0.95 and 0.07, respectively. Interestingly, the lower informational efficiency level, that is, lower entropy level and higher statistical complexity, is recorded from the onset of the crisis to late December 2020. From that point on, the informational efficiency level steadily increases, marking the period of the short squeeze frenzy. Lastly, for the DJIA and the S&P 500 indices, the efficiency level does not significantly

[15] Testing the procedure by considering alternative windows, i.e. a two-year window, with 500 business days, and step of one day produces almost similar results, although quantifiers depict lower fluctuation.

change between the two periods, while for the Russell 2000 index the informational efficiency level increases.

Similarly, based on sliding window methodology, fig. 4 depicts only the normalized Shannon's entropy quantifier. Using one- and-a-half-year window, equivalent to about 350 business days, and shifting the series through time with a step of 1 day, we calculate the efficiency changes of the Shannon entropy for the total time series. One interesting issue stands out by looking the two first graphs of fig.4. Comparing the High Short Interest Index with GameStop for the pre-Covid-19 period, one could easily notice the strong co-movement of the series with the correlation coefficient of 0.60. Two main features of the informational efficiency quantifiers stand out during the pre-Covid-19 period: The similar trough point of the fluctuation of the values appears for both indices that took place in September 2013, as well as the peak point reached around March-April 2015. However, during the Covid-19 period, their paths diverged significantly with the correlation coefficient becoming strongly negative (-0.77). While the High Short Interest Index efficiency quantifier decreases significantly and deteriorates during the health crisis, the GameStop efficiency quantifier gradually increases its value, after an initial decrease at the onset of the crisis. The change in trend appears to have taken place just at the time of the short squeeze engagement. As for the information efficiency of the main stock exchange indices, DJIA and the S&P 500 decreased initially and stayed on average at the same level while the Russell 2000, after the drop, recorded an upward trend with enormous variability.

5. Conclusion

Our study analyzed the price movement of a number of heavily shorted stocks for the period of January 2011 – just after the Great Recession – until the end of December 2021. We divided the sample into two sub-periods and applied the permutation entropy approach to a number of stock exchange indices. We demonstrated that the informational efficiency level of the high short interest index – as quantified by the complexity entropy causality relation – decreased significantly and became more complex during the Covid-19 period than during the pre-Covid-19 period. Therefore, we confirm previous studies that sort selling in times of distress could amplify volatility and price declines further [8,9]. It is important to compare such behavior with the quantifiers estimated from the DJIA and the S&P 500 indices, which do not reveal any significant informational change between the two sub-periods. Against this background, GameStop stock price, which was subject to high shorting interest, by Hedge Funds and short sellers and consequently to short squeeze, exhibited the opposite behavior, with increased informational efficiency level, during the Public Health Crisis? The change in price information behavior is attributed solely to the triggered short squeeze in January 2021.

The above results are supported by the sliding window methodology, which measures the time variation. While, for the case of the high short interest index, most of the data points are on the upper left hand side of the phase, for GameStop, the permutation entropy effectively detects the dynamic changes in price behavior and confirms the previous results. For the DJIA and the S&P 500, the efficiency level does not fluctuate significantly, while the Russell 2000 increases at the onset of the crisis. Although the Public Health Crisis spread throughout the financial markets, the liquidity provided immediately by the Fed and the cash payments legislated by the government helped the financial markets to recover steadily and to test new record levels during the health crisis.

For the last 15 years or so, the Security and Exchange Commission (SEC) has shown a high degree of concern with the activity of the short sellers, following sharp market price declines. Despite the severity of the health crisis and the abrupt decrease of the prices, regulators did not implement any restrictions in short selling to help stabilize the markets as they did with great assiduity in the 2008 crisis, when they issued a temporary ban on the short selling of a number of financial stocks.

The outcome of our study offers some practical insights for practitioners and regulators in the stock exchange markets. Firstly, regulators should consider that Covid-19 crisis impacted informational efficiency in a non-uniform manner and this should be a sign of refocusing on stocks with high short interest. As for the practitioners, extreme outcomes in the markets, such as the Covid-19 period following the Great Recession of 2008, have an impact on the welfare of investors and shareholders and in terms of predictability, the time varying process of the information efficiency gives support to fundamental trading analysis strategy, containing probably forecasting signals. Lastly, with respect to portfolio management, the drop in the efficiency level particularly for the high short interest stocks could be used as an indication for portfolio rebalancing/asset allocation guidance and diversification.

Future studies could expand our findings by taking into consideration a greater number of high short interest indices, especially by sector and by testing other major financial crises.

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Figure 1. The evolution of security price changes for selected stocks and indices.

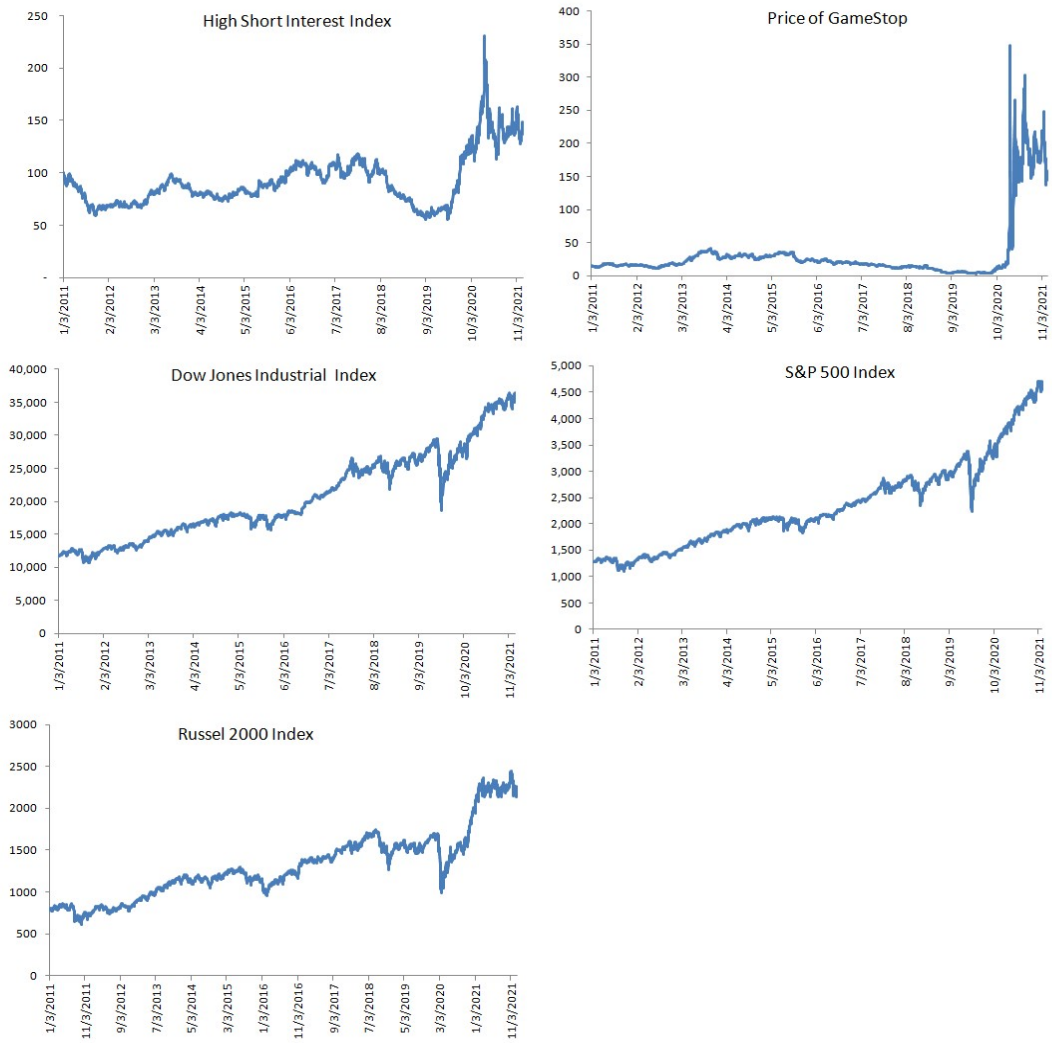

Figure 2. Localization of the various security prices and indices in the Complexity Entropy Causality Plane with d=4 and t=1, before and during the Covid-19 crisis. We also depict the quantifiers, (located at the lower right hand area) after randomly shuffling the data, for the purpose of removing any temporal correlations.

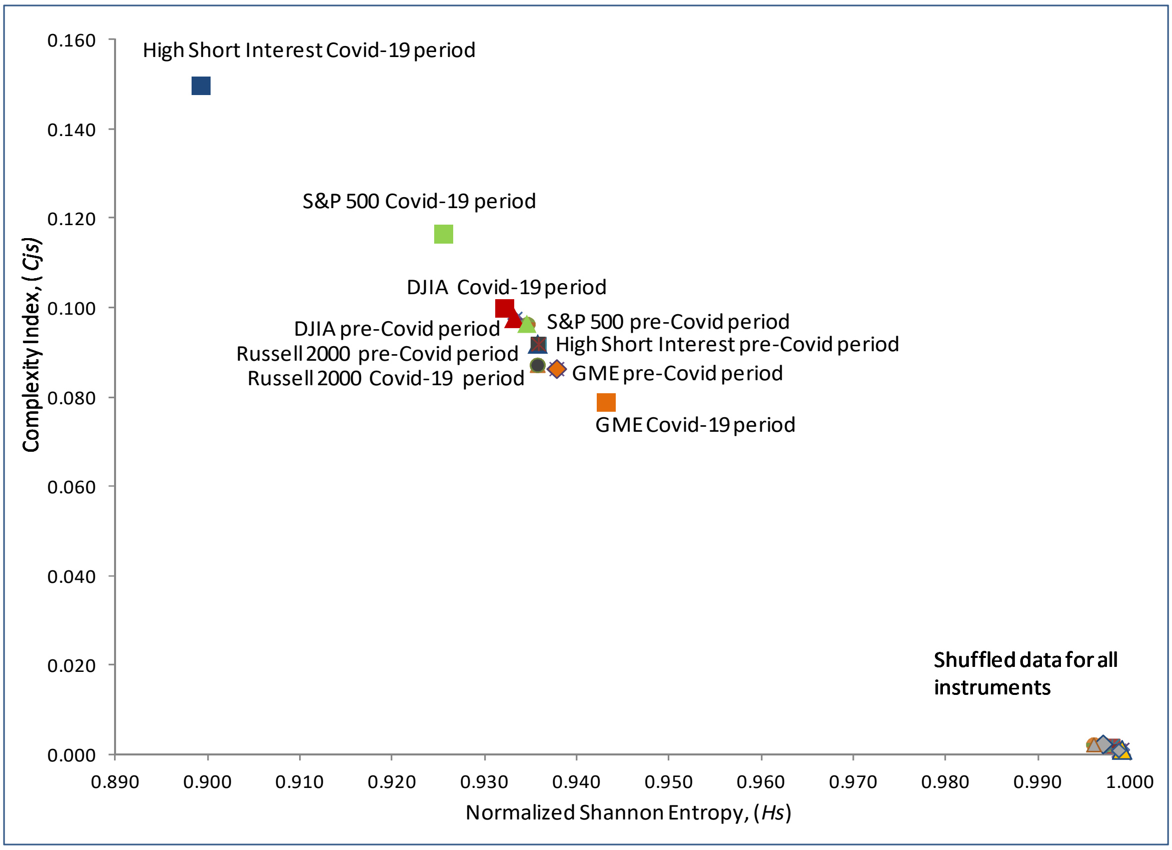

Figure 3. Time evolution of positions of stock indices in the complexity–entropy causality plane before and during the Covid-19 crisis. The points highlighted with red color depict the Covid-19 period. For the Covid-19 period , High Short Interest Index and BBE exhibit less informational efficiency (lower entropy and higher complexity).

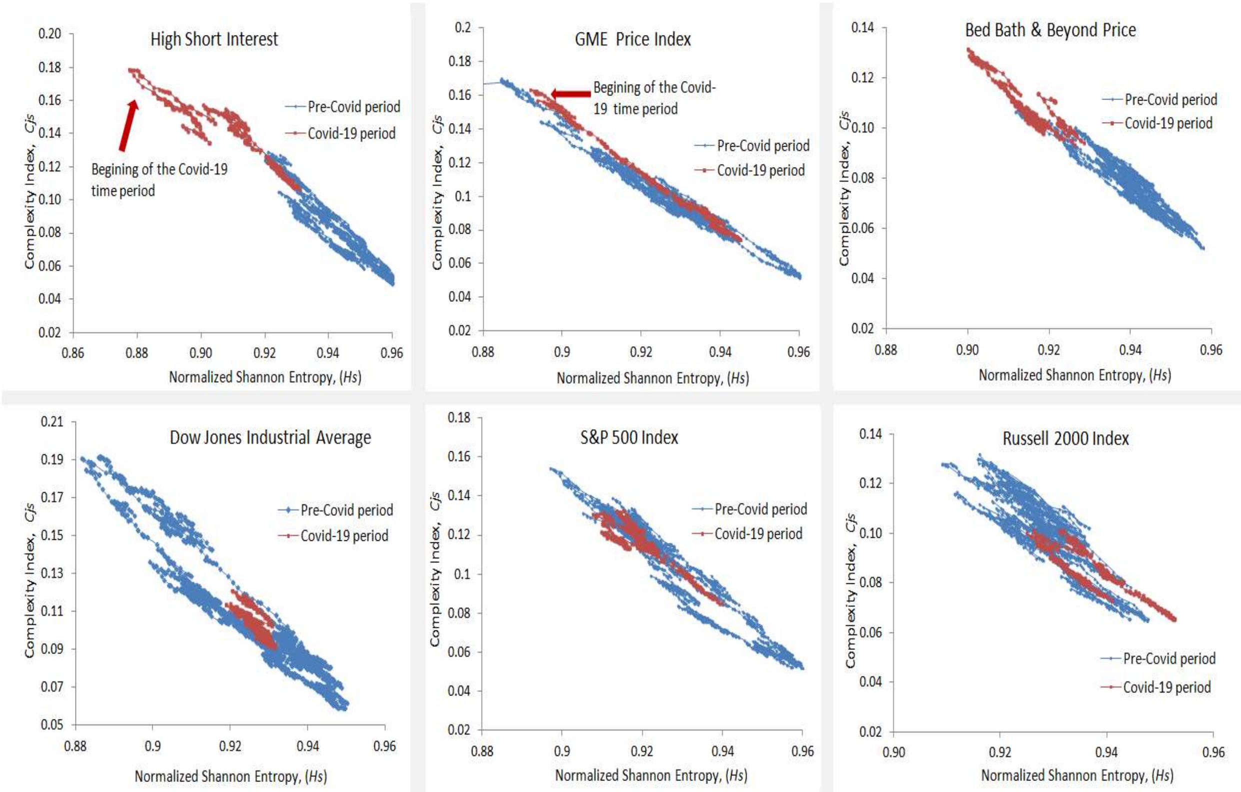

Figure 4. Time evolution of the efficiency level for all stock indices, in terms of Normalized Shannon Entropy, before and during the Covid-19 crisis. Based on the rolling approach, with one- and-a-half-year window and shifting the series through time with a step of 1 day.

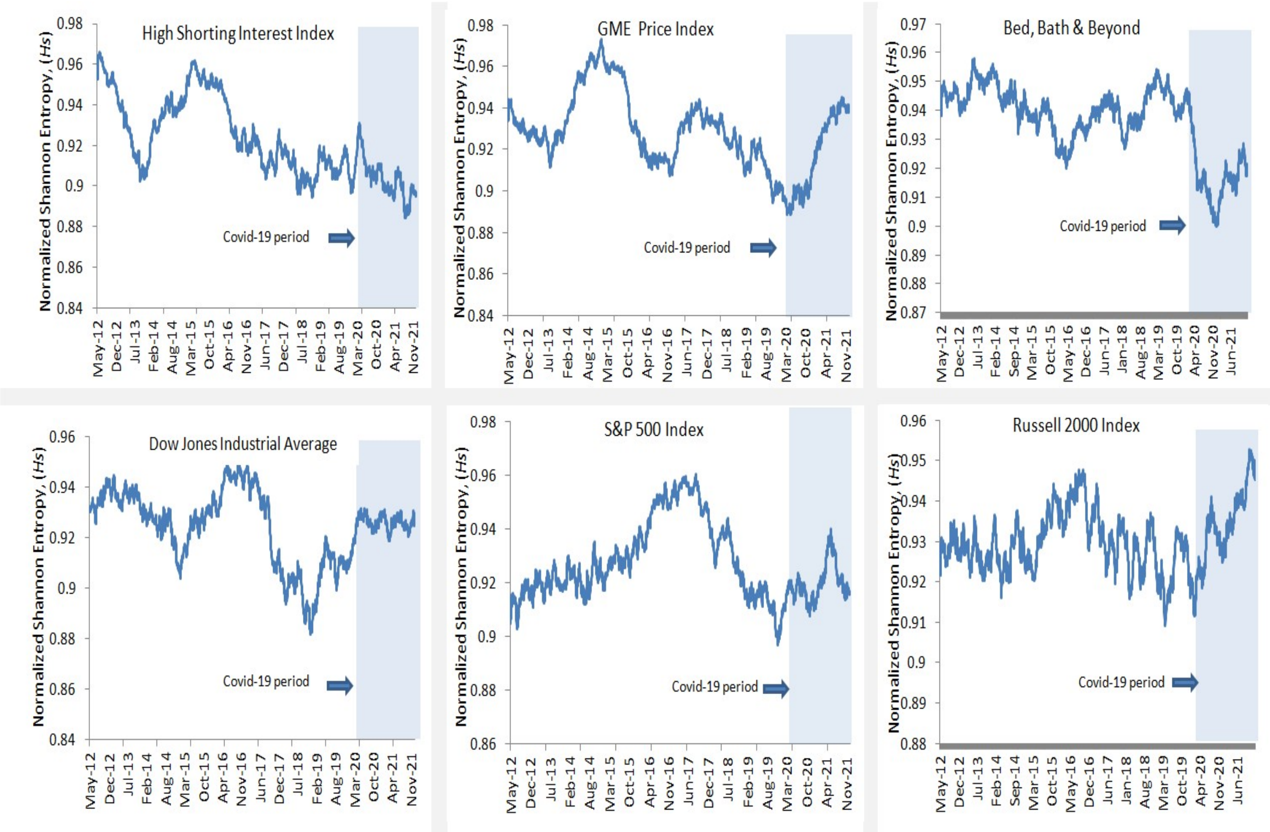

Table 1. Descriptive statistics of selected indices, based on the rate of return.

Sample	High Short Interest Index	GameStop	DJIA	S&P 500	Russell 2000
COVID-19					
mean	0.0026	0.0156	0.0014	0.0016	0.0019
median	0.0025	-0.0010	0.0013	0.0018	0.0013
max	0.2551	1.3484	0.1137	0.0938	0.0939
min	-0.1424	-0.6000	-0.0690	-0.0589	-0.1042
std	0.0327	0.1374	0.0141	0.0134	0.0192
kurt	9.707	33.165	13.653	9.352	4.649
skew	0.873	3.983	1.029	0.719	0.010
Pre-Covid 19					
mean	-0.0001	-0.0001	0.0003	0.0003	0.0002
median	-0.0001	0.0008	0.0006	0.0006	0.0009
max	0.1165	0.1750	0.0936	0.0929	0.0777
min	-0.1079	-0.3555	-0.1293	-0.1198	-0.1427
std	0.0149	0.0280	0.0100	0.0102	0.0129
kurt	5.526	19.824	23.926	18.945	13.581
skew	0.174	-1.473	-1.528	-1.236	-1.198
Total					
mean	0.0003	0.0024	0.0005	0.0005	0.0005
median	0.0002	0.0006	0.0007	0.0007	0.0010
max	0.2551	1.3484	0.1137	0.0938	0.0939
min	-0.1424	-0.6000	-0.1293	-0.1198	-0.1427
std	0.0190	0.0614	0.0108	0.0108	0.0141
kurt	18.032	150.895	21.723	16.584	10.923
skew	0.932	7.646	-0.619	-0.627	-0.707

Table 2. Quantifiers for the Normalized Shannon Entropy and Complexity Measure. Also we depict quantitatively the inefficiency level for all stock market indices.

	Pre-Period (Jan.2011-Feb.2020)			Covid-19 Period (Feb.2020-Dec.2021)		
Index	$\boldsymbol{H_S}$	$\boldsymbol{C_{JS}}$	***Inefficiency***	$\boldsymbol{H_S}$	$\boldsymbol{C_{JS}}$	***Inefficiency***
High Short Interest	0.936	0.092	**0.112**	0.899	0.150	**0.180**
GameStop	0.938	0.086	**0.106**	0.943	0.079	**0.097**
DJIA	0.933	0.098	**0.118**	0.932	0.100	**0.121**
S&P 500	0.935	0.096	**0.116**	0.926	0.116	**0.138**
Russel 2000	0.936	0.092	**0.112**	0.936	0.087	**0.108**
Mean	0.935	0.093	**0.113**	0.927	0.106	**0.129**
Standard Deviation	0.002	0.004	**0.005**	0.017	0.028	**0.033**