"Credit Market Jitters in the course of the Financial Crisis: A Permutation Entropy approach in measuring informational efficiency in financial assets".

Fotios M. Siokis*

Abstract: We explore the evolution of the informational efficiency for specific instruments of the U.S. money, bond and stock exchange markets, prior and after the outbreak of the Great Recession. We utilize the permutation entropy and the complexity-entropy causality plane to rank the time series and measure the degree of informational efficiency. We find that after the credit crunch and the collapse of Lehman Brothers the efficiency level of specific money market instruments' yield falls considerably. This is an evidence of less uncertainty included in predicting the related yields throughout the financial disarray. Similar trend is depicted in the indices of the stock exchange markets but efficiency remains in much higher levels. On the other hand, bond market instruments maintained their efficiency levels even after the outbreak of the crisis, which could be interpreted into greater randomness and less predictability of their yields.

Keywords: Permutation Entropy, Financial Crisis, Financial Markets, Informational Efficiency

*University of Macedonia, Thessaloniki, Greece
e-mail address: fsiokis@uom.gr

1. Introduction

There is no doubt that the Great Recession was one of the most virulent periods in the history of the US economy. The burst of the housing bubble caused the worst financial meltdown since the Great Depression. Not only had greatly impacted the US economy, which according to NBER went into a recession in December 2007 and lasted until June 2009, but it was immediately transmitted to the World's financial markets. Consequently, the financial crisis led to a severely impairment of interbank money markets to an unprecedented decline of the liquidity in the fixed income securities, to a serious credit crunch and lastly to a vast turbulence in the stock exchange markets where security prices plunked extraordinarily. The meltdown in prices revived the debate of whether markets are truly efficient, and the celebrated Efficient Market Hypothesis received a concerted attack by many analysts, traders and market strategists. After all, a complex system such as the stock exchange market reveals its structure better when it is under stress.

Based on the Efficient Market Hypothesis (EMH), financial prices are described as efficient since they reflect all available information and follow a rather "Random walk" procedure where no one could gain systematically or above average return [1,2]. As the new information arises every day, the market immediately absorbs and incorporates this information into the securities prices. In other words, the stock market has no memory which means that yesterday's price change is not dictating and influencing the behavior of today's price change. But for the last couple of decades a number of economists had put into question the validity of the EMH especially during anxious times. In particular, the so-called dot com crisis- lasted for the period of late 1990 to early 2000-had convinced many analysts of the existence of pricing irregularities in stock returns for at least a short time of period and consequently of the failure of the EMH[1]. As Grossman and Stiglitz [4] stated because information is costly, prices cannot perfectly reflect the information, which is available, because if it did those who spend resources to obtain it would receive no compensation[2]

The EMH, which is associated with the idea of a "random walk," did not find supportive evidence in, Barkoulas and Baum [6] who investigated EMH for the US stock returns. In addition Lo and MacKinlay [7] rejected the hypothesis that stock prices behave as true random walk, based on short-run serial correlations which are not zero. Ito and Sugiyama [8] found that the inefficiency level varies through time in the US stock market. Di Matteo et al.

---

[1] Robert Shiller [3] Irrational Exuberance, Princeton, Princeton University Press, 2000

[2] For an extensive discussion on Efficient Market Hypothesis (EMH) please read Burton G. Malkiel (2003) [5]

[9] studied the scaling properties of daily Foreign Exchange rates, Stock Market indices and fixed income instruments utilizing the Hurst exponent. One interesting finding which is related to our investigation was the strong deviation of the scaling exponent for the 3 months maturity instrument, which according to authors was strongly influenced by the central bank decisions. Bariviera et al. [10] studied the informational efficiency of the corporate and sovereign bond markets of seven EU countries right after the outbreak of the financial crisis of 2007. By analyzing the evolution over time of the Hurst exponent, as a measure of long-range memory and using the DFA approach they detect different memory dynamics in corporate and sovereign bond series after the financial crisis. In particular, the crisis deteriorates the informational efficiency of corporate bonds and enhances the efficiency of the sovereign bond markets. Also the relationship of the degree of efficiency and the predictability in financial time series was a subject of investigation (Eom et al. [12]). By using the Hurst exponent concept for 60 different stock market indices they find a strong positive relationship between market efficiency and predictability.

The entropy concept and in particular the conditional entropy, was utilized by Zhang (1999) in measuring stock exchange efficiency. Zunino et al. [13] used the complexity entropy causality plane, to distinguish the stage of stock market development. They've showed that developed markets exhibit higher permutation entropy and lower complexity values than the emergent markets and revealed the presence of significant time correlations and some degree of order. In addition, they report that the temporal correlations are the main factor of stock market inefficiency. In the same vein, Zunino et al.[14] utilized the complexity-entropy causality plane to unveil the presence of correlations in the daily values of bond indices of developed and emerging markets. They demonstrate that permutation entropy is higher for developed countries than for emerging ones, and market size is correlated with permutation entropy. Bariviera et al. [15] applied the same technique to detect changes in the underlying stochastic/chaotic process that governs the movements of interest rates and especially on Libor rate. Using sliding windows they reveal anomalous behavior in the Libor rate especially around the time of the 2007-2008 crisis. Zunino et al. [16] by applying permutation min-entropy dynamically analyzed the structure of the daily values of European corporate bond indices for the period of 2001 until 2015. They conclude that some sectors of the economy like financial services exhibit less information efficiency due to the 2008 crisis. Lastly, several works applied the entropy concept to quantify the efficiency level in various financial markets [17-21].

The aim of this paper is to study the evolution of the informational efficiency of representative instruments of the U.S. money, bond and stock exchange markets during anxious time. The analysis of such extreme events would provide helpful insights into underlying complexity of the financial system. By identifying the statistical properties of the

financial market events under stress, we hope to enhance our understanding of the mechanisms determining the dynamics and to develop diagnostic models in predicting financial meltdowns. In particular we're interested in studying the behavior of the informational efficiency before and after the recent financial crisis of the Great Recession. We utilize the 1, 3 and 6 month yields of the Treasury Bills (TB), the 2, 5 and 10 year sovereign Bond yields and the three main stock exchange indices, namely the Dow Jones Industrial Average, the S& P 500 and the Nasdaq Composite Index. In order to evaluate the degree of informational efficiency we utilize a novel technique based on the entropy concept, which is defined in the next section.

The remainder of the paper is organized as follows. In the following section we describe the information-permutation theory. In Section 3 we describe the data used followed by the presentation and discussion of the empirical results obtained from the different instruments of the financial markets. In section 4 we summarize the findings of the paper and conclude.

2. Methodology

2.1. Permutation entropy

In the information theory, entropy is used rather as a general concept and it is expressed in terms of a discrete set of probabilities. Therefore, in order to calculate the so-called entropy quantifier, for a specific time series, the associated probabilistic distribution should first be estimated. A number of methodologies have been proposed for estimating the probability distribution. The major ones are: 1) the Fourier analysis introduced by Powell and Percival [22], 2) the wavelet transform by O. A. Rosso, M. L. Mairal [23], 3) the symbolic dynamic analysis [24, 25] and, lastly, 4) a procedure called the permutation entropy introduced by Bandt and Pompe (2002) (B&P) [26, 27]. The B&P approach is mainly based on the celebrated Shannon entropic measure and it has found a wide variety of applications-spanning from financial markets, to astrophysical plasmas [28] to medical issues, like epileptic seizures, [29-31], heartbeat dynamics [32,33] and tracking the effects of anesthetic drugs [34,35] among others. It measures the complexity of arbitrary time series in an environment of ordinal pattern and the comparison of adjacent values, within time series, captures time causality. The main advantages as set forth by Bariviera et al. (2015) [15] are the following. Firstly it makes no assumption about the underlying stochastic process governing interest rates and secondly it avoids causation problems derived by interaction or by different stochastic dynamics, since we're working with one time series at a time. We could also add its simplicity, fast calculation process and its robustness.

However, by itself measures of entropy do not quantify adequately the degree of structure in a process. For that matter, an effective statistical complexity measure was introduced by Lamberti et al. [36], which assists of detecting essential details of the dynamics and differentiate various degrees of periodicity and chaos[3]. 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, from which the calculation of entropy and complexity is straightforward.

Given a time series $\{x_t: t = 1,..., N\}$, an embedding dimension $D > 1$, and a 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 to the ranking of the the x_i in ascending order, namely $x_{\pi t} < x_{\pi t+1} < ... < x_{\pi t+(d-1)}$. In order to have a unique result, if $x_i = x_j$ where $i < j$, then in 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 $NL - d + 1$ length d segments s in the series and all d! permutations π of order d by

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

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 information entropy as:

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

Where the log is base two, given the binary data, the permutation entropy value lies between 0 and log(d!) when the probability $P_i = 1/d!$ and the Shannon entropy index takes the highest value which is $\log_2(d!)$.

[3] For a thorough understanding and a review of permutation entropy and its applications, please see Zanin et al. (2012) [37]

2.2. Complexity entropy causality plane

By dividing the Shannon entropy by the $\log_2$ (d)! we get the so called Normalized permutation entropy (*H[P]*).

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

In this specification, possible values of the normalized permutation entropy are between 0 and 1 where value of 1 means that the time series under consideration is completely random whereas when value is close to 0, the sequence is very regular and someone could predict with great certainty which of the probable outcomes will take place.

The permutation entropy depends heavily on choosing the right embedding dimension of d. Based on a number of empirical studies choosing a lower d number, i.e. 1 or 2 will not work properly since there are only few distinct states, and a very large d number of permutations can causes memory restrictions. Therefore, based on Bandt and Pompe the right embedding dimension falls between d=3 and 7, given the length of the times series. In our case we work with low order number by setting d=4 and the time delay τ=1.

By using the permutation entropy, quantifiers take into account the randomness of an arbitrary time series, but not the degree of correlational structure in the time series. For that matter a statistical complexity measure (SCM) is developed, as the so-called Jensen Shannon complexity, or $C_{JS,}$ of the distribution P of N probabilities associated with a time series defined as follows[4] [5].

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

Where *H[P]* is the normalized Shannon entropy, and Q_J is the disequilibrium, which is defined in terms of the Jensen–Shannon divergence, while $P_e = \{1/N, \ldots 1/N\}$ is the uniform probability. The Jensen–Shannon *(JS)* divergence quantifies the difference between at least two probability distributions and is useful to compare the symbol-composition of different sequences [37]. Also, the quantity Q_J, will be different from zero if there are more likely states among the accessible ones. Once the disequilibrium is normalized such that $0 \leq C_{JS} \leq 1$ then

[4] The statistical complexity measure was introduced by Lopez-Ruiz et al. (1995) [38] and advanced by Rosso et al.(2007) [39], the so called CH-plane (normalized Shannon entropy, *H*, and Jensen-Shannon Complexity, *C*).

[5] A generalized complexity-entropy causality plane has been recently introduced in terms of the Tsallis q entropy. This approach seems to be more powerful for characterizing the presence of long-range correlations. For further details please see[40]

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

Where S is the Shannon entropy and $H[P]$ is the normalized Shannon entropy. It is worth noting that the SCM (C_{JS} complexity measure) is not a trivial function of the entropy because it depends on two different probability distributions the one associated with the system under analysis P and the uniform distribution P_e. Furthermore it has been shown that, for a given H value, there exists a range of possible SCM values[6].

3. Data and empirical results

We analyze daily yield levels of specific fixed income instruments along with daily price levels of specific stock exchange indices before and after of the 2007 financial crisis. Specifically we utilized data from 1, 3 and 6 month Treasury Bills (TBs), 2, 5 and 10 year Bonds yield and form the Stock Market the indices of S&P 500, Dow Jones Ind., and Nasdaq Composite. Data are taken from Bloomberg covering the period from the beginning of 2002 to late 2013 and divided into two equal non overlapping segments[7]. We label the first sample from 2002 until the end of 2007 as the pre-crisis period and the second sample spanning from 2008 until 2013 as the crisis/post crisis period. Each sample consists of 1322 daily observations. The reason for dividing the sample in such manner is to extract information contained in the time series before and during/after the 2008 financial crisis.

Based on the permutation entropy method we compute the quantifiers for the money, capital and stock exchange markets information efficiency. The Permutation entropy and the statistical complexity are estimated for embedding dimension d=4 and embedding delay τ=1. The pattern length of 4 is chosen given the criterion that N>>d!. We've also estimated the permutation entropy and the *JC* statistical complexity with embedding dimension d=3 and d=5 and time delay τ=1, just to ensure behavioral similarity with the values estimated with d=4.

As Zunino et al. (2010) argue if the time series is purely random, based on Fama's sense, then permutation entropy reaches the optimum (maximum) level of 1 and the statistical complexity reaches the minimum level of 0. In other words the optimal level for a financial

[6] For further information, please see Soriano et al.[41]

[7] The ISIN codes for the instruments, in Bloomberg are the following. GB1:GOV for the 1-month TB, GB3 and GB6 for the 3 and 6-month TBs respectively. GT2:GOV for the 2-year sovereign Bond, GT5 and GT10 for the 5 and 10-year Bonds. SPX:IND for the S&P 500 Index, INDU and CCMP for the Dow Jones and Nasdaq Composite respectively.

market is to reach the (1, 0) point of this Complexity Entropy Causality Plane, which probably applies to the strong-form EMH, where the market is efficient by reflecting all available information, both, public and private. Figure 1 presents the complexity entropy causality plane for the money, bond and stock exchange markets for the two periods and the localization of each instrument for each market is displayed. Note that in the bonds market all instruments quantifiers compile a closed cluster of points. The three quantifiers for both sub-periods are located in the right low corner, in the area of higher permutation entropy value, between 0.94-0.96 and lower statistical complexity, between 0.06 – 0.08, with the 2-year bond to exhibit the bigger deviation between the two sub-periods. Naturally it suggests that there is no memory in the bonds market, meaning that yesterday's price change is not dictating and influencing the behavior of today's price change. Putting differently the bonds market exhibits random behavior for both sub-samples. In contrast to bonds market quantifiers, all money market instruments, for both sub-periods, clearly exhibit lower permutation entropy and higher statistical complexity values. This outcome is translated into a lower efficiency level, although one could've been expecting the opposite, given the much higher liquidity levels existing in the money market. More importantly, during and after the crisis, all money market quantifiers are located further left and up on the diagram, dictating much lower entropy values and higher complexity, thus lower efficiency level. Especially the 6-month TB yield is exhibiting permutation entropy of 0.86 and complexity of 0.242.

Also, table 1 reports the values of the permutation entropy and the permutation *JS* statistical complexity of the financial instruments, for the two sub periods with different embedding dimensions d=3, d=4 and d=5 and time delay t=1[8]. Mean and standard deviation values are calculated for comparison purposes between the markets and the two sub-periods. According to table 1, for the period of 2008-2013 all money market instruments are the least efficient compared with the previous period (i.e.2002-2007) and compared with the bond market instruments, regardless of the embedding dimension values. This result is unanticipated, since during a financial crisis, money market instruments are considered safe assets, due to the short maturity and high credit rating. On this ground, one justification could be given-which of course requires further investigation. Due to the interbank markets shut down, the demand for government securities for repo transactions increased dramatically, as the crisis unfolded, resulting in US government collateral to become extremely scarce. The triggered "flight to safety" led to higher demand for high-quality short- term Treasury collaterals, and the increased reluctance by the investors to lend treasury securities, pushed the Treasury rates and general collateral rates to zero levels, an evidence of impaired market

[8] Due to limited space, in table 1 we report the JS complexity values only for d=4. But values for d=3 and d=5 are available upon request.

functioning[9]. In fact, the announcement of the Lehman Brothers insolvency, in the morning of September 15 2008, drove the 1month TB yield down by more than 100 basis points, from 1.37% to 0.28%.

As for the stock exchange indices, all quantifiers get values greater that 0.925 with the Nasdaq index to be the least stable, when it comes to the post crisis period.

Next we analyze the time evolution of the quantifiers in an attempt to sketch dynamically the inefficiency level and to identify if the underlying process changes during the different periods. Considering a three-year long window, corresponding to about 750 days and shifting through the time series with a step of 1 day, we calculate the time variation of the permutation entropy and JS statistical complexity for the subsamples[10]. By this methodology changes in the underlying stochastic process are considered. Figure 2 depicts the progression of the locations of the various instruments for all markets, within the entropy-complexity causality plane, setting d=4 and τ=1. There are two time periods for each instrument, with the first to start from 2002 until the end of 2007 and the second from 2008 to 2013.

The main observation of figure 2 is related with the changing position of the instruments' yield over time. All TB instruments are depicting lower entropy and higher complexity area as we moving from the pre to during and post crisis periods. Especially for the 6-month TB, quantifiers are moving to lower entropy and higher statistical complexity, suggesting an increase of inefficiency trough time. As for the bonds' yield, the efficiency level seems to remain around the same locus for both pre and post periods. Lastly, for the stock exchange indices, although there is a loss of efficiency for the post crisis period, still the level remains quite high with the Nasdaq index to exhibit the lower entropy and higher statistical complexity.

On the same vain and based on the sliding window methodology we depict in fig.3 the normalized Shannon entropy quantifier. It can be easily noticed that the information efficiency for the money market instruments is strongly affected by the sub-prime crisis. The information efficiency level deteriorates as we're moving through time and especially for the yield of the 6-month TB where the efficiency reaches the 0.75 level. Even for the stock exchange indices, it is evident the decreasing trend of the information efficiency level beginning immediately after the advent of the credit crunch and the fall of the Lehman Brothers. The downward trend lasted for about two years, before it was changed into a positive one. The change in trend appears to be taken place just at the time where the U.S.

[9] There were numerous comments in the news regarding the impaired functioning of the Treasury market during the crisis and the breakdown in the clearing mechanism, while primary dealer settlement fails continued to rise.

[10] We've also tested the procedure by considering a two-year window, corresponding to 500 days, and the results are almost the same, although quantifiers depict higher fluctuation.

economy exited from the Great Recession, based on the announcement of the National Bureau of Economic Research (NBER). Only the bonds' yield and, especially the 5-year and 10-year maturity instruments kept their efficiency level intact, during and after the disruption period. The information efficiency level for the 2-year yield deteriorates but it remained in very high efficiency levels. The increased efficiency level for the bonds' market, especially after the outbreak of the crisis, could be attributed to the large purchases made by the Treasury, based on the Large-Scale Asset Purchase (LSAP) program, in an attempt to lower long-term interest rates by decreasing the risk premium[11].

Lastly, based on the estimated normalized permutation entropy values we calculate the mean and standard deviation for each market. Figure 4 depicts the mean and the magnitude of the standard deviation through time. One can see that as we're approaching the time of the credit crunch and later the fall of the Lehman Brothers the standard deviation is reduced significantly, indicating the so-called synchronization of the markets or rather the convergence of the yields of the different-maturity instruments. It is evident that in money, bonds and stock exchange markets the standard deviation of the permutation entropy remains at low levels just before the outbreak of the crisis. After 2008 a strong divergence between the various instruments is depicted, with much broader in the case of the money market, where there is a constant increase in the standard deviation of the permutation entropy. Also, although the mean of the permutation entropy decreases for both money and stock exchange markets, in the later case seems not significant, since the mean value remains at very high levels (around 0.92), while in the case of the money market the mean decreases significantly to around 0.80.

4. Conclusion

In this paper we attempt to analyze the behavior of specific instruments in the U.S. money and capital markets and the major indices in the Stock exchange markets, during the recent financial crisis. By dividing the sample size into two equal sub-sets we test the pre and post crisis periods. With the help of the permutation quantifiers we find that the money market's instruments exhibit less efficiency during the post crisis period than the pre period. In the other two markets the degree of efficiency for all instruments remains marginally at the same level regardless of the period.

[11] Since short-term nominal interest rates were at the so-called zero lower bound, the purchases of long-term maturity instruments aimed at decreasing the relevant interest rates through narrowing risk premium. The risk premium is calculated as the difference between long-term and short-term interest rates. This is based -to a certain degree- to the so-called "portfolio balance" effect introduced by Tobin (1958) [42] where purchases of long term debt instruments bid up the price of the asset and hence lower its yield.

Next considering the sliding window methodology we measure the time variation of the complexity entropy causality relation. We find that the efficiency level of the bond instruments fluctuates around a narrow band, whereas, for the money market instruments it deteriorates as we moving forward from the time of the credit crunch and the insolvency of Lehman Brothers. In fact the efficiency level is not recovered to the pre crisis levels, even three years after the outbreak of the crisis. This finding is puzzling given that in periods of financial distress capital flights to "quality" and in particular to short-term Treasury instruments. Especially for the 6-month T-bill yield the efficiency level continually decreased to the 0.80 point. On the other hand the deterioration of the efficiency level means that the yields of the short-term treasury debt are less uncertain during financial disarray.

Finally, it is equally important to note the decreasing pattern of the informational efficiency, for the stock exchange indices, from around the credit crunch time to June 2009, where officially the recession had ended. Based on the above findings and taking into consideration the various (non) conventional policies implemented by the Federal Reserve, further research is required in order to explain the impairment of the money market during the Great Recession period

Acknowledgment: I would like to thank the referees for their valuable comments and Mr. George Argyroudis for excellent research assistance.

References

1. E.F. Fama, Efficient capital markets: a review of theory and empirical work, Journal of Finance 25 2 (1970) pp. 383–417.

2. E.F. Fama, Efficient capital markets: II, Journal of Finance 46 5 (1991) pp. 1575–1617.

3. Robert Shiller, Irrational Exuberance, Princeton, Princeton University Press 2000.

4. S. J. Grossman, and J. E. Stiglitz, On the Impossibility of Informationally Efficient Markets, American Economic Review 70:3 (1980) pp. 393–408.

5. B.G. Malkiel, The Efficient Market Hypothesis and Its Critics, Journal of Economic Perspectives 17 1 (2003) pp. 59 – 82.

6. J.T. Barkoulas and C.F. Baum, Long-term dependence in stock returns, Economics Letters 53 (1996) 253–259.

7. A. W. Lo, and A. C. MacKinlay, A Non-Random Walk Down Wall Street, Princeton: Princeton University Press 1999.

8. M. Ito, S. Sugiyama, Measuring the degree of time varying market inefficiency, Economics Letters 103 (2009) 62–64

9. T. Di Matteo, T. Aste, M. M. Dacorogna, Long-term memories of developed and emerging markets: Using the scaling analysis to characterize their stage of development, Journal of Banking and Finance 29 (2005) 827–851.

10. A.F. Bariviera, M.B. Guercio, L.B. Martinez, A comparative analysis of the informational efficiency of the fixed income market in seven European countries, Economics Letters 116 (2012) 426–428.

11. C. Eom, S. Choi, G. Oh, W.-S. Jung, Hurst exponent and prediction based on weak-form efficient market hypothesis of stock markets, Physica A 387 (2008) 4630–4636.

12. Yi-Cheng Zhang, Toward a theory of marginally efficient markets, Physica A 269 1 (1999) Pages 30–44.

13. L. Zunino, M. Zanin, B.M. Tabak, D.G. Pérez, O.A. Rosso, Complexity-entropy causality plane: A useful approach to quantify the stock market inefficiency, Physica A 389 9 (2010) pp. 1891–1901.

14. L. Zunino, A.F. Bariviera, M.B. Guercio, L.B. Martinez, O.A. Rosso, On the efficiency of sovereign bond markets, Physica A 391 18 (2012) pp. 4342–4349.

15. A.F. Bariviera, M.B. Guercio, L.B. Martinez, O.A. Rosso, The (in)visible hand in the Libor market: an information theory approach, Eur. Phys. J. B 88 8 (2015) p. 208. 12

16. L. Zunino, A.F. Bariviera, M. B. Guerio, L.B. Martinez, O.A. Rosso, Monitoring the informational efficiency of European corporate bond markets with dynamical permutation min-entropy, Physica A 456 (2016) 1-9.

17. G. Oh, S. Kim, C. Eom, Market efficiency in foreign exchange markets, Physica A 382 1 (2007) pp. 209–212.

18. W.A. Risso, The informational efficiency and the financial crashes, Res. Int. Bus. Finance 22 3 (2008) pp. 396–408.

19. J. Alvarez-Ramirez, E. Rodriguez, G. Espinosa-Paredes, Is the US stock market becoming weakly efficient over time? Evidence from 80-year-long data, Physica A 391 22 (2012), pp. 5643–5647.

20. E. Martin, E. Rodriguez, R. Escarela-Perez, J. Alvarez-Ramirez, Multiscale entropy analysis of crude oil price dynamics, Energy Econ. 33 5 (2011) pp. 936–947.

21. A. Ortiz-Cruz, E. Rodriguez, C. Ibarra-Valdez, J. Alvarez-Ramirez, Efficiency of crude oil markets: Evidences from informational entropy analysis, Energy Policy 41 (2012) pp. 365–373.

22. G. E. Powell, I. C. Percival, A spectral entropy method for distinguishing regular and irregular motion of Hamiltonian systems, J. Phys. A: Math. Gen. 12 (1979) 2053–2071.

23. O. A. Rosso, M. L. Mairal, Characterization of time dynamical evolution of electroencephalographic epileptic records, Physica A 312 (2002), 469–504.

24. Mischaikow, K.; Mrozek, M.; Reiss, J.; Szymczak, A. Construction of symbolic dynamics from experimental time series. Phys. Rev. Lett. 82 (1999), 1144–1147

25. C. S. Daw, C. E. A. Finney, E. R. Tracy, A review of symbolic analysis of experimental data, Rev. Sci. Instrum. 74 (2003) 915–930.

26. C. Bandt and, B. Pompe, Permutation entropy: A natural complexity measure for time series, Phys. Rev. Lett. 88 17 (2002).

27. M.T. Martin, A. Plastino, O.A. Rosso, Generalized statistical complexity measures: Geometrical and analytical properties, Physica A 369 2 (2006) 439–462

28. P. J. Weck, D. A. Schaffner, M. R. Brown, and R. T. Wicks, Permutation entropy and statistical complexity analysis of turbulence in laboratory plasmas and the solar wind, Phys. Rev. E 91 023101 (2015).

29. Y. Cao, W.W. Tung, J.B. Gao, V.A. Protopopescu, L.M. Hively, Detecting dynamical changes in time series using the permutation entropy, Phys. Rev. E 70 (2004), 046217.

30. X. Li, G. Ouyang, D. Richards, Predictability analysis of absence seizures with permutation entropy, Epilepsy Res. 77 (2007) 70–74 13

31. A. Bruzzo, B. Gesierich, M. Santi, C. Tassinari, N. Birbaumer, G. Rubboli, Permutation entropy to detect vigilance changes and preictal states from scalp EEG in epileptic patients. A preliminary study, Neurol. Sci. 29 (2008) 3–9.

32. B. Frank, B. Pompe, U. Schneider, D. Hoyer, Permutation entropy improves fetal behavioural state classification based on heart rate analysis from biomagnetic recordings in near term fetuses, Medical and Biological Engineering and Computing (2006) 44:179

33. C. Bian, C. Qin, QDY. Ma, Q. Shen, Modified permutation-entropy analysis of heartbeat dynamics, Phys. Rev. E 85 (2012) 021906.

34. E. Olofsen J. W. Sleigh A. Dahan, Permutation entropy of the electroencephalogram: a measure of anaesthetic drug effect, British Journal of Anaesthesia 101 6 (2008) 810-821

35. X. Li, S. Cui, L.J. Voss, Using permutation entropy to measure the electroencephalographic effects of sevoflurane, Anesthesiology 9 (2008), 109, 448-456

36. P. W. Lamberti, M. T. Martin, A. Plastino, and O. A. Rosso, Intensive entropic nontriviality measure, Physica A 334 119 (2004) 119-131.

37. M. Zanin, L. Zunino, O. Rosso and D. Papo, Permutation Entropy and Its Main Biomedical and Econophysics Applications: A Review, Entropy 2012 14 8 1553-1577.

38. R. Lopez-Ruiz, H.L. Mancini, X. Calbet, A statistical measure of complexity, Phys. Lett. A 209 1995 321-326.

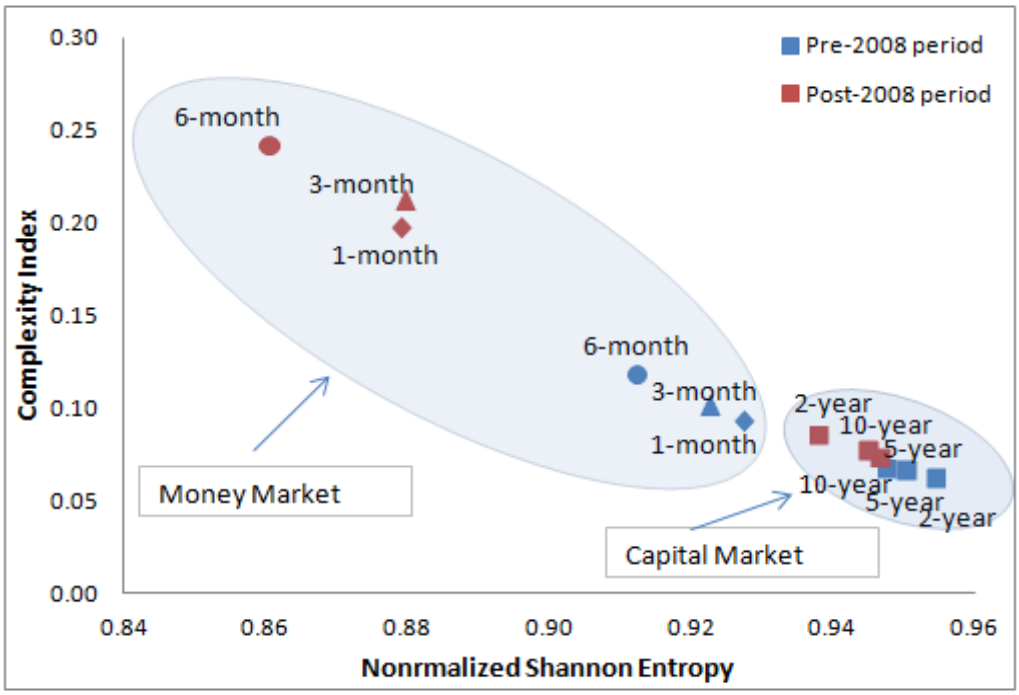
39. O. A. Rosso, H. A. Larrondo, M. T. Martin, A. Plastino, and M. A. Fuentes, Distinguishing Noise from Chaos, Phys. Rev. Lett. 99 (2007) 154102.

40. H. V. Ribeiro, M. Jauregui, L. Zunino, and E. K. Lenzi, Characterizing time series via complexity-entropy curves, Physical Review E 95, (2017) 062106

41. M.S. Soriano, L. Rosso, O.A. Fischer and C.R. Mirasso, Time Scales of a Chaotic Semicondactor Laser With Optical Feedback Under the Lens of a Permutation Information Analysis, IEEE Journal of Quantum Electronics, 47 (2) (2011) 252-261

42. Tobin, James, Liquidity Preference as Behavior Towards Risk, Review of Economic Studies 25 (1958) 124-31

Figure 1. Position of the Money and Capital markets instruments and the Stock Exchange Indexes. Two different time periods in the complexity-normalized Shannon entropy causality plane with embedding dimensions d = 4 and time delay τ = 1.



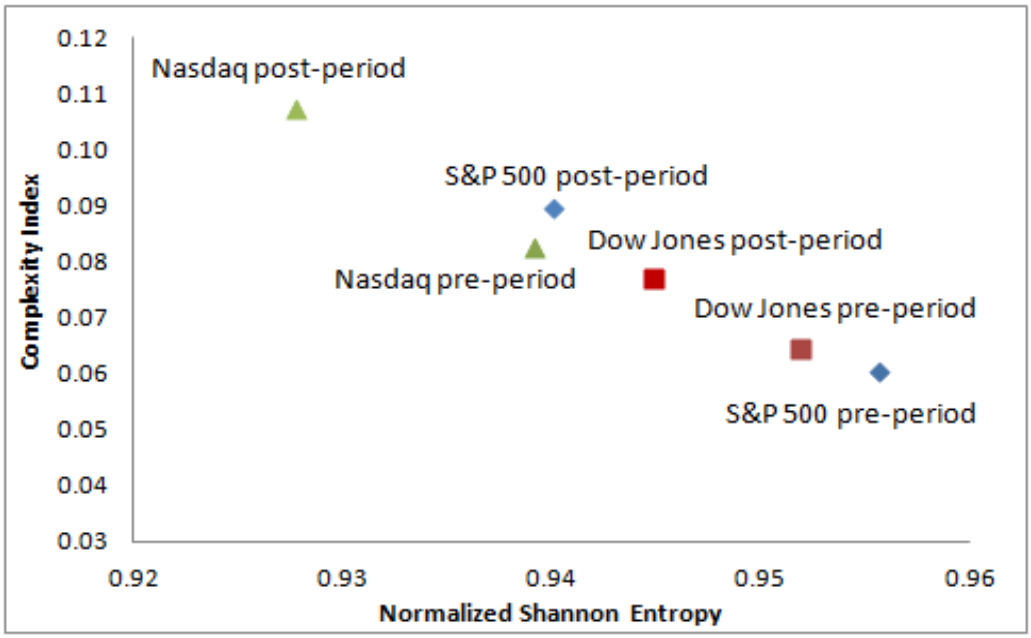
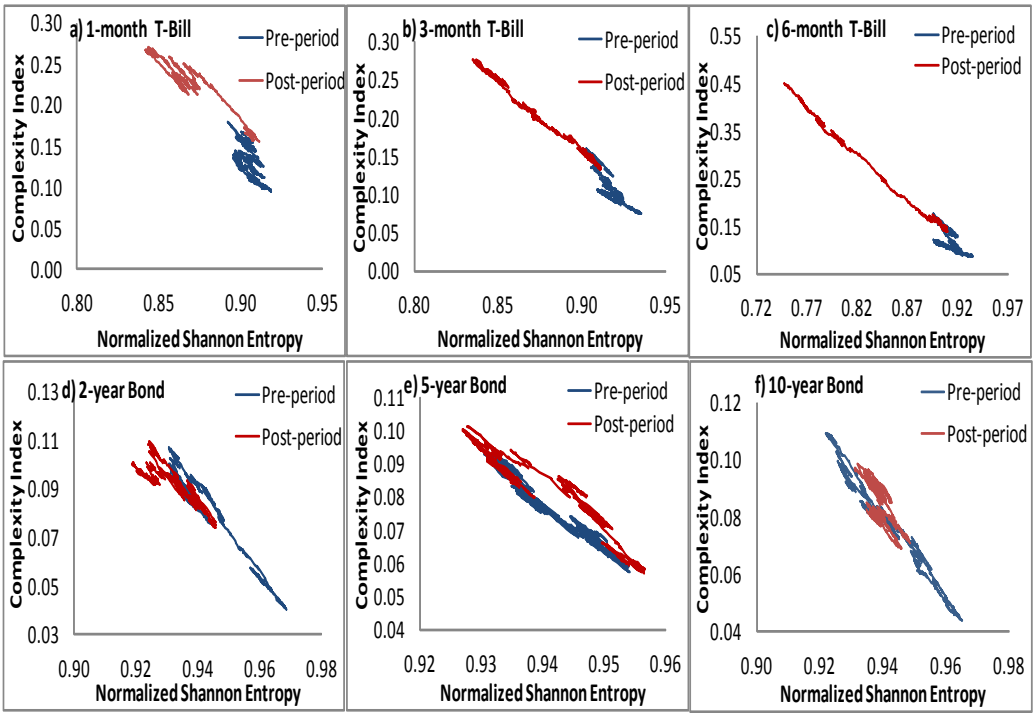


Figure 2. Complexity Entropy Causality Plane for different periods. Movement of permutation quantifiers for various instruments, with D=4, t=1, window 750 points and step d=1.

Panel a) Money & Capital Markets Instruments



Panel b) Stock Market Indices

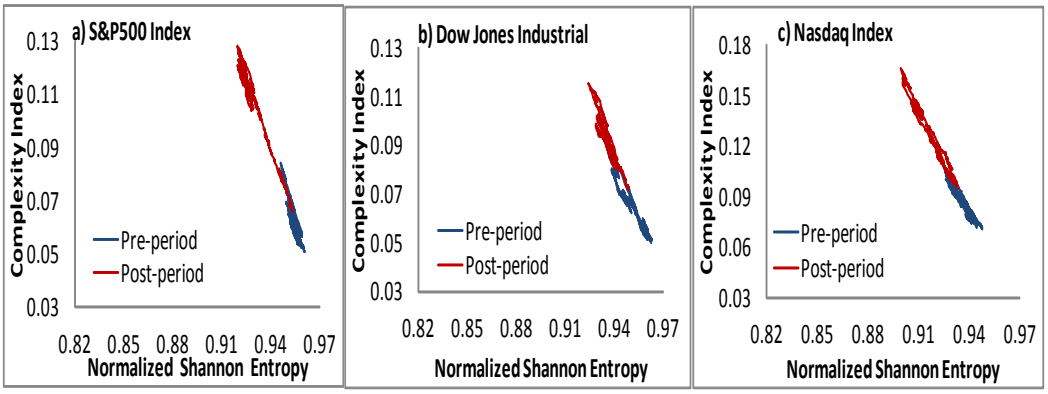


Figure 3. Permutation entropy evolution for a) money market instruments, b) capital market instruments and c) stock exchange indices. Ssliding windows with N=750, D=4, δ=1 and t=1.

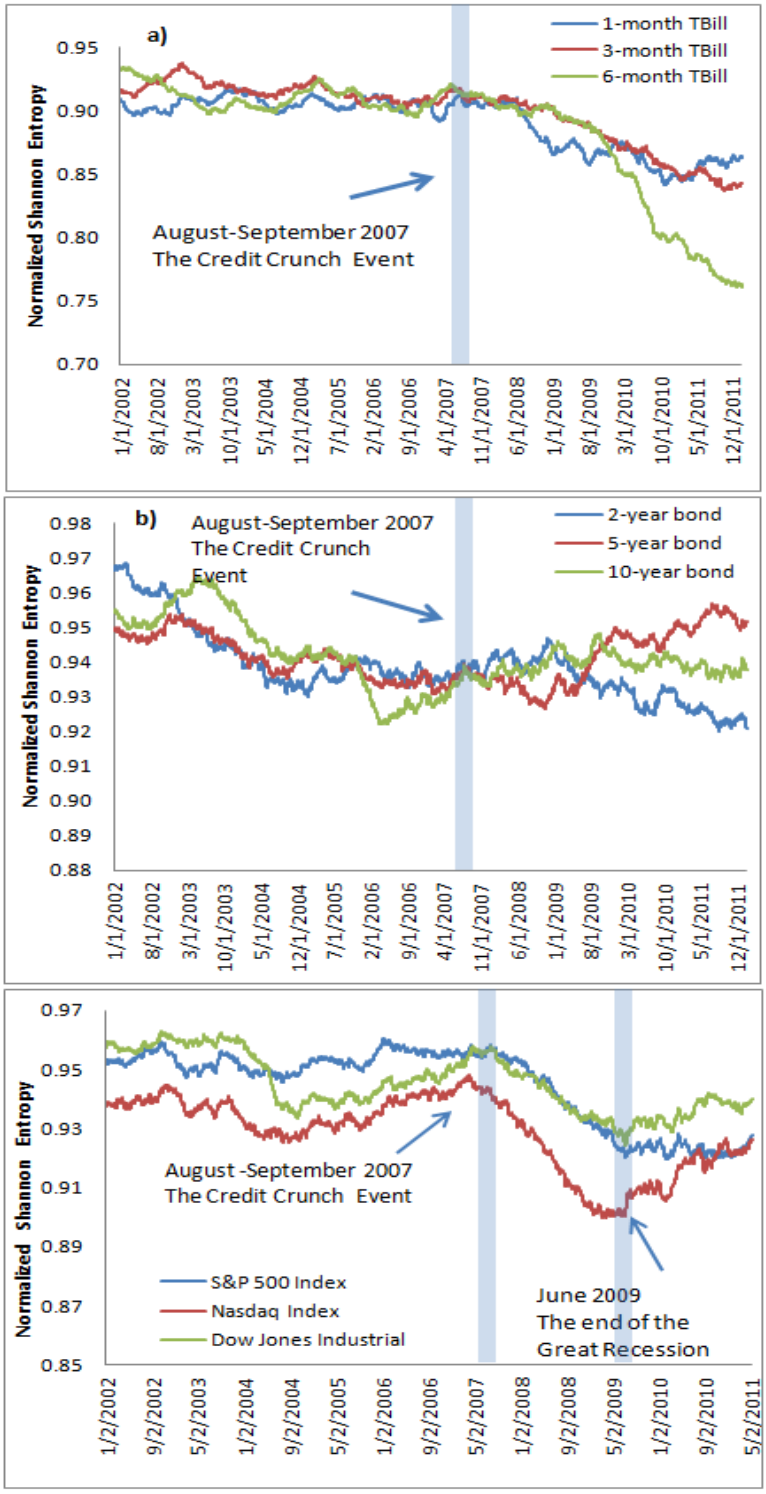


Figure 4. Mean and +- 1 standard deviations (shaded areas) of the normalized Shannon entropy for the three markets a) Money, b) Capital and c) Stock exchange, using the sliding window process with number observations N=750, D=4 δ=1 and t=1.

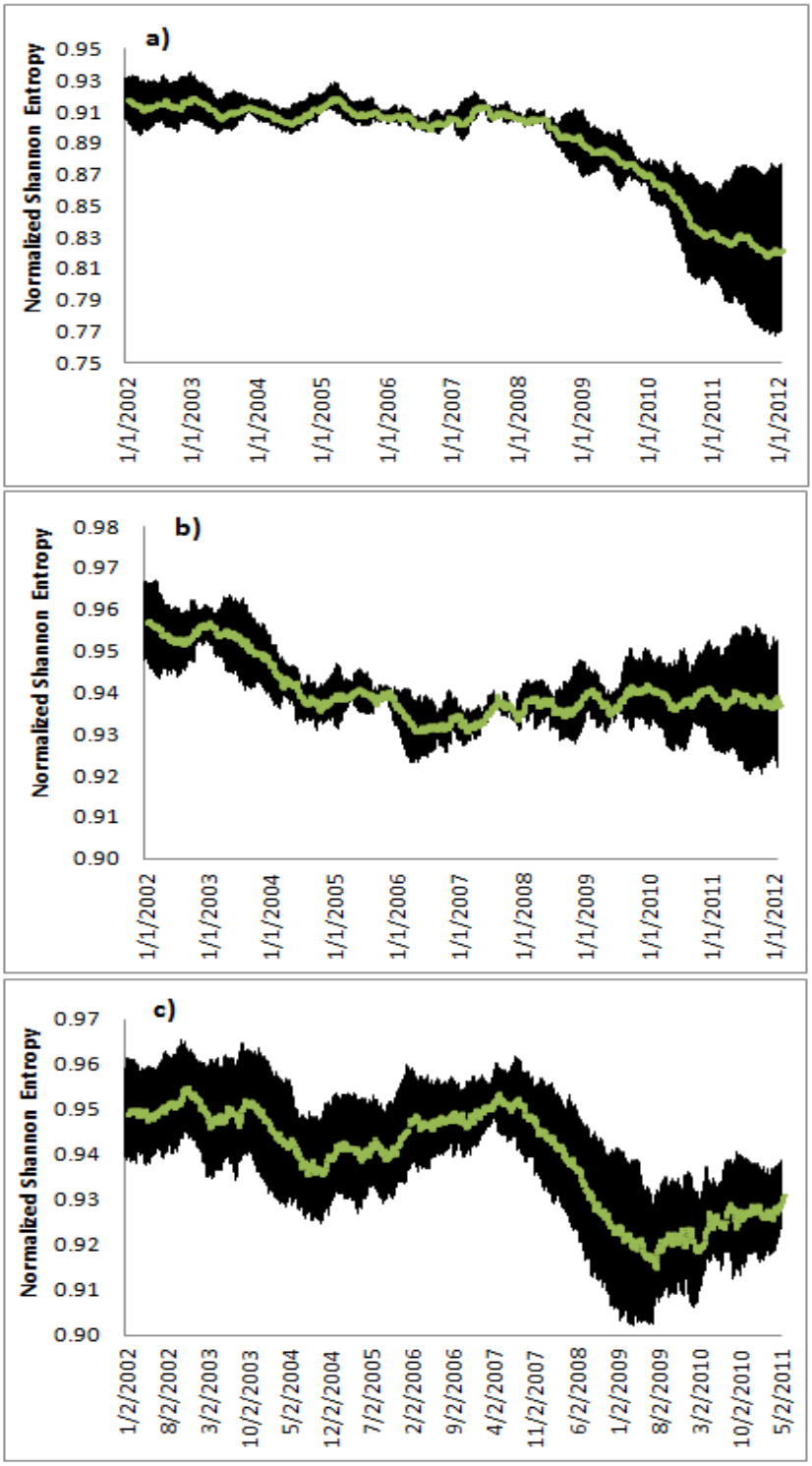


Table 1. Permutation Entropy and *JS* Statistical Complexity of specific instruments of Money, Capital and Stock Exchange Markets, with different embedding dimensions and t=1.

Instrument	Pre-Period 2002-2007				Post-Period 2008-2013			
	H_S			C_{JS}	H_S			C_{JS}
	d=3	**d=4**	d=5	**d=4**	d=3	**d=4**	d=5	**d=4**
Money Market								
1-month T-Bill	0.949	**0.912**	0.874	**0.118**	0.915	**0.880**	0.851	**0.212**
3-month T-Bill	0.953	**0.923**	0.893	**0.101**	0.923	**0.879**	0.853	**0.197**
6-month T-Bill	0.955	**0.927**	0.900	**0.092**	0.905	**0.861**	0.829	**0.242**
Mean	0.952	**0.921**	0.889	**0.104**	0.914	**0.873**	0.844	**0.217**
Std. Dev.	0.003	**0.008**	0.013	**0.013**	0.009	**0.011**	0.013	**0.023**
Capital Market								
2-year Bond	0.980	**0.954**	0.924	**0.063**	0.965	**0.938**	0.913	**0.086**
5-year Bond	0.977	**0.948**	0.919	**0.068**	0.967	**0.947**	0.917	**0.074**
10-year Bond	0.976	**0.950**	0.922	**0.068**	0.964	**0.945**	0.919	**0.078**
Mean	0.978	**0.951**	0.922	**0.067**	0.965	**0.943**	0.916	**0.079**
Std. Dev.	0.002	**0.003**	0.003	**0.003**	0.001	**0.005**	0.003	**0.006**
Stock Market								
S&P 500 Index	0.978	**0.956**	0.927	**0.060**	0.968	**0.940**	0.909	**0.090**
Dow Jones Industrial	0.979	**0.952**	0.921	**0.064**	0.973	**0.945**	0.914	**0.077**
NASDAQ Index	0.970	**0.939**	0.909	**0.083**	0.961	**0.928**	0.898	**0.107**
Mean	0.975	**0.949**	0.919	**0.069**	0.967	**0.938**	0.907	**0.091**
Std. Dev.	0.005	**0.009**	0.009	**0.012**	0.006	**0.009**	0.008	**0.015**