

Accepted Manuscript

On the efficiency of sovereign bond markets

Luciano Zunino, Aurelio Fernández Bariviera, M. Belén Guercio,
Lisana B. Martinez, Osvaldo A. Rosso

PII: S0378-4371(12)00302-0
DOI: 10.1016/j.physa.2012.04.009
Reference: PHYSA 13773

To appear in: *Physica A*

Received date: 29 January 2012

Please cite this article as: L. Zunino, A. Fernández Bariviera, M. Belén Guercio, L.B. Martinez, O.A. Rosso, On the efficiency of sovereign bond markets, *Physica A* (2012), doi:10.1016/j.physa.2012.04.009

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.



Highlights of the manuscript "On the efficiency of sovereign bond markets" by Luciano Zunino, Aurelio Fernández Bariviera, M. Belén Guercio, Lisana B. Martinez and Osvaldo A. Rosso

- Efficiency of sovereign bond markets is analyzed.
- The complexity-entropy causality plane is implemented to reach this goal.
- Correlations and hidden structures in the daily values of bond indices are unveiled.
- Consistency with qualifications assigned by major rating companies is obtained.
- A link between the entropy measure, economic growth and market size is also found.

On the efficiency of sovereign bond markets

Luciano Zunino^{a,b}, Aurelio Fernández Bariviera^c, M. Belén Guercio^c, Lisana B. Martinez^c,
Osvaldo A. Rosso^{d,e}

^a*Centro de Investigaciones Ópticas (CONICET La Plata - CIC), C.C. 3, 1897 Gonnet, Argentina*

^b*Departamento de Ciencias Básicas, Facultad de Ingeniería, Universidad Nacional de La Plata (UNLP),
1900 La Plata, Argentina*

^c*Department of Business, Universitat Rovira i Virgili, Av. Universitat 1, 43204 Reus, Spain*

^d*LaCCAN/CPMAT - Instituto de Computação, Universidade Federal de Alagoas, BR 104 Norte km 97,
57072-970 Maceió, Alagoas - Brazil*

^e*Laboratorio de Sistemas Complejos, Facultad de Ingeniería, Universidad de Buenos Aires. 1063 Av.
Paseo Colón 840, Ciudad Autónoma de Buenos Aires, Argentina*

Abstract

The existence of memory in financial time series has been extensively studied for several stock markets around the world by means of different approaches. However, fixed income markets, i.e. those where corporate and sovereign bonds are traded, have been much less studied. We believe that, given the relevance of these markets, not only from the investors', but also from the issuers' point of view (government and firms), it is necessary to fill this gap in the literature. In this paper, we study the sovereign market efficiency of thirty bond indices of both developed and emerging countries, using an innovative statistical tool in the financial literature: the *complexity-entropy causality plane*. This representation space allows us to establish an efficiency ranking of different markets and distinguish different bond market dynamics. We conclude that the classification derived from the complexity-entropy causality plane is consistent with the qualifications assigned by major rating companies to the sovereign instruments. Additionally, we find a correlation between permutation entropy, economic development and market size that could be of interest for policy makers and investors.

Keywords: sovereign bond market efficiency, complexity-entropy causality plane, permutation entropy, permutation statistical complexity, Bandt and Pompe method, ordinal time series analysis

PACS: 89.65.Gh (Economics; econophysics, financial markets, business and management),

05.45.Tp (Time series analysis), 89.70.Cf (Entropy and other measures of information)

1. Introduction

The study of the informational efficiency is maybe one of the most elusive issues in financial economics. In spite of the fact that the first model of an informational efficient market was based on the price changes of French government bonds [1], the literature focused its efforts on the study of stock markets rather than bond markets. The reason for this bias is probably twofold. On the one hand, stock markets trading figures are much larger than bond markets. On the other hand, sovereign bonds¹ began to be traded in exchange markets much more recently in time for many countries, specially for emerging ones. More details about the development of fixed income markets for emerging countries can be found in Refs. [3, 4]. Among the studies on the fixed income markets we can cite Ref. [5] in which January effect in returns of corporate bonds of the Dow Jones Composite Bond Average is found, Ref. [6] in which patterns of daily seasonality in high yield corporate bonds are observed, and Ref. [7] where it is shown the existence of daily seasonalities in the Spanish sovereign bonds for different maturities. Also the patterns of comovements in government bond market yields have been recently analyzed by implementing the minimum spanning tree approach [8, 9]. Useful conclusions are obtained by examining the dynamic evolution of market linkages.

The traditional definition of informational efficiency corresponds to a market where prices fully reflect all available information [10]. Therefore, the key element in assessing efficiency is to determine the information set against which prices should be tested. Informational

Email addresses: lucianoz@ciop.unlp.edu.ar (Luciano Zunino), aurelio.fernandez@urv.net (Aurelio Fernández Bariviera), mariabelen.guercio@urv.net (M. Belén Guercio), lisanabelen.martinez@urv.net (Lisana B. Martinez), oarosso@fibertel.com.ar, oarosso@gmail.com (Osvaldo A. Rosso)

¹“A bond is an instrument in which the issuer (debtor/borrower) promises to repay to the lender/investor the amount borrowed plus interest over some specified period of time”. Definition extracted from Ref. [2, p. 213]. “Bonds issued by autonomous nation states are included in sovereign debt”. Definition extracted from Ref. [2, p. 223].

21 efficiency is classified into three categories, depending on this information set [11, 12]. The
22 first category is the weak efficiency, where stock prices reflect all the information contained
23 in the history of past prices. The second category is semi-strong efficiency, where the infor-
24 mation set is all public known information. Finally, the third category is strong efficiency,
25 where prices reflect all kind of information, public and private. Although it may seem at
26 first sight a sign of irrationality, random changes in stock prices reflect the quest of ratio-
27 nal investors to catch mispriced securities in the market. The Efficient Market Hypothesis
28 (EMH) is a necessary condition for the existence of equilibrium in a competitive market, in
29 which arbitrage opportunities cannot exist. Ross [13] indicates that this definition evokes
30 the idea that prices are the result of decisions made by individual agents and, therefore, they
31 depend on the underlying information. As a corollary, with the same information set it is not
32 possible to obtain superior returns. It implies, also, that future returns depend to a great
33 extent not only on historic information but also on the new information that arrives at the
34 market. Therefore, an investor, whose information set is the same or inferior to the market
35 information set, cannot beat the market. In addition, investors cannot control the flow of
36 their informative endowment towards the market, since their own transactions (according
37 to its direction and volume) act as signals to the market, tending, thus, to an equalization
38 of the informative sets of the different participants in the market. This produces that, in
39 average, participants cannot beat the market on a regular basis. In an attempt to relax such
40 strict assumptions, Grossman and Stiglitz [14] expand the concept of efficiency, arguing that
41 when information is costly, prices will reflect the information of informed individuals, but
42 only partially, so that information gathering is rewarded.

43 The aim of this paper is to analyze the sovereign bond market efficiency. More precisely,
44 we want to: (i) classify bond indices, giving a rationale for the bond qualifications of the
45 main rating agencies such as Standard & Poor's (S&P) and Moody's and (ii) analyze the
46 link between sovereign bond market efficiency, economic development and market size. The
47 relationship between economic growth and financial system development has been exten-
48 sively studied in the economic literature [15–21]. Nevertheless, these studies consider the
49 financial system only composed by the banking sector and the stock market. There is a

50 scarce literature that includes the bond market and their results are contradictory [22–25].
51 The present paper extends the coverage of the empirical literature, considering a potential
52 relationship between economic growth and the development of sovereign bond markets, as
53 an important part of the financial system.

54 In order to quantify the efficiency related to government bond market indices we use
55 the *complexity-entropy causality plane*, i.e. the representation space with the permutation
56 entropy of the system in the horizontal axis and an appropriate permutation statistical
57 complexity measure in the vertical one. This novel information-theory-tool was recently
58 shown to be a practical and robust way to discriminate the linear and nonlinear correlations
59 present in stock and commodity markets [26, 27]. The location in the complexity-entropy
60 causality plane allows to quantify the inefficiency of the system under analysis because the
61 presence of temporal patterns derives in deviations from the ideal position associated to a
62 totally random process. Consequently, the distance to this random ideal location can be
63 used to define a ranking of efficiency. As will be shown in detail below, we have found
64 that this permutation information-theory-tool is also useful for detecting and quantifying
65 the presence of correlations and hidden structures in the temporal evolution of government
66 bond markets.

67 This article contributes in several ways to the research field. First, to the best of our
68 knowledge, this is the most comprehensive study of efficiency in the sovereign bond markets
69 covering a total of thirty bond indices of both developed and emerging countries. Second,
70 we detect a coherence of agencies' ratings with the time series efficiency endowment. Third,
71 we find a statistically significant link between bond market randomness and economic de-
72 velopment and market size. Fourth, we prove the practical utility of the complexity-entropy
73 causality plane for quantifying efficiency in a financial context.

74 The remainder of the paper is organized as follows. In the next section, in order to keep
75 our description as self-contained as possible, we introduce the complexity-entropy causality
76 plane. In Sec. 3 we present the data and results. Finally, in Sec. 4, the main conclusions of
77 this paper are summarized.

78 2. Complexity-entropy causality plane

Black box time series, given by the discrete set $\{x_t, t = 1, \dots, N\}$, recorded from observable quantities associated to a system are very often the starting point to study the underlying dynamical phenomenon. They should be carefully analyzed in order to extract relevant information for simulation and forecasting purposes. Information-theory-derived quantifiers can be good candidates for this task because they are able to characterize some properties of the probability distribution associated with the observable or measurable quantity. Shannon entropy is the most paradigmatic example. Its usefulness as a measure of the volatility phenomenon in the financial domain has been proved [28]. Given any arbitrary discrete probability distribution $P = \{p_i : i = 1, \dots, M\}$, Shannon's logarithmic information measure is given by $S[P] = -\sum_{i=1}^M p_i \ln p_i$. It is equal to zero when we are able to predict with full certainty which of the possible outcomes i whose probabilities are given by p_i will actually take place. Our knowledge of the underlying process described by the probability distribution is maximal in this instance. In contrast, this knowledge is minimal for a uniform distribution. It is well known, however, that the degree of structure or patterns present in a process is not quantified by randomness measures and, consequently, measures of statistical or structural complexity are necessary for a better characterization [29]. This is why we have proposed to consider also the statistical complexity for the analysis of financial time series [26, 27]. The opposite extremes of perfect order and maximal randomness (a periodic sequence and a fair coin toss, for example) are very simple to describe because they do not have any structure. The former situation is fully predictable and the latter one has a very simple statistical description. The statistical complexity should be zero in both these cases. At a given distance from these extremes, a wide range of possible degrees of physical structure exists, that should be discriminated by the complexity measure. In this work we have considered the effective statistical complexity measure (SCM) introduced by Lamberti *et al.* [30] since it is able to detect essential details of the dynamics and discriminate different degrees of periodicity and chaos. This statistical complexity measure is defined, following

the seminal and intuitive notion advanced by López-Ruiz *et al.* [31], through the product

$$\mathcal{C}_{JS}[P] = \mathcal{Q}_J[P, P_e] \mathcal{H}_S[P] \quad (1)$$

of the normalized Shannon entropy

$$\mathcal{H}_S[P] = S[P]/S_{\max} \quad (2)$$

79 with $S_{\max} = S[P_e] = \ln M$, ($0 \leq \mathcal{H}_S \leq 1$) and $P_e = \{1/M, \dots, 1/M\}$ the uniform dis-
 80 tribution, and the disequilibrium \mathcal{Q}_J defined in terms of the Jensen-Shannon divergence.
 81 That is, $\mathcal{Q}_J[P, P_e] = \mathcal{Q}_0 \mathcal{J}[P, P_e]$ with $\mathcal{J}[P, P_e] = \{S[(P + P_e)/2] - S[P]/2 - S[P_e]/2\}$ the
 82 above-mentioned Jensen-Shannon divergence and \mathcal{Q}_0 a normalization constant, equal to the
 83 inverse of the maximum possible value of $\mathcal{J}[P, P_e]$. This value is obtained when one of the
 84 components of P , say p_m , is equal to one and the remaining p_i are equal to zero. Note that
 85 the above SCM depends on two different probability distributions, the one associated to the
 86 system under analysis, P , and the uniform distribution, P_e . Furthermore, it was shown that
 87 for a given value of \mathcal{H}_S , the range of possible \mathcal{C}_{JS} values varies between a minimum \mathcal{C}_{JS}^{\min} and
 88 a maximum \mathcal{C}_{JS}^{\max} , restricting the possible values of the SCM in a given complexity-entropy
 89 plane [32]. Thus, it is clear that important additional information related to the correla-
 90 tional structure between the components of the physical system is provided by evaluating
 91 the statistical complexity measure. Of course there exist many other complexity measures.
 92 For a comparison among them see the paper by Wackerbauer *et al.* [33].

93 In order to calculate the two above-mentioned information-theory-derived quantifiers, a
 94 probability distribution should be estimated from the time series associated to the measur-
 95 able quantity of the system. The Bandt and Pompe permutation methodology was employed
 96 in our analysis due to its simplicity and effectiveness [34]. This efficient symbolic technique,
 97 based on the ordinal relation between the amplitude of neighboring values, arises naturally
 98 from the time series and allows to avoid amplitude threshold sensitivity dependences. It is
 99 clear that, with this way of symbolizing time series, some details of the original amplitude in-
 100 formation and variability are lost. However, a meaningful reduction of the complex systems
 101 to their basic intrinsic structure is provided. Furthermore, the ordinal pattern distribution

102 is invariant with respect to nonlinear monotonous transformations. Thus, nonlinear drifts
 103 or scalings artificially introduced by a measurement device do not modify the quantifiers'
 104 estimations, a property highly desired for the analysis of experimental data. These are the
 105 main advantages with respect to more conventional methods based on range partitioning.
 106 The ordinal pattern probability distribution is obtained once we fix the embedding dimen-
 107 sion D (pattern length) and the embedding delay time τ . The former parameter, D , refers
 108 to the number of symbols that forms the ordinal pattern. Its choice depends on the length
 109 N of the time series in such a way that the condition $N \gg D!$ must be satisfied in order
 110 to obtain a reliable statistics. It is worth remarking that there are $D!$ possible permuta-
 111 tions, and accessible states, for a D -dimensional vector. For practical purposes, Bandt and
 112 Pompe recommend $3 \leq D \leq 7$ [34]. The embedding delay, τ , is the time separation between
 113 symbols, which is directly related to the sampling time of the time series. By changing the
 114 embedding delays of the symbolic reconstruction, different time scales are taken into ac-
 115 count. Hereafter, we have fixed $\tau = 1$, focusing the analysis on the highest frequency (daily
 116 values) contained within the time series. Please see Refs. [26, 27] for further details about
 117 the Bandt and Pompe permutation methodology. A very related approach, based on com-
 118 puting the number of forbidden ordinal patterns present in time series, has been successfully
 119 used to find evidence of determinism in noisy time series [35]. By employing this methodol-
 120 ogy, Zanin [36] has found a clear deterministic behavior for the ten years U.S. bond interest
 121 rates. In the present work the normalized Shannon entropy, \mathcal{H}_S (Eq. (2)), and the SCM,
 122 \mathcal{C}_{JS} (Eq. (1)), are evaluated using the permutation probability distribution. Defined in this
 123 way, these quantifiers are usually known as *permutation entropy* and *permutation statistical*
 124 *complexity* [37]. They characterize the diversity and correlational structure, respectively, of
 125 the orderings present in the complex time series.

126 The complexity-entropy causality plane (CECP) was introduced in Ref. [38] as the repre-
 127 sentation space obtained with the permutation entropy of the system in the horizontal axis
 128 and the permutation statistical complexity in the vertical one. The term causality takes into
 129 consideration that the temporal correlation between successive samples is included through
 130 the Bandt and Pompe recipe used to estimate both information-theory quantifiers. This

131 two-dimensional (2D) diagram was shown to be particularly efficient to distinguish between
 132 the deterministically chaotic and stochastic nature of a time series since the permutation
 133 quantifiers have distinctive behaviors for different type of motions. According to the find-
 134 ings obtained by Rosso *et al.* [38], chaotic maps have intermediate \mathcal{H}_S values while \mathcal{C}_{JS}
 135 reaches larger values, very close to the limit ones. For regular processes, both quantifiers
 136 have small values, close to 0. Finally, totally uncorrelated stochastic processes are located
 137 in the planar location associated with \mathcal{H}_S and \mathcal{C}_{JS} near 1 and 0, respectively. It has also
 138 been found that $1/f^\alpha$ correlated stochastic processes with $1 < \alpha < 3$ are characterized by
 139 intermediate permutation entropy and intermediate statistical complexity values. Within
 140 the econophysics framework, it has been recently shown that this information-theory-derived
 141 approach is an effective tool for distinguishing the stage of stock and commodity markets
 142 development [26, 27].

143 3. Data and results

144 In this paper we analyze the daily values of thirty bond indices, corresponding to twenty
 145 one developed and nine emerging markets, from 3rd January, 2000 until 7th September,
 146 2011, giving a total of $N = 3047$ data points for each bond daily record. All data were
 147 collected from Datastream database. The codes and names of these indices are presented
 148 in Table 1. We worked with two different indices elaborated by Citigroup: World Govern-
 149 ment Bond Index (WGBI) and Global Emerging Market Sovereign Bond Index (ESBI). The
 150 selection of these indices is based on their general characteristics that guarantee a uniform
 151 calculation across countries and the availability of a sufficiently long time series. WGBI in-
 152 cludes sovereign debts denominated in the domestic currency, with a minimum size of USD
 153 20 billion and a minimum credit quality of Baa3/BBB- by Moody's or Standard & Poor's
 154 (S&P). ESBI includes US dollar-denominated emerging market sovereign debts issued in
 155 the global, US and Eurodollar markets with a minimum size of USD 500 million, and max-
 156 imum credit rating of Baa1/BBB+ by Moody's or S&P, excluding debts into default. An
 157 overview about the categories of government bonds by these agencies is shown in Table 2.
 158 Credit ratings is an appraisal about the credit risk of a debt instrument and/or an issuer and

159 are provided by specialized firms. These ratings are relative rather than absolute opinions
160 about credit quality, i.e. about the ability of an issuer to fulfill its financial obligations on
161 time. These opinions are important to increase the information flow across the market and
162 are useful for the different participants in the market: investors, intermediaries and issuers.

163 We select indices that contain long maturity bonds (7-10 years) because, as explained
164 in Ref. [39], the returns of these bonds are not heavily influenced by short-term monetary
165 policy and home bias, but reflects global investor preferences, global savings trends and
166 international risk appetite. Among all the countries available we made a selection that
167 allows us to work with a large number of countries and a long time coverage.

168 Locations of the different sovereign bond markets in the CECP are estimated from the
169 daily indices for different embedding dimensions (pattern length) ($D = 4$, $D = 5$ and $D = 6$).
170 In Fig. 1 we can observe that developed and emerging bond markets are clearly discrimi-
171 nated in this representation space. In particular, we detect that developed markets exhibit
172 higher permutation entropy and lower permutation statistical complexity whereas emerging
173 markets present lower permutation entropy and higher permutation statistical complexity.
174 This indicates that bond indices corresponding to developed markets exhibit more random
175 behavior than those associated with emerging markets, which means higher informational ef-
176 ficiency in developed markets and, consequently, less predictability. Additionally, we observe
177 that developed markets conform a compact cluster, different from the pattern of emerging
178 markets that are more scattered on this representation space. It is worth remarking that
179 these findings appear to be independent of the pattern length selected for the symbolic
180 reconstruction of the original time series.

181 As can be seen in Fig. 2, we have also detected that, within developed markets, Eurozone
182 countries are more closed together, indicating that the price dynamics are very similar. This
183 situation could be caused by the existence of a common currency that avoids the exchange
184 rate risk, remaining only the credit and liquidity risks, as suggested in Ref. [40]. Note that
185 only Ireland (identified by the number 9 in Fig. 2) is not included in the Eurozone cluster.
186 Its permutation entropy is lower and its statistical complexity is higher due to a constant

Table 1: Sovereign bond indices analyzed in this paper.

WGBI		ESBI	
Country	Datastream code	Country	Datastream code
1. Australia	SBAD70U	1. Argentina	CGESARL
2. Austria	SBAS70U	2. Brazil	CGESBRL
3. Belgium	SBBF70U	3. Chile	CGESCLL
4. Canada	SBCD70U	4. Malaysia	CGESMYL
5. Denmark	SBDK70U	5. Mexico	CGESMXL
6. Finland	SBFN71\$	6. Philippines	CGESPHL
7. France	SBFF70U	7. Turkey	CGESTKL
8. Germany	SBDM70U	8. Uruguay	CGESUGL
9. Ireland	SBIR71\$	9. Venezuela	CGESVZL
10. Italy	SBIT70U		
11. Japan	SBJY70U		
12. Netherlands	SBDG70U		
13. New Zealand	CGNZ71\$		
14. Norway	CGNW71\$		
15. Poland	SBPL7T\$		
16. Singapore	CGSI71\$		
17. Spain	SBSP70U		
18. Sweden	SBSK70U		
19. Switzerland	SBSZ70U		
20. United Kingdom	SBUK70U		
21. United States	SBUS70L		

Table 2: Bond rating by Moody's and Standard & Poor's. Source: Own elaboration based on information retrieved from <http://www.moodys.com> and <http://www.standardandpoors.com>.

	Moody's	S&P
	Aaa	AAA
	Aa1	AA+
	Aa2	AA
	Aa3	AA-
Investment grade	A1	A+
	A2	A
	A3	A-
	Baa1	BBB+
	Baa2	BBB
	Baa3	BBB-
	Ba1	BB+
	Ba2	BB
	Ba3	BB-
Speculative grade	B1	B+
	B2	B
	B3	B-
	Caa1	CCC+
	Caa2	CCC
	Caa3	CCC-
	Ca	CC
	C	C

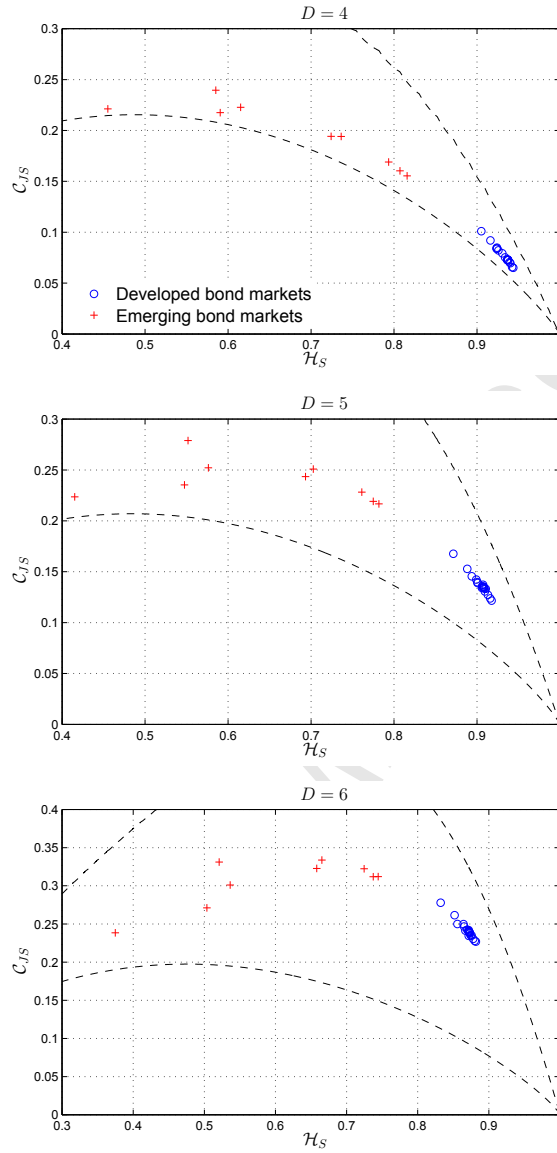


Figure 1: (Color online) Location of the developed and emerging bond markets, according to the indices elaborated by Citigroup (daily data from 3rd January, 2000 until 7th September 2011, $N = 3047$ data points), in the CECP with embedding dimensions $D = 4$ (upper plot), $D = 5$ (central plot) and $D = 6$ (lower plot), and time delay $\tau = 1$. We also display the minimum and maximum possible values of the complexity measure (dashed lines). For further details about the range of possible SCM values see Ref. [32].

187 behavior during the period from 31st May, 1999 to 28th April, 2000². This highly regular
188 local dynamics strongly affects the global permutation quantifiers' estimations. Focusing on
189 developed government bond markets, we perform a similar analysis for the WGBI beginning
190 on 2nd April, 2002 ($N = 2462$ data points). In this way, the constant behavior observed
191 in the Ireland bond index is avoided. Moreover, a new index (SBPE71\$) associated to
192 another country member of the Eurozone, Portugal (identified by the number 22 in Fig. 3),
193 is included because of data availability. As can be concluded from Fig. 3, the previous finding
194 is confirmed, i.e. the Eurozone countries conform a well-defined cluster in the CECP. It is
195 clear that the monetary policy harmonization within the Eurozone increases the financial
196 integration [8].

197 Another important result is that the classification derived from the CECP is coher-
198 ent with the qualification made by rating agencies. In fact, markets with better ratings
199 (Baa3/BBB- or better) are more random and behave more efficiently. On the other hand,
200 emerging countries (with a maximum qualification of Baa1/BBB+) have lower permutation
201 entropy values, which indicate a more regular behavior. This results allows us to confirm
202 that emerging and developed bond markets differ in their informational efficiency from a
203 information-theory-viewpoint.

204 In light of the results obtained, we investigate if the permutation entropy, that quantifies
205 the random behavior of the bond indices, is related to the developmental stage of the econ-
206 omy and/or to the market size. If bond markets were a pure random walk, their associated
207 entropy values would be maximized. On the other hand, if the bond indices were somewhat
208 correlated, then their entropy would not attain its maximal value [41]. Dependence of the
209 data generating process introduces patterns in the time series. Hence, the permutation en-
210 tropy decreases because the ordinal patterns are distant from sharing the same probability.
211 In order to assess the relationship between permutation entropy and the country develop-
212 ment we perform a non-parametric regression between the estimated values for the entropy
213 quantifier and the gross domestic product (GDP) per capita, measured in constant dollars

²There were no trades on the bonds of WGBI Ireland index during this period of time and, consequently, the index remained constant and no returns were recorded.

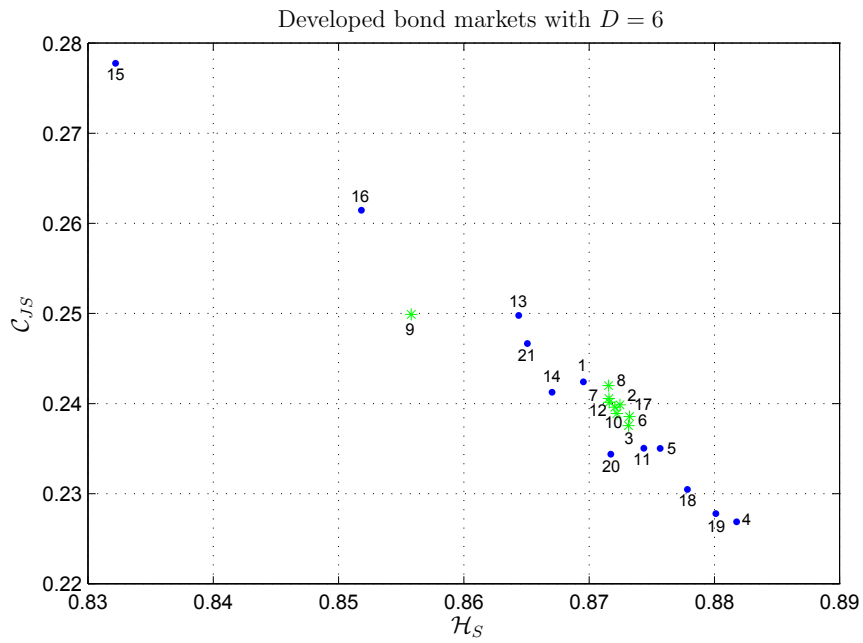


Figure 2: (Color online) Location of the different developed bond markets (daily data from 3rd January, 2000 until 7th September 2011, $N = 3047$ data points) in the CECP with embedding dimension $D = 6$ and time delay $\tau = 1$. A similar grouping is obtained for $D = 4$ and $D = 5$. Numbers indicate WGBI bond indices listed in Table 1. Eurozone sovereign bond markets are identified with green stars.

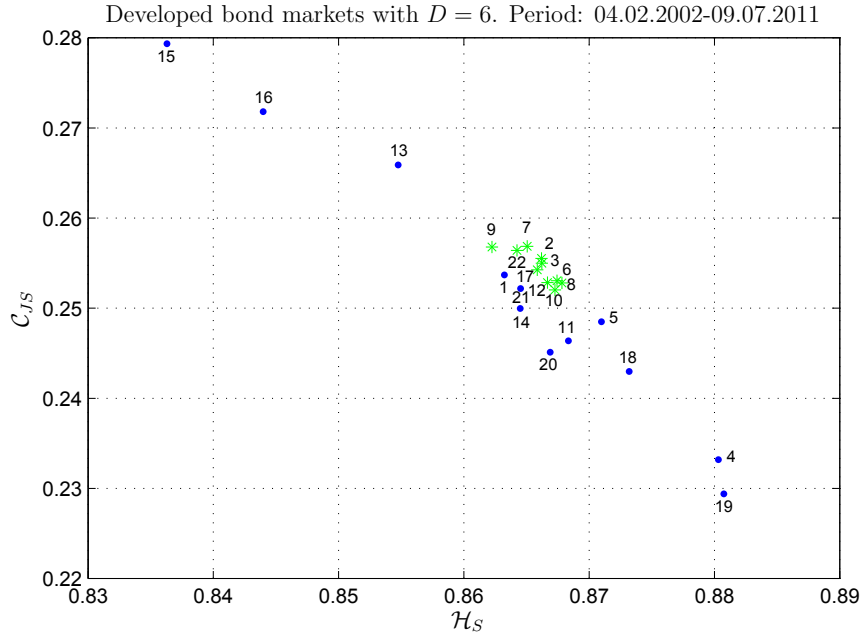


Figure 3: (Color online) Location of the different developed bond markets (daily data from 2nd April, 2002 until 7th September 2011, $N = 2462$ data points) in the CECP with embedding dimension $D = 6$ and time delay $\tau = 1$ for the WGBI beginning on 2nd April, 2002. Similar results are obtained for $D = 4$ and $D = 5$. Numbers indicate WGBI bond indices listed in Table 1. Portugal bond index is identified by the number 22. Eurozone sovereign bond markets are identified with green stars.

Table 3: Non-parametric rank correlation between permutation entropy, economic development (GDP per capita) and bond market size (Public bond market capitalization/GDP).

Variable	Test	N	Coefficient	P-value
GDP per capita (constant 2000 USD)	Kendall's tau-b	30	0.513	0.000
	Spearman's rho	30	0.706	0.000
GDP per capita (PPP constant 2005 USD)	Kendall's tau-b	30	0.375	0.004
	Spearman's rho	30	0.582	0.001
Public bond market capitalization/GDP	Kendall's tau-b	29 ^a	0.281	0.032
	Spearman's rho	29 ^a	0.417	0.024

^a The regression does not include Uruguay because the bond market capitalization corresponding to this country is not available at Ref. [42].

214 and at purchasing power parity (PPP). The results (see Table 3) show a moderate to strong
 215 relationship between permutation entropy and the development proxies. Additionally, and
 216 in order to study the effect of market size on the efficiency of the bond market, we perform a
 217 non-parametric regression between permutation entropy and a size proxy. We select the ra-
 218 tio of bond market capitalization to GDP as a variable that is representative of the market's
 219 depth [42]. Table 3 shows a moderate relationship between permutation entropy and market
 220 size, which highlights the usefulness of permutation entropy in financial time series analysis.
 221 In fact, these results are important in two aspects. The first one is that permutation entropy
 222 is positively related with the stage of economic development. The second one is that this
 223 quantifier is also affected by market size. These findings can be of great value for policy
 224 makers in order to set measures for improving the informational efficiency of bond markets.

225 4. Conclusions

226 We used the complexity-entropy causality plane in order to unveil the presence of cor-
 227 relations and hidden structures in the daily values of thirty bond indices. We detect that

228 the qualifications given by the main rating agencies are coherent with the location of the
229 associated time series in this representation space. In this sense, we expanded the literature
230 of EMH to a market that was not sufficiently studied in this aspect. Additionally, we find a
231 link between the entropy measure, economic growth and market size. In fact, permutation
232 entropy is higher for developed countries than for emerging ones, and market size is corre-
233 lated with permutation entropy, being the bigger markets the ones with higher permutation
234 entropy. In future works we would like to study the comovements and efficiency evolution
235 of government bond markets.

236 **Acknowledgements**

237 Luciano Zunino and Osvaldo A. Rosso were supported by Consejo Nacional de Investiga-
238 ciones Científicas y Técnicas (CONICET), Argentina. Lisana B. Martinez acknowledges the
239 support of a PhD scholarship from Department of Business of Universitat Rovira i Virgili,
240 Spain. Osvaldo A. Rosso gratefully acknowledges support from CNPq, Brazil.

241 **References**

- 242 [1] L. Bachelier, *Théorie de la spéculation*, Annales scientifiques de l'École Normale Supérieure, Paris,
243 1900.
- 244 [2] P. Newman, M. Milgate, J. Eatwell (Eds.), *The New Palgrave Dictionary of Money & Finance*, Palgrave
245 Macmillan, 1992.
- 246 [3] I. Bustillo, H. Velloso, *Bond markets for Latin American debt in the 1990s*, CEPAL Working Paper,
247 ECLAC-CEPAL, 2000.
- 248 [4] *The development of bond markets in emerging economies*, BIS Papers 11, Bank for International
249 Settlements, 2002.
- 250 [5] S. D. Jordan, B. D. Jordan, *Seasonality in daily bond returns*, *The Journal of Financial and Quanti-*
251 *tative Analysis* 26 (1991) 269–285.
- 252 [6] G. J. Alexander, M. G. Ferri, *Day-of-the-week patterns in volume and prices of Nasdaq high-yield*
253 *bonds*, *The Journal of Portfolio Management* 26 (2000) 33–40.
- 254 [7] A. Fernández Bariviera, J. de Andrés Sánchez, *¿Existe estacionalidad diaria en el mercado de bonos*
255 *y obligaciones del estado? Evidencia empírica en el período 1998-2003*, *Análisis Financiero* 98 (2005)
256 16–21 (in Spanish).

- 257 [8] C. G. Gilmore, B. M. Lucey, M. W. Boscia, Comovements in government bond markets: A minimum
258 spanning tree analysis, *Physica A* 389 (2010) 4875–4886.
- 259 [9] J. Dias, Sovereign debt crisis in the European Union: A minimum spanning tree approach, *Physica A*
260 391 (2012) 2046–2055.
- 261 [10] E. F. Fama, *Foundations of finance: Portfolio decisions and securities prices*, Basic Books, New York,
262 1976.
- 263 [11] H. V. Roberts, Stock-market “patterns” and financial analysis: Methodological suggestions, *The*
264 *Journal of Finance* 14 (1959) 1–10.
- 265 [12] E. F. Fama, Efficient capital markets: A review of theory and empirical work, *The Journal of Finance*
266 25 (1970) 383–417.
- 267 [13] S. A. Ross, *Neoclassical finance*, Princeton University Press, Princeton (NJ), 2004.
- 268 [14] S. J. Grossman, J. E. Stiglitz, On the impossibility of informationally efficient markets, *The American*
269 *Economic Review* 70 (1980) 393–408.
- 270 [15] J. A. Schumpeter, *The Theory of economic development :an inquiry into profits, capital, credit, interest,*
271 *and the business cycle*, Harvard University Press, Cambridge (MA), 1911.
- 272 [16] R. E. Cameron, *Banking in the early stages of industrialization: a study in comparative economic*
273 *history*, Oxford University Press, New York, 1967.
- 274 [17] R. W. Goldsmith, *Financial Structure and Development (Study in Comparative Economics)*, Yale
275 University Press, New Haven (CT), 1969.
- 276 [18] R. I. McKinnon, *Money and Capital in Economic Development*, Brookings Institution Press, 1973.
- 277 [19] R. G. King, R. Levine, Finance and growth: Shumpeter might be right, *Quarterly Journal of Economics*
278 108 (1993) 717–737.
- 279 [20] J. De Gregorio, P. E. Guidotti, Financial development and economic growth, *World Development* 23
280 (1995) 433–448.
- 281 [21] P. Arestis, A. D. Luintel, K. B. Luintel, *Does Financial Structure Matter?*, Economics Working Paper
282 Archive 399, The Levy Economics Institute, 2004.
- 283 [22] C. R. Harvey, *Does the bond market do better than the stock market in predicting economic growth?*,
284 SSRN eLibrary (1989).
- 285 [23] G. Fink, P. Haiss, S. Hristoforova, *Credit, bonds, stocks and growth in seven large economies*, Eu-
286 ropainstitut, WU Vienna University of Economics and Business, Vienna (2006).
- 287 [24] G. Fink, P. Haiss, G. Vukšić, Contribution of financial market segments at different stages of develop-
288 ment: Transition, cohesion and mature economies compared, *Journal of Financial Stability* 5 (2009)
289 431–455.
- 290 [25] A. Terceño, M. B. Guercio, Economic growth and development of the financial system. A comparative

- 291 analysis, *Investigaciones Europeas de Dirección y Economía de la Empresa* 17 (2011) 33–46.
- 292 [26] L. Zunino, M. Zanin, B. M. Tabak, D. G. Pérez, O. A. Rosso, Complexity-entropy causality plane: a
293 useful approach to quantify the stock market inefficiency, *Physica A* 389 (2010) 1891–1901.
- 294 [27] L. Zunino, B. M. Tabak, F. Serinaldi, M. Zanin, D. G. Pérez, O. A. Rosso, Commodity predictability
295 analysis with a permutation information theory approach, *Physica A* 390 (2011) 876–890.
- 296 [28] S. R. Bentes, R. Menezes, D. A. Mendes, Long memory and volatility clustering: is the empirical
297 evidence consistent across stock markets?, *Physica A* 387 (2008) 3826–3830.
- 298 [29] D. P. Feldman, C. S. McTague, J. P. Crutchfield, The organization of intrinsic computation:
299 Complexity-entropy diagrams and the diversity of natural information processing, *Chaos* 18 (2008)
300 043106.
- 301 [30] P. W. Lamberti, M. T. Martín, A. Plastino, O. A. Rosso, Intensive entropic non-triviality measure,
302 *Physica A* 334 (2004) 119–131.
- 303 [31] R. López-Ruiz, H. L. Mancini, X. Calbet, A statistical measure of complexity, *Phys. Lett. A* 209 (1995)
304 321–326.
- 305 [32] M. T. Martín, A. Plastino, O. A. Rosso, Generalized statistical complexity measures: Geometrical and
306 analytical properties, *Physica A* 369 (2006) 439–462.
- 307 [33] R. Wackerbauer, A. Witt, H. Atmanspacher, J. Kurths, H. Scheingraber, A comparative classification
308 of complexity measures, *Chaos, Solitons & Fractals* 4 (1994) 133–173.
- 309 [34] C. Bandt, B. Pompe, Permutation entropy: A natural complexity measure for time series, *Phys. Rev.*
310 *Lett.* 88 (2002) 174102.
- 311 [35] J. M. Amigó, S. Zambrano, M. A. F. Sanjuán, True and false forbidden patterns in deterministic and
312 random dynamics, *Europhys. Lett.* 79 (2007) 50001.
- 313 [36] M. Zanin, Forbidden patterns in financial time series, *Chaos* 18 (2008) 013119.
- 314 [37] O. A. Rosso, L. Zunino, D. G. Pérez, A. Figliola, H. A. Larrondo, M. Garavaglia, M. T. Martín,
315 A. Plastino, Extracting features of Gaussian self-similar stochastic processes via the Bandt & Pompe
316 approach, *Phys. Rev. E* 76 (2007) 061114.
- 317 [38] O. A. Rosso, H. A. Larrondo, M. T. Martín, A. Plastino, M. A. Fuentes, Distinguishing noise from
318 chaos, *Phys. Rev. Lett.* 99 (2007) 154102.
- 319 [39] M. S. Kumar, T. Okimoto, Dynamics of international integration of government securities' markets,
320 *Journal of Banking & Finance* 35 (2011) 142–154.
- 321 [40] L. Codogno, C. Favero, A. Missale, Yield spreads on EMU government bonds, *Economic Policy* 18
322 (2003) 503–532.
- 323 [41] L. Zunino, M. Zanin, B. M. Tabak, D. G. Pérez, O. A. Rosso, Forbidden patterns, permutation entropy
324 and stock market inefficiency, *Physica A* 388 (2009) 2854–2864.

- 325 [42] T. Beck, A. Demirgüç-Kunt, Financial institutions and markets across countries and over time: data
326 and analysis, The World Bank Policy Research Working Paper No. 4943 (May 2009).