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Monitoring the informational efficiency of European corporate bond markets with dynamical permutation min-entropy

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HIGHLIGHTS

- Informational efficiency of corporate bond markets is studied.
- Permutation min-entropy is implemented to unveil hidden temporal structures.
- Effects of the 2008 credit crisis are addressed.
- Heterogeneous impact of the crisis on different economic sectors is confirmed.
- Sectors related to the financial economy are more vulnerable to the crisis impact.

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ABSTRACT

In this paper the permutation min-entropy has been implemented to unveil the presence of temporal structures in the daily values of European corporate bond indices from April 2001 to August 2015. More precisely, the informational efficiency evolution of the prices of fifteen sectorial indices has been carefully studied by estimating this information-theory-derived symbolic tool over a sliding time window. Such a dynamical analysis makes possible to obtain relevant conclusions about the effect that the 2008 credit crisis has had on the different European corporate bond sectors. It is found that the informational efficiency of some sectors, namely banks, financial services, insurance, and basic resources, has been strongly reduced due to the financial crisis whereas another set of sectors, integrated by chemicals, automobiles, media, energy, construction, industrial goods & services, technology, and telecommunications has only suffered a transitory loss of efficiency. Last but not least, the food & beverage, healthcare, and utilities sectors show

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a behavior close to a random walk practically along all the period of analysis, confirming a remarkable immunity against the 2008 financial crisis.

1. Introduction

One of the richest fields for the application of econophysics methods is Finance. Financial markets produce a large amount of ready-to-use time series, which could be examined via concepts and methods of statistical physics [1]. Particularly, informational efficiency and long-range dependence have been recurrent topics in the finance literature. Over a century ago the French mathematician Bachelier developed the first rational expectation model proposing a random walk model for the bond prices on the Paris Bourse [2]. Such a walk is a random process whose increments are uncorrelated (fair game pattern). Lately, Samuelson [3] gave a formal proof about the random character of speculative prices, and Fama [4] introduced the celebrated Efficient Market Hypothesis (EMH). This efficiency hypothesis was then subdivided into three categories, *i.e.* weak, semi-strong and strong, according to the information set reflected in prices [5]. In empirical studies the weak-form of the EMH has been mainly considered. It requires that today price reflects the information of the sequence of past prices, excluding the possibility of finding profitable trading strategies systematically. Despite all these seminal contributions, the quest for a stochastic model that reflects asset prices remains as an open and controversial issue [6].

Nowadays, it is widely recognized that the random walk model of prices can be considered only as a first approximation of price behavior. Within this avenue of research, most of researchers concentrated on testing the efficiency of different financial markets by estimating the Hurst exponent H ($H \in (0, 1)$) as a way to characterize long-range dependence phenomena (*e.g.*, Refs. [7–22], among many others). The interested reader may refer to Ref. [23] for a comprehensive survey about different Hurst exponent estimators. A Hurst exponent $H \neq 0.5$ is, in principle, an evidence of the presence of memory effects in the time series under analysis. For $H > 0.5$ persistence or positive long-term memory is found whereas $H < 0.5$ indicates anti-persistence or negative long-term memory. The deviation from the uncorrelated, ideal state ($H = 0.5$) is considered as a signature of inefficiency since price fluctuations could be predicted, allowing for risk-free profitable trading strategies. Indeed, it has been shown that large profits can be obtained from persistent than anti-persistent markets, both with exactly the same deviation from the memoryless case, *i.e.* $|H - 1/2|$ [24]. However, Hurst exponent estimators are usually biased by the presence of heavy tails [25], finite-size effects [26], and/or short-range dependence [27,28] generating doubts about the reliability of their results. These drawbacks can lead to the erroneous identification of memory effects, $H \neq 0.5$, in true uncorrelated financial records [29]. On the other hand, the inappropriate application of the estimation methods can also lead to the spurious identification of anti-persistent behavior in financial time series [23,30]. Furthermore, Bassler et al. [31] have shown that the estimation of the Hurst exponent alone cannot be used to determine either the existence of long-term memory or the efficiency of markets since a Hurst exponent $H \neq 1/2$ might be perfectly consistent with Markov processes with nonstationary increments. Consequently, several researchers have focused on looking for alternative or complementary approaches to quantify the underlying temporal correlation structures of financial time series. Particularly, descriptors derived from information theory, especially entropy measures, have been proposed for such a goal. These measures are of more general applicability since they are model-independent, *i.e.* not linked to a specific stochastic model. Additionally, entropy approaches have the salient ability to account for nonlinear dependences. Gulko [32], Zhang [33] and Darbellay and Wuertz [34] were probably the first to demonstrate the usefulness of entropy concepts to characterize financial time series. Later, Pincus and Kalman [35] confirmed that approximate entropy can be used as a marker of market stability. In the last decade, other entropy-related methodologies have been introduced to quantify market efficiency in foreign exchange [36], stock [37–42], commodity [43–45], and bond [46–48] market indices. Interest rate time series have been also characterized using an information theory approach [49,50]. We need to emphasize here the starring role played by the permutation entropy in some of the above-mentioned studies. It is also worth mentioning the Efficiency Index (EI), introduced by Kristoufek and Vosvrda, that incorporates long-term memory, fractal dimension and entropy in a single measure [51–53]. Actually, it has been observed that the entropy measure has a stronger effect in the final efficiency ranking when the EI is applied to different stock market indices across the world [52]. In the present study, a very recently introduced entropy measure, namely the permutation min-entropy, is implemented for quantifying the market efficiency. This fast and simple symbolic tool has been shown particularly suitable for dealing with the identification of intricate temporal structures from time series data [54].

Despite the importance of fixed income markets in the composition of investment portfolios and in company and government financing, there are very few empirical studies about their informational efficiency. The fixed income markets are divided into two categories, depending on the legal status of the issuer. Corporate bond markets refer to debt instruments issued by private and public corporations whereas sovereign bond markets include debt instruments whose borrowers are autonomous nation states. Estimating the Hurst exponent through a rolling window approach, Bariviera et al. [55] have detected that the 2008 financial crisis affects more the informational efficiency of the corporate than the sovereign bond indices of seven European Union countries. Later, following a similar analysis, the same authors have observed that the financial turmoil has a uneven effect on the informational efficiency of fifteen sectorial indices of European corporate bonds between 2001 and 2013 [56]. Taking into consideration that corporate bond markets are very large in volume and popular between portfolio managers, a careful analysis of the temporal structures that govern their underlying dynamics for understanding and modeling purposes is fully justified.

The aim of this paper is to analyze the time-varying informational efficiency and the impact of the 2008 financial crisis on sectorial indices of European corporate bonds. Permutation min-entropy has been estimated using a sliding window approach in order to unveil the presence of hidden correlations during certain time periods within the financial series. This research contributes to the literature in four different aspects. First, the informational efficiency of corporate bond markets is analyzed. Second, a novel symbolic entropic quantifier is proposed to identify the presence of memory phenomena in these financial time series. Third, the time-varying efficiency of the most important and recognized sectors of the economy is monitored and compared. And fourth, the uneven effect of the last financial crisis across the different sectors is discriminated.

The remainder of the paper is organized as follows. In the next section, permutation min-entropy, *i.e.* the symbolic information-theory-derived quantifier estimated for identifying and characterizing the presence of hidden temporal correlations in the financial time series, is briefly described. In Section 3 the financial dataset is presented. Empirical results obtained are detailed in Section 4. Finally, Section 5 provides the main conclusions of the performed research.

2. Permutation min-entropy

Entropy is a concept widely used to quantify the disorder and uncertainty of dynamical systems. In particular, within the econophysics community, entropic quantifiers are usually used as descriptors of the diversity (unpredictability) of the market dynamics [43,42,45]. Shannon entropy is the most paradigmatic example. Given any arbitrary discrete probability distribution $P = \{p_i : i = 1, \ldots, M\}$, Shannon's logarithmic information measure is given by

$$S[P] = -\sum_{i=1}^{M} p_i \ \ln p_i. \quad (1)$$

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. The Rényi entropy or Rényi information measure of order α is a generalization of the Shannon entropy given by

$$R_\alpha[P] = \frac{1}{1-\alpha} \ln \left(\sum_{i=1}^{M} p_i^\alpha \right). \quad (2)$$

The order α ($\alpha \geq 0$ and $\alpha \neq 1$) is a bias parameter: $\alpha < 1$ privileges rare events, while $\alpha > 1$ privileges salient events. The Shannon entropy $S[P]$ is recovered in the limit as $\alpha \to 1$. The analysis of the Rényi entropy as a function of α allows a better characterization of the process under study than just the Shannon entropy counterpart, and its application on financial time series is not new [57,58]. In the limit as $\alpha \to \infty$, $R_\alpha[P]$ converges to the min-entropy $R_\infty[P]$. Indeed, it can be shown that $R_\infty[P]$ is a function of the highest probability only. More precisely,

$$R_\infty[P] = -\ln \left(\max_{i=1,\ldots,M} p_i \right). \quad (3)$$

In order to calculate any information-theory-derived quantifier, a probability distribution should be estimated from the time series associated to the measurable quantity of the system. The encoding scheme introduced by Bandt and Pompe (BP) [59], to extract the probability distribution associated with an input signal, considers the temporal ranking information (ordinal or permutation patterns) of the time series. Based on the ordinal relation between the amplitude of neighboring values of a given data sequence, the BP recipe is better suited to cope with usual problems (nonstationarities, nonlinearities, noise distortions) encountered when studying real time series. This local ordinal symbolic procedure, that naturally arises from the time series, inherits the causal information that stems from the temporal structure of the system dynamics. It also avoids amplitude threshold dependences that affect other more conventional symbolization recipes based on range partitioning [60]. Moreover, this symbolic procedure is applicable to noisy real time series from all class of systems, deterministic and stochastic, without the need to require any assumption about the generating process [61]. Given all these useful properties, the BP permutation methodology was employed in the present analysis. The procedure can be better illustrated with a simple example; let us assume that we start with the time series $X = \{5, 4, 7, 10, 11, 8, 3\}$. Two parameters, the embedding dimension $D > 1$ ($D \in \mathbb{N}$, number of symbols that form the ordinal pattern) and the embedding delay τ ($\tau \in \mathbb{N}$, time separation between symbols) are chosen, and next, the time series is partitioned into subsets of length D with delay τ similarly to phase space reconstruction by means of time-delay-embedding. The elements in each new partition (of length D) are replaced by their rank in the subset. For example, if we set $D = 3$ and $\tau = 1$, there are five different three-dimensional vectors associated with X. The first one $(x_0, x_1, x_2) = (5, 4, 7)$ is mapped to the ordinal pattern (102) since $x_1 \leq x_0 \leq x_2$. The second three-dimensional vector is $(x_0, x_1, x_2) = (4, 7, 10)$, and (012) will be its related permutation because $x_0 \leq x_1 \leq x_2$. The procedure continues so on until the last sequence, (11, 8, 3), is mapped to its corresponding motif, (210). Afterward, an ordinal pattern probability distribution,

$$P_{BP} = \{p(\pi_i),\ i = 1, \ldots, D!\}, \tag{4}$$

can be obtained from the time series by computing the relative frequencies of the $D!$ possible permutations π_i. Continuing with the example: $p(\pi_1) = p(012) = 2/5$, $p(\pi_2) = p(021) = 0$, $p(\pi_3) = p(102) = 1/5$, $p(\pi_4) = p(120) = 0$, $p(\pi_5) = p(201) = 1/5$, and $p(\pi_6) = p(210) = 1/5$. Ordinal pattern probability distribution P is obtained once we fix the embedding dimension D and the embedding delay time τ. Taking into account that there are $D!$ potential permutations for a D-dimensional vector, the condition $N \gg D!$, with N the length of the time series, must be satisfied in order to obtain a reliable estimation of P [62]. For practical purposes, BP suggest in their cornerstone paper [59] to estimate the frequency of ordinal patterns with $3 \leq D \leq 7$ and time lag $\tau = 1$ (consecutive points). For further details about the BP methodology, we strongly recommend Refs. [63–65], where the construction principle of ordinal patterns and all possible orderings (patterns) for different embedding dimensions are clearly illustrated.

Shannon entropy (Eq. (1)), Rényi entropy (Eq. (2)) and min-entropy (Eq. (3)) evaluated by implementing the ordinal pattern probability distribution (Eq. (4)) are known as permutation entropy [59], Rényi permutation entropy [58] and permutation min-entropy [54], respectively. The latter permutation quantifier has been shown specially appropriate for identifying and characterizing the underlying temporal correlations that are present in complex time series. Moreover, permutation min-entropy (PME) has a better performance than the other permutation quantifiers for detecting structural changes in time series and distinguishing between different sets of physiological recordings in normal and pathological conditions [54]. It should be noted that long-range correlations in the time series are reflected in the relative frequency of the ordinal patterns, *i.e.* some particular patterns appear more often than the others due to the memory effect, and the estimated ordinal pattern probability distribution (Eq. (4)) is different from the equiprobable one expected for an uncorrelated stationary stochastic process (white noise). As stated by Alvarez-Ramirez et al. [42] the existence or not of exploitable patterns in price changes is the cornerstone for testing market efficiency. Within this framework, PME seems to be particularly suited for characterizing and monitoring financial market efficiency.

3. Data

Daily data from the *Markit iBoxx* corporate bond indices of fifteen sectors aggregated at European level have been used for the present analysis. These fixed income benchmark indices are designed to reflect the performance of euro denominated investment grade corporate debt. More specifically, indices classified by sectors of activity have been examined. These sectors are banks, financial services, insurance, basic resources, chemicals, automobiles, media, food & beverage, energy, healthcare, construction, industrial goods & services, technology, telecommunications, and utilities. For a thorough description of index methodology, please see Ref. [66]. All data used in this paper were retrieved from DataStream. The period under examination is from April 2, 2001 to August 31, 2015. Time counting was performed over trading days, skipping weekends and holidays. Thus, a total of 3761 observations were considered. The choice of the beginning of the series is due to availability of data. Besides, in order to make comparisons, all corporate bond sectorial indices were studied for the same time period. The 2008 credit turmoil is covered in the analyzed period.

Most research on financial markets focus on returns, *i.e.* the logarithmic difference of two consecutive indices, because they are stationary. However, in this work, daily bond indices have been directly analyzed even though their associated time series are clearly non-stationary. Several reasons justify this choice. First, prices and returns contain the same information about long-range dependence [23]. Second, dynamic symbolization schemes, such as the Bandt & Pompe recipe, are recommended when the observed data are not completely stationary or when changes in time are more significant than absolute measurement values [67]. Third, it has been observed that in the case of the permutation entropy and in order to discriminate time series, better results are obtained for prices than returns [39]. Finally, fourth, it has been shown that PME is particularly useful for characterizing fractional Brownian motions, a widely known family of non-stationary, self-similar, Gaussian stochastic processes with stationary increments [54].

4. Empirical results

We have analyzed the time evolution of the permutation min-entropy for the daily indices in order to quantify how the efficiency of European corporate bonds is changing with time. A rolling window of 1024 datapoints, that corresponds to a period of four years approximately, has been initially fixed. This window length is selected because it coincides with the political cycles in most countries. Within the dynamical approach, the time window is then rolled one point forward eliminating the first observation and including the next one, and the quantifier is re-estimated. These procedure is repeated until the end of the time series. In total, 2737 PME values have been estimated, each one from data samples of the same size. Afterward, time series for the PME were smoothed using a 20-points moving average for improving the visualization of the global tendencies. Fig. 1 depicts the results obtained from this analysis for the fifteen sectorial indices. Normalized PME with respect to its maximum, *i.e.* $\ln D!$ obtained from an equiprobable ordinal pattern probability distribution, is plotted. Computed quantifier value is always associated with the last date of the related window. Taken into account the length of the

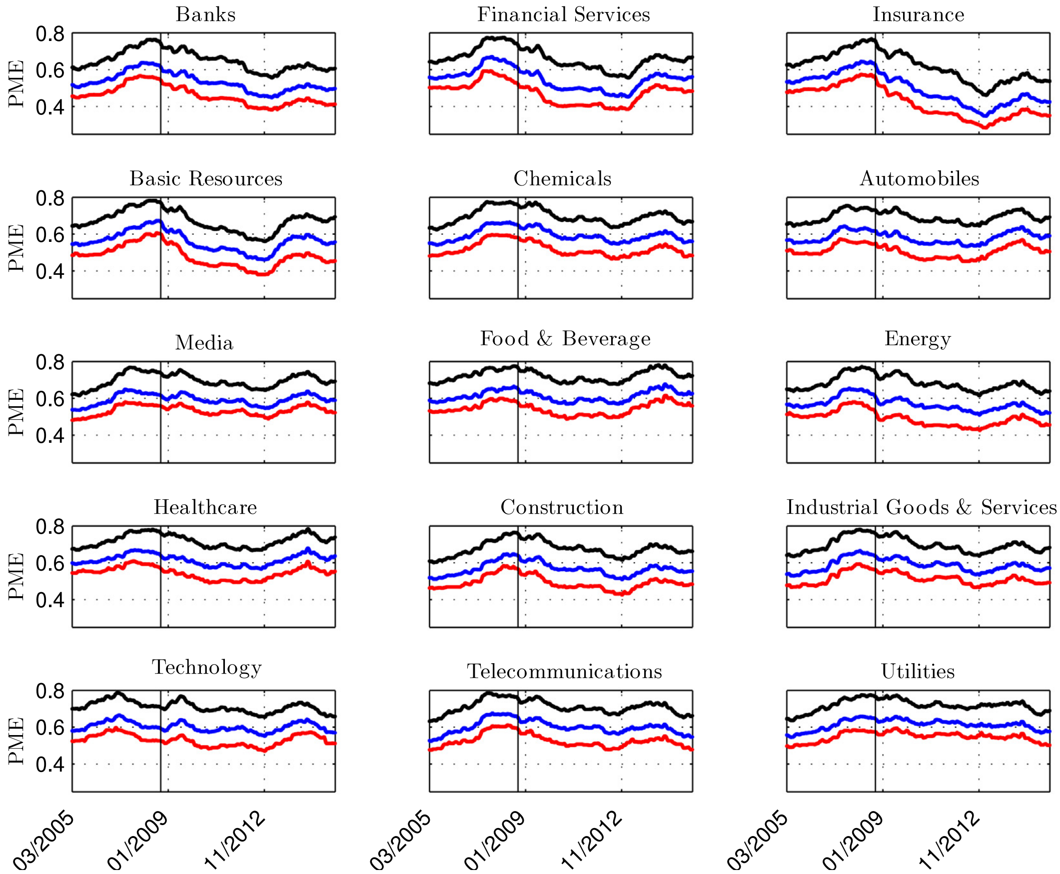

Fig. 1. Time evolution of the normalized PME for the different European corporate bond sectorial indices. A rolling window of 1024 datapoints (around four years) and step equal to one have been implemented for the dynamical analysis. Embedding dimensions $D = 3$ (black curve), $D = 4$ (blue curve), and $D = 5$ (red curve) with embedding delay $\tau = 1$ (daily data) were used for the BP symbolization. Original PME curves were smoothed through a 20-points moving average. The vertical continuous black line indicates the date of the Lehman Brothers bankruptcy. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

time series under analysis, BP symbolizations with embedding dimensions $D \in \{3, 4, 5\}$ and embedding delay $\tau = 1$ have been carried out. Ordinal patterns generated by these parameters correspond to three, four and five consecutive days. It can be easily concluded that the informational efficiency is notably affected by the 2008 credit crisis. It is worth remarking here that the collapse of Lehman Brothers on September 15, 2008 is frequently recognized in the literature as the landmark for the last financial crisis [68–70]. PME evolutions show an increasing behavior before this date in practically all cases. A higher entropy value is related to a more diverse and, consequently, less predictable market dynamics. After the financial crisis, dynamical PME values decrease confirming worse efficiency levels (higher predictability) than in the preceding period. The abrupt downward trend observed for the first four sectors – banks, financial services, insurance, basic resources – confirms that they result particularly vulnerable to the crisis impact. The other sectors suffer a more transitory effects, returning faster to the values estimated for the PME quantifier in the pre-crisis period. Note that these findings are independent of the embedding dimension D.

With the intention to achieve a more formal and robust statistical characterization of the deviation from the expected Gaussian random walk ideal state, we have calculated a dynamical significance measure. Similarly to a standard surrogate data analysis, one thousand independent Gaussian random walks of length $N = 1024$ were simulated,[1] and the mean and standard deviation of the PME values for this set of realizations have been estimated. Subsequently, the measure of significance introduced by Theiler et al. [71] is applied:

$$\mathcal{S}(\psi) = \frac{|\psi_{orig} - \langle \psi_{rw} \rangle|}{\sigma_{\psi_{rw}}} \tag{5}$$

where ψ denotes the statistical measure (PME in our case), ψ_{orig} is the value obtained for this measure for the original time series, and $\langle \psi_{rw} \rangle$ and $\sigma_{\psi_{rw}}$ represent the average and standard deviation, respectively, of the "surrogate" values computed

[1] They were generated via the function *wfbm* of MATLAB with $H = 0.5$. Please see the following link for further details: http://www.mathworks.com/help/wavelet/ref/wfbm.html.

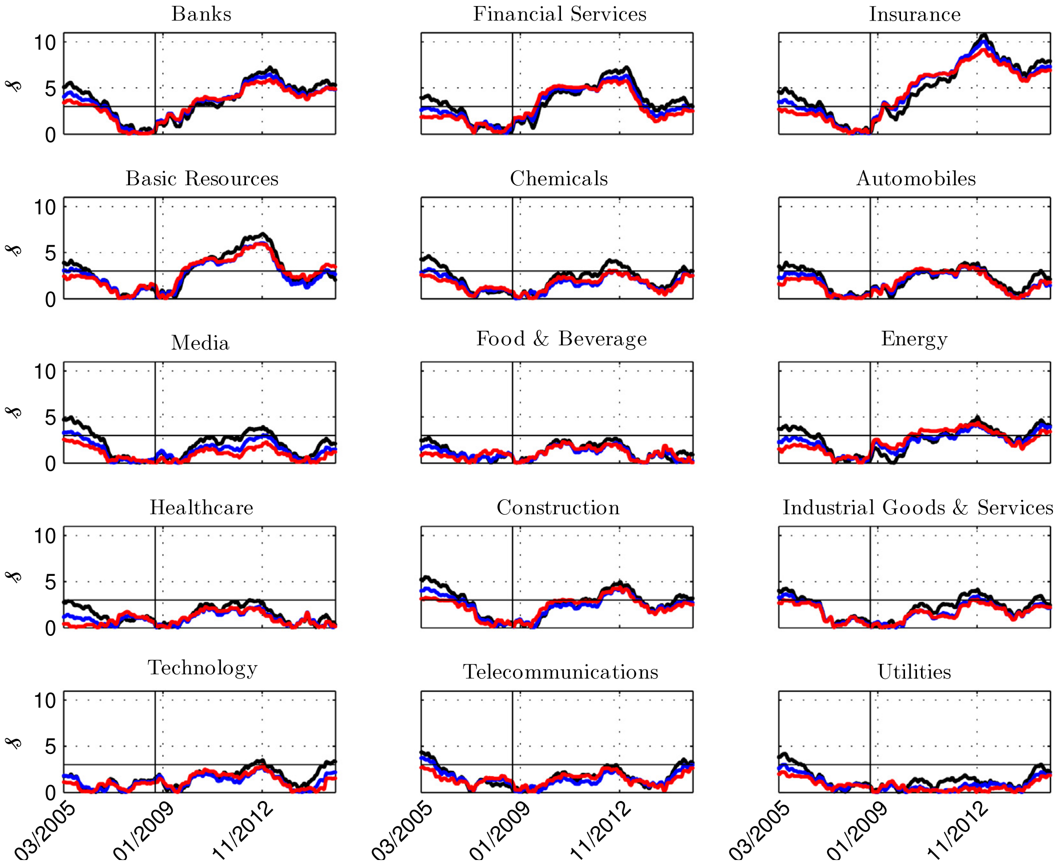

Fig. 2. Time-varying significance $\mathcal{S}$ (Eq. (5)) for the fifteen European corporate bond sectorial indices. The same dynamical analysis and parameters of Fig. 1 have been used. Results for embedding dimensions $D = 3$ (black curve), $D = 4$ (blue curve), and $D = 5$ (red curve) with embedding delay $\tau = 1$ (daily data) are plotted. The vertical and horizontal continuous black lines indicate the date of the Lehman Brothers bankruptcy and the three sigmas threshold criterion, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

for the random walk sequences. Defined in this way, the significance $\mathcal{S}$ is a dimensionless quantity that reports the distance to the benchmark state in number of "sigmas". The three sigmas detection criterion is often considered in surrogate analysis for a significant rejection of the null hypothesis. Translated to our study, $\mathcal{S} > 3$ is taken by us as a robust statistical confirmation of the deviation from the efficient expected state, due to the presence of temporal structures in the original financial data. In Fig. 2 the time-varying statistical significance for the fifteen European corporate bond sectorial indices are shown. The same dynamical analysis and parameters of Fig. 1 have been employed. On the one hand, results obtained confirm that the first four sectors are notably altered by the credit crisis: memory effects are observed in their dynamics after the crisis and the efficient market hypothesis should be rejected. Indeed, banks and insurance sectors show an inefficient behavior until now. On the other hand, for the food & beverage, healthcare, and utilities sectors the null hypothesis of a random walk dynamics cannot be discarded because the quantifier values estimated for simulated and real dataset are very similar practically along all the considered period of analysis.

We have also performed a more local dynamical analysis, by using a rolling windows of 300 datapoints and step equal to one datapoint, with the intention to get a more precise identification in time of the crisis impact. In this case, embedding dimensions $D \in \{3, 4\}$ with embedding delay $\tau = 1$ have been used. The surrogate analysis was conducted by generating 1000 independent Gaussian random walks of length equal to the size of the window, *i.e.* $N = 300$ datapoints. Estimated significance curves, smoothed with a moving average of 20 days, are depicted in Fig. 3. Obtained results are in accordance with those derived from the previous, more global, analysis.

According to our results, the heterogeneous impact of the financial crisis on the informational efficiency of the corporate bond market across different economic sectors has been confirmed. Since the inception of the financial crisis, sectors related to the real economy have been less affected in terms of informational efficiency. On the contrary, bonds of firms related to the financial economy have reduced their levels of informational efficiency. This could be due to herding effect, which move investors away of long positions in financial companies. Another explanation could be the perception of more uncertainty, increasing risk and/or the presence of asymmetric information regarding the valuation of the financial strength of companies within the financial sector.

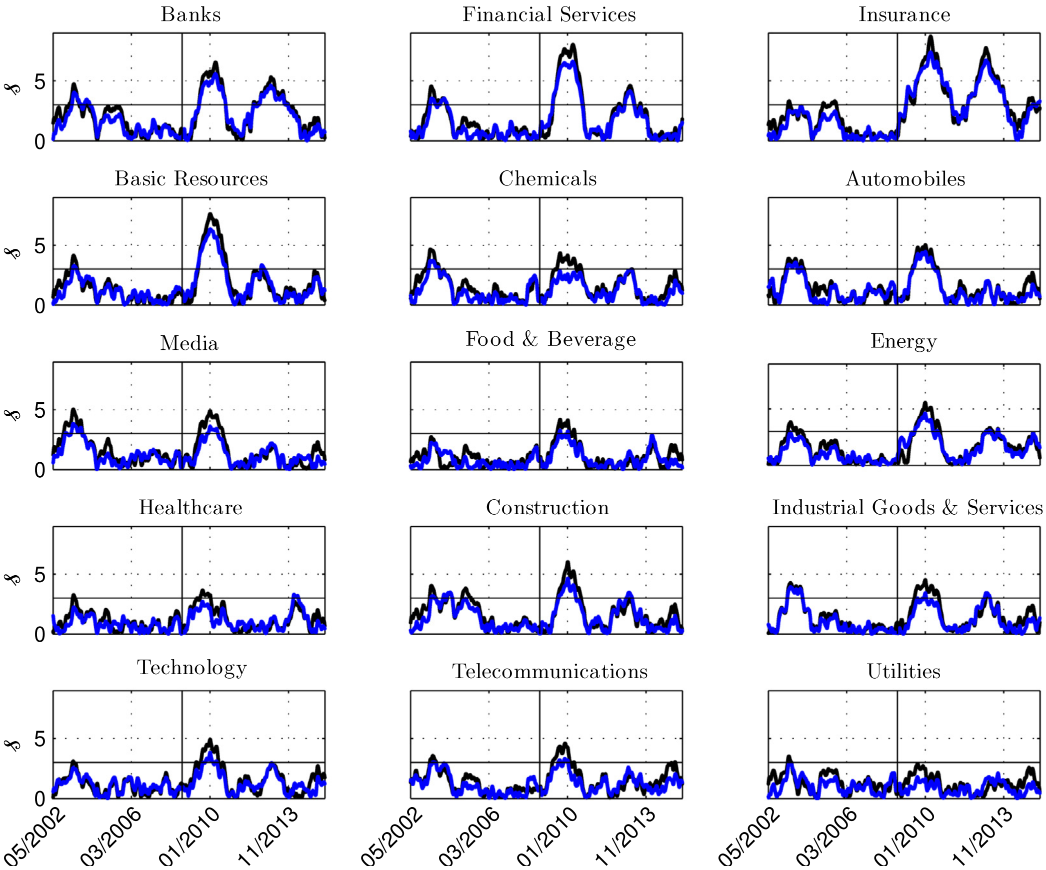

Fig. 3. Time-varying significance $\mathcal{S}$ (Eq. (5)) for the fifteen European corporate bond sectorial indices with a rolling window of 300 datapoints and step equal to one datapoint. BP symbolizations with embedding dimensions $D = 3$ (black curve) and $D = 4$ (blue curve), and embedding delay $\tau = 1$ (daily data) have been implemented. The vertical and horizontal continuous black lines indicate the date of the Lehman Brothers bankruptcy and the three sigmas threshold criterion, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Another important result is that before the crisis, all sectors present similar efficient behaviors. The crisis produces what we can call "decoupling", *i.e.* each sector follows its own dynamic. Whereas during the pre-crisis period all indices exhibit similar efficiency indices, in the post-crisis there is not only a decrease in the mean efficiency but also an increase in its dispersion.

5. Conclusions

The time-varying market efficiency of daily prices of European corporate bond sectorial indices has been carefully analyzed from an informational entropy viewpoint. Permutation min-entropy, a novel symbolic quantifier, has been dynamically estimated through a sliding time window scheme. The diversity of patterns present in the sequence of corporate bond price movements is characterized by this symbolic measure. Moreover, the presence of hidden temporal correlations can be robustly unveiled. Through this dynamical analysis the permeability of particular sectors – banks, financial services, insurance and basic resources – to the 2008 credit turmoil is clearly evidenced. The other sectors appear to be much more immune to the crisis. Particularly, the food & beverage, healthcare, and utilities sectors exhibit an efficient dynamics, without significant signs of the presence of memory effects, almost along all the period of analysis. As a consequence of the financial crisis, sectors that are more closely related to the financial economy, *e.g.* banks, insurance, financial services, have reduced significantly their levels of informational efficiency whereas sectors more related to the real economy, *e.g.* healthcare and utilities, maintain their levels of informational efficiency. All sectors behave roughly "synchronized" before the crisis but they rapidly decouple after it. These findings are consistent with and also extend those previously found by some of us through a rolling window scheme with the more conventional Hurst approach [56]. Thus, alternative and complementary evidences regarding the informational efficiency of corporate bond markets and about their permeability to the effects of the last financial crisis have been provided. We consider that these results can be of help to investors for defining innovative portfolio strategies. In this aspect, if a market is less efficient, this could indicate that returns could be more predictable. Consequently, investors could follow active portfolio strategy. This strategy would provide extra returns, but at the expense of dedicating more time to collect and analyze market information to conform profitable strategies. On the contrary, more efficient market sectors are ideal for a passive investment strategy, since returns will not be predictable. In other words, less efficient markets allow for arbitrage opportunities. Looking at the market as a whole, we can say that higher returns could be obtained by following a buy-and-hold strategy in the most efficient sectors and an active portfolio strategy in the most affected sectors such as financial services, insurance, banks and basic resources. Finally, our results could be suitable to advise policymakers in order to produce prudential regulation aimed to reduce distortions in the financial markets.

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