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PÓS-GRADUAÇÃO EM ECONOMIA

SÉRIE

ESTUDOS ECONÔMICOS CAEN

Chaos in world banking sector?

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Chaos in world banking sector?

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HIGHLIGHTS

- We analyze data generating process of banking sector indices
- Those sectorial portfolios may be governed by stable non-Gaussian stochastic dynamics
- Banking system seems to be efficient
- Nonlinearities play an important role in explaining returns on banking companies' equities

ABSTRACT

We help asset pricing researchers that are trying linear data analysis and they are not satisfied with their results. We deal with a lack of study on dynamics of sectorial indices. We find that main worldwide banking sector indices exhibit nonlinear and nonchaotic characteristics; a sign of efficient sector. We claim that one should rely on nonlinear pricing kernel-based relations to take into account for portfolios or stocks of banking companies.

JEL Codes: C61, G12, G14, G21.

Keywords:
Random sectorial indices
Efficient banking system
Nonlinear asset pricing models

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1. Introduction

We add to the asset pricing theory by finding evidences that worldwide banking sector indices seem to be generated from a nonlinear and nonchaotic system. Based on linearity hypothesis, all irregular behavior of the banking system should be due to some random external input to the financial market. However, in a nonlinear and chaotic financial world one has to deal with very irregular data without time dependent inputs. This means, in brief, that Cardano's (1565) random walk model to describe asset returns, widely used up to early 1970s, should not be more seem so useful.

Although a number of recent empirical studies have found robust evidence of nonlinearity in the short-run movements and the incapacity of linear models in capturing their complexity, we are not suspecting here those sectorial indices time series are nonlinear. The only hint that nonlinear behavior plays a role comes from the data itself: the signal is not compatible with the assumption that it is created by Gaussian random process with only linear correlations. To be more precise, from March 30, 2009 to December 31, 2013 we find that financial sector indices are stationary, heteroskedastic and leptokurtic and according to Matos et al. (2018), they share an equilibrium relationship so that they cannot move independently in the short- and long-run. Those time series are not Gaussian but rather driven by probability distribution functions as Johnson SU, Error, Hyperbolic Secant and Laplace.

This context motivates us to infer about nonlinear dependence by employing BDS test and to evidence it those indices are random or chaotic based on the spectrum of Lyapunov exponents. Our results are relevant since enables us to help to answer the following question: what can still be done if all we have are some hints that the data are not properly described by a linear model with Gaussian inputs? In other words, so important as characterizing financial dynamics as random and nonlinear is adopting a more appropriate model to explain risk premium of equities of banking companies.

Section 2 analyses dataset. Section 3 illustrates the setup of the approach and reports main findings. Section 4 is devoted to final remarks. Details of embedding dimension results are in the Appendix.

2. Worldwide Financial Sector Indices

We apply nonlinear and chaotic time series analysis in a sample of main worldwide financial sector indices, which is comprised by the banking, insurance and financial intermediation companies. We collect financial sector index data for G20 economies, covering a period seen as sufficiently extensive: at least one thousand daily observations. Our final cross-section is composed by indices of Australia, Brazil, Canada, France, Germany, India, Mexico, UK, USA and Russia, covering the period from March 30, 2009 to December 31, 2013, 1255 observations. In order to have a balanced database, we adjust data series to make these calendars uniform, since the countries have different calendars in terms of working days. The criterion is to use any day that was a working day in any of the economies.

In our final sample remain proxies of this banking thermometer of countries located in five continents, with a greater presence of European and North American countries. Unfortunately, some relevant financial markets, such as Japanese or Chinese, do not provide time series of its respective sectorial indices, or these series are very recent.

Figure 1 shows daily nominal net return on financial sector indices in terms of the local investor´s currency, based on the time series for the end-of-day quote while Table 1 reports summary statistics and some useful statistical tests.

We can highlight volatility clusters and higher oscillations, mainly between 2011 and 2012, a period characterized by the sovereign debt crisis in some European countries. The country whose index has the highest cumulative gain in the period was India, with 189%, while DAX All banks in Germany has suffered great impact with this crisis and had the worst cumulative gain, only 26%, and the highest cumulative loss among these indices, 64%. TSX Financials in Canada was less volatile considering all measures used here. Its drawdown was only 22%.

All series are leptokurtic with a higher intensity for CNX Finance in India, an evidence that suggests the frequency of occurring large losses. These skewness and kurtosis are a strong evidence that the series do not follow a Gaussian distribution. We apply Jarque and Bera (1981) test and the result suggests the rejection of the null hypothesis of normality at the 1% significance level for all indices. We also rank probability distribution functions considering a range with over 60 statistical distributions, based on the metric proposed by Anderson and Darling (1952). Some of the best ranked distributions are Johnson SU, Error, Hyperbolic Secant and Laplace. Based on ADF test, there is no unit root at the level of significance of 1%. We also use ARCH–LM test and find that at 1% level of significance, eight series reject the null hypothesis of homoscedasticity, and at 10% of significance level, no series seems to be homoscedastic.

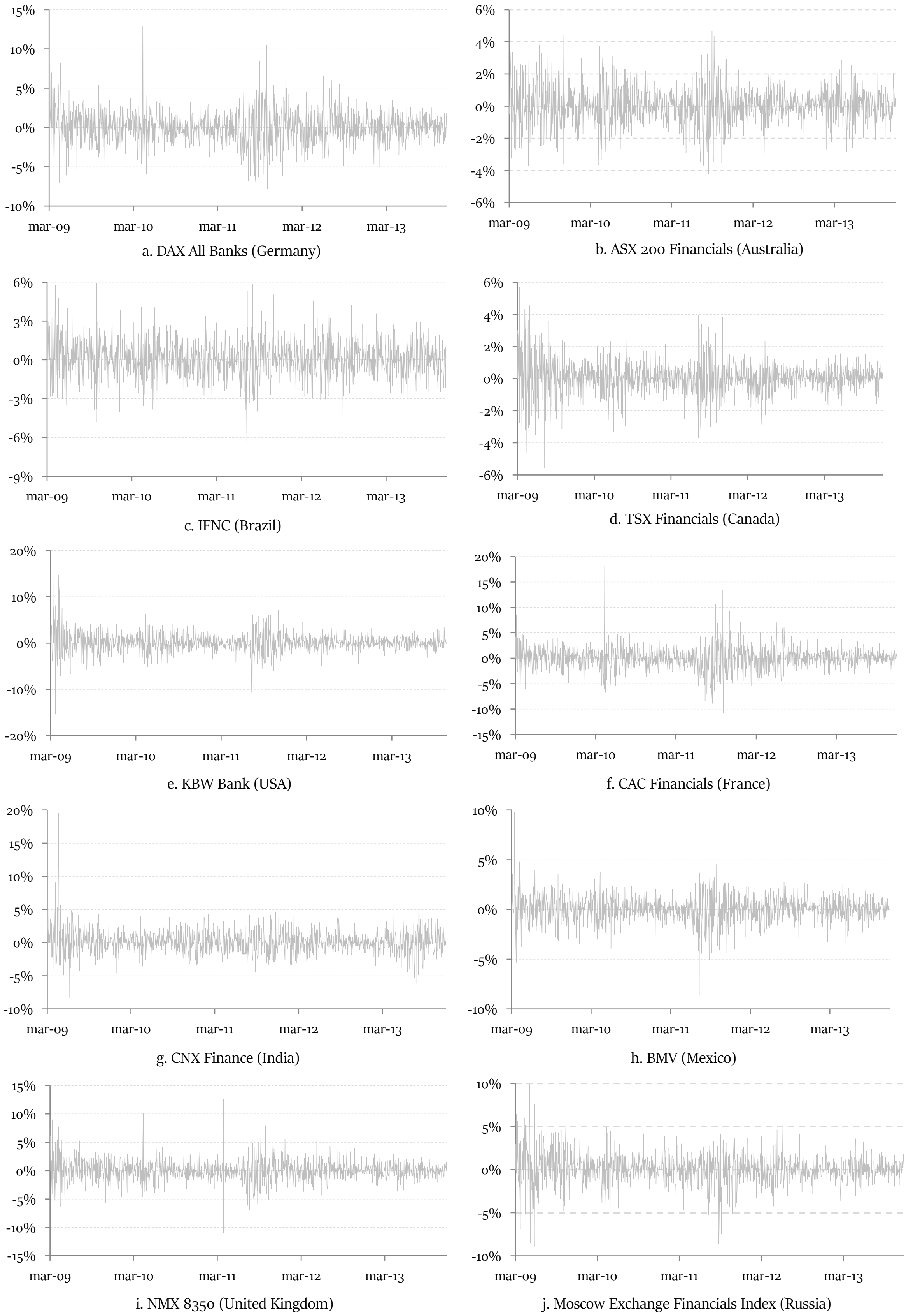

Fig. 1. Nominal net returns on main worldwide financial sector indices [a]

[a] This figure plots daily nominal net return on financial sector index in terms of the local investor´s currency, from March 30, 2009 to December 31, 2013. Data source: Bloomberg.

Table 1. Summary statistics and specific tests applied to returns on main worldwide financial sector indices [a]

Metrics/Index	CNX Finance (India)	DAX All Bankx (Germany)	KBW Bank (USA)	IFNC (Brazil)	ASX 200 Financials (Australia)	CAC Financials (France)	BMV (Mexico)	NMX 8350 (U. Kingdom)	TSX Financials (Canada)	Moscow Exchange Financial Index (Russia)
Panel a. Summary statistics										
Gain										
Mean	0.099%	0.040%	0.100%	0.068%	0.052%	0.075%	0.071%	0.065%	0.062%	0.090%
Cumulative	189.568%	26.288%	164.755%	107.037%	77.167%	91.304%	121.279%	84.289%	104.275%	156.607%
Risk										
Standard deviation	1.701%	2.091%	2.116%	1.427%	1.165%	2.158%	1.279%	1.818%	1.033%	1.700%
Semivariance	1.119%	1.455%	1.428%	1.000%	0.822%	1.488%	0.920%	1.224%	0.734%	1.207%
Drawdown	37.596%	64.268%	41.933%	32.094%	30.582%	53.983%	33.881%	43.546%	22.050%	47.426%
3^{rd} e 4^{th} moments										
Asymmetry	1.337	0.263	0.790	0.045	0.037	0.551	-0.110	0.593	-0.048	-0.123
Kurtosis	17.818	5.914	15.827	4.831	4.329	9.726	8.211	9.032	6.653	7.122
Panel b. Specific tests										
Best fitting distribution - Anderson and Darling (1952)										
Distribution	Error	Hiperbolic secant	Johnson SU	Error	Hiperbolic secant	Error	Johnson SU	Laplace	Laplace	Laplace
Statistic	1.151	0.582	2.853	0.856	0.492	0.407	0.912	1.277	0.778	0.932
Normal distribution - Jarque and Bera (1981)										
Statistic	11901.280 ***	4615.530 ***	8768.740 ***	177.140 ***	93.610 ***	2440.530 ***	1429.540 ***	1986.080 ***	702.500 ***	896.710 ***
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Stationarity - ADF test										
Statistic	-11.086 ***	-10.725 ***	-12.009 ***	-11.585 ***	-10.443 ***	-10.973 ***	-11.009 ***	-10.842 ***	-11.263 ***	-10.206 ***
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Heteroskedasticity - ARCH LM test										
Statistic	2.826 *	13.123 ***	5.980 **	46.015 ***	29.628 ***	19.846 ***	4.493 **	68.444 ***	49.245 ***	17.645 ***
p-value	[0.093]	[0.000]	[0.015]	[0.000]	[0.000]	[0.000]	[0.034]	[0.000]	[0.000]	[0.000]

[a] Statistics of daily series of returns on returns on main worldwide financial sector indices from March 30, 2009 to December 31, 2013. Data source: Bloomberg.
* p-value <0.1. ** p-value <0.05. *** p-value <0.01.

3. Empirical Exercise

First, we detect the presence of nonlinear dependence in banking indices time series. We apply a procedure based on the phase space reconstruction framework widely used, as in Scheinkman and LeBaron (1989), Hsieh (1993) and Chu (2003). We differ because we examine sectorial indices rather than equities or market indices as S&P 500, FTSE or SZSE.

The concept of this representation rather than a time or frequency domain approach is the hallmark of nonlinear dynamical time series analysis. It assumes the Takens' (1981) theorem which ensures that the attractors for any dynamic system can be recovered through the delay process. To summarize, even if a time series of an index, $r_t, t = 1, \dots, T$, is part of a $N-$dimensional deterministic economic model, when testing for the presence of nonlinearity, we do not need time series data on the remaining $N-1$ variables in the system if the available time series is embedded. In principle, one can do without measurements of the "unobservable" r_t by utilizing, in its place, vectors $z_t = (y_t, \dots, y_{t+M-1})$ of long enough histories of the observable. This length M of the vector z_t is the embedding dimension.

Aiming to infer about its significance, we apply BDS test, based on the asymptotic distribution theory introduced by Brock, Dechert and Scheinkman (1987) specifically developed for Grassberger-Procaccia-Takens measures of correlation dimension. In Table 2 we report only minimum embedding dimension and its respective BDS statistic for each banking index. We find a rejection of the null hypothesis, i.e. minimum embedding dimension are not null for all banking indices. It means data are no independent and identically distributed (IID), implying some serial dependence. Since in the procedure linear dependence has been removed, the serial dependence is thus nonlinear. For a more detailed graphical analysis considering up to 14^{th} embedding dimension, one should see the Figure 2 in our appendix.

Table 2. Analysis of time series dynamics [a]

Financial sector index	Country	Nonlinear time series analysis			Chaotic time series analysis
		Minimum embedding dimension	BDS statistic	Standard error	Maximum Lyapunov exponent
CNX Finance	India	9	0.03095 ***	0.00316	0
DAX All Bankx	Germany	9	0.04330 ***	0.00318	0
KBW Bank	USA	8	0.09603 ***	0.00427	0
IFNC	Brazil	8	0.01648 ***	0.00358	0
ASX 200 Financials	Australia	8	0.06226 ***	0.00378	0
CAC Financials	France	10	0.06398 ***	0.00277	0
BMV	Mexico	9	0.03971 ***	0.00318	0
NMX 8350	U. Kingdom	8	0.04033 ***	0.00392	0
TSX Financials	Canada	9	0.08896 ***	0.00363	0
Moscow Exchange Financial Index	Russia	9	0.06621 ***	0.00362	0

[a] Analysis of nonlinear and chaotic dynamics applied to the daily time series of returns on banking sector indices from March 30, 2009 to December 31, 2013. Embedding dimension analysis based on the algorithm proposed by Cao (1997). Data source: Bloomberg.
* p-value <0.1. ** p-value <0.05. *** p-value <0.01.

Second, we examine whether the system is chaotic, i.e. the underlying process is nonlinear, deterministic and sensitive to initial conditions. In sum, the fact that asset return trajectories diverge over the course of time would not in itself be a problem if it were only very slow. Otherwise, an exponentially fast separation indicates a chaotic behavior.

Since BDS test is unable to distinguish between nonlinear deterministic chaos and stochastic systems, we use Rosenstein's (1993) algorithm to measure Lyapunov exponent. This metric measures the average rate of spread between two nearby trajectories, a characteristic for the system underlying the data that quantifies the strength of chaos. The local divergence property as a sign of a chaotic dynamic is formalized by requiring that the largest Lyapunov exponent, L, be positive, where L is given by

$$L = \lim_{t\to\infty} \frac{1}{t} \sum_{n=0}^{t-1} |f'(r_n)| \tag{1}$$

We assume that our underlying process follows a scalar dynamic system given by $r_{n+1} = f(r_n)$ where $f(.)$ is continuously differentiable. Results in Table 2 suggest null maximum exponents for all banking systems. This finding suggests a stable banking system with stochastic components and non-Gaussian increments. The literature recognizes that developing and non-efficient markets are suitable for chaotic analysis due to the number of underlying risk drivers is fewer than those in developed and efficient markets such as banking sector in greatest economies in the world.

4. Concluding Remarks

According to da Costa et al. (2016) the contrasting performance of the asset pricing tests in level – Euler equations useful to estimate consumption-based models – and in its log-normalized versions or in widely used linear approaches, as Capital Asset Pricing Model (CAPM), Arbitrage Pricing Theory (APT) or multifactor models involve considerably higher complexity and do not exempt one from making additional assumptions beyond what is needed to test the orthogonality restrictions that characterize tests in levels.

Here we add to this discussion by addressing specifically the behavior of times series of returns on portfolios composed only of stocks of banking, insurance and financial intermediation companies in some of most relevant economies. We find that main worldwide financial sector indices are nonlinear and nonchaotic and therefore should not be linear the models developed to explain their risk premia movements. This means, in brief, that although we have not yet used all the tools available to make definitive quantitative statements, not even applying them to broader panels of assets, our evidence suggests that one should rely on nonlinear pricing kernel-based relations in level, at least to take into account for portfolios or stocks of banking companies.

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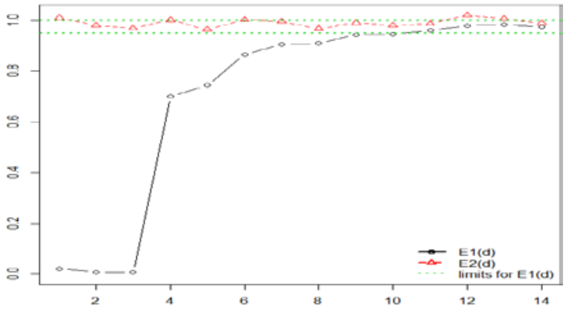
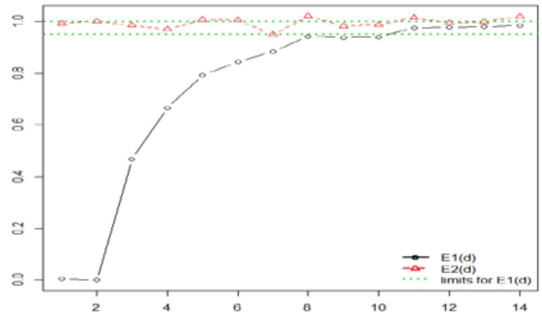
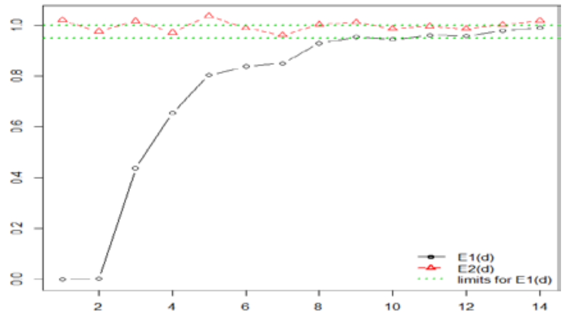
Appendix. Dimension embedding



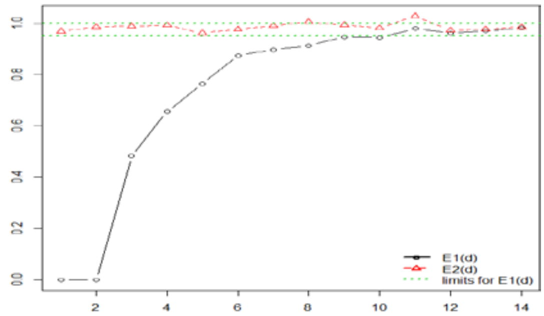
a. DAX All Banks (Germany)



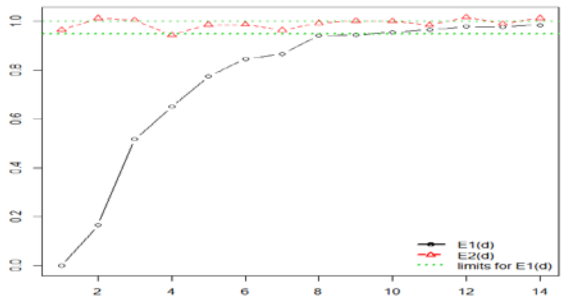
b. ASX 200 Financials (Australia)



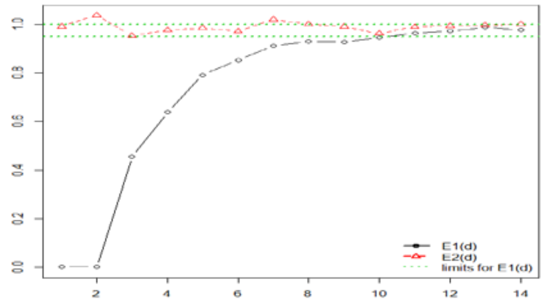
c. IFNC (Brazil)



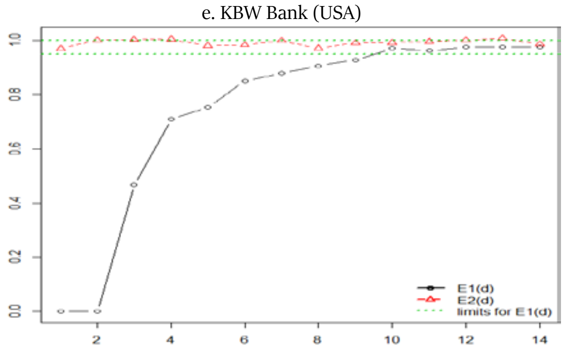
d. TSX Financials (Canada)



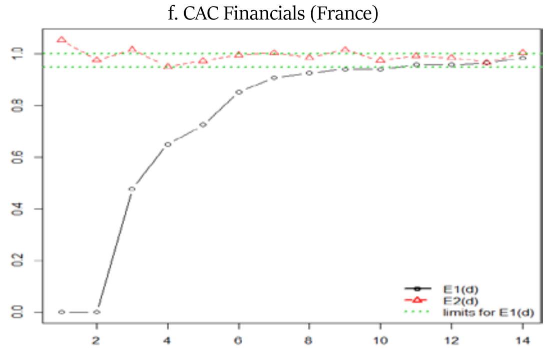
e. KBW Bank (USA)



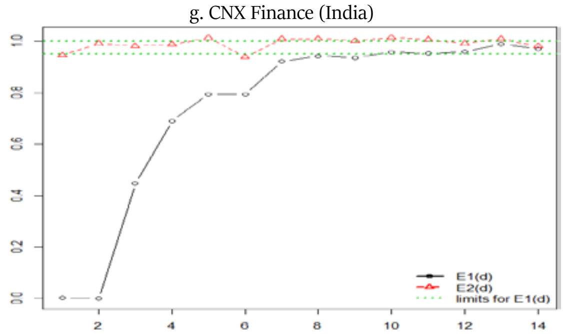
f. CAC Financials (France)



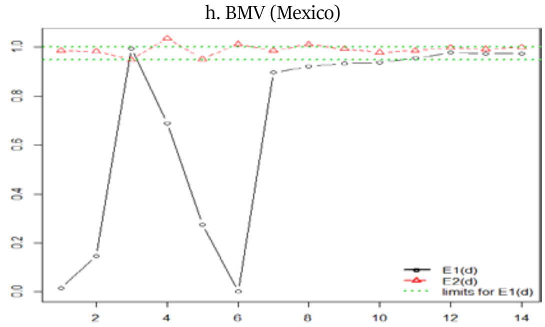
g. CNX Finance (India)



h. BMV (Mexico)



i. NMX 8350 (United Kingdom)



j. Moscow Exchange Financials Index (Russia)

Fig. 2. Embedding dimension analysis applied to net returns on main worldwide financial sector indices [a,b]

[a] This figure plots embedding dimensions for daily nominal net return on financial sector index in terms of the local investor´s currency, from March 30, 2009 to December 31, 2013. Data source: Bloomberg.

We help asset pricing researchers that are trying linear data analysis and they are not satisfied with their results. We deal with a lack of study on dynamics of sectorial indices. We find that main worldwide banking sector indices exhibit nonlinear and nonchaotic characteristics; a sign of efficient sector. We claim that one should rely on nonlinear pricing kernel-based relations to take into account for portfolios or stocks of banking companies.

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