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Foreign exchange rate entropy evolution during financial crises

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HIGHLIGHTS

- We examine the effects of financial crisis on foreign exchange markets.
- The evolution of Shannon entropy is measured for eighteen foreign exchange rates.
- Financial crisis are associated with significant increase of exchange rate entropy.
- Periods of economic uncertainty are preceded by periods of low entropy values.

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ABSTRACT

This paper examines the effects of financial crises on foreign exchange (FX) markets, where entropy evolution is measured for different exchange rates, using the time-dependent block entropy method. Empirical results suggest that financial crises are associated with significant increase of exchange rate entropy, reflecting instability in FX market dynamics. In accordance with phenomenological expectations, it is found that FX markets with large liquidity and large trading volume are more inert — they recover quicker from a crisis than markets with small liquidity and small trading volume. Moreover, our numerical analysis shows that periods of economic uncertainty are preceded by periods of low entropy values, which may serve as a tool for anticipating the onset of financial crises.

1. Introduction

Foreign exchange rates play a crucial role in the world's largest and most liquid financial market: the foreign exchange (FX) market. Currency fluctuations have far-reaching effects on economic activity such as imports and exports, price inflation, and economic growth [1,2]. Besides small fluctuations at all times, exchange rates exhibit drastic movements during periods of financial crisis [3–5], which can be partly explained by flows to and from safe haven currencies as investors seek more reliable assets [5]. Understanding the dynamics of such movements in FX markets can be crucial for anticipating global effects of future financial crises.

Bachelier [6] proposed a Brownian motion model for stock prices suggesting that differences in prices can be described by random processes. As a result, a market theory evolved from Bachelier's work which showed that if a market is efficient

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then prices will exhibit random walk behavior. The efficient market hypothesis (EMH) for FX markets claims that all information relevant to the exchange rate is already incorporated into the present value of a currency [7,8]. However, various studies [9–12] show that financial markets can become inefficient and deviate from a random walk behavior. Many statistical methods have been proposed to measure market efficiency [9,13–16], recently more attention has been focused on entropy based methods such as approximate entropy [17,18], multiscale entropy [19], permutation entropy [20], Shannon entropy, Renyi entropy, and Tsallis entropy [21,22]. The present paper uses Shannon entropy which was shown to be a successful quantitative tool in studies of different phenomena such as in data fusion [23], communication [24], physiology [25,26], geophysics [27], astrophysics [28], hydrology [29], engineering [30], and finance [31].

The concept of entropy has been extensively used in finance [32–37]. Derived from the standard Boltzmann–Gibbs (BG) statistical mechanics, Shannon entropy measures the amount of disorder in a system. Shannon [38] postulated that entropy could be applied to any series where probabilities exist, which resulted in many works [21,34,39,40] measuring entropy in financial time series. Entropic analysis has also drawn much attention in finance because it can extract information otherwise obscured by the chaotic structure of the series [21,36]. Since standard entropy measures do not work well with nonstationary time series, time-dependent entropy measures have been introduced [35,41–43], which produce temporal evolution of entropy.

In this paper, we analyze the effects of financial crises on FX markets using a multiple symbol discretization scheme which captures all the possible trends on a daily temporal scale, together with local window amplitude scaling that permits simultaneous analysis of both small and large exchange rate fluctuations. The evolution of entropy is measured for eighteen different foreign exchange rates in a period from 1971 to 2014. Entropy changes are investigated during different financial crises, such as the 1973 oil crisis and the global financial crisis of 2007, and compared between different FX markets.

The rest of this paper is organized as follows. Section 2 introduces Shannon entropy and the time-dependent entropy method. In Section 3 we describe the data and present the experimental results. Finally, conclusions are drawn in Section 4.

2. Time-dependent block entropy

Entropy is a measure of disorder in the system. In information theory, Shannon entropy can be viewed as the average amount of information encoded in a pattern drawn from a probability distribution [38]. The classical Shannon entropy is given by

$$S(Z) = -\sum_{i=1}^{m} p_i \log p_i \tag{1}$$

where Z is a discrete random variable with possible values $z_1, \ldots, z_m$ and p_i is the probability of Z assuming the value z_i. Note that the entropy is maximum $S(Z) = \log m$ when all values $z_i,\ i = 1, \ldots, M$, are equally probable, or more precisely $p_1 = p_2 = \cdots = p_m = 1/m$. However, the entropy is minimum $S(Z) = 0$ when a single value z_i accumulates all the probability and is certain to occur. For financial time series, entropy approaching $\log m$ suggests the series is nearly random and can be interpreted as high market efficiency [44].

Since entropy describes the average uncertainty of a sequence, it is not always useful for analyzing nonstationarities [36], thus different information measures can be applied to nonstationary time series. The time-dependent entropy measure is based on the sliding window technique and yields a temporal evolution of entropy. Given a time series $Z = z_1, \ldots, z_N$, the sliding window is defined as $X_n = z_{1+n\Delta}, \ldots, z_{w+n\Delta}$, $n = 0, 1, \ldots, \left[\frac{N}{\Delta}\right] + (w - \Delta - 1)$ where $w \le N$ is the window size, $\Delta \le w$ is the sliding step, and operator $[.]$ denotes taking integer part of the argument. The values of the time series in each window X_n are now divided into a set of M disjoint intervals $I_1, \ldots, I_M$, and each interval is assigned a distinct symbol. The original windows X_n are transformed into a symbolic representation X'_n by substituting each of the values $z_i,\ i = 1 + n\Delta, \ldots, i = w + n\Delta$ by the symbol corresponding to the interval to which that value z_i belongs. The entropy of the window X_n is finally determined by analyzing $w - L + 1$ consecutive overlapping symbolic sequences (blocks) of length L in the symbolic window X'_n:

$$S(X'_n) = -\sum_{i=1}^{M^L} p_n(Y_i) \log p_n(Y_i) \tag{2}$$

where $Y_i,\ i = 1, \ldots, M^L$ are all possible symbolic sequences of length L that can be constructed using M symbols. The probability $p_n(Y_i)$ is calculated as the ratio between the number of sequences Y_i and the total number of sequences in the window $w - L + 1$.

3. Data and results

We analyze daily fluctuations of 18 different foreign currency exchange rates ranging from 1971 to 2014 [45,46]. Currency names, alphabetic symbols, market strength, and periods analyzed are listed in Table 1. The strength of an FX market is determined by its liquidity and trading volume: a strong market has large liquidity and large trading volume,