A POST KEYNESIAN FRAMEWORK OF EXCHANGE RATE DETERMINATION

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Kapitel 3: Entropy evolution of Latin American exchange rates.

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Un tema central en la tesis es la distinción entre orden y caos. Una distinción paradójica porque en el fondo, el caos tiene estructura. En la tesis aparecen dos tipos de aleatoriedad, la propiamente caótica y la aleatoriedad producto de interacciones con el entorno. Hay un tercer tipo de aleatoriedad no discutida en la tesis pero que está aquí, en los agradecimientos, y de alguna manera está en todas partes. Me refiero a ese tercer tipo de aleatoriedad que responde a un orden oculto e impenetrable, imposible de descifrar. Al menos no con los instrumentos convencionales de la razón. Comienzo agradeciendo a ese misterio insondable por ponerme en el camino de tantas personas dulces y maravillosas. Agradezco que me haya llevado hasta una persona tan increíblemente extraordinaria como la profesora Barbara, y a ella le agradezco por todo, y digo así, por todo, porque no me alcanzan las palabras. Muchas gracias querida profesora Barbara. El primer artículo lo escribí con mi querido amigo y maestro, el profe Brida. Conocerlo y tener su amistad ha sido uno de los tantos actos que me hacen evocar a ese orden misterioso. Agradezco a todos mis amigos, de México y Berlín, por ser tan solidarios. A Vero y Carlos que tan amablemente me recibieron en su casa. Aún recuerdo como si fuese ayer el día que Vero me fue a recibir al aeropuerto. Aquí en Berlín nació mi hija Marianne Aurora, ¿cómo no estar agradecido con esta bella ciudad y con su gente? Son muchos quienes me han dado una mano, a todos muchas gracias de todo corazón. A la gente de la Universidad, a quienes tuvieron la visión de crear un programa como el Entre-Espacios, a quienes pensaron que era buena idea becar estudiantes y a quienes en México y Alemania han defendido el derecho a la educación pública y gratuita. A mis profesores y compañeros porque de todos algo me llevo. A la linda y dulce familia de Mariana les agradezco todo su apoyo, ánimos y afecto. A Mariana, amor de mi vida y regalo del universo, muchas gracias por todo esposita hermosa. Como decía Benedetti, es tan lindo saber que usted existe. Tu presencia es mi inspiración. Tú y Aurora son lo mejor que me ha pasado, ¿de qué planeta llegaron barriletes cósmicos? Aurora, muchas gracias por todo querida hijita, todavía no lees pero si de grande lees estas palabras debes saber que iluminaste mi vida. Volví a nacer el día que llegaste. Agradezco a mis tías, tíos, primas y primos por las alegrías, su amor y tantas travesías compartidas. A Diego, José Carlos, Ximena, Ana Fernanda, Sofi, Pablo, Gabito y Andrés, maquinitas de amor y alegría. También agradezco a quienes ya no están y a quienes mucho debo. El día que nació Aurora sentí su amorosa presencia. Por supuesto, agradezco a mamá Mary, a mis queridas, guapas y siempre presente hermanas y a mis lindos y amorosos padres, mis viejos queridos, mi tesoro más preciado y huéspedes distinguidos de mi corazón. A todos muchas, muchas gracias.

Prayer clears the mist
and brings back peace to the soul.
Every morning, every evening
let the heart sing,
La ilaha il Allah,
“There is no reality but God”

Rumi

A mamá y papá, como siempre

A Mariana y Aurora, por todo

CONTENT

0. INTRODUCTION

Foreign exchange markets are complex systems comprising many interacting elements that exhibit numerous forms of emergent collective dynamics. This point holds particular relevance for Latin American countries, in which the volatility of the financial flows is related to irregular fluctuations in exchange rates. Post-Keynesian economics argues that this instability is an intrinsic attribute of the financial and monetary system. A logical consequence of this proposition is that in studying exchange rate dynamics we must employ analytical tools that assume this fact. In this regard, Rosser (2003) argues that the paradigm of complexity, also known as paradigm of irregularity, offers a foundation for fundamental uncertainty in post-Keynesian economics. In this dissertation, we follow this approach in order to analyze Latin American exchange rates. In what follows, we argue that the post-Keynesian approach in conjunction with the paradigm of complex systems provides a better understanding of the exchange rate determination.

I. Combining paradigms on exchange rates: post-Keynesian economics and Complex dynamics

One of the main criticisms made by post-Keynesian economists against economic orthodoxy is its approach to the economy in terms of a closed system, in which all of the variables of interest exclusively react to economic forces, whereby the analysis tends to omit political, institutional or historical factors. By contrast, post-Keynesians seek to offer more comprehensive explanations, more in line with perspectives that view the economy as an open system.

The distinction between a closed and open system can be analyzed in terms of how time and uncertainty are included. The closed-system epistemology of the neoclassical approach is a metaphor of Newtonian space in which time is constituted by points or positions, while the post-Keynesian approach proposes an open system epistemology where the openness would imply a relative time, in which non-deterministically evolving structures, interrelations and creativity unfold (Dow 2017, Lawson 1997). According to Henry (1993), Davidson (1982) and Godley and Lavoie (2007), the question about time is one of the key principles of post-Keynesian economics.

Time is thought of in terms of an open space, in which time and uncertainty emerge from a set of relations: time has a duration that extends – in the words of Shackle – between memory and expectation (O'Driscoll and Rizzo 2002). These are temporary relationships that are not independent from each other but rather overlap and eventually they come into conflict. The introduction of time in post-Keynesian models allows us to take into account issues that are often ignored, such as uncertainty and the nature of uncertainty itself. Including historical time, real time or subjective time allows us to consider a fundamental characteristic of the flow of time, namely its irreversibility. Accordingly, the passage of time adds new information, modifies perspectives and generates new comparison horizons. The economic results are not independent of the actions taken in the past, but rather depend on the errors of foresight made by the economic agents. The irreversibility of time produces a qualitative difference between the past and future, which translates into the degree of uncertainty.

For Keynes, uncertainty is the main factor in the process of forming expectations, which are understood not in a classic probabilistic sense but rather as subjective evaluations of economic agents about the future outcome of their present actions. This diversity of degrees that separate the very probable from the very uncertain translates into a heterogeneity of temporal relationships, framed in the interaction between psychological variables, expectations, uncertainty and animal spirits. Accordingly, the post-Keynesian approach describes a behavior in which change and evolution are central characteristics of the economic activity. Time is not an empty instant but a relationship full of content. In his critique of the Arrow-Debreu model, Smolin proposes a description of the economy that abandons the absolute-Newtonian framework and instead makes use of a relational framework describing interactions between its elements:

> "Quantities are absolute when they can be applied to one entity alone, without reference to if it is isolated or part of a larger system. They are relational when they describe relationships between entities that interact with each other. Physics made the transition from an absolute-Newtonian-way of understanding space and time to a relational view with the invention of Einstein's theory of general relativity. Classical economics appears to be based on an absolute framework in which prices given by one trader to one good are meaningful, whether that trader lives on an island with one other trader or is part of a diverse and complex economy. This may suffice to characterize equilibrium but to describe the dynamics of equilibrium we must model the trades between pairs of agents as they disagree over prices, and this requires a relational framework" (Smolin, 2009: 32).

This is the idea that underlies post-Keynesian economics. Hence, this section proposes thinking of post-Keynesian economics in terms of an open system. In what follows, we show that the bridge that connects the post-Keynesian economics with the paradigm of complexity is their understanding of the concept of uncertainty, as we shall see below.

As one of the leading theorists of the post-Keynesian view, Harvey (2009) argues that neoclassical models have not been successful in explaining exchange rates, particularly their cycles of volatility. Harvey highlights that exchange rates are determined by international investors who demand currencies to adjust their portfolios, whereby these decisions are shaped by psychological and institutional elements. Harvey (2006a) argues that neoclassical models have failed because they are based on a closed epistemology that perceives economics as a closed system independent of any social, psychological or cultural consideration. In this approach, the exchange rate is determined by the international supply and demand of each currency. The demand comes from imports, foreign direct investment and portfolio investment, although the latter is the most important factor. The readjustment in the composition of the portfolio depends on expectations, and since these are volatile, the exchange rate is volatile. Thus, in the post-Keynesian approach, the change in investor sentiment has a major impact on the determination of exchange rates.

Regarding the paradigm of complexity, Rosser (2003) argues that it offers a foundation for fundamental uncertainty in Keynesian and post-Keynesian models. The paradigm of complexity corresponds with a worldview in which apparently disordered systems hide an order whose code is unknown. This paradigm of complexity has been present in a wide range of fields such as physics, chemistry and biology, while it has had a relatively recent impact on other areas such as economics, systems theory, cybernetics and artificial intelligence.

Complexity comprises four sub-types, known as the four Cs: chaos theory, cybernetics, catastrophe theory, and the "broad tent of complexity" (Rosser 2005). Chaos theory is a mathematical theory that analyzes irregular processes in which it is not possible to make predictions (Moosa and Bhatti 2010). A chaotic process is deterministic (i.e. it is generated by a well-defined equation or algorithm), although in appearance it looks like a random phenomenon. A characteristic of chaotic phenomena is sensitivity to initial conditions, i.e. a minor variation in the initial conditions has a major impact on the future fluctuations of the system. In the case of exchange rates, Copeland (1994) presents a model showing that the random behavior produced by the introduction of the stochastic error term in linear equations can also be produced by a simple deterministic non-linear model. The simplest non-linear model that can produce chaotic behavior is represented by the well-known logistic function, which can reproduce dynamics of the overshooting model.

Developed by Norbert Wiener (1961), cybernetics has had a relatively limited application in economics, although Oskar Lange (1970) was the first to highlight that the economy is a cybernetic system, since it deals with collections of elements connected to each other through a cause-effect chain. This idea is behind the analogy of Lange, in which he compares the market economy with the functioning of a computer, whereby interactions between demand and supply are equivalent to iterations and recursive processes in a computer (Lange 1967, Limas 2018). On the other hand, catastrophe theory – formulated by the French mathematician René Thom – models phenomena characterized by sudden changes that lead to qualitative transformations. Thus, catastrophe theory focuses on the study of discontinuities of dynamic systems, such as the behavior of an action in the stock market. The classic work of catastrophe theory is Zeeman's (1974) model of stock market crashes. Finally, we have the "broad tent of complexity", which emphasizes the use of agent-based simulation modeling.

The common ground in this paradigm is the idea of complex dynamics, which refers to erratic movements due to endogenous causes. Hence, uncertainty and randomness arise as natural results of these processes. Thus, entropy appears as a key concept in this context, given that it comprises uncertainty and randomness as the two sides of the same coin. Entropy – a concept born in physics (Rovelli 2015) and then generalized to other fields by Claude Shannon (Shannon 1948, Cockshot *et al* 2012) – is the main tool in analyzing processes that follow complex dynamics. Entropy can be understood as a measure of information content. Intuitively, we can think of information in terms of either its ability to diminish our ignorance or a lack of data.

The most common example is tossing a coin: if the coin is fair, we cannot predict which side it will fall on. Thus, when the coin is thrown and the result is observed, our ignorance decreases. However, if the coin is charged and we know it, then tossing the coin does not add new information. Entropy is greater in the first case, namely there is more uncertainty than in the case of a charged coin. In general terms, it is a measure of dispersion, uncertainty, disorder and diversification. Although in this context "randomness" and "disorder" are understood as equivalent terms, Floridi (2010) prefers to use "randomness" since it is a syntactic concept, while "disorder" has a strong semantic load, thus being subject to interpretations of different types.

In economics, entropy has been used as a metaphor for market processes. According to Smith (2015), the economic concept of *tâtonnement* is analogous to the physical concept of "entropic forces". Hence, individual molecules restore equilibrium in a random manner because the equilibrium situation is the most probable state. Thus, the molecules are coordinated by entropy. In the case of *tâtonnement*, individual agents restore balance by informing the Walrasian auctioneer of their equilibrium prices, who in turn coordinates the price dynamics until the equilibrium is reached.

The first economist to recognize the importance of entropy and the second law of thermodynamics – which he referred to as "the most economic of physical laws" – is Nicholas Georgescu-Roegen (Screpanti Zamagni 1993). In his work The Entropy Law and the Economic Process (Georgescu-Roegen, 1971), Georgescu-Roegen proposed combining economic analysis with environmental impact using entropy as the link between the two. In addition, the inclusion of entropy allows including historical time or real time, which – as noted in the previous section – have been ignored by economic theories that see the economy as a closed system.

Besides the already-mentioned Roegen (1971), Jaynes (1991) is one of the main works in which it is possible to grasp the scope that the concept of entropy has for the economic analysis. According to Jaynes, classical economists – particularly since Adam Smith – consider the economic problem in terms of an analogy with mechanics, and in particular they relied on the concept of mechanical equilibrium. However, macroeconomics is much more like a thermodynamic system rather than a mechanical one. Thus, the macroeconomic system not only moves in response to the forces assumed in the prevailing theories, but could also move in the direction in which entropy is increasing, given the restrictions imposed by nature and the government. In the same way, a thermodynamic system approaches equilibrium following the direction in which entropy is increasing, given the restrictions imposed by the conservation of mass and energy.

The economic system could stagnate in the state that it is in, unless it is shaken by a source of randomness, which Jaynes calls dither. Thus, dither is any turbulence introduced into macroeconomic variables through fluctuations in the underlying microeconomics.

According to Jaynes, the idea of dither was anticipated by Keynes in the form of "animal spirits", based on which economic agents behave erratically. In this framework, dither not only introduces random uncertainty in the macroeconomic variables, but also systematically orients the movement of the economy. In this sense, expectations play a crucial role and changes in dither are the result of agents who go from a "pessimistic" to a "confident" state or from a "poor" to a "prosperous" one. Thus, following Jaynes, the “animal spirits” would be driven by entropic forces and its dynamic would be represented by the entropy of the system.

As Rosser (2003, 2005) has argued, dynamic complexity provides a basis for fundamental uncertainty in Keynesian and post-Keynesian models, particularly due to its approach to randomness. This approach is useful in analyzing Harvey (2009), where exchange rates are marked by volatility and this in turn is strongly linked to uncertainty. It is interesting to note here how his approach to uncertainty corresponds – at least in intuitive terms – with the notion of entropy. Following Keynes, Harvey explains in relation uncertainty that:

> “Because in general our knowledge of the future is “vague and scanty”, the information of which we are aware plays a disproportionate role in our forecasts. For example, if event X depends on factors A, B, C, D, and E, but because of the nature of the world we are only able to know *one piece of information* at any given time (A, for example), it will play a larger role in our forecast of X than if A, B, C, D, and E were known.”
>
> (Harvey 2009: 50, emphasis added).

Here, Harvey identifies uncertainty as knowing just *one piece of information*. The emphasis is added because in econophysics and information theory *pieces of information* are known as *bits,* and Shannon entropy is defined as a measure of uncertainty, randomness or a lack of information and its units are bits (Shannon 1948).

II. Research question

This doctoral thesis addresses the analysis of the Latin American exchange rates, aiming to determine the structure of this set of currencies. Thus, the guiding research question is the following: what is the taxonomy of this currency network? To answer this question we aim to characterize the exchange rates in terms of their co-movements and also in terms of their entropy levels. This research question is addressed by the following hypotheses.

The taxonomy of the network is related to the degree of financial openness. The reason for this is that the degree of openness of the capital account is closely linked to the volatility of the financial flows, which in turn influence the dynamics of the exchange rate. It could be expected that countries with similar levels of financial liberalization show similar levels of volatility in their capital flows and consequently the movements of their exchange rates show similarity. Second, the taxonomy of the network is also related to the presence or absence of inflation targeting (IT) regimes. Within an IT regime, central banks in Latin America would be more prone to letting their currency appreciate against the USD to reach price stability. As a result, this monetary policy framework should augment currency co-movements during episodes of appreciation. Additionally, since in fixed exchange rate regime randomness is zero, whereas in pure floating regimes currencies follow random walk processes, the third hypothesis states that the degrees of flexibility are related to degrees of randomness. Thus, high entropy is associated with floating regimes and low entropy with fixed ones.

III. Essays on exchange rates: key findings and contribution to research

Research on exchange rates has focused on the analysis of co-movements, particularly in East Asia around the Renminbi or in other regions with the US dollar or the Euro as the main anchors. However, these studies have overlooked the analysis of the Latin American currencies as a whole, from its geographic perspective. This doctoral dissertation addresses this issue from a point of view framed within both the post-Keynesian and the Complexity approaches. The three single papers[1] of this cumulative dissertation can be divided into two broad thematic topics: entropy and co-movements. Paper 1 and 3 characterize exchange rates dynamics in terms of entropy, whereas paper 2 focuses on co-movements. In addition to its theoretical approach based on post-Keynesian economics, the three papers have the use of symbolic dynamics in common. The following section provides a short summary of the main findings and contributions of each essay. Because each article seeks to stand on its own, some arguments -as well as the way the discussion is framed- are similar in more than one of them.

[1] Papers 1 and 2 have been already published:

Brida, J. and E. Limas, A post Keynesian framework of exchange rate determination: a dynamical approach. Dynamics of Continuous, Discrete and Impulsive Systems, 25 (2018), 409-426.

Limas, Erick, An application of minimal spanning trees and hierarchical trees to the study of Latin American exchange rates. Journal of Dynamics & Games, 2019, 6 (2): 131-148.

Paper 1. A post-Keynesian framework of exchange rate determination: a dynamical approach

In the first article, we present a mathematical approach to analyze the exchange rate dynamics under the post-Keynesian framework developed by Kaltenbrunner (2011, 2015). In this model, the exchange rate evolution is driven by expectations and is represented as a first-order difference equation that allows non-linear dynamics that display irregular fluctuations related to the presence of endogenous mechanisms. Therefore, these fluctuations are not the consequence of random shocks but rather due to intrinsic forces associated with non-linear relations. In order to analyze the exchange rate determination, in this paper we utilize three tools: regime dynamics, symbolic dynamics and entropy.

Symbolic dynamics is introduced to represent multi-regime dynamics. The process of symbolization translates a classical trajectory in a given state space into a trajectory in the space of regimes. Departing from the concepts of regime and symbolic dynamics, we use a measure of complexity, namely the notion of entropy. Using entropy, we demonstrate that the model produces a rich variety of dynamic behaviors of different complexity depending on parameter values. For a continuous range of parameter values, the model is capable of generating cyclical, quasi-cyclical and chaotic fluctuations. The paper finds a symbolic sequence that represents the case of Brazil during the period between 2002 and 2008. For six years, its exchange rate remained trapped within a regime of appreciating, before subsequently moving towards a regime of depreciation. On the other hand, the cases of the Asian and Mexican crises can be seen as two examples of one of the sequences analyzed, in which catastrophic depreciations arose (in 1997 in Asia and 1994 in Mexico) and then their exchange rates remained trapped in the appreciation regime.

Paper 2. An application of minimum spanning tress and hierarchical tress to the study of Latin American exchange rates

In the second paper, we analyze a group of nine Latin American currencies with the aim of identifying clusters of exchange rates with similar co-movements. The study considers the exchange rates of nine Latin American countries: Argentina, Brazil, Chile, Colombia, Honduras, Mexico, Peru, Uruguay and Venezuela. We analyze daily data from January 16, 2007 until December 29, 2017. In this article, the study of currency relationships is formulated as a network problem, where each currency is represented as a node and the relationship between each pair of currencies as a link.

We find that the currency network has structural features that are stable over time; for example, the lempiras and the Venezuelan bolivar were always located in the same cluster and the Argentinian peso always gravitated around this cluster. On the other hand, the Mexican peso, the Chilean peso, the Colombian peso, the Peruvian sol and the Brazilian real compose the largest cluster of the network. Within this cluster, the Peruvian sol tended to have the most heterogeneous behavior. By contrast, the Mexican peso, the Chilean peso and the Brazilian real tended to occupy central positions in the network. They were usually the ones with the most connections and were connected to more than one cluster. By being in contact with more than one cluster, these currencies function as channels of information flows between the clusters. Using data regarding the degree of financial liberalization as well as the distinction between IT and non-IT countries, the analysis suggests that the taxonomy obtained is economically relevant. The countries with the lowest level of financial liberalization are Argentina, Honduras and Venezuela, which is consistent with the analysis of clusters, since the co-movements of these three countries' currencies have always been grouped. On the other hand, Brazil, Chile, Colombia and Mexico show an intermediate level of financial liberalization, and these countries were always part of the same cluster, whereas Peru and Uruguay have the highest level of financial liberalization. This is particularly relevant in the case of Uruguay, since the Uruguayan peso was the currency that showed the most divergent behavior.

On the other hand, the results observed are also relevant in terms of the distinction between IT and non-IT. Out of the sample analyzed, Brazil, Chile, Colombia, Mexico and Peru are IT countries. The co-movements of these currencies were part of the same cluster. Alternatively, Argentina, Honduras and Venezuela had the US dollar as an anchor, which would explain the similarity of their co-movements. These countries have used the US dollar as an anchor with the aim of achieving price stability.

Paper 3. Entropy evolution of Latin American exchange rates

In the third paper, we analyze the entropy evolution of nine Latin American currencies before and after the financial crisis of 2008. The study considers the exchange rates of Argentina, Brazil, Chile, Colombia, Honduras, Mexico, Peru, Uruguay and Venezuela and covers the period from 2003 to 2015.

In this third paper, we utilize the concept of entropy to analyze the evolution of the exchange rates in terms of the randomness of the third kind[2]. This randomness is produced

[2] In general terms, randomness could be classified as ideal or trivial randomness (randomness derived from the absence of rules), randomness of the first kind (when it emerges as a result of our inability to find the rules that

by the continuing interaction between "subsystems" or between open systems: as they interact, they exchange information and modify their levels of randomness.

The main contribution of this paper is threefold. First, we identify cycles in the evolution of entropy. In particular, we observe the presence of entropic bubbles, the entropy equivalent of financial bubbles, consistent with previous findings by Stosic *et al* (2016). Second, we introduce an entropic ordering that allows to distinguish between exchange rate regimes. In an extreme case, an entropy of zero refers to fixed exchange rate, whereas maximum entropy indicates floating regimes. To my knowledge, the question of whether entropy and exchange rate regimes are related has not been analyzed in previous studies. Finally, related to the previous point, in this paper we also ask whether the currencies with higher entropy – those that have a tendency to float – show signs of a "fear of floating" (Calvo and Reinhart 2002). To answer this question, we introduce a statistical randomness test based on the entropy measure (Risso 2007). The results reject randomness, which implies that pure flotation regimes are not present.

dictate the evolution of process), randomness of the second kind (usually known as chaos, i.e. randomness due to sensitivity to the initial conditions) and randomness of the third kind (also known as stochasticity, i.e. randomness generated by the continuing effects of the environment (see Tsonis, 2008).

IV. Conclusion

This doctoral thesis contributes to an understanding of Latin American exchange rates by focusing on a relatively unexplored research topic, the linkages between complex dynamics and the post-Keynesian analysis of exchange rates. This is an important issue, as it draws attention to the dynamic patterns and irregular fluctuations in Latin American exchange rates. In this thesis the linkages between volatility, uncertainty and randomness are explored and is it shown that entropy, in conjunction with the analysis of co-movements, provides a meaningful economic taxonomy.

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1. A POST-KEYNESIAN FRAMEWORK OF EXCHANGE RATE DETERMINATION: A DYNAMICAL APPROACH

with Juan Gabriel Brida

Abstract

This article presents a mathematical approach to exchange rates dynamics. Following a post-Keynesian approach for exchange rate determination, we develop a model in which the dynamics are driven by expectations. The model is capable of producing a rich variety of dynamic behaviors, whose complexity is characterized by using the entropy measure. It is important to note that this analysis does not use random shocks to introduce irregular fluctuations; rather, these arise due to the presence of intrinsic forces associated with non-linear relations. This work also introduces the notion of "economic regime" or "regime of performance" and shows how it can be used to analyze exchange rates under the post-Keynesian framework. This approach contributes to the debate upon these issues, since literature has not provided a comprehensive explanation regarding the volatility of exchange rates in emerging peripheral economies.

Keywords: Regime Dynamics; Symbolic Dynamics; Entropy.
JEL Classification: A10; B41; O40
Mathematics Subject Classification: 91B62

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2. AN APPLICATION OF MINIMUM SPANNING TRESS AND HIERARCHICAL TRESS TO THE STUDY OF LATIN AMERICAN EXCHANGE RATES

Abstract

This paper analyzes a group of nine Latin American currencies with the aim of identifying clusters of exchange rates with similar co-movements. In this work, the study of currency relationships is formulated as a network problem, where each currency is represented as a node and the relationship between each pair of currencies as a link. The paper combines two methods, symbolic time series analysis (STSA) and a clustering method based on the minimal spanning tree (MST), from which we obtain a hierarchical tree (HT). STSA comprises transforming a given time series into a symbolic sequence with the aim of identifying patterns in the set of data. The MST condenses the core information on the global structure of the network and its main advantage is that it strongly simplifies comparisons by significantly reducing the number of elements to be compared. We identify two main clusters in the currency network, as well as specific currencies that function as transmission channels between clusters. Using data regarding the degree of financial liberalization as well as the distinction between inflation targeting (IT) and non-IT countries, the analysis suggests that the obtained taxonomy is economically relevant.

Keywords. Exchange rate; Minimum Spanning Tree; Hierarchical Tree; Symbolic Time Series Analysis.
JEL Classification: C65, E12, F31
Mathematics Subject Classification: 91C20, 91B80, 91B55.

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3. ENTROPY EVOLUTION OF LATIN AMERICAN EXCHANGE RATES

Abstract

This paper analyzes the entropy evolution of nine Latin American currencies. We identify cycles in the evolution of entropy. In particular, we observe the presence of entropic bubbles, the entropy equivalent of financial bubbles. The paper also addresses the question of differences in exchange rate regimes, particularly how to distinguish them. We propose an entropic ranking based on the entropy measure to identify exchange rate regimes. Finally, the paper introduces a statistical randomness test based on the entropy measure. The results reject randomness.

Keywords. Exchange rate; Symbolic Time Series Analysis, Entropy.
JEL Classification: C65, E12, F31
Mathematics Subject Classification: 91C20, 91B80, 91B55.

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I. Introduction

A major characteristic of the current system of exchange rates – which has been in operation since the early-1970s – is exchange rate volatility (Moosa 2005). This issue is particularly important in the case of developing and emerging countries, in which exchange rate volatility is one of the main concerns and volatile movements are the rule rather than the exception (Kaltenbrunner 2015, Harvey 2006a). According to Harvey (2009), exchange rate volatility is due to speculative investor behavior in search of short-term capital gains. In his model, the readjustment in the composition of the portfolio investment is driven by expectations, and since the expectations are volatile, the exchange rate is volatile.

The concept of volatility denotes the spread of all likely outcomes of an uncertain variable. Usually, in financial markets, it is understood as the spread of asset returns (Poon 2005). In the case of exchange rates, it refers to short-run fluctuations around its average (Moosa 2005). Statistically, volatility is often measured as the sample standard deviation. Sometimes, variance is used also as a volatility measure. Since variance is simply the square of standard deviation, it makes no difference whichever measure we use when comparing the volatility of two assets.

Standard deviation is widely used due to its simplicity, whereby it is easy to calculate and interpret: it measures average departures of the time series from its mean. Nevertheless, it also shows some disadvantages. First of all, it is severely affected by extreme values. A second disadvantage is that it only captures linear relationships, being incapable of detecting non-linear dynamics. A third drawback is that since it only measures the spread of a distribution, standard deviation, has no information about its shape. The exception is the normal distribution, in which we are able to reproduce the probability distribution with only two parameters, the mean and the standard deviation (Poon 2005).

An alternative route to analyze exchange rate volatility is by applying the concept of entropy. This concept was first utilized in physics and then generalized by Claude Shannon in the realm of information theory. Intuitively, Shannon entropy can be considered as an index of ignorance, disorder, uncertainty or a lack of information and it has proven an effective means of detecting randomness in a set of data. In this paper, we utilize this concept to analyze nine Latin American currencies before and after the financial crisis of 2008. The study considers the exchange rates of Argentina, Brazil, Chile, Colombia, Honduras, Mexico, Peru, Uruguay and Venezuela and covers the period from 2003 to 2015.

The main contribution of this paper is threefold. First, following Harvey (2009), for whom currency prices go through cycles of volatility related to uncertainty, we identify cycles in the evolution of entropy. In particular, we observe the presence of entropic bubbles – the entropy equivalent of financial bubbles – consistent with previous findings by Stosic *et al* (2016).

Second, the paper addresses the “knotty question of differences in exchange rate regimes - specifically, with how to distinguish them” (Cardoso 2000). Given that we are dealing with randomness of the third kind (randomness produced by the continuing interaction between “subsystems” or between open systems), we introduce an entropic ranking. Thus, exchange rates with (high/low) entropy imply (low/high) interactions with other subsystems. Consequently, the hypothesis here is that central bank interventions diminish entropy levels. The main implication is that by observing the entropy, we would infer the kind of exchange rate regime of each currency. In an extreme case, an entropy of zero would mean a fixed exchange rate, whereas maximum entropy would indicate floating regimes. Our findings are in line with Levy-Yeyati and Sturzenegger (2016), although in their analysis they require five variables (foreign assets, foreign liabilities, central government deposits, monetary base and the exchange rate) while ours involves only one (exchange rate).

Finally, related to the previous point, this paper also asks whether currencies with higher entropy – those that have a tendency to float – show signs of a "fear of floating" (Calvo and Reinhart 2002). To answer this question, we introduce a statistical randomness test based on the entropy measure (Risso 2007). The results reject randomness in all cases, which implies that pure flotation regimes are not present.

The remainder of this paper is organized as follows: Section 2 discusses the concepts of entropy, randomness and how they have been applied to economics. Section 3 presents the methodology of this paper. Section 4 introduces the data, whereas section 5 presents and discusses the empirical results. Finally, section 6 draws conclusions.

II. Entropy

In his work "Analytic Economics: Issues and Problems", Nicholas Georgescu-Roegen stated that the second law of thermodynamics – in which entropy plays a crucial role – was "the most economic of physical laws" (Georgescu-Roegen 1966). The object of study of classical thermodynamics is the thermodynamic system, which refers to any finite macroscopic region of the universe that is considered as a coherent whole for some reason (Cockshott *et al* 2012). One of its fundamental principles is the second law of thermodynamics, which explains which changes are possible and which are not. Hence, it holds strong importance for science and our understanding of the universe (Atkins 2010).

The quantity that measures the irreversible progress of heat in one direction is known as entropy, thanks to the German physicist Rudolf Clausius (in ancient Greek, entropy means transformation). The formulation of the second law according to Clausius essentially highlighted the impossibility of a process in which the cold was transferred to a hot body. The entropy of Clausius – indicated by the letter S – is an amount that either increases or remains constant but never decreases in an isolated process, namely:

$$\Delta S \geq 0 \qquad (1)$$

The above-mentioned relationship is known as the second law of thermodynamics. This equation is the only one in physics for which there is some difference between the past and future. Also called the law of increasing entropy, it affirms that the entropy of an isolated system never diminishes. Thus, changes that reduce entropy do not occur in an isolated system. When a system is not isolated, it is possible that its entropy decreases, albeit only if it is accompanied by a greater or equal increase in the entropy of its environment. If we assume that our universe is an isolated system, then all of the transformations that occur result in a constant increase in entropy as time passes. Accordingly, the second law of thermodynamics is our only reference about the direction in which time flows. This fact was revealed by an Austrian physicist, Ludwig Boltzmann, whose intuition allowed him to understand that the growth of entropy and the increase of disorder are two sides of the same coin. It is the progressive and natural evolution of disorder that gradually leads us to less particular situations (Rovelli 2015).

Boltzmann established that the entropy of a system is directly proportional to the logarithm of the weight, W, of the equilibrium state:

$$S = k \ ln \, W \qquad (2)$$

where W (the weight of the macrostate) is the number of microstates corresponding to a given macrostate and the constant of proportionality $k = 1.38 \times 10^{-23} JK^{-1}$is the Boltzmann constant.

Here, the key point is that in, the context of the second law of thermodynamics, probability emerges from the fact that our interactions with the world only account for some aspects of reality. In this regard, the arrow of time from the past to the future does not emerge as an exact description of reality, but rather as a fuzzy description subject to uncertainty. It is important to emphasize once again that the second law is only valid for closed systems that cannot exchange information with their surroundings. Accordingly, if a system is open to external influences, entropy can deviate from what is established in the second law, i.e. entropy can decrease. This idea is key in our analysis, because as we shall see, exchange rate entropies increase and decrease, which is consistent with the open system epistemology that underlies the post-Keynesian approach. In the next sub-section, the concept of entropy is generalized to mean the average information associated with any probability distribution.

a) Shannon entropy

The origin of the theory of information is due to Claude Shannon, who in the middle of the last century published a revolutionary work that would lay the foundations of the mathematical theory of communication (Cockshott *et al*, 2012; Shannon 1963). Shannon's goal was to determine the ability of a telephone or telegraph line to transmit information. In order to measure the amount of information transmitted, Shannon started from the idea that the "information content of a message" depends on how surprising the message is: if a message is less likely, then it contains more information. Shannon argued that the messages transmitted could be encoded in terms of the presence or absence of electrical impulses, namely as binary digits or bits. According to Shannon, a bit would be the amount of information required by the recipient of a message to decide between two equally likely alternatives. As a result, Shannon obtained a formula showing the "shortest possible encoding for a stream of distinct messages, given the probabilities of their individual occurrences":

$$H(X) = -K \sum_i p_i log_2 p_i \qquad (3)$$

Where K is a positive constant. As Shannon himself explains:

> "Quantities of the form $H = -\sum_i p_i log_2 p_i$ (the constant K merely amounts to a choice of a unit of measure) play a central role in information theory as measures of information, choice and uncertainty. The form of H will be recognized as that of entropy as defined in certain formulations of statistical mechanics where p_i is the probability of a system being in cell i of its phase space. H is then, for example, the H in Boltzmann's famous H theorem. We shall call $H = -\sum_i p_i log_2 p_i$ the entropy of the set of probabilities $p_1, \ldots, p_n$. If x is a chance variable we will write H(x) for its entropy; thus x is not an argument of a function but rather a label for a number, to differentiate it from H(y) say, the entropy of the chance variable y." (Shannon 1963: 11).

Thus, as highlighted by Cockshott *et al* (2012), information and entropy are the same. Following (Shannon 1963: 11), figure 1 shows the entropy H in the case of two possibilities with probabilities p and q = 1 – p, where

$$H = -(p log p + q log q) \qquad (4)$$

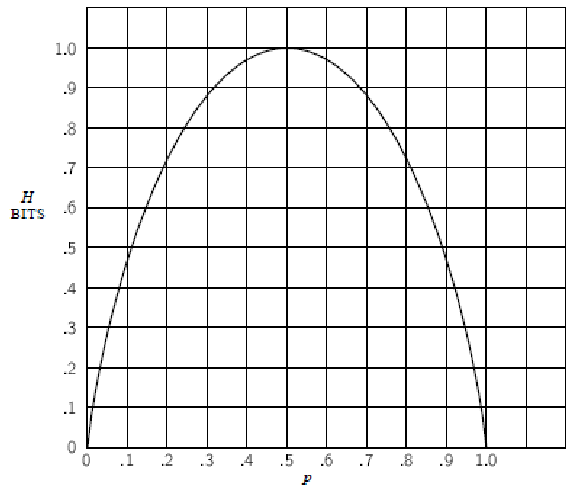

Figure 1. Entropy in the case of two possibilities with probabilities p and (1-p). Source: (Shannon 1963).

It will reach its maximum value of $H(X) = \log_2 n$ for the uniform distribution, while the minimum of 0 is attained for a distribution where one of the probabilities p_i is 1 and the rest are 0. Thus, high levels of entropy are obtained for probability distributions with high levels of randomness. Although in this context "randomness" and "disorder" are understood as equivalent terms, for Floridi (2010) it is preferable to use "randomness" since it is a syntactic concept, while "disorder" has a strong semantic load and is therefore subject to interpretations of different types.

According to Tsonis (2008), there are at least three types of randomness. The first type corresponds with the unpredictability that emerges from algorithms or processes that are irreversible, which prevents us from obtaining the rules that govern the behavior of the system. It is also true that randomness could emerge from the absence of rules. However, according to Tsonis, in this case we would be faced with trivial randomness, since in mathematical systems and the physical world there is always some kind of underlying rule. The second type of randomness is that in which we know the rules but we are incapable of reaching infinite precision and infinite power. This type of randomness corresponds to chaos, which occurs in non-linear systems. In Brida and Limas (2018) – in which the authors develop a mathematical approach to the post-Keynesian exchange rate determination – this is precisely the kind of randomness that exists in the system.

Finally, we have the randomness of the third type, resulting from the interaction between different systems. As the systems interact, they exchange information. This information received by one of the systems may interfere with its own rules, thus producing an unexpected result. In this work, we are dealing with this type of interaction, in which an open system interacts with its environment and consequently the volatility of exchange rates increases or decreases, i.e. the randomness of exchange rates increases or decreases in terms of Shannon's entropy.

b) Entropy and economics

According to Smith (2015), the economic concept of *tâtonnement* is analogous to the physical concept of "entropic forces", in which individual molecules restore equilibrium in a random manner because the equilibrium state is the situation with the highest probability. This means that molecules are coordinated by entropy. In the case of *tâtonnement*, individual agents restore balance by informing the Walrasian auctioneer of their equilibrium prices, and it is the Walrasian auctioneer who coordinates the price dynamics until the equilibrium is reached.

The first economist to recognize the importance of entropy and the second law of thermodynamics – which he referred to as "the most economic of physical laws" – was Nicholas Georgescu-Roegen (Screpanti Zamagni 1993: 435). In his work The Entropy Law and the Economic Process (Georgescu-Roegen, 1971), Georgescu-Roegen proposed combining economic analysis with environmental impact using entropy as the link between the two. In addition, the inclusion of entropy allows including historical time or real time, which has been ignored by the economic theories that pose the economy as a closed system.

Besides the already-mentioned Roegen (1971), Jaynes (1991) is one of the main works in which it is possible to grasp the scope that the concept of entropy holds for economic analysis. According to Jaynes, classical economists – particularly since Adam Smith – posed the economic problem in terms of an analogy with mechanics, and in particular they relied on the concept of mechanical equilibrium. However, macroeconomics is much more like a thermodynamic system rather than a mechanical system. Accordingly, the macroeconomic system not only moves in response to the forces assumed in the prevailing theories, but could also move in the direction in which entropy is increasing, given the restrictions imposed by nature and the government (in the same way that a thermodynamic system approaches equilibrium following the direction in which entropy is increasing, given the restrictions imposed by the conservation of mass, energy, etc). In thermodynamics, the entropy of a macrostate is the logarithm of the number of microstates consistent with it. An analogous way, Jaynes highlights that the "economic entropy" S would be

$$S(X, Y, Z, \dots) = \ln W(X, Y, Z, \dots) \qquad (5)$$

where X, Y, Z are the macroeconomic variables of interest and W the number of different microeconomic ways in which the macrostate can be reached. The economic system could stagnate in the state that it is in, unless it is shaken by a source of randomness that Jaynes calls "dither." Thus, dither is any turbulence introduced into macroeconomic variables through fluctuations in the underlying microeconomics. According to Jaynes (1991), the idea of dither was anticipated by Keynes in the form of "animal spirits" due to which the economic agents behave erratically. In this framework, dither not only introduces random uncertainty in the macroeconomic variables, but it also systematically orients the movement of the economy. In this sense, expectations play a crucial role and changes in dither are the result of agents who went from a "pessimistic" to a "confident" state, or from a "poor" to a "prosperous" state.

Thus, the idea of applying the concept of entropy in economics has provided deep and diverse insights, although in recent years it has been mainly concentrated on stock markets analysis (Fiedor 2014, Dionísio *et al* 2012). In Bentes and Menezes (2012), the authors measure volatility in seven stock markets indexes employing standard deviation and the Tsallis and Shannon entropy and argue that entropies are more general and better suited for describing stock market volatility than variance or standard deviation. Zunino *et al* (2010) follows a similar approach to analyze the prices of equity indices and demonstrates that using entropies is useful to classify stock market dynamics. In reference to the Chinese financial market, Li *et al* (2016) shows that Shannon entropy is a good alternative to standard deviation as a measure of market volatility.

Entropy measures have also been utilized to develop early warning indicators for systemic risk. Billio *et al* (2015) estimate an early warning indicator for systemic risk based on entropy measures (Shannon, Tsallis and Renyi) and show that entropy indicators are effective indicators in forecasting and predicting banking crises. Regarding the stock market dynamics during financial crises, Gençay and Gradojevic (2017) conclude that the Tsallis entropy (a generalization of the Shannon entropy) is more appropriate as an early indicator of crisis in cases when the market movements are sudden and extreme, such as in the crash of 1987.

In terms of exchange rates, Traian *et al* (2017) analyzes the relationship between the information entropy of the distribution of intraday returns of the EUR/JPY exchange rate and measures of market risk and highlights that since the entropy of a distribution function takes into account the entire distribution, it has more informational content than the classical measures of market risk such as value-at-risk or expected shortfall. Matesanz and Ortega (2006) use Shannon entropy as an index to classify different real exchange rates dynamics and show that this measure is strongly correlated with economic growth. On the other hand, Villanueva and Niguidula (2017) investigate the effects of the 2008 financial crises on foreign exchange markets and conclude that most of the currencies analyzed experienced an increase in the exchange rate entropy after the financial crisis. Finally, in the first chapter of this dissertation, Brida and Limas (2018) present a dynamical post-Keynesian model of exchange rate determination, in which by using the entropy measure they show that this model is capable of generating cyclical, quasi-cyclical and even chaotic fluctuations in exchange rates. Next section presents the methodology.

III. Shannon entropy and symbolic time series analysis (STSA)

STSA comprises transforming a given time series into a symbolic sequence with the aim of identifying patterns in the set of data. Each value of the time series is transformed into a symbol in such a way that the original time series is transformed into a symbolic time series. Based on the analysis of the symbolic time series, it is possible to obtain information referring to the dynamics of the original time series. Once the original series have been transformed into symbolic series, we can measure the corresponding Shannon entropy.

In order to transform the original series into a symbolic one, it is necessary to introduce a partition into the state spaces of the original series, i.e. the set of values taken by the original series is partitioned into a finite number of regions. Subsequently, once the partition has been specified, each measurement of the original series is transformed into a symbol depending on which region of the partition the observation fell into. In this context, the set of symbols is known as the *alphabet*. In order to give an example, figure 2 shows the time series of the variation of the exchange rate of the Mexican peso against the dollar. It is a daily series starting on May 7, 2013 and ending on May 17, 2013. In the same figure, the horizontal line indicates the average value of the time series, $\mu = 0.0025$. This μ value is used as the threshold value separating the state space in two regions, namely deviations above and below the mean. In this example, the alphabet has two symbols, 0 and 1. Thus, when the original value is above the mean μ, the symbolic value is 1, whereas if the original value is below the mean μ, the symbolic sequence shows the value 0.

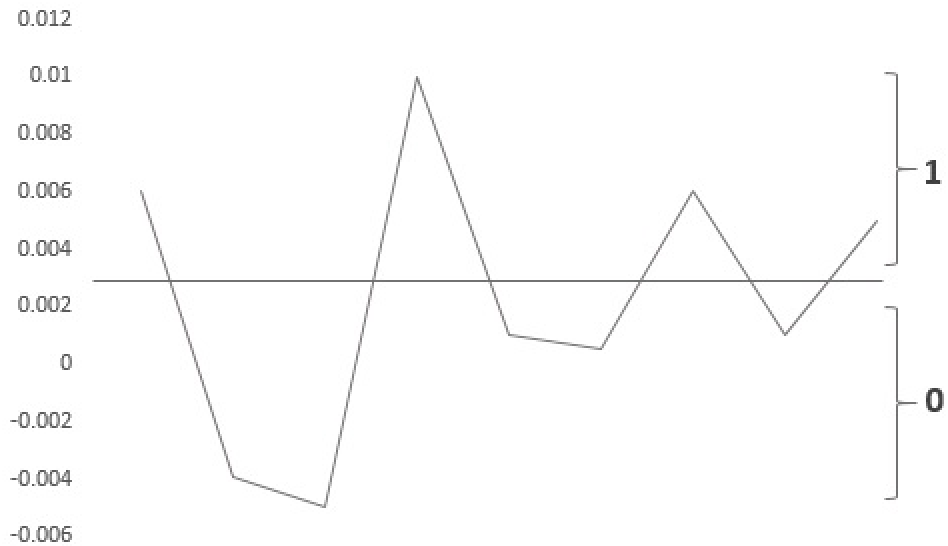

Figure 2. Illustration of symbolic encoding: variation of the exchange rate of the Mexican peso against the US dollar. The horizontal line represents the symbol partition, whereby data below the partition are represented by 0, and data above the partition are represented by 1. In this case, the frontier level is the trend of the series, $\mu = 0.0025$. Then, the original data time series is represented by the symbol sequence S = 100100101. Thus, the original series is transformed into the symbolic sequence S = 100100101. These symbolic sequences are called *words* in the symbolic dynamics literature and they represent paths or patterns, i.e. which regions of the partition are visited by the variable in each period.

Since the binary symbolization distinguishes only between movements above or below the mean, we introduce multi-symbol partitions in order to capture information of changes of different sizes in the series, such as increasing or decreasing trends (Stosic *et al* 2016). Thus, in this paper, we use three kind of partitions. First, we utilize the average of each time series to make the corresponding partition. Consequently, the state space is divided into two regions, above and below the trend. If the value of the series is below its trend, the symbol used is 0, and 1 otherwise. In the second partition (four symbols), we divide the domain into four sets: i) below minus one standard deviation; ii) between minus one standard deviation and the average; iii) between the average and one standard deviation; and iv) above one standard deviation. In the third symbolization (six symbols), we divide the domain into six sets: i) below minus two standard deviations; ii) between minus two standard deviations and minus one standard deviation; iii) between minus one standard deviation and the average; iv) between the average and one standard deviation; v) between one standard deviation and two standard deviations; and vi) above two standard deviations. Thus, in the first kind of partition (using two symbols), the data is symbolized according to the following rule:

$$s_i = 0 \; if \; \Delta e_i \leq \mu_i$$
$$s_i = 1 \; if \; \Delta e_i > \mu_i \tag{6}$$

Where Δe_i is the change in the exchange rate of currency i, μ_i is the trend of Δe_i and s_i is the corresponding symbolic value. In the second kind of partition (using four symbols), the data is symbolized according to the following rule:

$$s_i = 0 \quad if \quad \Delta e_i < -\sigma_i$$
$$s_i = 1 \quad if \quad -\sigma_i \leq \Delta e_i < \mu_i \tag{7}$$
$$s_i = 2 \quad if \quad \mu_i \leq \Delta e_i < \sigma_i$$
$$s_i = 3 \quad if \quad \sigma_i \leq \Delta e_i$$

Where Δe_i is the change in the exchange rate of currency i, σ_i the standard deviation, μ_i is the trend of Δe_i and s_i is the corresponding symbolic value. Figure 3 shows the time series of the variation of the exchange rate of the Mexican peso against the dollar presented in figure 2, albeit with the four-symbol encoding. Thus, in this case the original series is transformed into the symbolic sequence S = 200311212.

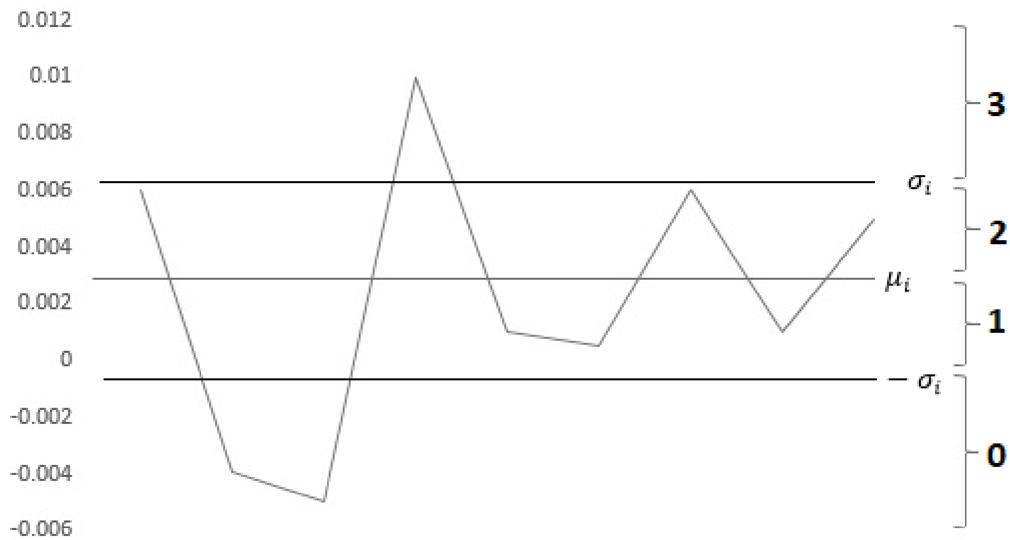

Figure 3. Illustration of symbolic encoding with four symbols. The original data time series is represented by the symbol sequence S = 200311212.

In the third kind of partition (using six symbols), the data is symbolized according to the following rule:

$$s_i = 0 \qquad if \qquad \Delta e_i < -2\sigma_i$$

$$s_i = 1 \qquad if \qquad -2\sigma_i \leq \Delta e_i < -\sigma_i$$

$$s_i = 2 \qquad if \qquad -\sigma_i \leq \Delta e_i < \mu_i \tag{8}$$

$$s_i = 3 \qquad if \qquad \mu_i \leq \Delta e_i < \sigma_i$$

$$s_i = 4 \qquad if \qquad \sigma_i \leq \Delta e_i < 2\sigma_i$$

$$s_i = 5 \qquad if \qquad 2\sigma_i \leq \Delta e_i$$

Where Δe_i is the change in the exchange rate of currency i, σ_i the standard deviation, μ_i is the trend of Δe_i and s_i is the corresponding symbolic value. Figure 4 shows the six symbolic encoding of the time series of the variation of the exchange rate of the Mexican peso against the dollar. In this case, the original series is transformed into the symbolic sequence S = 200311212.

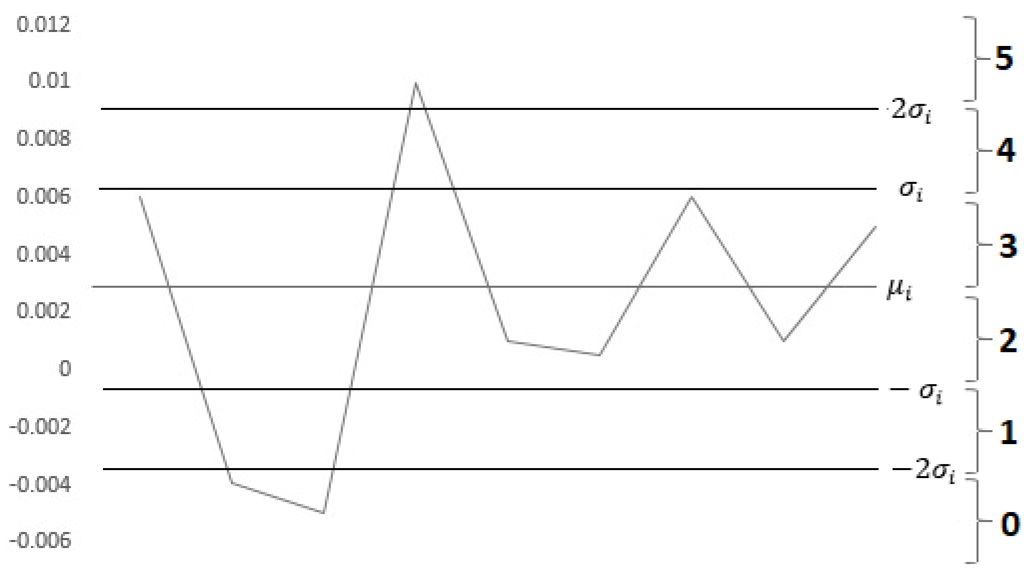

Figure 4. Illustration of symbolic encoding with six symbols. The original data time series is represented by the symbol sequence S = 300522323.

Once the original series have been transformed into symbolic series, in the second step we measure the corresponding normalized Shannon entropy. Given a discrete set of data points $x_1, x_2, \ldots, x_n$ – each one of them with probability $p_1, p_2, \ldots, p_n$ of being pulled out from a data set – the normalized Shannon entropy is defined as follows:

$$h(X) = \frac{-\sum_i p_i log_2 p_i}{log_2 n} \quad (9)$$

where $0 \leq h(X) \leq 1$

with

$h(X) = 1$ if and only if $(p_1, p_2, \ldots, p_n) = \left(\frac{1}{n}, \ldots, \frac{1}{n}\right)$

and

$h(X) = 0$ if and only if $p_i = 1$ for some i.

For random data and equiprobable partitions, we should have $h(X) = 1$ and for non-random data it should be $0 \leq h(X) < 1$, while lower $h(X)$ implies more deterministic structure. In order to capture the temporal evolution of entropy, in this work the normalized Shannon entropy is computed by applying the sliding window technique (Stosic *et al* 2016). Estimations are made using rolling windows of one year and sliding steps of one day. The next section presents the data, before section 5 presents the empirical results of this paper.

IV. Data

The study considers the exchange rates of nine Latin American countries: Argentina, Brazil, Chile, Colombia, Honduras, Mexico, Peru, Uruguay and Venezuela. We analyze daily data from February 1, 2003 until December 31, 2015. In the case of Uruguay, the period analyzed goes from January 16, 2007 to December 31, 2015. Data are obtained from the Pacific Exchange Rate Exchange Rate Service, which is available online. In order to denote the currencies, we follow the ISO4217 standard by using three-letter codes (table 1). In this analysis, the exchange rate is defined as the value of one currency in relation to the US dollar (USD).

Country	Currency	Currency code
Argentina	Argentinian peso	Ars
Brazil	Brazilian real	Brl
Chile	Chilean peso	Clp
Colombia	Colombian peso	Cop
Mexico	Mexican peso	Mxn
Peru	Peruvian Sol	Pen
Honduras	Lempira	Hnl
Uruguay	Uruguayan peso	Uyu
Venezuela	Venezuelan Bolivar	Vef

Table 1. Countries, currencies and three-letter codes

V. Results

In this section, we present the empirical results of this article. In the first sub-section, we present the entropy evolution of nine Latin American currencies before and after the financial crisis of 2008. Based on these results, sub-section 2 introduces an entropic ranking and discusses its implications for the exchange rate regimes debate. Finally, sub-section 3 ascertains whether the currencies with higher entropy – namely those that have a tendency to float – show signs of "fear of floating" (Calvo and Reinhart 2002). This sub-section introduces a statistical randomness test based on the entropy measure.

a) Entropy evolution and entropic bubbles

This subsection focuses on the six symbol partition. Figure 5 shows the entropy evolution of the nine Latin American currencies. Following Harvey (2009), we observe the presence of cycles of volatility, which for most of the currencies were at its strongest during the global financial crisis. This result is in line with previous studies in which entropy has been utilized to analyze volatility in exchange rates. For instance, Wang, Xie and Han (2012) found that entropy in developed and emerging foreign exchange markets (Asia and Africa) increased during the global financial crisis. Ishizaki and Inoue (2013) also observed the same effect in the entropy of the dollar-yen exchange rate. The authors pointed out that high levels of entropy indicate "confusion in the market". Similarly, Stosic *et al* (2016) analyzed the entropy of 18 foreign currency exchange rates (among them the Brazilian real and the Mexican peso), and found that financial crises are associated with a significant increase of the exchange rate entropy.

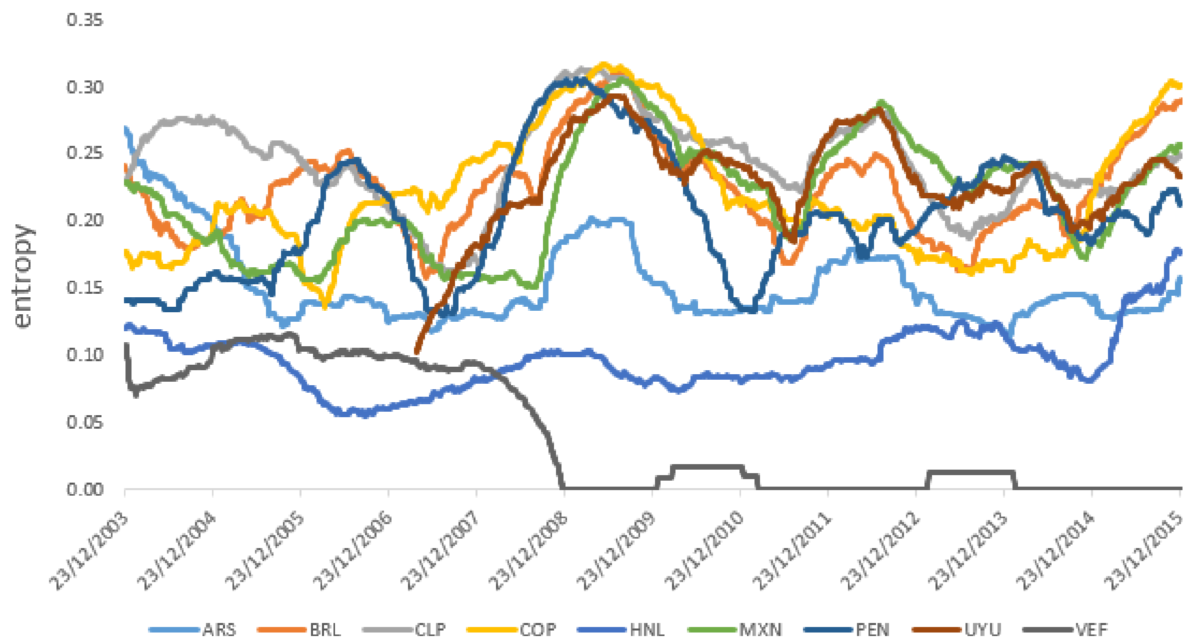

Figure 5: Entropy evolution of exchange rates.

In particular, during the global financial crisis, we observe the presence of *entropic bubbles*, the entropy equivalent of financial bubbles, consistent with previous findings by Stosic *et al* (2016). An entropic bubble is a sharp deviation of the entropy from its mean. It starts with upward movements and ends when entropy returns to its mean level. Entropic bubbles have two parameters: amplitude (A) and period (P). Amplitude is given by the difference between the maximum entropy and the mean, whereas the period refers to the duration of the bubble (measured in days). As an example, figure 6 shows the entropic bubble in the case of the Brazilian real, and table 2 presents the amplitudes and periods of entropic bubbles formed for each currency during the global financial crisis.

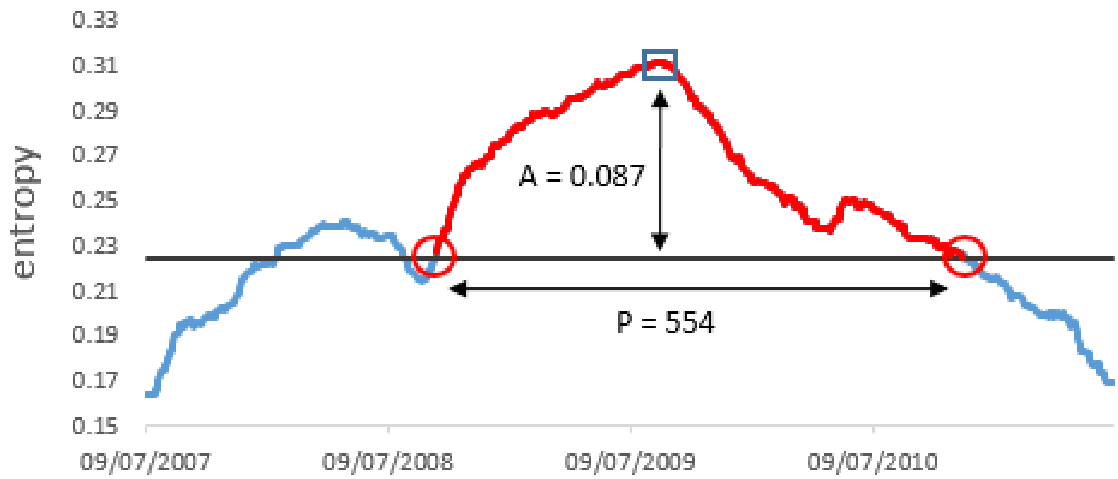

Figure 6: Entropy bubble for Brazilian real during the global financial crisis. The amplitude is the difference between the maximum (blue square) and the mean (horizontal line). The period is the distance, in days, between both red circles.

Currency	Amplitude (A)	Period (P)
ARS	0.050	297
BRL	0.087	554
CLP	0.070	686
COP	0.097	780
HNL	0.007	247
MXN	0.088	627
PEN	0.102	567
UYU	0.063	384
VEF	0	0

Table 2: Amplitudes and periods of entropy bubbles during the global financial crisis

Table 3 presents a ranking in which currencies are ordered by their amplitude and period levels. We observe that currencies with the shortest amplitude and period are ARS, HNL and VEF (in that order) whereas the rest of the currencies show higher amplitudes and periods. One plausible explanation is that Argentina, Honduras and Venezuela have less flexible exchange rate regimes. Accordingly, during a financial crisis, either the movement in the exchange rates is smoothed by central bank interventions, or the exchange rates remain fixed (which implies zero entropy). On the other hand, in the case of floaters, since central banks interventions are more limited, entropy faces fewer restrictions and tends to increase freely. Thus, the size of bubbles (amplitude and period) may signal differences in exchange rate regimes. The relationship between entropy and exchange rate regimes is what we study next.

Ranking	Amplitude	Period
1	PEN	COP
2	COP	CLP
3	MXN	MXN
4	BRL	PEN
5	CLP	BRL
6	UYU	UYU
7	ARS	ARS
8	HNL	HNL
9	VEF	VEF

Table 3: Currencies ordered by decreasing magnitude in Amplitude and Period

b) Entropy and exchange rate regimes

This sub-section addresses the "knotty question of differences in exchange rate regimes - specifically, with how to distinguish them" (Cardoso 2000). Central bank interventions mainly aim to (i) reduce volatility, (ii) stabilize the nominal and real exchange rate, or (iii) smooth the pace of depreciation or appreciation (Moosa 2005). These central bank interventions are framed within the notion of regime: according to the flexibility of exchange rates, exchange rate regimes can be classified as perfectly fixed exchange rates, fixed but adjustable exchange rates, and perfectly flexible exchange rates. Other classifications are fixed but flexible within a band, fixed but adjustable and flexible within a band, and flexible exchange rates with market intervention. The IMF considers the exchange rate arrangements of conventional pegs, stabilized arrangements, crawl-like arrangements, pegged exchange rates within horizontal bands, other managed arrangements, hard pegs (no separate legal tender and currency boards), floating arrangement and free floating (IMF 2017).

The main problem with exchange rate regimes is that it has been observed that central banks deviate from what they declare, mainly due to the fear of floating (Calvo and Reinhart 2002). On a similar line, Levy-Yeyati and Sturzenegger (2000a) show that floaters intervene in practice, whereas those that claim to have fixed exchange rates periodically devalue in reality. In the case of central banks that announce that their regime is one of limited flexibility, Eichengreen (1999b) argues that in practice they try to hold the price of their currencies within a relatively narrow range.

Levy-Yeyati and Sturzenegger (2000a) proposed a classification of exchange rate regimes based on the volatility of three variables: nominal exchange rate, changes in the nominal exchange rate and international reserves. According to Reinhart and Rogoff (2004), an important drawback in this methodology is that it does not classify countries when one variable is not available. Consequently, Kawai (2003) proposes a classification that utilizes only the observed volatility in exchange rates, in which volatility refers to percentage variations in exchange rates. The author identifies three categories: pegged (for values below 0.75 percent), intermediate (volatility between 0.75 and 1.5) and flexible (volatility above 1.5). The main advantage of this methodology is that volatility – measured as a percentage – is easy to interpret and compute. However, as in the case of standard deviation and variance, it is affected by extreme values, it does not detect non-linear dynamics in the data and finally it does not provide information about the underlying probability distribution.

In order to overcome these limitations, this sub-section proposes an entropic ordering based on the entropy measure, with the aim of addressing the issue of exchange rates classification. It is important to observe that exchange rates regimes imply interactions between markets and central banks, whereby we are dealing with randomness of the third kind (randomness produced by the continuing interaction between "subsystems" or between open systems). Thus, exchange rates with high/low entropy imply low/high interactions with other subsystems. In an extreme case, an entropy of zero would mean a fixed exchange rate, whereas maximum entropy would indicate pure floating regimes.

The idea of utilizing entropy to classify countries comes from Matesanz and Ortega (2006), in which an entropic ordering is introduced as an index to classify different real exchange rate dynamics. The authors find that this ordering, based on the Shannon entropy, is highly correlated with the intensity of GDP growth drops in periods with currency crisis. This idea is also present in Brida and Limas (2018), in which it is shown that entropy discriminates between different complexity levels depending on the parameter values.

In this work, we utilize entropy to classify currencies according to their degree of randomness. High entropy (i.e. high randomness) is associated with pure floating regimes, in which exchange rates move following a random walk process (Fama 1965). On the other hand, in fixed exchange rate regimes, randomness is absent, and consequently, entropy is zero. Table 4 shows the entropic ordering, from higher to lower entropy. We estimate the entropy using 2, 4 and 6 symbols. The value of each period corresponds to the average entropy of that year.

2 symbols													
Ranking	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
1	PEN	PEN	CLP	CLP	CLP	CLP	UYU	CLP	CLP	CLP	COP	MXN	UYU
2	MXN	BRL	PEN	PEN	MXN	BRL	MXN	UYU	COP	BRL	UYU	COP	CLP
3	COP	CLP	MXN	COP	COP	COP	CLP	COP	BRL	MXN	BRL	BRL	MXN
4	CLP	ARS	BRL	BRL	PEN	MXN	ARS	BRL	ARS	COP	PEN	UYU	BRL
5	BRL	MXN	COP	MXN	BRL	UYU	PEN	ARS	UYU	UYU	CLP	PEN	COP
6	ARS	COP	ARS	ARS	ARS	PEN	COP	PEN	PEN	ARS	MXN	CLP	PEN
7	HNL	HNL	HNL	VEF	UYU	ARS	BRL	MXN	MXN	PEN	ARS	ARS	ARS
8	VEF	VEF	VEF	HNL	VEF	HNL	HNL	HNL	HNL	HNL	HNL	HNL	HNL
9	-	-	-	-	HNL	VEF	VEF	VEF	VEF	VEF	VEF	VEF	VEF
4 symbols													
Ranking	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
1	ARS	CLP	CLP	BRL	COP	COP	CLP	CLP	CLP	CLP	MXN	CLP	BRL
2	BRL	ARS	BRL	CLP	BRL	BRL	COP	COP	UYU	MXN	PEN	MXN	COP
3	MXN	MXN	COP	PEN	CLP	CLP	BRL	MXN	MXN	UYU	UYU	PEN	CLP
4	CLP	BRL	MXN	MXN	MXN	PEN	PEN	BRL	COP	BRL	CLP	UYU	MXN
5	COP	COP	PEN	COP	PEN	UYU	MXN	UYU	BRL	COP	BRL	BRL	UYU
6	PEN	PEN	ARS	ARS	ARS	MXN	UYU	PEN	PEN	PEN	COP	COP	PEN
7	HNL	HNL	VEF	VEF	UYU	ARS	ARS	ARS	ARS	ARS	ARS	ARS	ARS
8	VEF	VEF	HNL	HNL	VEF	HNL	HNL	HNL	HNL	HNL	HNL	HNL	HNL
9	-	-	-	-	HNL	VEF	VEF	VEF	VEF	VEF	VEF	VEF	VEF
6 symbols													
Ranking	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
1	ARS	CLP	CLP	BRL	COP	COP	COP	CLP	CLP	MXN	MXN	CLP	COP
2	BRL	ARS	BRL	CLP	BRL	CLP	CLP	COP	UYU	UYU	PEN	UYU	BRL
3	CLP	MXN	COP	PEN	CLP	PEN	BRL	MXN	MXN	CLP	UYU	MXN	CLP
4	MXN	BRL	MXN	COP	MXN	BRL	PEN	UYU	COP	BRL	CLP	PEN	UYU
5	COP	COP	PEN	MXN	PEN	UYU	MXN	BRL	BRL	COP	BRL	BRL	MXN
6	PEN	PEN	ARS	ARS	ARS	MXN	UYU	PEN	PEN	PEN	COP	COP	PEN
7	HNL	HNL	VEF	VEF	UYU	ARS	ARS	ARS	ARS	ARS	ARS	ARS	HNL
8	VEF	VEF	HNL	HNL	VEF	HNL	HNL	HNL	HNL	HNL	HNL	HNL	ARS
9	-	-	-	-	HNL	VEF	VEF	VEF	VEF	VEF	VEF	VEF	VEF

Table 4: Entropic ordering

Although there are differences between the rankings (for instance, Argentina is ranked #1 with 4 and 6 symbols in 2003, whereas with 2 symbols it is ranked #6), we observe structural features: Argentina, Honduras and Venezuela tended to occupy the lower places, whereas countries considered as floaters occupied the highest positions. Next, we focus our analysis in the 6-symbol encoding and, following the idea of Kawai (2003), in which exchange rates are classified according to their degrees of variation, we complement the entropic ordering introducing the notion of entropic regime. In the first chapter of this dissertation we utilized the mathematical concept of regime, in conjunction with the concept of entropy, in order to characterize the exchange rate dynamics. In particular, we analyzed three types of regimes: regimes of low entropy, in which the exchange rate is highly predictable; regimes of intermediate entropy; and chaotic regimes in which exchange rates are unpredictable. Based on these ideas, in this section we classify entropy into three broad categories: low entropy, intermediate entropy and high entropy.

In order to reach this aim, we introduce a partition that separates the domain in three equidistant regions: low entropy - for those currencies with entropy below $\frac{1}{3}$ of the maximum entropy observed during the corresponding period, intermediate entropy - for currencies between $\frac{1}{3}$ and $\frac{2}{3}$ of the maximum entropy, and high entropy - for currencies above $\frac{2}{3}$ of the maximum entropy. Figure 7 shows the three regions and table 5 the results, in which within each entropic regime currencies are classified in descending order according to their entropic ordering.

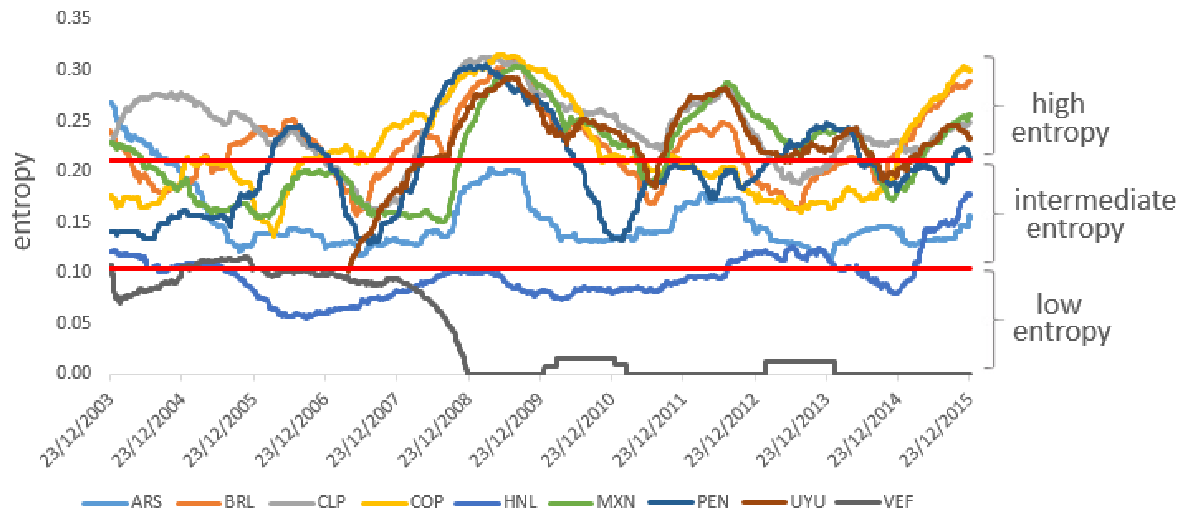

Figure 7: Entropy evolution and entropic regimes

As we expected, HNL and VEF are mainly grouped with the low entropy currencies. In Levy and (2015), these countries are classified either as crawling peg or as fix regimes. On the other hand, with the exception of Argentina during 2003 and 2004, in the high entropy group we have countries usually considered as floaters; although in Levy and (2015) Argentina appears as floater in 2003 – 2005, 2008 – 2009 and 2012-2013. These results suggest that low entropy currencies are associated with fixed regimes and high entropy corresponds with floating regimes.

Entropy	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
high	ARS BRL CLP MXN	CLP ARS MXN	CLP BRL	BRL CLP PEN	COP	COP CLP PEN BRL UYU	COP CLP BRL PEN MXN UYU	CLP COP MXN UYU BRL	CLP UYU MXN COP	MXN UYU CLP BRL	MXN PEN UYU	CLP UYU MXN PEN BRL	COP BRL CLP UYU MXN
intermediate	COP PEN HNL VEF	BRL COP PEN HNL	COP MXN PEN ARS VEF	COP MXN ARS VEF HNL	BRL CLP MXN PEN ARS UYU	MXN ARS	ARS	PEN ARS	BRL PEN ARS	COP PEN ARS HNL	CLP BRL COP ARS HNL	COP ARS	PEN HNL ARS
low		VEF	HNL	VEF HNL	VEF HNL	HNL VEF	HNL VEF	HNL VEF	HNL VEF	VEF	VEF	HNL VEF	VEF

Table 5: Entropic regimes and entropic ordering. Within each entropic regime, currencies are classified in descending order according to their entropic ordering.

We observe that this classification is related to the cluster analysis developed in the second chapter of this dissertation (Limas 2019), where we analyze co-movements between currencies. Honduran lempiras and Venezuelan bolivar were within the same cluster and the Argentinian peso was always gravitating around this cluster, whereas the Mexican peso, the Chilean peso, the Colombian peso, the Peruvian sol and the Brazilian real were together in the same cluster. Thus, the first cluster is linked with low levels of entropy, and the second with higher levels of entropy.

Finally, in the next subsection, we introduce a statistical randomness test based on the entropy measure (Risso 2007). As we shall we, the results reject randomness, which implies that pure flotation regimes are not present.

c) A randomness test: do Latin American exchange rates follow random walk processes?

In this section, we analyze whether exchange rates follow a random walk process. If that were the case, we might discard the presence of central bank interventions, since they introduce no-random dynamics. In order to address this question, we utilize a random test based on the measure of entropy (Risso 2007). The main advantage of this test is that neither variance process nor normal distribution is necessary to be assumed. This test is based on the two-symbol partition introduced above. Using 2 symbols, 0 and 1, we have that

$$s_i = 0 \; if \; \Delta e_i \leq \mu_i$$

$$s_i = 1 \; if \; \Delta e_i > \mu_i \qquad (10)$$

Where Δe_i is the variation in the exchange rate of currency, i, μ_i is the trend of Δe_i and s_i is the corresponding symbolic value. If this process is completely random, it should follow a Bernoulli distribution, with probability $\frac{1}{2}$ for each symbol. The probability function is the following:

$$P(s) = \begin{cases} \frac{1}{2} & if \quad s = 0 \\ \frac{1}{2} & if \quad s = 1 \\ 0 & otherwise \end{cases} \qquad (11)$$

In completely random processes, the normalized Shannon entropy should produce h = 1. On the other hand, if there is no uncertainty about the outcome (i.e. all the probability is concentrated in one symbol), then the entropy is zero. Given these facts, Risso (2007) introduced the R-statistic, which is defined as follows:

$$\mathrm{R} = 1 - \mathrm{h} \tag{12}$$

If the process is completely random (i.e. $h = 1$), the R-statistic takes the value 0, whereas if $h = 0$, $R = 1$. In order to obtain the probability distribution of R, 10,000 time series were simulated, in which the values 0 and 1 have the same probability. Under the null hypothesis of randomness, $H_0 : R = 0$, the null hypothesis is rejected if the R-statistic is larger than the critical value. This test analyzes both daily randomness and combinations of 2, 3, 4, and 5 consecutive days. In one day, there are 2 possible results, 0 or 1 and the process is random if each result has a probability of 1/2. In two consecutive days, there are 2^2 possible results, (i.e. (0,0), (0,1), (1,0),(1,1)) and the process is random if each possible sequence has a probability of 1/2^2. In three days, there are 2^3 possible results and the process is random in sequences of three days if each sequence has a probability near $1/2^3$. In sequences of four days, the process is random if each sequence of four days has a probability near $1/2^4$, and in five days, the process is random if each sequence has probability near $1/2^5$. Table 6 shows the critical values at 95% and table 7 presents the R-statistic for the different currencies.

R-1 day	R-2 days	R-3 days	R-4 days	R-5 days
0.0009	0.0011	0.0014	0.0019	0.0027

Table 6. Critical values at 95% for R-statistic. Source Risso (2007)

In all cases, except for Chile when considering 1-day sequences, the R-statistic is larger than critical values. This implies that the null hypothesis that exchange rates are completely random is rejected. This result is consistent with "fear of floating" (Calvo and Reinhart 2002) and is also in line with Wang, Xie and Han (2012), where the authors find that randomness in emerging foreign exchange markets is lower than in developed FX markets.

Currency	R-1 day	R-2 days	R-3 days	R-4 days	R-5 days
ARS	0.0071	0.0073	0.0091	0.0114	0.0211
BRL	0.0016	0.0036	0.0024	0.0069	0.0082
CLP	0.0000*	0.0014	0.0023	0.0052	0.0085
COP	0.0021	0.0025	0.0029	0.0070	0.0103
HNL	0.2889	0.2950	0.2957	0.2980	0.3068
MXN	0.0043	0.0045	0.0069	0.0059	0.0123
PEN	0.0025	0.0027	0.0044	0.0084	0.0098
UYU	0.0639	0.0156	0.0180	0.0285	0.0329
VEF	0.5602	0.5612	0.5706	0.5743	0.5824

Table 7. Test of Randomness (R=1-h)

Conclusions

In this work, we analyzed the entropy evolution of nine Latin American currencies. We identified cycles in the evolution of entropy as well as the presence of entropic bubbles. The results suggest that the size of bubbles (in terms of their amplitude and period) may signal differences in exchange rate regimes. Second, the paper introduced the notions of entropic ranking and entropic regime and found that currencies with low entropy are linked to crawling peg or fix regimes, whereas high entropy is associated with floating regimes. Finally, a randomness test rejected that currencies follow random walk processes. This work may be extended in order to include other partitions and classification methods.

APPENDIX

Randomness test: critical Values for different samples

Critical Values at 5%					
Sample Size	**R1**	**R2**	**R3**	**R4**	**R5**
30	0.08170	0.11970	0.10620	0.21340	0.28110
60	0.05190	0.05650	0.06960	0.10380	0.14980
90	0.02900	0.03710	0.04820	0.06680	0.09860
100	0.02900	0.03440	0.04360	0.05950	0.08740
200	0.01420	0.01670	0.02120	0.02910	0.04210
300	0.00930	0.01140	0.01470	0.01930	0.02740
500	0.00560	0.00680	0.00860	0.01150	0.01630
600	0.00460	0.00550	0.00720	0.00970	0.01360
900	0.00300	0.00370	0.00470	0.00640	0.00890
1,000	0.00280	0.00330	0.00420	0.00560	0.00800
2,000	0.00140	0.00170	0.00210	0.00280	0.00400
3,000	0.00090	0.00110	0.00140	0.00190	0.00270
5,000	0.00050	0.00070	0.00090	0.00110	0.00160
6,000	0.00050	0.00060	0.00070	0.00090	0.00130
9,000	0.00031	0.00037	0.00047	0.00063	0.00088
10,500	0.00026	0.00032	0.00040	0.00054	0.00076

Source: Risso (2007)

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SUMMARY

This cumulative dissertation consists of three independent papers on Latin American exchange rates. The three works have in common that volatility and uncertainty play a crucial role for the understanding of exchange rates. The first study, “A post-Keynesian framework of exchange rate determination: a dynamical approach”, presents a mathematical approach to exchange rates dynamics. Following a post-Keynesian approach for exchange rate determination, we develop a model where the dynamics are driven by expectations. The model is capable of producing a rich variety of dynamic behaviors whose complexity is characterized by using the entropy measure. This work also introduces the notion of dynamic regime and shows how it can be used to analyze exchange rates under the post Keynesian framework. This approach contributes to the debate upon these issues, since literature has not provided a comprehensive explanation regarding the volatility of exchange rates in emerging peripheral economies. The second study, “An Application of Minimum Spanning Tress and Hierarchical Tress to the Study of Latin American Exchange Rates”, analyzes a group of nine Latin American currencies with the aim to identify clusters of exchange rates that present similar co-movements. In this work the study of currency relationships is formulated as a network problem where each currency is represented as a node, and the relationship between each pair of currencies as a link. The paper combines two method: Symbolic Time Series Analysis (STSA) and a clustering method based on the Minimal Spanning Tree (MST) from which we obtain a Hierarchical Tree (HT). Symbolic Time Series Analysis consists of the transformation of a given time series into a symbolic sequence with the aim of identifying patterns in the set of data. The Minimal Spanning Tree condenses the core information on the global structure of the network, and its main advantage is that it greatly simplifies

comparisons by dramatically reducing the number of elements that must be compared. We identify two main clusters in the currency network, as well as specific currencies that function as transmission channels between clusters. Using data regarding the degree of financial liberalization, as well as the distinction between inflation targeting (IT) and non-IT countries, the analysis suggests that the obtained taxonomy is economically relevant. In the third study, “Entropy evolution of Latin American exchange rates”, we analyze the entropy evolution of nine Latin American currencies before and after the financial crisis of 2008. We utilize the concept of entropy to analyze the evolution of the exchange rates in terms of the ‘randomness of the third kind’. This randomness is produced by the continuing interaction between open-systems; as they interact, they exchange information and modify their levels of randomness. The main contribution of this chapter is threefold: First, we identify cycles in the evolution of entropy. Particularly, we observe the presence of entropic bubbles. Second, we address the question of differences in exchange rate regimes. We introduce an entropic ranking and classify currencies. Thereby we show that low entropy is associated with fix regimes, and high entropy with floating regimes. Finally, we introduce a statistical randomness test based on the entropy measure. The results reject randomness in all cases, which implies that pure flotation regimes are not present.

ZUSAMMENFASSUNG

Die vorliegende, kumulative Dissertation besteht aus drei eigenständigen Arbeiten über lateinamerikanische Wechselkurse. Diese drei haben gemeinsam, dass Volatilität und Unsicherheit als entscheidende Faktoren für das Verständnis, wie Wechselkurse funktionieren, identifiziert wurden. Das erste Kapitel, „A post-Keynesian framework of exchange rate determination: a dynamical approach“, beschreibt einen mathematische Herangehensweise zur Wechselkursdynamik. Ausgehend von einem postkeynesianischen Ansatz zur Wechselkursbestimmung, entwickeln wir ein Modell, bei dem die Dynamik von den Erwartungen bestimmt wird. Das Modell ist in der Lage eine Vielzahl von dynamischen Verhaltensweisen zu erzeugen, deren Komplexität durch die Verwendung des Entropiemaßes charakterisiert wird. Diese Arbeit führt auch in den Begriff des dynamischen Regimes ein und zeigt, wie er zur Analyse von Wechselkursen im postkeynesianischen Rahmen verwendet werden kann. Dieser Ansatz trägt zur Debatte über diese Fragen bei, da die Literatur keine umfassende Erklärung für die Volatilität der Wechselkurse in Schwellenländern der Peripherie liefert. Die zweite Studie, „ An Application of Minimum Spanning Tress and Hierarchical Tress to the Study of Latin American Exchange Rates“, analysiert eine Gruppe von neun lateinamerikanischen Währungen mit dem Ziel, Cluster von Wechselkursen mit ähnlichen Co-Bewegungen zu identifizieren. In dieser Arbeit wird die Untersuchung von Währungsbeziehungen als Netzwerkproblem formuliert, wobei jede Währung als Knoten, und die Beziehung zwischen jedem Währungspaar als Verbindung dargestellt wird. Der Artikel kombiniert zwei Methoden: die symbolische Zeitreihenanalyse (STSA) und eine Clustering-Methode, die auf dem Minimal Spanning Tree (MST) basiert. Daraus erhalten wir einen hierarchischen Baum (HT). Die symbolische Zeitreihenanalyse besteht in der Umwandlung einer bestimmten Zeitreihe in eine symbolische Folge mit dem Ziel, Muster in der Datenmenge zu identifizieren. Der *Minimal Spanning Tree* verdichtet die Kerninformationen über die globale Struktur des Netzwerks und hat den Hauptvorteil, dass Vergleiche erheblich vereinfacht werden, indem die Anzahl der zu vergleichenden Elemente drastisch reduziert wird. Wir identifizieren zwei Hauptcluster im Währungsnetzwerk, sowie bestimmte Währungen, die als Übertragungskanäle zwischen Clustern fungieren. Unter Verwendung von Daten zum Grad der Finanzliberalisierung, sowie zur Unterscheidung zwischen Inflation Targeting (IT) und Nicht-IT-Ländern, lässt die Analyse darauf schließen, dass die ermittelte Taxonomie wirtschaftlich relevant ist. In der dritten Studie, „Entropy evolution of Latin American exchange rates“, analysieren wir die Entropieentwicklung von neun lateinamerikanischen Währungen vor und nach der Finanzkrise von 2008. Wir verwenden das Konzept der Entropie, um die Entwicklung der Wechselkurse im Hinblick auf die Zufälligkeit der dritten Art zu analysieren. Diese Zufälligkeit entsteht durch die ständige Interaktion zwischen offenen Systemen; während der Interaktion tauschen sie Informationen aus und ändern ihre Zufälligkeitsebenen. Der Hauptbeitrag dieses Kapitels teilt sich in drei Teile auf. Zunächst identifizieren wir Zyklen in der Entwicklung der Entropie. Hierbei beobachten wir insbesondere das Vorhandensein von entropischen Blasen. Zweitens befassen wir uns mit der Frage der Unterschiede in den Wechselkursregelungen. Hierzu führen wir ein entropisches Ranking ein und klassifizieren Währungen. Wir zeigen, dass niedrige Entropie mit festen Regimen verbunden ist und hohe Entropie mit Flotationsregimen. Schließlich führen wir einen statistischen Zufallstest ein, der auf dem Entropiemaß basiert. Die Ergebnisse lehnen in allen Fällen die Zufälligkeit ab, was impliziert, dass keine reinen Flotationsregime vorhanden sind.

LIST OF PUBLICATIONS

Brida, Juan Gabriel and Erick Limas. (2018). A post Keynesian framework of exchange rate determination: A dynamical approach. Dynamics of Continuous, Discrete and Impulsive Systems Series B: Applications and Algorithms. 25. 409-426. Available at https://www.researchgate.net/publication/328800192_A_post_keynesian_framework_of_exchange_rate_determination_A_dynamical_approach

Limas, Erick. (2019). An application of minimal spanning trees and hierarchical trees to the study of Latin American exchange rates. Journal of Dynamics & Games, 6 (2): 131-148. Available at https://www.doi.org/10.3934/jdg.2019010

Erklärung gemäß § 4 Abs. 2 der Promotionsordnung

Hiermit erkläre ich, dass ich mich noch keinem Promotionsverfahren unterzogen oder um Zulassung zu einem solchen beworben habe und die Dissertation in der gleichen oder einer anderen Fassung bzw. Überarbeitung einer anderen Fakultät, einem Prüfungsausschuss oder einem Fachvertreter an einer anderen Hochschule nicht bereits zur Überprüfung vorgelegen hat.

Ich erkläre außerdem, dass ich meine Dissertation selbstständig verfasst habe.

Berlin, 30.05.2019,

Erick Limas

Erklärung gemäß § 10 Abs. 3 der Promotionsordnung

Hiermit erkläre ich, dass ich für die Dissertation folgende Hilfsmittel verwendet habe:

Das Statistikprogramm R für die Datenaufbereitung, statistische Analysen und numerische Berechnungen sowie das Tabellenkalkulationsprogramm MS Excel.

Berlin, 30.05.2019,

Erick Limas