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A FIRM'S PERSPECTIVE ON ECONOPHYSICS-BASED CURRENCY RISK ANALYSIS

Summary: In this article the authors presents an approach to quantifying currency risk based on the methodology of econophysics. This article continues the authors' study into the currency risk, this time simplifying it for the purpose of rendering it useful for companies without technical abilities. A method of analysing the dependencies between currencies based on correlations is introduced to facilitate the analysis of currency risk involved in being exposed to one or more foreign currencies. Also a model estimating a risk-free horizon is introduced and tested against price formation models and empirical data from FX markets.

Keywords: risk, exchange rate, predictability, econophysics.

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1. Introduction

Inquiries into the nature and forecasting of financial risk are of the utmost importance to financial studies, and are a very timely problem indeed. There is a multitude of approaches, most of which are concentrated on Value-at-Risk and its derivatives. However, there are also heterodox approaches being proposed however. For instance, in our previous study we analysed the uncertainty in financial data using information-theoretic tools [Fiedor 2014]. In this study we aim to use a similar framework to analyse currency risk. Thus we analyse how information theory can provide useful ways to quantify uncertainty in the price formation processes governing exchange rates. Using the information theoretic approach we also perform a network analysis helpful in portfolio optimisation. A technical approach to exchange rate risk using an econophysics framework concentrating on technical analysis useful for researchers and professional international investors is the subject of a separate study [Fiedor, Hołda 2015]. But such an approach may prove difficult to be used by companies without the necessary know-how, thus in this paper we review a company's viewpoint on the same problem, proposing certain simpler measures helpful in quantifying the currency risk. As in the global economy, an ever growing number of companies have to manage currency risk on an ongoing basis [Allayannis et al. 2001] it follows that some of these companies will not have the tools necessary to use the complicated models necessary to accurately describe the complex markets. Strategies trying to eliminate currency risk require, however, a thorough understanding of the nature of the exchange rate risk and its connotations with the company's operations, as well as the methods dealing with the consequent risk [Barton, Shenkir, Walker 2002], but it is conceivable that such a goal can be achieved with a simpler methodology without losing too much precision. Nonetheless in this study we are trying to achieve simplicity instead of precision, thus some of the solutions may appear simplistic. The hardest task in preparing a hedging strategy against exchange rate risk is most often connected with the complex nature of measuring currency risk exposure, and this paper deals with reducing this complexity.

In fact, exchange rate risk is a problem especially for companies which are not specialised in financial operations. These companies usually do not have the knowledge necessary to accurately quantify, analyse and manage currency risk. This task is then usually performed by corporate treasuries. Additionally many large multinational companies create risk committees to supervise the management of exchange rate risk [Lam 2003]. Such a state of affairs provides evidence for the importance of risk management in companies. On the other hand, international investors who do have the know-how, usually manage exchange rate risk independently from the underlying investments, considering the currencies themselves as separate assets [Allen 2003]. Nonetheless in both cases identifying and quantifying exchange rate risk is of vital economic importance.

This paper aims to introduce and test on market data a novel approach using the paradigm of econophysics and information theoretic approach to quantifying uncertainty on financial markets, especially aimed at companies and not investment professionals, i.e. a simplified approach for the purpose of easier application by most companies. Econophysics is a research field which applies theories and methods originally developed by physicists (mostly in statistical physics, of which the information theory is the foundation through the principle of maximum entropy [Cover, Thomas 1991]) in order to solve problems in economics [Mantegna, Stanley 2000; Takayasu 2002]. Such an approach combines the solid methodology of statistical mechanics with a thorough understanding of economic phenomena.

The organisation of the paper is as follows: in section 2 we briefly review exchange rate risk, with standard measurements. In section 3 we present the approach used in the last study and a simplified version for use by companies. In section 4 we present the methodology used in this study. In section 5 we present the results of the empirical application for testing our methodology. In section 6 we discuss these results, while section 7 concludes this paper with conclusions and ideas for future research.

2. Quantification of exchange rate risk

Here we briefly recall the exchange risk and standard ways to measure it, for a more detailed description see our technical paper on currency risk [Fiedor, Hołda 2015]. The definition of exchange rate risk is well-established as unexpected exchange rate changes in the value of the firm [Madura 1989]. We note that exchange rate risk does not stem from expected or predictable changes, thus the notion of predictability is inherent in such risk, even if rarely used directly to quantify it. Usually it is defined as either the possible direct loss or indirect loss caused by an unexpected exchange rate move.

Commonly the impact of exchange rate changes on a company is measured through the concept of the implied value-at-risk (VaR) from exchange rate moves. In order to do this, the types of risks a company can be exposed to must be identified and the amount of risk quantified [Hakala, Wystup 2002]. Exchange rate risk is usually qualified into three types [Madura 1989; Shapiro 1996]:

1. Transaction risk, or cash flow risk associated with exchange rate changes and their effects of receivables and payables. Every transaction denominated in a foreign currency carries an exchange change risk to the company.
2. Translation risk, which relates to the effects of exchange rate on the consolidation of a foreign subsidiary to the company's balance sheet. Such risk is usually measured by the exposure of net assets to potential exchange rate changes.
3. Economic risk, which relates to the effects of exchange rate changes on the company's present value of future operating cash flow (revenue and operating expenses).

Identification is essential to the management of currency risk, as is the measurement of this risk. Only well-defined and quantified currency risk can present a basis for a hedging strategy.

There is a general agreement in the literature that any inquiry into financial market risk should involve quantile (VaR) estimation [Embrechts, Kluppelberg, Mikosh 1997]. Nonetheless, VaR estimation is a general methodology within which we can find numerous specific methods used to assess the value-at-risk of the distribution of losses and profits. Within all of these methods the calculation of VaR consists in estimating the maximal possible loss resulting from holding a given portfolio for a fixed period using the volatility of such portfolio as a measure of risk over the studied period of time.

The Value-at-Risk measures exchange rate risk (e.g. is an estimate of the risk associated with a foreign currency position), over a given time period under normal conditions [Holton 2003]. Assuming a holding period of t days and a confidence level of 1-α, the VaR measures the maximum loss on the foreign currency position, if the t-days period is not one of the worst α proportion of t-days periods, assuming normal conditions, VaR can be calculated using a variety of models of which the most commonly used are:

1. The historical analysis, which assumes that current currency returns will have the same distribution as they had in the past.

2. The variance-covariance model, which assumes that currency returns are always normally distributed and that the change in the value of the foreign exchange position is linearly dependent on all currency returns.

3. Monte Carlo simulations, which assume that future currency returns will be randomly distributed.

There are problems with Value-at-Risk. In particular it is not a measure in the mathematical sense [Artzner et al. 1999]. Thus coherent measures of risk have been introduced which need to satisfy four axioms: subadditivity, positive homogeneity, monotonicity, and translation invariance. Expected shortfall is one of such measures [Acerbi, Tasche 2002].

Quantifying risk, as described above, is a prerequisite to managing this risk, but in this paper we only deal with the former. Since those are separate issues we are leaving the risk management techniques outside the scope of this research paper. For reviews of those methods see [Allayannis, Ofek 2001; Glen, Jorion 1993; Jacque 1981].

3. Econophysics and currency risk in companies

As stated above, currency risk is connected with the effect of unexpected exchange rate changes. In a separate study we have established that risk does not reside in the currency rate changes themselves, but rather in the ability to predict them. As such, one can analyse currency risk through observing the predictability of exchange rate changes [Fiedor, Hołda 2015]. This is often neglected in the economic analyses, or explained away with the predictive power of the specific predictive model. Meanwhile information theory provides a way to analyse the predictability of a price formation process in a formal way. The entropy rate of a dynamic process (which price formation processes are) measures the uncertainty remaining in the information produced by the studied process given the complete knowledge of the past. Therefore it is a natural measure of the difficulty faced in predicting the evolution of the process [Navet, Chen 2008]. We will use the notion of entropy rate to analyse currency risk in this paper.

Not all economic agents treat currency risk (or any risk) in the same manner. Thus we will divide our analysis into two parts. In a separate paper [Fiedor, Hołda 2015] we have looked into currency risk as seen by an agent with broad financial knowledge and then into currency risk as seen by an economic agent without detailed know-how of the financial markets.

Economic agents which are competent in financial markets will manage their risk actively, changing their hedging strategy as the situation arises. In this sense, such agents should prefer to have exposure denominated in foreign currencies which are more predictable in their rate to the base currency of the agent. The entropy rates (inverse of predictability) for various currencies denominated in PLN have been estimated in our separate study and are presented on Figure 1 [Fiedor, Hołda 2015].

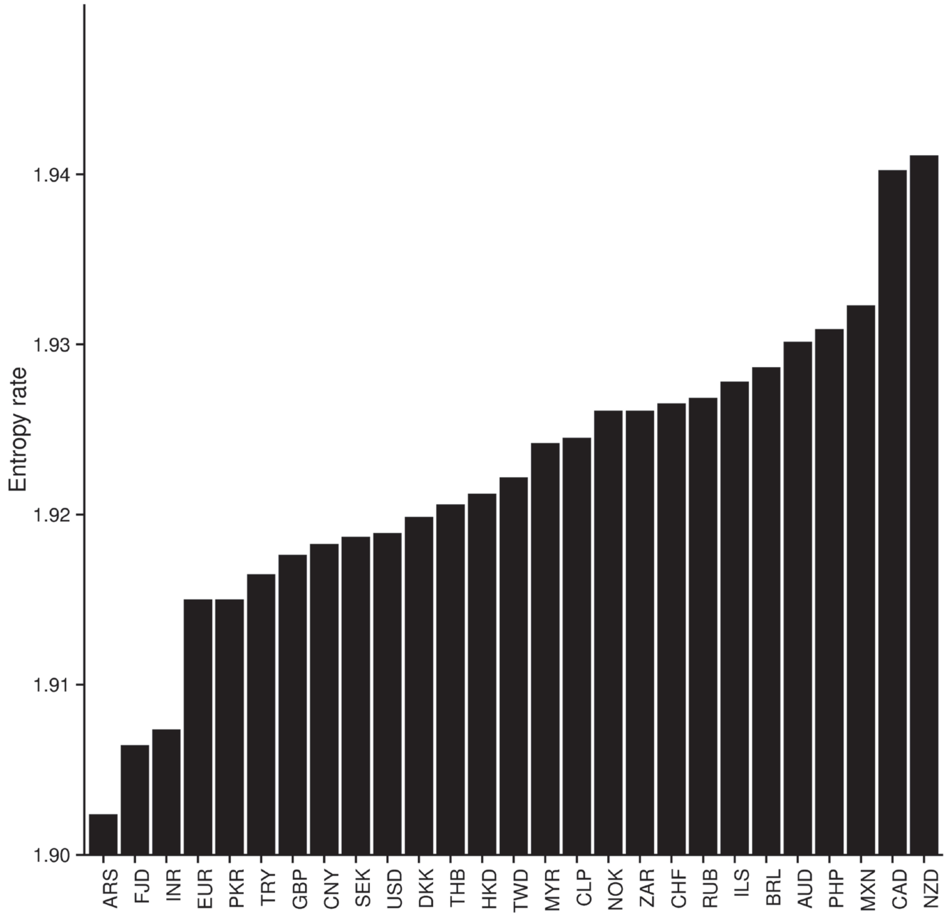

Fig. 1. Entropy rate estimates

Source: [Fiedor, Hołda 2015].

The analysis is quite different for an agent which does not possess a solid knowledge of financial markets. Such an agent will most likely only make a decision about foreign currency transaction and not pursue the predictions. Therefore the predictability analysis does not work in the same way as above, but as can be seen in Figure 2, there is a consistent negative correlation between the entropy rate and safe horizon (T in the model below) for the studied 110 pairs of currency exchange rates. This figure shows the correlation coefficient between the entropy rate (reverse of predictability) and the horizon in days for which the exchange rate will not exceed the assumed maximum loss (as a multiplication of historical standard deviation, $\frac{\delta_{max}}{\delta_0}$ below). This means that the more predictable the currency exchange rate the longer the safe horizon, ergo the less the risk.

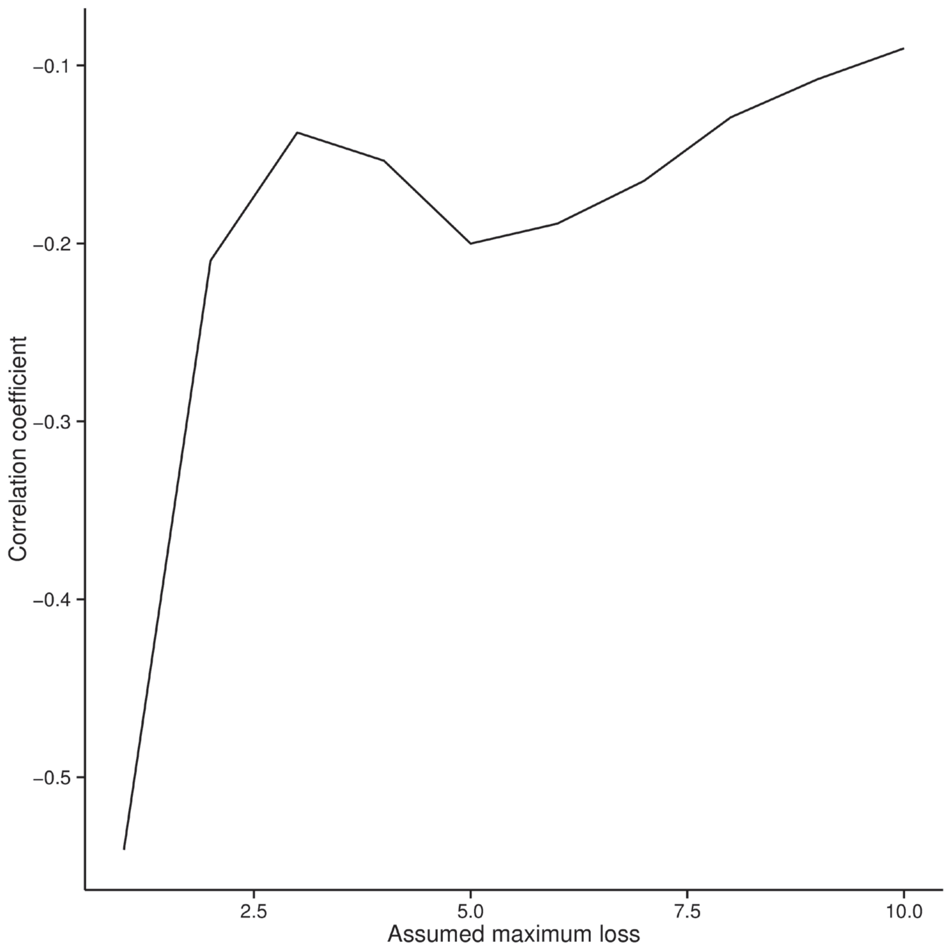

Fig. 2. Correlation between safe horizon and entropy rates for studied currency pairs

Source: own calculations.

Keeping this in mind, we propose a model in many ways similar and extending the VaR methodology, inspired by chaotic fluid mechanics. In our model we relate the maximal allowable exchange rate change (in terms of standard deviation) with the risk-free time horizon for a given level of statistical significance. Then the mentioned time horizon is defined as:

$$T = a\left(\frac{\delta_{\max}}{\delta_0}\right)^b,$$

where: T – time horizon free of currency risk; δ_{max} – maximal deviation from the starting exchange rate considered safe [%]; δ_0 – historical standard deviation of the exchange rate; $b = c + d\alpha$ – speed of the exchange rate divergence; α – level of statistical significance.

Parameters α, c, d are to be found from empirical data, while δ_0 is calculated from historical data, and δ_{max}, α are the choice of the economic agent. Equivalently δ_{max} can be estimated if T is fixed as an agent's choice. But we propose that more often companies will have a set maximum loss and want to know the safe investment horizon, hence the formulation above.

We can use another method based in econophysics to solve another problem in currency risk analysis. This will work for all kinds of agents, and thus has been presented in a separate study [Fiedor, Hołda 2015]. In many cases the agent will need to choose not one currency but a basket of currencies, and then analyse the risk of such a construct. Then it is useful to analyse the interdependencies between the currencies so as to minimise risk according to the classical portfolio theory of Markowitz [Markowitz 1952], stating that low or negative correlations between assets composing a portfolio reduce risk. To do that we can employ hierarchical clustering. In a separate study [Fiedor, Hołda 2015], we have used mutual information to account for the non-linearity in market behaviour [Hsieh 1989], but in this study we will simplify this analysis and base it on correlation as it is often done [McDonald et al. 2005]. This method is also able to produce networks based on the interdependencies for easier analysis. According to the portfolio theory, the lower the correlation or mutual information between two currencies, the less risky they are as constituent parts of the portfolio. For this purpose, exchange rates denominated in base currency for the economic agent should be used. If we use the currencies denominated in a neutral instrument, such as gold, silver or platinum, then we can also combine the risk of a foreign currency by the correlation or mutual information between the two exchange rates of the foreign currency and the base currency. Note that this time the bigger the correlation the less risk, since then the foreign currency will deviate less from the base currency, and as such will be more predictable with regard to the same.

4. Methodology

The previous section provided a sketch of the methodology of this paper, the technical aspects of which will be now revealed. In a separate study we have defined an estimator of entropy rate and mutual information [Fiedor, Hołda 2015]. In this paper we need a method for estimating the parameters of the presented model from simulated and market data. We will also simplify the method for creating networks based not on mutual information but on correlations. These ignore non-linear relationships, but are easier to calculate.

To create networks based on correlations we need to define correlation coefficient and a related metric. This method is widely known in econophysics but relatively unknown in mainstream economics hence we will present it here. An Euclidean metric based on Pearson's correlation coefficient ρ is defined as:

$$d(i, j) = 1-\rho^2.$$

Such a similarity measure can be calculated easier than mutual information, thus facilitating the usefulness of this analysis for smaller companies. Having a similarity matrix filled with pairwise Pearson's correlation coefficients we can define methods for constructing hierarchical networks based on this matrix for the purposes of studying financial markets. Such methods filter important information out of the characteristic vector describing the system, and allow for an easier analysis of the most important information within the system, making the understanding of the nature of the system easier to obtain. These methods are well-known and we only briefly define the used methods, that is the ones for creating minimal spanning trees and planar maximally filtered graphs. The distance matrix D containing $d(X, Y)$ for all studied pairs is defined as above. From D we create an ordered list S, in which the distances are listed in decreasing order.

The minimal spanning tree (MST) is created by using the ordered list S, and starting from the pair with the largest similarity measure D an edge is added to the graph between elements X and Y if and only if the graph obtained this way is still a forest or a tree. After all the appropriate links are added, such a graph is always reduced into a tree [Tumminello et al. 2005; Tumminello, Lillo, Mantegna 2010].

Less constrained graphs can also be constructed, where the genus is fixed: $g=k$. Such graphs are created similarly: from the ordered list S, starting from the pair with the largest similarity measure, we add an edge between that pair if and only if the resulting graph can still be embedded on a surface of genus $g \leq k$. Such a graph is less topologically restrictive than MST, and always contains the relevant MST and also additional loops and cliques [Tumminello et al. 2005]. Then if $g = 0$ the resulting graph is planar. Such a graph is the simplest extension of the MST, and is called the Planar Maximally Filtered Graph (PMFG). Each element in such a graph has to participate in at least one clique of three elements, thus such a graph is a topological triangulation of the sphere [Tumminello et al. 2005]. Larger cliques are not allowed.

The minimal spanning tree is very effective in carrying only the most relevant dependencies due to the topological restrictions, and hence makes it easy to analyse the financial markets, especially visually. When a less restrictive structure is needed the natural candidate is the planar maximally filtered graph. Thus we use both these structures, but it is worth noting that other structures have also been proposed [Tumminello, Lillo, Mantegna2010].

We also propose a simple model inspired by fluid mechanics to estimate the safe horizon of foreign investment. The proposed model is estimating a period during which the exchange rate will not change by a set amount, defined in terms of historical standard deviation. Thus it is relatively easy to calibrate the results to a given market or price formation model. Of course a large sample of time series describing prices is needed. Having these, we can divide it into two parts, the first used for calculating historical standard deviation, and the other one for testing. We find the number of periods it takes for every studied time series to deviate more than x standard deviations from the start of the test period, for a given range of x (we use 1-10). With these values for a large number of time series, we can find out what the risk-free horizons are for different statistical significance looking at percentiles. Having such numbers we can calibrate the parameters of the model to fit the time series. We will prototype the fit based on two price formation models, the stochastic volatility model and the Sznajd model, which are both relatively simple, but use different approaches. We will then see if the proposed model fits well with the theoretical price formation models.

The stochastic volatility model is based on a stochastic approach standard for econometrics. Here for testing we use a specific version:

$$S(t) = S_0 e^{\left(\sigma_t W_t + \left(\mu - \frac{1}{2}\sigma_t^2\right)t\right)},$$

where W_t is a Wiener process and σ_t defines volatility as a separate Brownian motion:

$$\sigma_t = \sigma_0 e^{\left(\vartheta W_t + \left(\tau - \frac{1}{2}\vartheta^2\right)t\right)},$$

We assumed:

$$S_0 = 100,\ t \in (0.30000),\ \mu = 0,\ \sigma_0 = 0.01,\ \tau = 0,\ \vartheta = 0.0001.$$

Such a process is stable.

The Sznajd model, on the other hand, is closer to econophysics in using an agent-based approach. Here we use a simplified version in which we have a one-dimensional vector of market agents who can either be bulls (1) or bears (−1). Then we have two rules for the propagation of the market opinions:

1. If $S_i S_{i+1} = 1$ then S_{i-1} and S_{i+2} take the opinion of the pair $\{S_i, S_{i+1}\}$.
2. If $S_i S_{i+1} = -1$ then S_i takes a random value.

Based on these, the market price is a mean of all the agent's opinion, the evolution of which is studied using Monte Carlo simulations.

Having prototyped the model with its parameters for two price formation models, we will also fit this for market data for exchange rates to see if it also works well for currency markets, and whether the parameters would be significantly different from the ones obtained from the theoretical models.

5. Experimental results

For this study we have used the currency rates from the database available at: http://fx.sauder.ubc.ca/data.html. This database is based on the official daily rates used by the Bank of Canada. We have used data for the years 2002-2013, for currency rates denominated in PLN and XAG (and EUR, USD, GBP for model testing). We consider the log changes of these rates. For the purpose of calculating the entropy rate and the mutual information as specified above, we discretize them into four quartiles (see discussion in [Fiedor 2014] for details on this methodology and its robustness; the results are robust with respect to this choice, with the exception of using just two quantiles – such a setup ignores volatility and is not sufficient for successful analyses). From the mutual information we create the distances used in network topology.

All figures in this paper, except Figure 1, consist solely in the results obtained in the study.

The Minimal Spanning Tree and the Planar Maximally Filtered Graph for currency pairs based on PLN are shown in Figures 3 and 4. Size denotes centrality in the network, colour denotes continent.

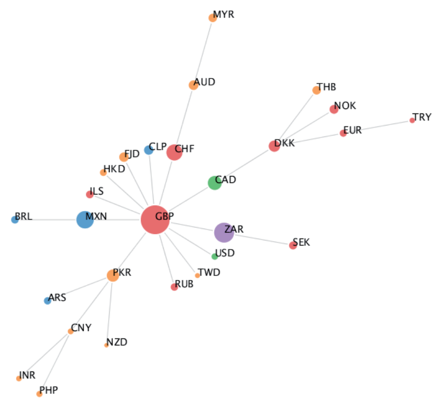

Fig. 3. MST for currency rates vs PLN

Source: own calculations.

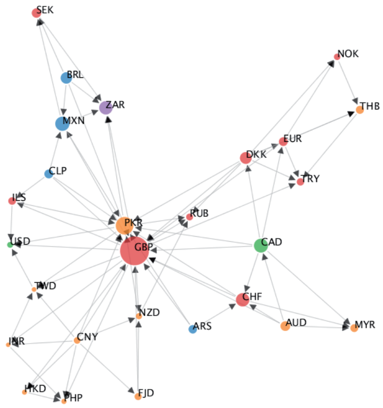

Fig. 4. PMFG for currency rates vs PLN

Source: own calculations.

The Minimal Spanning Tree and the Planar Maximally Filtered Graph for currency pairs based on XAG are shown in Figures 5 and 6.

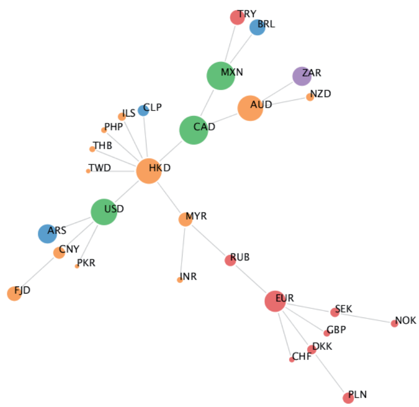

Fig. 5. MST for currency rates vs XAG

Source: own calculations.

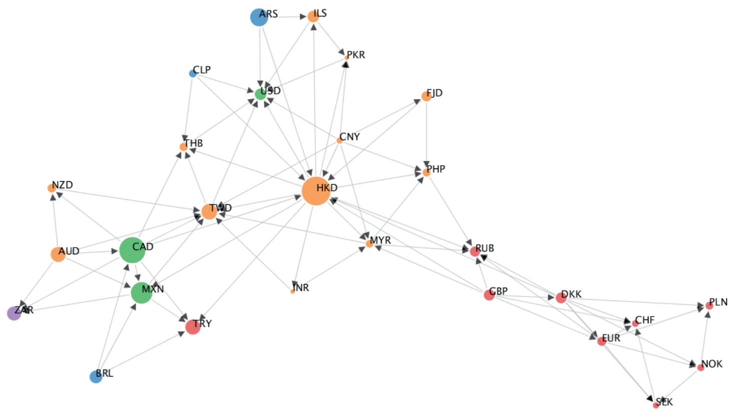

Fig. 6. PMFG for currency rates vs XAG

Source: own calculations.

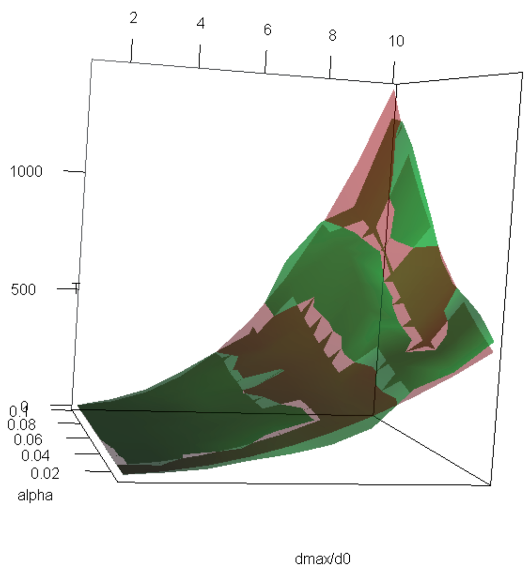

Fig. 7. Model vs stochastic volatility model simulations

Source: own calculations.

For the stochastic volatility model we ran Monte Carlo simulations and obtained the parameters for our model:

$$T = \left(6 - \widehat{H}_{l-z}\right)\left(\frac{\delta_{max}}{\delta_0}\right)^{2+5.5\alpha}.$$

In Figure 7 we can see how theoretical risk-free horizon (red) relates to the horizon obtained from simulations (green).

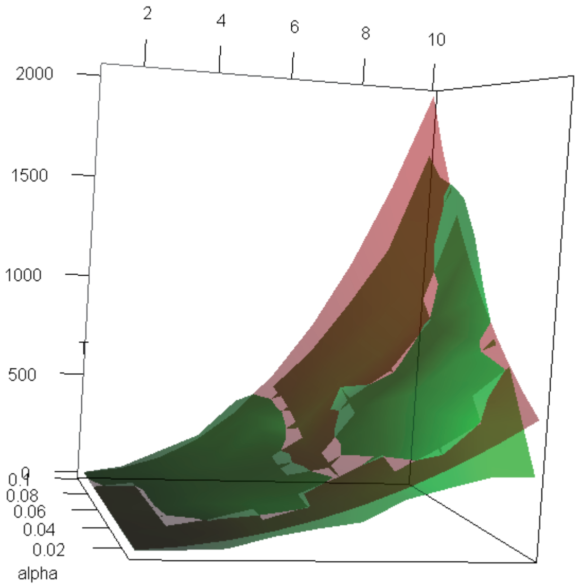

Fig. 8. Model vs Sznajd model simulations

Source: own calculations.

For the Sznajd model we obtained:

$$T = \left(7 - \widehat{H}_{l-z}\right)\left(\frac{\delta_{max}}{\delta_0}\right)^{2+6\alpha}.$$

In Figure 8 we can see how theoretical risk-free horizon (red) relates to the horizon obtained from simulations (green).

In the two figures we can see that our model fits the behaviour of the well-known price formation models well. Thus we have also estimated the parameters for 110 currency pairs:

$$T = \left(7 - \widehat{H}_{l-z}\right)\left(\frac{\delta_{max}}{\delta_0}\right)^{1.6+6.5\alpha}.$$

In Figure 9 we can see the same as above for this application. As can be seen, the real life results are not as simple as the model, but the model is quite correct as an indicator of risk for non-specialist economic agents who want to assess a risk-free horizon for their currency exposure.

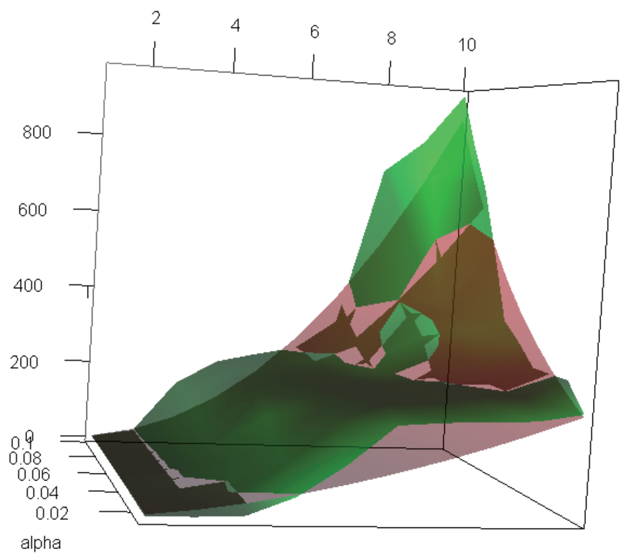

Fig. 9. Model vs FX data

Source: own calculations.

6. Discussion

The proposed model can estimate the risk-free horizon for a given acceptable loss with a good accuracy for both price formation models (Figures 7 and 8), thus we find it to be performing well against the standard assumptions of financial econometrics. This model also performs relatively well for historical data (Figure 9), but a test on another set of data should be performed to test the robustness of this specification. Nonetheless it is safe to conclude that the general form of the model is corroborated by the models and data from the forex markets. The tweaking may only be necessary in the specifications of parameters.

Further Figures (3 to 6) show a network approach popular in econophysics, simplified to only account for linear dependencies between currency rates (as opposed to methodology from our separate study using mutual information). Using this approach, economic agents can easily see the risk associated both with choosing a single currency to be exposed with (Figures 5 and 6), and a basket of currencies (Figures 3 and 4). Contrasting Figures 3 to 6 with networks obtained using mutual information in our separate study [Fiedor, Hołda 2015], we can conclude that these are close enough to allow such simplified analysis to be sensible. Such illustrative networks can be helpful for companies in making quick decisions, but the underlying distances between nodes can of course also be analysed more formally.

7. Conclusions and further research

In this paper we have analysed an approach to quantifying and analysing currency risk based on econophysics and an information-theoretic approach simplified from our more technical study aimed at professional investors and researchers [Fiedor, Hołda 2015] for the purpose of easier application by most companies. We propose that such an approach can be informative for both experienced investors and companies without financial know-how if properly specified. Further studies should be performed to test the robustness of the model specification and the effects of the entropy rate on realized losses. Further studies should also be performed using similar methodology on other markets, such as stock markets. Finally, further studies should look into comparing and merging methodologies using historical simulation, GARCH and the copula-based approaches.

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PERSPEKTYWA FIRMY W EKONOFIZYCZNEJ ANALIZIE RYZYKA WALUTOWEGO

Streszczenie: W artykule autorzy prezentują analizę ryzyka walutowego opierająca się na metodologii ekonofizyki. Niniejszy artykuł jest kontynuacją wcześniejszych badań na temat ryzyka walutowego, upraszczającą analizę na potrzeby przedsiębiorstw bez wiedzy specjalistycznej. Metoda analizy zależności między wieloma kursami walut, bazująca na korelacjach między walutami, zostaje przedstawiona tak, aby wspomóc analizę ryzyka kursowego związaną z transakcjami w jednej walucie obcej lub ich większej liczbie. Dodatkowo przedstawiono prosty model estymacji horyzontu wolnego od ryzyka. Zostaje on przetestowany przy użyciu symulacji modeli cenotwórczych oraz danych z rynku walutowego.

Słowa kluczowe: ryzyko, kursy walutowe, przewidywalność, ekonofizyka.