Chapter 1
Influence Networks in the Foreign Exchange Market

Arthur M.Y.R. Sousa, Hideki Takayasu, and Misako Takayasu

Abstract The Foreign Exchange Market is a market for the trade of currencies and it defines their relative values. The study of the interdependence and correlation between price fluctuations of currencies is important to understand this market. For this purpose, in this work we search for the dependence between the time series of prices for pairs of currencies using a mutual information approach. By applying time shifts we are able to detect time delay in the dependence, what enable us to construct a directed network showing the influence structure of the market. Finally, we obtain a dynamic description of this structure by analyzing the time evolution of the network. Since the period of analysis includes the great earthquake in Japan in 2011, we can observe how such big events affect the network.

1.1 Introduction

The Foreign Exchange Market is a market in which currencies are traded; it is continuously open during the weekdays and it has the largest transaction volume among the financial markets (average of $5.3 trillion/day in April 2013 [1]). The importance of this market is that it defines the relative values of currencies and affects other markets, such as the stock markets [2].

In this market, traders can make orders for buying and selling which are organized in the order book according to their corresponding prices. The highest price of the buy orders in a given time is called best bid and the lowest price of the sell orders, best ask, and their average defines the mid-quote; a deal occurs when the best bid meets the best ask.

A.M.Y.R. Sousa (✉) • M. Takayasu
Department of Computational Intelligence and Systems Science, Interdisciplinary Graduate School of Science and Engineering, Tokyo Institute of Technology, G3-52 4259 Nagatuta-cho, Yokohama 226-8502, Japan
e-mail: yamashita.a.ai@m.titech.ac.jp

H. Takayasu
Sony Computer Science Laboratories Inc., 3-14-13 Higashigotanda, Shinagawa-ku, Tokyo 141-0022, Japan

H. Takayasu et al. (eds.), *Proceedings of the International Conference on Social Modeling and Simulation, plus Econophysics Colloquium 2014*, Springer Proceedings in Complexity, DOI 10.1007/978-3-319-20591-5_1

Information about dependence between price fluctuations of currencies is important to understand the foreign exchange market. Several studies try to model this market and access those dependences [3–5]. However there are no studies on the influence structure in this market and the time evolution of the dependences. To contribute to fill this gap, we analyse the dependences in foreign exchange data during a period of 3 weeks using the mutual information, a non-linear dependence measure from the information theory [6, 7]. By doing a time shift analysis we can infer temporal dependence between markets making possible the construction of directed networks that show the influence structure of the foreign exchange market.

1.2 Data and Method

We analyze the foreign exchange data of the Electronic Broking Services (EBS) by ICAP. This data contains the orders for pairs of currencies in a resolution of 0.1 s. Here we use the 6 currencies with the largest transaction volume: USD (United States dollar), EUR (Euro), JPY (Japanese yen), GBP (Pound sterling), AUD (Australian dollar) and CHF (Swiss franc) in the period between 2011, March, 07th and 2011, March, 25th, each day from 22:00:00 to 21:59:59 GMT. The chosen period is a special one because it includes the great earthquake in Japan on 2011, March, 11th and the announcement of the intervention in the foreign exchange market as a response to the effects of the earthquake on 2011, March, 17th [8]. For this data we define the price *P(t)* as the last mid-quote, where t is the real time in intervals of 0.1 s. As an example of the data, Fig. 1.1 shows the price *P(t)* for the market USD/JPY on 2011, March, 09th, before the great earthquake in Japan.

We work with the sign of the difference of price *P(t)* [9]:

$$S(t) = sign[P(t) - P(t-1)], \tag{1.1}$$

so that we obtain a time series for each pair of currencies with the symbols $+$ (price increasing), $-$ (price decreasing) and 0 (price unchanged). By comparing two of these time series, we can identify 4 states not containing 0: $(+, +)$, $(+, -)$, $(-, +)$ and $(-, -)$. The removal of the states with 0, e.g. $(+, 0)$, is an important step because then we compare the series only when there is activity in both of them, avoiding issues regarding the volume difference and the time zone difference. Table 1.1 illustrates the number of occurrence of each state when comparing the EUR/USD with other markets on 2011, March, 07th (time series of each market with 863,999 points).

Studies in financial markets commonly use the Pearson correlation coefficient as a measure to infer dependence [5, 10]. But the correlation coefficient detects only linear correlation between two variables, not having information about the dependence. The mutual information on the other hand deals direct with the probability distributions being a measure not only for linear and non-linear correlations, but also for dependence. The mutual information is zero if and only if the random variables

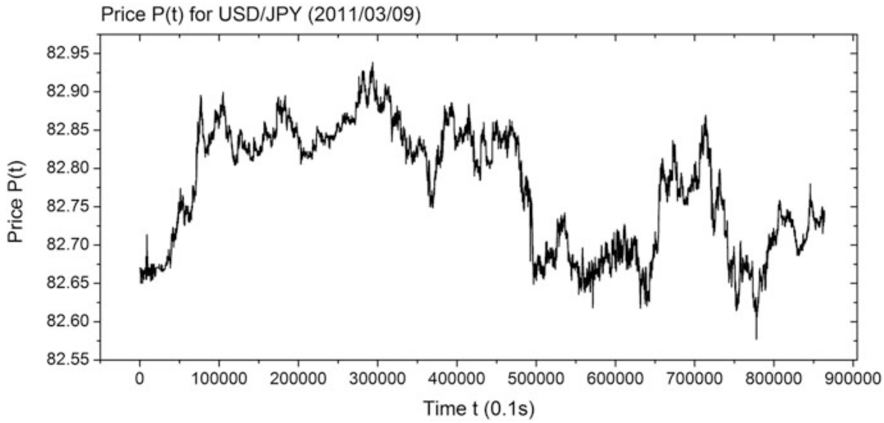

Fig. 1.1 Price P(t) for the market USD/JPY on 2011, March, 09th. Here we work with the sign of the difference of the price P(t)

Table 1.1 Number of states for EUR/USD and other markets on 2011, March, 07th (no time shift)

Market	(+, +)	(+, −)	(−, +)	(−, −)	0[a]
AUD/JPY	3256	2904	2941	3303	851,595
AUD/USD	2425	1707	1591	2332	855,944
CHF/JPY	125	129	184	184	863,377
EUR/AUD	55	59	66	48	863,771
EUR/CHF	3817	3061	3160	3895	850,066
EUR/GBP	3956	3305	3272	4086	849,380
EUR/JPY	5351	3918	3956	5202	845,572
GBP/AUD	53	47	45	53	863,801
GBP/CHF	43	47	56	52	863,801
GBP/JPY	4791	4431	4238	4807	845,732
GBP/USD	3088	2359	2533	3134	852,885
USD/CHF	2874	3656	3689	3032	850,748
USD/JPY	5822	7131	7081	5743	838,222

[a](+, 0), (−, 0), (0, 0), (0, −), (0, +)

are independent. There are evidences that mutual information can reveal aspects ignored by the correlation coefficient and studies comparing both measures [11–13]. Another reason for using mutual information in this work is that we are dealing with symbolic series, in which the numerical values that are taken in account for the correlation coefficient have no meaning.

The mutual information *I(X;Y)* between two random variables X and Y:

$$I(X;Y) = \sum_{x} \sum_{y} p(x,y) log \frac{p(x,y)}{p(x)p(y)}, \tag{1.2}$$

which can also be expressed in term of the entropies H:

$$I(X;Y) = H(X) - H(X \mid Y) \tag{1.3}$$

or

$$I(X;Y) = H(Y) - H(Y \mid X). \tag{1.4}$$

H(X) is the entropy of the random variable X and can be understood as a measure of its uncertainty. Similarly, $H(X \mid Y)$ can be seen as the uncertainty of X given Y. Thus, one interpretation for the mutual information is the reduction in the uncertainty of a random variable given the knowledge of the other. If the variables are independent, the knowledge of one variable does not give information about the other and then the mutual information is zero.

The final dependence measure we use is the global coefficient:

$$\lambda(X;Y) = \sqrt{1 - e^{-2I(X;Y)}}, \tag{1.5}$$

This quantity has desired characteristics for a dependence measure, as taking value zero for independent variables and being in the range [0;1] [14], and has been used in financial data [12].

In order to compute the global coefficient of the financial series, we estimate the probability of each state using the relative frequency in a time window of 1 day. We also determine a significance level to decide if the computed coefficient is significantly different from the one of a random series; we randomize the analysed series and calculate the global coefficient until it reaches a stationary value which corresponds to the coefficient for the corresponding random series and we take this value as the significance level.

1.3 Results and Discussion

For each two pairs of currencies we compute the global coefficient for their sign time series as function of the time shift between them. For this data, we find four general types of structures according to the presence of peaks that represent dependence between the markets, as illustrated in Fig. 1.2.

- No peak: no dependence between markets.
- Peak at time shift zero: both markets are synchronized. External influences (e.g. economic news) make the markets to have similar behaviour, the change in the price occurs simultaneously in both markets.

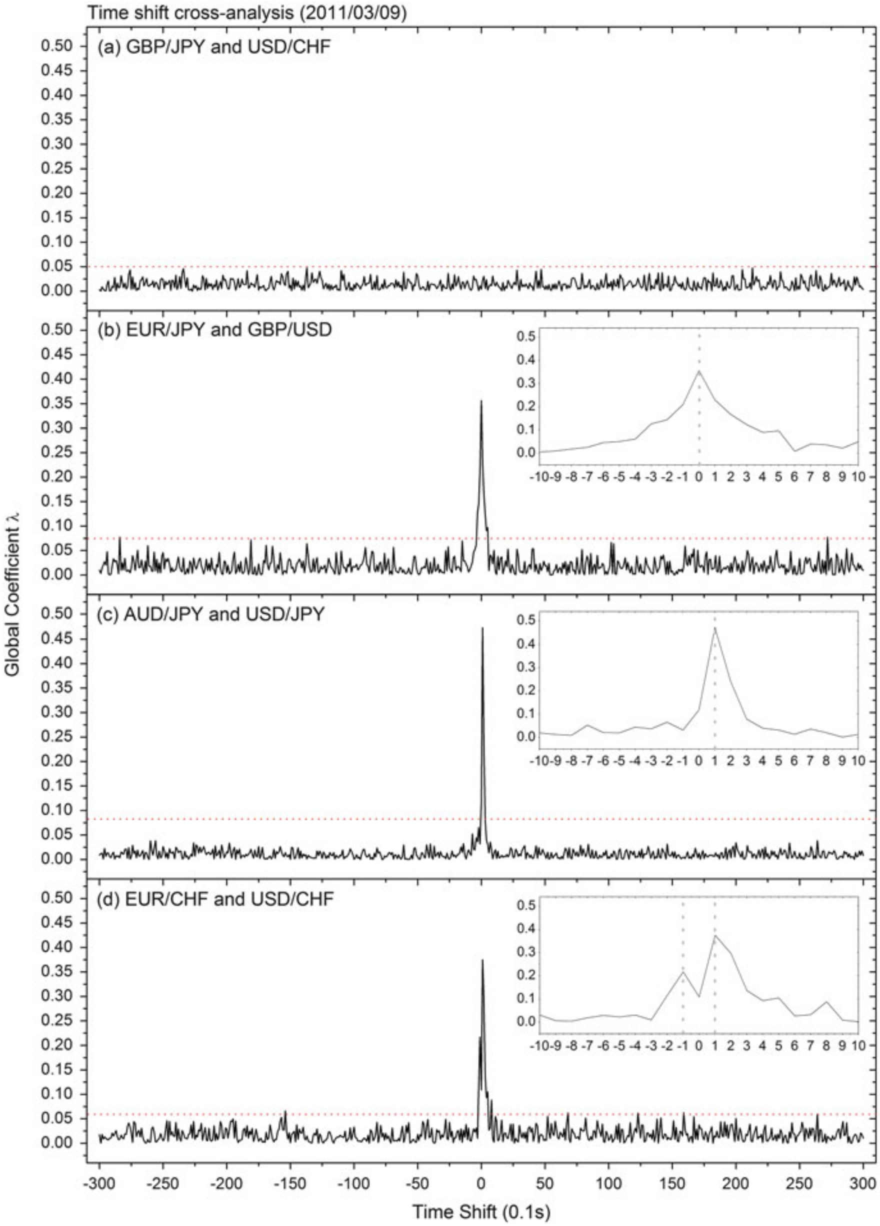

Fig. 1.2 Examples of results for the time shift cross-analysis. (**a**) GBP/JPY and USD/CHF on 2011, March, 09th: no dependence between the markets, same result for random time series. (**b**) EUR/JPY and GBP/USD on 2011, March, 09th: dependence at time shift 0. (**c**) AUD/JPY and USD/JPY on 2011, March, 09th: dependence when the USD/JPY series is shifted 0.1 s forward in relation to the AUD/JPY series. (**d**) EUR/CHF and USD/CHF on 2011, March, 09th: dependence at time shift 0.1 s in both directions. *Dotted lines* indicate the significance level

- Peak at a time shift different of zero: one market influences the other, i.e., there is an internal influence. This means that the past of one market affects the present of the other market, which could be interpreted as an information flow.
- Two peaks at time shifts in both directions: there are also internal influences, but in this case both markets affect each other during the analysed period.

We can build an influence network defining the pairs of currencies as nodes and adding the links according to the time shift cross-analysis between the markets that correspond to the nodes: (a) no peak: no link; (b) peak at time shift zero: undirected link; (c) peak at a time shift different from zero: directed link from the market that influences the other one, i.e., the market that goes ahead, whose past values affects the present values of the other market; (d) two peaks at time shifts in both directions: extraverted link.

We proceed with this analysis for all weekdays from 2011, March, 07 to 2011, March, 25. In this period two important events took place: the great earthquake in Japan on March, 11 and the announcement intervention in the foreign exchange market on March, 17. Figures 1.3, 1.4 and 1.5 show the time evolution of the influence network with day resolution during those 3 weeks. Figure 1.6 shows the time evolution of the different types of links in the influence network.

We observe that the structure does not present major changes within the first week from March, 07th to March, 10th, before the earthquake in Japan. Some characteristic features are: (a) EUR/USD and USD/JPY are the nodes with higher out-degree, meaning those are the markets that always go ahead being followed by the others, and (b) almost no extraverted links (with exception of link between USD/CHF and EUR/CHF, which is always present), i.e., information flows only in one direction, creating a hierarchy of importance between the markets.

From March, 11th (first week) to March, 17th (second week), which corresponds to the period between the earthquake in Japan and the intervention, we notice that the influence network changes compared to the structure in the first week. An important change is the increase in the number of directed and extraverted links, suggesting the interdependence between markets becomes stronger (not only due external influences, but internal ones). The new extraverted links that appeared involve the nodes EUR/USD and USD/JPY, that continue being the most important nodes (highest out degree), but now they are also influenced by other markets. One possible interpretation is that the players of these important markets are now being more careful, waiting for the information of other markets to decide to change the price.

After the announcement of the intervention on March, 17th, we observe another change in the structure, specially the disappearance of the extraverted link between EUR/USD and USD/JPY. Gradually the influence network returns to a structure similar to the one of the first week (before the earthquake).

Those results suggest that the event of the earthquake affected the dependence between markets and the event of the announcement of the intervention contributed for the return of the market to a state previous the earthquake, i.e., it was efficient in the sense of reversing the changes caused by the earthquake in the foreign exchange

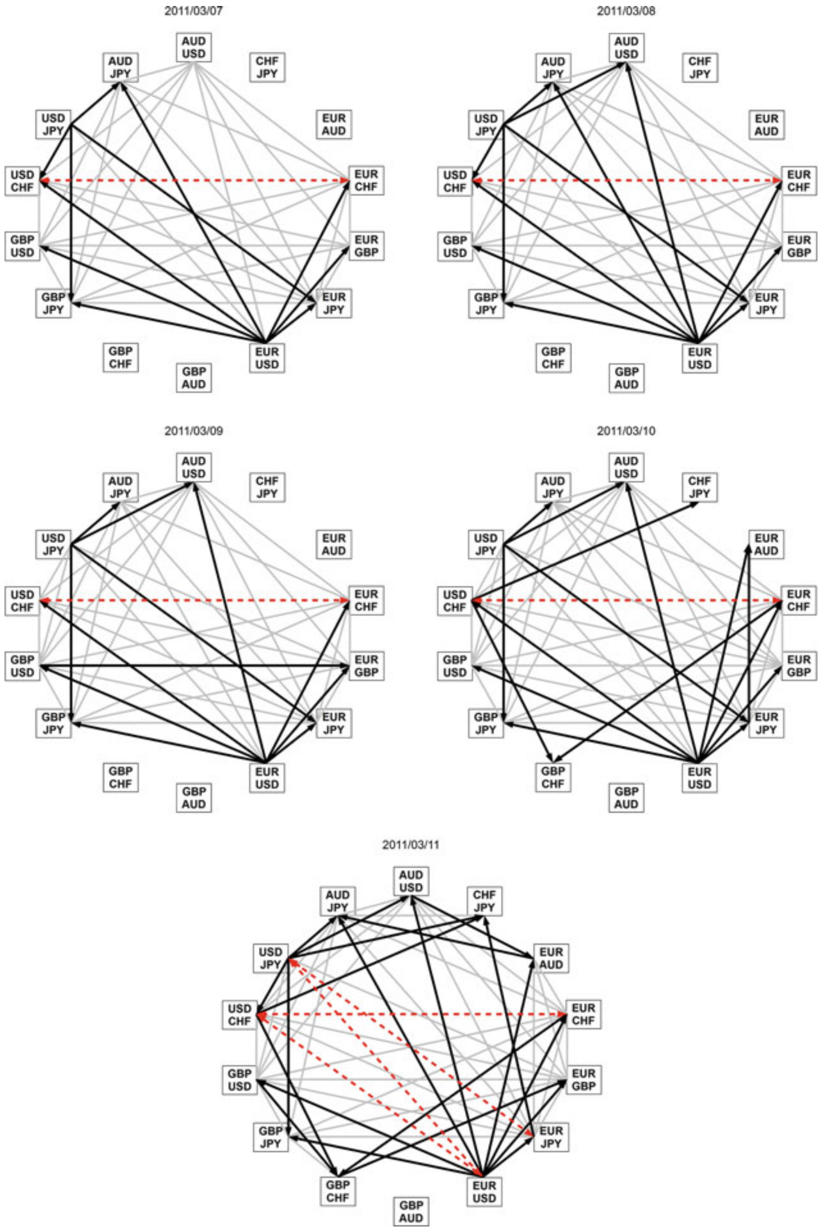

Fig. 1.3 Influence Networks of the Foreign Exchange Market for the currencies USD, EUR, JPY, GBP, AUD and CHF from 2011, March, 07th to 2011, March, 11th. The Great Earthquake in Japan took place on 2011, March, 11th. In this network nodes represent the pairs of currencies and there are three types of links according to the time shift cross-analysis: (i) undirected link (*gray*) corresponding to peak at time shift zero; (ii) directed link (*black*), peak at a time shift different from zero, in this case 0.1 s, from the market that influences the other one; (iii) extraverted link (*red*), two peaks at time shifts, also 0.1 s, in both directions

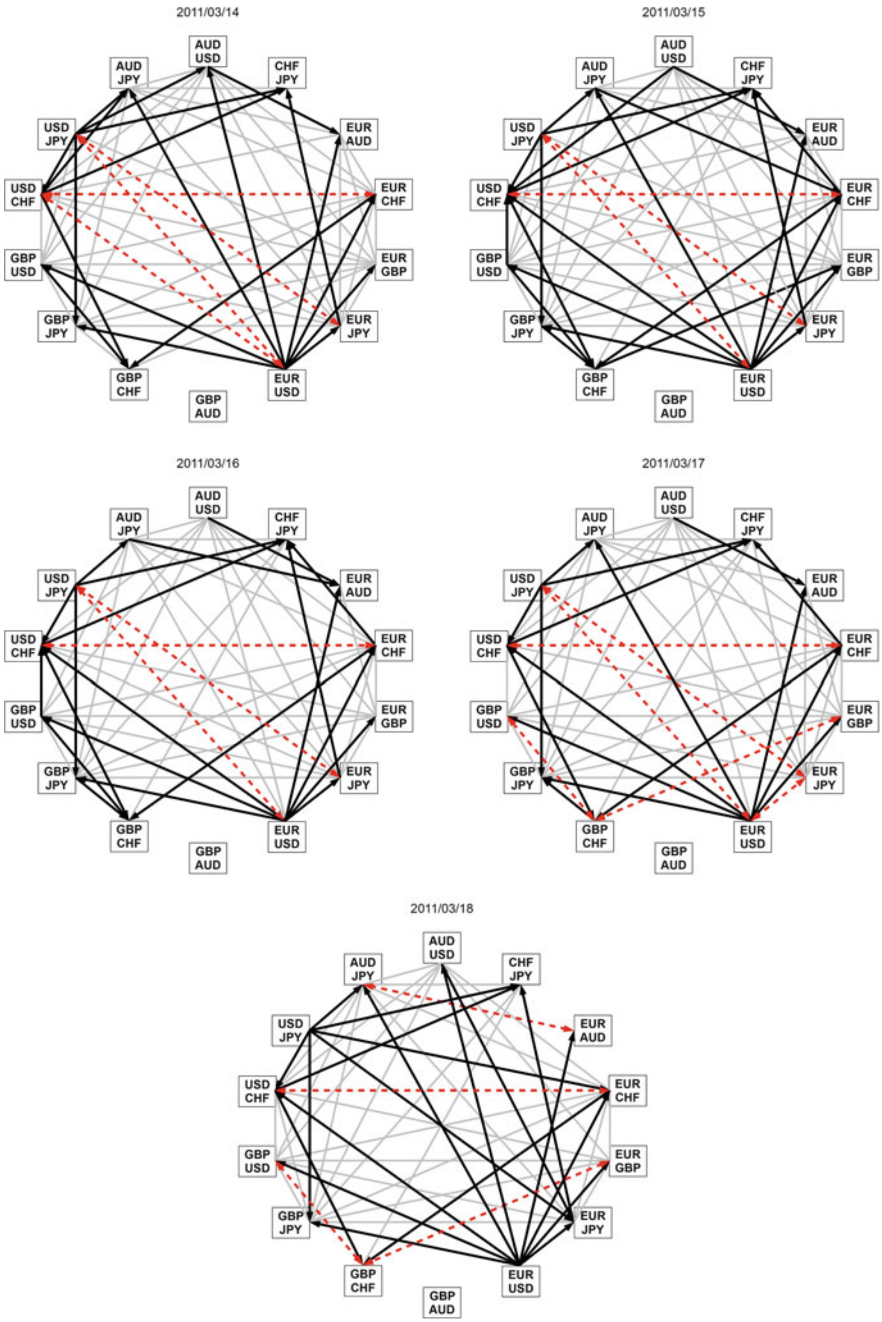

Fig. 1.4 Influence Networks of the Foreign Exchange Market for the currencies USD, EUR, JPY, GBP, AUD and CHF from 2011, March, 14th to 2011, March, 18th. The Intervation in the Foreign Exchange Market was announced in the end of 2011, March, 17th

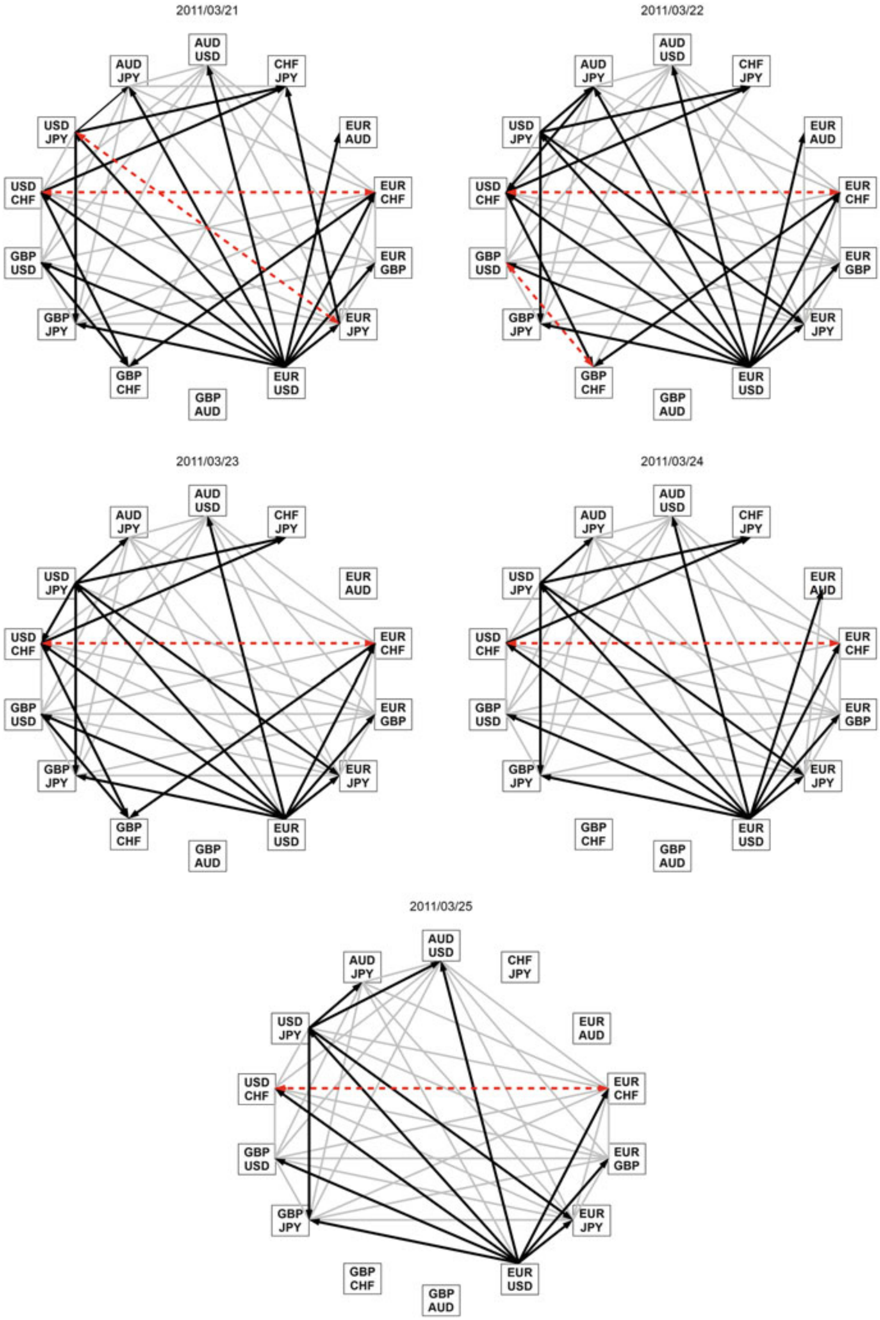

Fig. 1.5 Influence Networks of the Foreign Exchange Market for the currencies USD, EUR, JPY, GBP, AUD and CHF from 2011, March, 21st to 2011, March, 25th

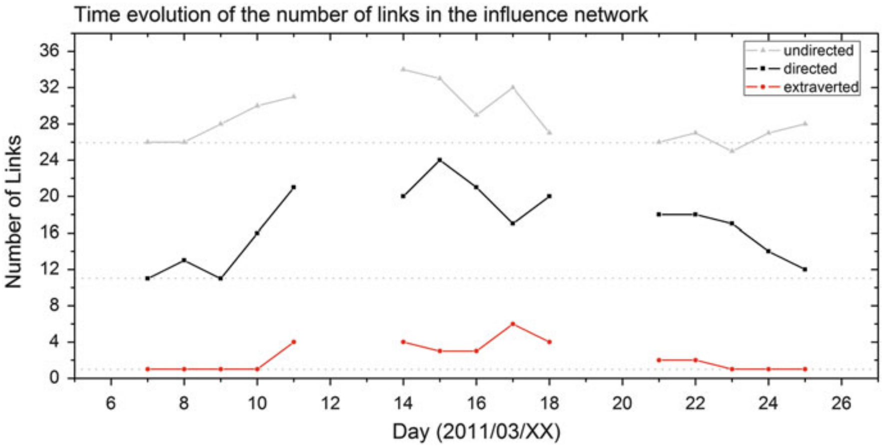

Fig. 1.6 Time evolution of the number of the different types of links in the influence network from 2011, March, 07th to 2011, March, 25th. *Dotted lines* indicate the number of links on 2011, March, 07th

market. It is possible that other factors besides the intervention contributed to the stabilization of the market; to discuss this aspect, it would be necessary the analysis of other periods where stability was reached with no intervention.

1.4 Final Remarks

In this paper we used a non-linear dependence measure based on the mutual information to access the dependence between pairs of currencies of the foreign exchange market. We analysed the sign of price difference of these markets from 2011, March, 07th to 2011, March, 25th, a period that includes the great earthquake in Japan and the intervention. By applying a time shift between the sign series we obtained different dependence structures between markets and then constructed an influence network based on them. The analysis of the influence network and its time evolution showed that the markets EUR/USD and USD/JPY are the most important nodes, with the information flowing from them to the other markets. It also suggested that the event of the earthquake changed the influence structure of the network, intensifying the interdependence between markets and changing the dynamics of the markets EUR/USD and USD/JPY; and the announcement of the intervention was effective in reverting the effects of the earthquake: changes could be observed in the day right after the announcement and the network totally returned to the state previous the earthquake in less than 1 week. The results represent a contribution to understand how the foreign exchange market reacts to big events and thus what can be done in periods of crisis. The analysis can also be useful to predict the behavior of one market based on the past behavior of another, if there is an influence relationship between them.

One important observation is that in the time shift cross-analysis the typical time shift is 0.1 s, i.e., when we have a market influencing another the time delay is 0.1 s. This fact is possibly related to the resolution of the data, also 0.1 s. We analysed the same data but with resolution 1s and could not detect time delay between markets as we found for resolution 0.1 s. We still need to study if we can detect the directionality between markets in other time resolution data or if the resolution 0.1 s is essential to detect such feature. Further researches also should include other currencies, a larger period of analysis and the possibility of time windows smaller than 1 day.

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