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An Analysis of Contagion in Emerging Currency Markets Using Multivariate Extreme Value Theory*

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Abstract

The objective of this paper is to analyze short-term contagion effects in emerging currency markets.

The originality of our paper lies in our survey used to present the microstructure of emerging currency markets and our empirical approach to contagion analysis through an estimation of tail dependence between pair currencies employing multivariate extreme value theory for the verification of results of our survey.

Key words: Contagion, Multivariate Extreme Value Theory, Currency, Survey, Graph
JEL classification: G15

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* Views expressed in the paper are those of the authors and do not necessarily reflect those of the Bank of Japan, the Institute for Monetary and Economic Studies, and Barclays Global Investors.

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Contents

1. Introduction

The objective of this paper is to analyze short-term contagion effects in emerging currency markets using multivariate extreme value theory. Contagion can be defined as a channel through which shocks are propagated from one country to another (Rigobon [2001]), and we define it more specifically as tail dependence between emerging market currencies in this paper. Our focus is on short-term aspects of currency contagion, and therefore broker perspectives.

Empirically, it is difficult to recognize contagion since contagion starts suddenly and we do not know whether unidentifiable common factors in the market exist or not (Rigobon [2001]). However, practical experience in currency markets suggests that market participants tend to sell emerging market currency X when large selling pressure appears for emerging market currency Y, even with little knowledge about Y. This is because broker behavior might be affected by such factors as use of similar risk management systems or broker reports distributed to investors. For example, the following quote is from a broker report in August 2001: "maintain long USD (the US dollar)/short CLP (the Chilean peso) as a cheap hedge against the possibility of a default and removal of the peg in Argentina." These market dynamics can be tested directly by tail dependence between each pair of currencies. Unfortunately, so far there has not been enough analysis done on this subject, particularly by market participants, and therefore these market dynamics have not yet been well explored (Evans [2001] and Soejima [2000]). In this paper, we investigate contagion in emerging currency markets from this perspective.

We surveyed eight large currency brokers to analyze the microstructure of emerging currency markets. We sought to find cases where if brokers believed that emerging market currency X had depreciated substantially and the market is illiquid, they would instead use neighbor currency Y to hedge their exposures and in doing so, cause selling pressure on Y.

Based on analysis of our survey results, we found that graph theory is a useful tool (Bondy and Murty [1976]) for illustrating the microstructure of emerging currency markets.

To verify our survey results, we conducted empirical tests of contagion with hourly and daily data of emerging market currencies employing multivariate extreme value theory (Coles, Heffernan, and Tawn [1999], Embrechts, McNeil, and Strautman [2002], Husler and Reiss [1987], Poon, Rockinger, and Tawn [2001]). We empirically identified contagion at hourly frequency within the two groups of currencies defined in our survey and at daily frequency in one of the two groups, but not between groups.

The structure of this paper is as follows. First, we describe the hedging behavior of emerging market currency brokers using graphs constructed from our survey. Then, we test the graph structure empirically using multivariate extreme value theory for hourly and daily data and show our findings that tail dependence is observed in the recent case of the Argentine peso and its neighbor currencies.

2. Survey Results[1]

In order to detect the behavior of currency brokers in emerging currency markets, we surveyed eight large currency brokers which trade emerging market currencies in three major markets, i.e. London, New York, and Tokyo. Figure 1 is drawn by the following procedure based on the results of one part of our survey[2].

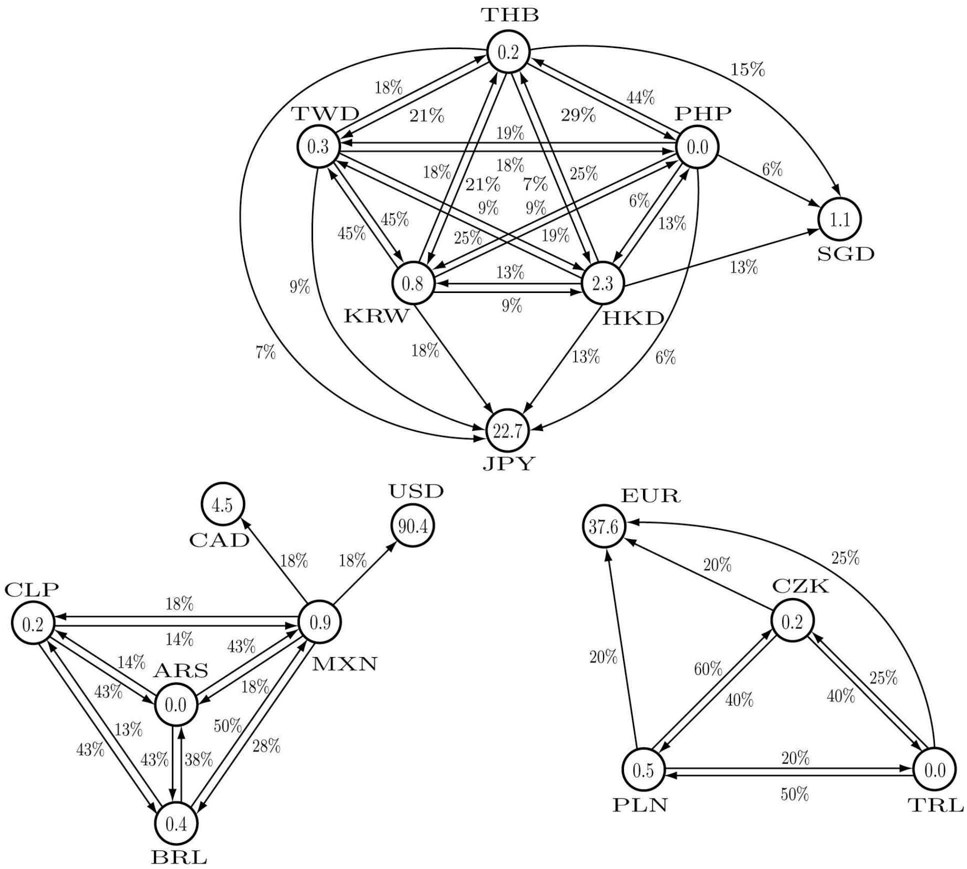
- Each vertex represents a currency. The number attached to each vertex corresponds to average daily turnover during April 2001 (BIS [2001]). Turnover implies level of liquidity.
- We draw a directed arc from currency X to another currency Y if some brokers (at least one broker) use Y as a proxy hedge currency for X under selling pressure.
- The weight of each arc is determined by the following:
  - -- First, calculate the ratio of brokers who use Y as a proxy hedge currency for X among all brokers. For example, if three brokers out of eight use Y as a proxy currency for X, we put 37.5% (=3/8) as the

[1] Eight large currency brokers responded to our survey on condition of anonymity. Also, some of the answers to our survey are only for our internal use and therefore we do not use them in our calculations here.
[2] See Appendix for questionnaire.

weight of the arc from X to Y.

-- After calculating the weight of each pair, we adjust the weight in order to get the sum of 100% at every vertex. For example, currency X has two currencies as proxy hedge currencies, Y and Z, and their weights are 60% and 80%, respectively. In this case, the weight of the arc from X to Y is adjusted to 60% / (60% + 80%) ≅ 43% and that of the arc from X to Z is adjusted to 57%.

Figure 1: Graphs constructed from our survey



Notes:

The weight of arcs in Figure 1 is drawn under two assumptions. One is that the share of respondent brokers in the survey equals that of trading turnover by each broker. The other is when a broker uses two proxy currencies in order to hedge a currency the hedge amount of two proxies is the same. It will be accurate if we use the real turnover of eight brokers in each currency pair in order to draw arcs for Figure 1. However, we are not allowed to use the turnover of each broker. A good thing is that the share of eight brokers in each currency pair trade is not very different, thus our simplified method well approximates the real weight of arcs.

ARS: Argentine peso; BRL: Brazilian real; CAD: Canadian dollar; CLP: Chilean peso; CZK: Czech koruna; EUR: EURO; HKD: Hong Kong dollar; JPY: Japanese yen; KRW: Korean won; MXN: Mexican peso; PHP: Philippine peso; PLN: Polish zloty; SGD: Singapore dollar; THB: Thai baht; TRL: Turkish lira; TWD: Taiwan dollar; USD: US dollar.

Figure 1 contains complete graphs as subgraphs. Here, a subgraph is a subset of an entire graph. A complete graph is a graph such that there exist arcs in both directions between every pair of vertices in the graph (Bondy and Murty [1976]). Since an arc from currency X to currency Y exists if Y is used to hedge X, a complete subgraph indicates a deep interdependence between any pair of currencies in the subgraph. However, a currency in a subgraph is not related to currencies in other subgraphs[3]. For example, proxy currencies for the Argentine peso are the Brazilian real, the Mexican peso, and the Chilean peso and they will be used as hedge currencies if the Argentine peso suffers selling pressure. However, brokers do not use the Argentine peso as a proxy for the Korean won, or vice versa, and this relation holds for any pair of vertices belonging to different subgraphs. Therefore, from Figure 1 it is natural to assume that contagion within a subgraph can be explained by its complete graph created by the hedging procedures of currency brokers. On the other hand, our survey shows that there are few links between subgraphs, and thus we could say that brokers hardly ever use currencies in another subgraph as proxy currencies.

We will see tail dependence between emerging market currencies empirically in the next section.

3. Empirical Analysis

Our survey reveals that one of the causes of contagion might be broker behavior. In this section, we empirically verify the possibility of contagion by applying multivariate extreme value theory to hourly and daily currency data. Our interest is to see whether currency contagion in a short period of time results from broker behavior.

[3] Actually, there are some exceptions. For example, there are links between SGD and HKD, THB and SGD, etc.

3.1 Data

In our empirical test, we use historical data of spot exchange rates for emerging market currencies against the US dollar, since the US dollar is considered one of the safe currencies. To analyze interdependence among subgraphs, we use average daily return of currencies in each subgraph formed by our survey. We try to show entire damage in a subgraph by the average return of currencies in a same subgraph under the assumption of equal trading turnover in each currency pair. Thus, if return of a currency in subgraph P is negatively correlated with that of another currency in P, it implicitly suggests that there is no large impact on P and P is not in an extreme situation.

Data we utilized:

- o Hourly data: from July 4, 2001 to September 30, 2001 from Reuters.
- o Daily data: from June 30, 1993 to July 31, 2001 from Bloomberg.

3.2 Data filtration

Generally speaking, it is easy to apply multivariate extreme value theory for i.i.d. (identically and independently distributed) data.

It is, however, difficult to filter high frequency data into i.i.d. data because of leptokurtosis (Wang [2001] and Watanabe [2000]) and higher order autocorrelation. Return data for emerging market currencies tend to show high peaks and long tails. This might be because many emerging countries basically try to manage their currency in a limited range whereas currency brokers sometimes sell these currencies for hedging, leading to huge price movement in a short period of time.

Therefore, several models can be used to estimate innovation terms ε_t, which satisfies i.i.d. characteristics, in the following.

$$R_t = \mu + \sum_{i=1}^{p} \beta_i R_{t-i} + \sigma_t \varepsilon_t, \qquad (1)$$

where R_t is return in period t, μ is a constant, β_i is the ith parameter of AR(p), and σ_t is the conditional standard deviation of R_t.

Variance σ_t^2 is estimated in the following four models (for details, see Watanabe [2000]).

(i) GARCH(m,n) model with three distributions of ε_t : (i-1) normal distribution, (i-2) *t*-distribution, and (i-3) generalized error distribution (GED). In GARCH(m,n) model, σ_t^2 is estimated by

$$\sigma_t^2 = \alpha + \sum_{k=1}^{n} \phi_k \sigma_{t-k}^2 \varepsilon_{t-k}^2 + \sum_{j=1}^{m} \theta_j \sigma_{t-j}^2, \qquad (2)$$

where $E(\varepsilon_t) = 0$ and $Var(\varepsilon_t) = 1$.

σ_t^2 is the conditional variance of R_t, ε_t is the innovation term at time t, ϕ_k is the k th parameter, θ_j is the j th parameter, and α is a parameter and must be positive.

(ii) EGARCH(m,n) model where the distribution of ε_t is normal. In EGARCH(m,n) model, σ_t^2 is estimated by

$$\ln \sigma_t^2 = \alpha + \sum_{k=1}^{n} \phi_k \frac{|\varepsilon_{t-k}| + \gamma_k \varepsilon_{t-k}}{\sigma_{t-k}} + \sum_{j=1}^{m} \theta_j \ln \sigma_{t-j}^2, \qquad (3)$$

where $E(\varepsilon_t) = 0$ and $Var(\varepsilon_t) = 1$.

σ_t^2 is the conditional variance of R_t, ε_t is the innovation term at time t, ϕ_k is the k th parameter, θ_j is the j th parameter, α is a parameter, and γ_k is the k th asymmetry parameter.

We filter our data based on the Box-Jenkins technique, which identifies and estimates a common process. See Box and Jenkins [1976] and Wang *et al.* [2001].

- o As an identification process, which is to determine if data are stationary and has any significant seasonality, we check the autocorrelation and partial autocorrelation function of the data, and determine AR process candidates based on the principle of parsimony. If not clear, we use AIC to arrive at determination.
- o Estimate innovation terms using equations (1) ~ (3).
- o Choose the model through diagnostic checking. We adopted the lowest Ljung-Box Q statistics, which test the higher order autocorrelation in the innovation terms taken from equations (1) ~ (3).

Let

$$r_j = \frac{\sum_{t=j+1}^{n} \varepsilon_t \varepsilon_{t-j}}{\sum_{t=1}^{n} \varepsilon_t^2}, \quad j = 1,2,\ldots, p. \tag{4}$$

Ljung-Box Q statistics is

$$Q = n(n+2)\sum_{j=1}^{p} \frac{r_j^2}{n-j}, \tag{5}$$

where Q has a limiting χ_p^2 distribution with p degrees of freedom, n is the number of observations, and ε_t is the innovation term of a model at time t. If $Q < \chi_{p,90\%}^2$, we can think that innovations are not autocorrelated at a 90% confidence level.

Many series have the zero order, $p = 0$, but hourly ARS, daily TWD, and HKD have the first order, $p = 1$.

Tables 1, 2, and 3 show the results of Ljung-Box Q statistics. * and ** indicate the model we have chosen. ** indicates statistically significant at a 90% confidence level. Almost all data filtered by at least one of the above four models are statistically significant at a 90% confidence level. These results support that filtered data are approximately i.i.d. Hourly data are captured by either GARCH model with GED or GARCH model with t-distribution or EGARCH, not by GARCH model with normal distribution which is usually assumed. This indicates characteristics such as concentrated speculations in a very short run, since GED and t-distribution have fatter tails than normal distribution. We can see a similar pattern in the filtering of the daily data of each currency return, although KRW is captured by GARCH with normal distribution. Daily subgraph data is captured by either GARCH with normal distribution or GARCH with GED.

Table 1: Ljung-Box Q statistics of hourly data

	PHP	KRW	TWD	HKD	MXN	BRL
GARCH normal	25.17	20.41	9.77	12.14	6.17	6.26
GARCH t-distribution	34.53	15.35	61.44	26.39	4.54**	0.04**
GARCH GED	9.21*	5.08**	2.19**	6.81*	13.39	4.92
EGARCH	25.31	8.82	3.34	32.42	8.35	25.34
	ARS	CLP	PLN	CZK	TRL	
GARCH normal	58.46	9.80	3.77	1.59	3.31	
GARCH t-distribution	58.95	50.11	4.90	1.44	3.34	
GARCH GED	15.74*	0.69**	2.58	1.30**	3.96	
EGARCH	59.14	17.55	1.28**	26.44	3.19**	

Table 2: Ljung-Box Q statistics of daily data

	PHP	KRW	TWD	HKD	MXN	BRL
GARCH normal	8.92	26.78*	26.86	74.94	6.81	4.43
GARCH t-distribution	0.01**	27.45	15.85*	82.02	0.01**	0.53**
GARCH GED	9.20	27.65	19.92	73.41	0.13	0.61
EGARCH	3.32	40.22	47.81	48.22*	15.19	11.79
	ARS	CLP	PLN	CZK	TRL	
GARCH normal	1.67	10.21	0.04	0.03	0.01	
GARCH t-distribution	1.85	10.48	0.07	0.01	0.01	
GARCH GED	1.33**	10.07*	0.03**	0.01**	0.01**	
EGARCH	1.84	11.17	0.03	0.02	0.04	

Table 3: Ljung-Box Q statistics of subgraph daily return data

	Asia	Europe	South America
GARCH normal	2.34**	0.40	0.88**
GARCH t-distribution	2.41	0.30	2.30
GARCH GED	2.36	0.29**	1.36
EGARCH	3.43	0.69	0.90

Notes:
Ljung-Box Q statistics of logarithmic return of spot exchange rate for emerging market currencies against the US dollar.
* and **: the models we have chosen.
**: statistically significant at a 90% confidence level.

3.3 Measuring contagion by multivariate extreme value theory

Linear correlation captures the relationship in the whole distribution of two data series. Therefore, it is not a good measure if dependence characteristics for the extremal sample cases, characterized as contagion in currency data, differ from other sample cases. Multivariate extreme value theory provides a good measure for analyzing dependence characteristics for extremal sample cases. We have used the same methodology as Poon, Rockinger, and Tawn [2001], who analyze the extreme multivariate dependence of pairs of international equity return series.

The following subsections explain the methodology.

3.3.1 Basis for measuring multivariate extreme value

In univariate extreme value theory, the probability of exceeding a certain threshold u, by a variable Z whose maximum follows a Fréchet distribution, is defined as follows. For $z > u$,

$$\Pr(Z > z) = \frac{L(z)}{z^{1/\delta}}, \tag{6}$$

where $L(z)$ is a slowly varying function[4], and δ is called tail index (Ledford and Tawn [1996]).

The slowly varying function is set to a constant number, or converted to a constant or slower function than power functions. We treat the slowly varying function as a constant c for all variables above the threshold in this paper.

The following Hill's estimator, equation (7), is used to calculate tail index δ of the excess values over the threshold independently taken from a Fréchet distribution.

$$\delta = \frac{1}{n_u} \sum_{j=1}^{n_u} \ln \frac{z(j)}{u}, \tag{7}$$

$$c = \frac{n_u}{N} u^{1/\delta}, \tag{8}$$

where n_u is the number of observations that exceed u, $z(1), z(2), \ldots, z(n_u)$ are those observations, and N is the total number of observations.

We transform bivariate returns (X,Y) to unit Fréchet marginals (S,T) using the following transformation, in order to remove the influence of the difference between forms of two original marginal distributions.

$$S = \frac{-1}{\ln F_x(X)} \text{ and } T = \frac{-1}{\ln F_y(Y)}, \tag{9}$$

where F_x and F_y are the marginal distributions of X and Y, respectively.

3.3.2 Conventional dependence measure, χ

It is interesting to see extremal dependence (tail dependence) between S and T, i.e. $\Pr(T > s \mid S > s)$ for large s. If S and T are perfectly dependent then $\Pr(T > s \mid S > s) = 1$. In contrast, if S and T are perfectly independent then $\Pr(T > s \mid S > s) = \Pr(T > s)$, which tends to 0 as $s \to \infty$. Here, defining $\chi = \lim_{s \to \infty} \Pr(T > s \mid S > s)$, where $0 \le \chi \le 1$, we have that variables are called asymptotically dependent if $\chi > 0$ and asymptotically independent if $\chi = 0$.

[4] The function satisfies $\lim_{x \to \infty} \frac{L(qx)}{L(x)} = 1$ for any $q > 0$.

Clearly, χ measures the degree of dependence that is persistent into the limit (Poon, Rockinger, and Tawn [2001]).

However, one drawback of χ is that it cannot provide a measure of the degree of asymptotic independence where $\chi = 0$. For example, the dependence of bivariate normal random variables with any value for the correlation less than one is known as $\chi = 0$.

3.3.3 An alternative dependence measure, $\bar{\chi}$

Facing the fact that χ cannot provide a measure of the degree of asymptotic independence where $\chi = 0$, Coles, Heffernan, and Tawn [1999] suggested an alternative dependence measure,

$$\bar{\chi} = \lim_{s \to \infty} \frac{2 \ln \Pr(T > s)}{\ln \Pr(T > s, S > s)} - 1. \tag{10}$$

$\bar{\chi}$ is an appropriate measure of asymptotic independence of extremal sample cases where $\chi = 0$.

Poon, Rockinger, and Tawn [2001] discuss that values of $\bar{\chi}$ have loose correspondence with states of tail dependence.

$\bar{\chi} > 0$ ~ Positive tail dependence.

$\bar{\chi} < 0$ ~ Negative tail dependence.

$\bar{\chi} = 0$ ~ Tail independence.

The pair of dependence measures, $\bar{\chi}$ and χ, gives sufficient information regarding tail dependence, and thus in this paper we use the set of $\bar{\chi}$ and χ for measuring tail dependence.

3.3.4 Calculation of $\bar{\chi}$ and χ

To estimate $\bar{\chi}$ and χ, we use the results in Ledford and Tawn [1996], where under weak conditions the estimation of two measures was established in equation (11).

$$\Pr(S > s, T > s) \approx L(s) s^{-1/\delta}, \tag{11}$$

as $s \to \infty$, where δ ($0 < \delta \leq 1$) is a constant and $L(s)$ is a slowly varying function. We also use the following equation for calculating $\overline{\chi}$ inferred from equation (9),

$$\Pr(T > s) = \Pr(S > s) \approx s^{-1}, \tag{12}$$

as $s \to \infty$.

By using equations (10), (11), and (12), we can get

$$\chi = 2\delta - 1. \tag{13}$$

Also, if we put $Z = \min(S,T)$, we can use univariate extreme value technique for the pair of S and T,

$$\begin{aligned} \Pr(Z > z) &= \Pr\{\min(S,T) > z\} \\ &= \Pr(S > z, T > z) \\ &= L(z) z^{-1/\delta}, \end{aligned} \tag{14}$$

for $z > u$, where u is a high threshold. From equations (6) and (14), it can be inferred that δ is the tail index. We can apply equation (7) for estimating it.

Therefore, given a high threshold u, equation (13) becomes

$$\overline{\chi} = \frac{2}{n_u}\{\sum_{j=1}^{n_u} \ln \frac{z(j)}{u}\} - 1, \tag{15}$$

where $z(1), z(2), ..., z(n_u)$ are the n_u observations of variable Z that exceeds u.

In addition, Poon, Rockinger, and Tawn [2001] show

$$Var(\overline{\chi}) = \frac{(\overline{\chi}+1)^2}{n_u}. \tag{16}$$

One of the dependence measures, χ, can be used for analyzing tail dependence if there is evidence of asymptotic dependence by calculating $\overline{\chi}$. In other words, χ can provide the degree of asymptotic dependence when $\overline{\chi} = 1$. If it is evident that $\overline{\chi} = 1$ is rejected statistically, there is no asymptotic dependence, thus $\chi = 0$. If there is no statistically significant evidence to reject $\overline{\chi} = 1$, we calculate χ, assuming that $\overline{\chi} = \delta = 1$. That is $\chi = \lim_{s\to\infty} L(s) = c$, as in equation (8). Therefore, we can calculate χ given a high threshold u and under the condition that $\overline{\chi} = 1$,

$$\chi = \frac{u n_u}{N}. \tag{17}$$

In addition, Poon, Rockinger, and Tawn [2001] show

$$Var(\chi) = \frac{u^2 n(N - n_u)}{N^3}. \quad (18)$$

In the empirical test, we first calculate $\bar{\chi}$ for detecting the existence of asymptotic dependence, and measure the degree of asymptotic dependence by χ for data series for which we cannot statistically reject the null hypothesis $\bar{\chi} = 1$.

3.4 Results

Next, we analyze characteristics of the return series (logarithmic change in currency price) of each currency, dependence between each pair of currencies in the same subgraph, and interdependence between subgraphs by using χ and $\bar{\chi}$. In multivariate extreme value theory, choice of a threshold value might affect a value of tail index, but there is no standard method to choose an appropriate threshold. Here, we arbitrarily choose thresholds in a range between the upper 4% and 6% where values of tail indices roughly converge in a stable range.

3.4.1 Hourly data

Descriptive statistics of hourly return data (Table 4)

Table 4 shows summary statistics of return data of emerging market currencies. All the currencies have large kurtosis and positive tail index, thus tails of their distributions are approximated to the tail of a Fréchet distribution. The tail indices of currencies in the fixed exchange rate regimes, i.e., the Argentine peso and the Hong Kong dollar, are relatively large.

Table 4: Descriptive statistics of hourly data

	PHP	KRW	TWD	HKD	MXN	BRL
Mean	0.0002	0.0004	0.0001	0.0000	0.0001	0.0002
Standard deviation	0.0015	0.0017	0.0007	0.0001	0.0016	0.0044
Skewness	-2.7978	4.1292	-0.9857	-0.4801	1.3703	-1.8312
Kurtosis	33.6608	20.1477	20.4122	27.2359	14.2864	25.6850
Tail index	0.3099	0.2461	0.2979	0.4845	0.5504	0.3514
	ARS	CLP	PLN	CZK	TRL	
Mean	0.0000	0.0001	0.0001	0.0001	0.0005	
Standard deviation	0.0002	0.0037	0.0031	0.0007	0.0075	
Skewness	0.3520	0.3560	0.9052	0.2684	1.8069	
Kurtosis	43.6172	57.2899	26.0489	14.5851	22.6605	
Tail index	1.1593	0.5843	0.3576	0.3240	0.4068	

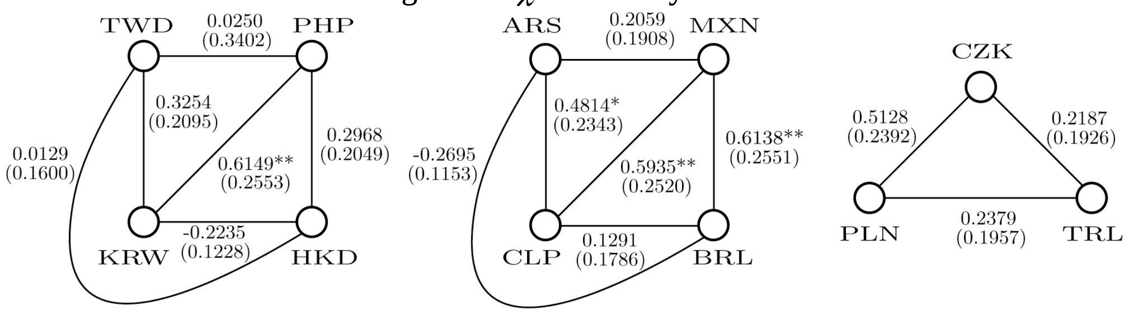
Notes:
Descriptive statistics of logarithmic return of spot exchange rate for emerging market currencies against the US dollar.
Tail index of innovation terms for the filtered data is Hill's estimator in equation (7).

Dependence measures of hourly return data (Figures 2, 3, and 4)

Here, we first estimate $\overline{\chi}$ for each pair of currencies in the same subgraph (Figure 2). Next, we calculate χ for pairs in which asymptotic dependence, i.e., $\overline{\chi}=1$, cannot be rejected (Figure 3). For reference, we also calculate linear correlation for each pair of currencies in a same subgraph. In the sample period (July 4 - September 30, 2001), we can find the asymptotic dependence of three pairs, KRW-PHP, CLP-MXN, and BRL-MXN, in each subgraph. This may show the existence of contagion between these currencies. χ, which provides the degree of asymptotic dependence when $\overline{\chi}=1$, is about 0.07 - 0.09 for these three pairs. Also, $\overline{\chi}$ for these pairs is larger than linear correlation.

Therefore, broker behavior may create contagion (tail dependence) in a short period of time, and tail dependence in a short period of time is different from whole dependence (linear correlation).

Figure 2: $\overline{\chi}$ of hourly data

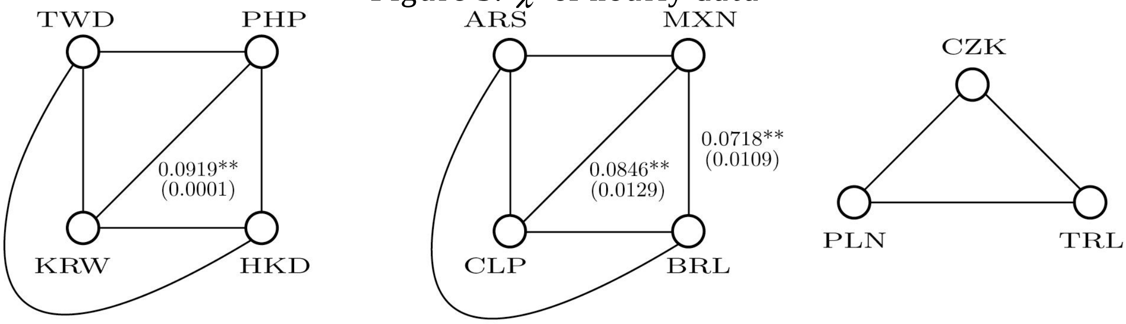


(a) Subgraph 1 (b) Subgraph 2 (c) Subgraph 3

Notes:

Values not in parentheses are $\overline{\chi}$ of logarithmic return of spot exchange rate (we use right tail of the distribution) for emerging market currencies against the US dollar.
Values in parentheses are standard deviation.
$\overline{\chi}$ is computed based on tail index estimation on Fréchet marginals.
* We can reject $\overline{\chi}=0$ at a 90% confidence level.
** We cannot reject $\overline{\chi}=1$ and we can reject $\overline{\chi}=0$ at a 90% confidence level.

Figure 3: χ of hourly data



(a) Subgraph 1 (b) Subgraph 2 (c) Subgraph 3

Notes:

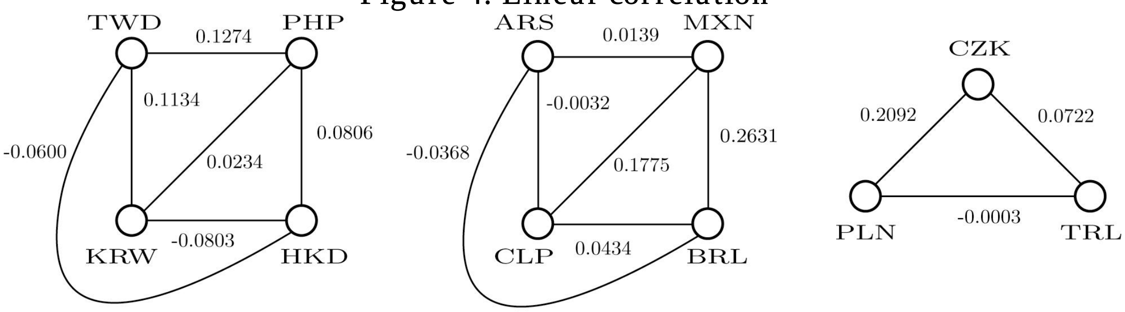
Values not in parentheses are χ of logarithmic return of spot exchange rate (we use right tail of the distribution) for emerging market currencies against the US dollar.

Values in parentheses are standard deviation.

χ is computed based on tail index estimation on Fréchet marginals.

** χ is statistically significant at a 90% confidence level.

Figure 4: Linear correlation



(a) Subgraph 1 (b) Subgraph 2 (c) Subgraph 3

Notes:

Values are linear correlations of logarithmic return of spot exchange rate for emerging market currencies against the US dollar.

Case Study: Subgraph 2 (Argentina, Brazil, Chile, and Mexico)

The Argentine peso is different from the other currencies in the subgraph, in that the Argentine government has adopted a currency board to set the value of the Argentine peso on one-to-one parity with the US dollar and its market is extremely illiquid. However in times of crisis, the currency might try to evade its own system and thus develop a strong relationship with other currencies. In other words, there might be low dependence between the Argentine peso and the other currencies unless the market fears the Argentine government to escape the system.

From Figure 2, asymptotic dependence in hourly data seems to exist between the Brazilian real and the Mexican peso and between the Chilean peso and the Mexican peso at a 90% confidence level. It might be justified by our survey where we found that the Mexican peso, the Brazilian real, and the Chilean peso are used as hedging currencies for the Argentine peso at weights of 43%, 43%, and 14% respectively. Thus, asymptotic dependence (tail dependence) occurs between pairs of neighbor currencies, as was the case in the Argentine peso crisis in the sample period (July 4 - September 30, 2001). This brings us important results that in the subgraph of the Argentine peso there is contagion among the currencies that faced less macroeconomic problems compared with the Argentine peso. In other words, some brokers hedge a currency in a crisis, which is illiquid or regulated, by using neighbor currencies and therefore contagion can occur in neighbor currencies. As a matter of fact, around July 2001 the Argentine economy was feared to be in default and abandon its currency board, which would constitute a crisis situation. At that time, brokers were recommending in their reports to hedge exposures for the Argentine peso using neighbor currencies such as the Chilean peso, and the neighbor currencies of the Argentine peso were very volatile. The Argentine government finally gave up the system in January 2002[5].

3.4.2 Daily data

Descriptive statistics of daily data (Table 5)

Table 5 shows summary statistics of the daily return of emerging market currencies. Like the hourly data, all the currencies have large kurtosis and positive tail index. Thus, the tails of their distributions are approximated to the tail of a Fréchet distribution. The tail indices of currencies for daily return are smaller than those for hourly return.

[5] The Argentine president Eduardo Duhalde announced the end of the currency board that adopted one-to-one parity with US dollar in January 2002. The president implemented a dual exchange rate in which the Argentine peso was floated for financial transactions and fixed for foreign and other transactions. Finally, in February 2002, the Argentine government adopted a free float system.

Table 5: Descriptive statistics of daily data

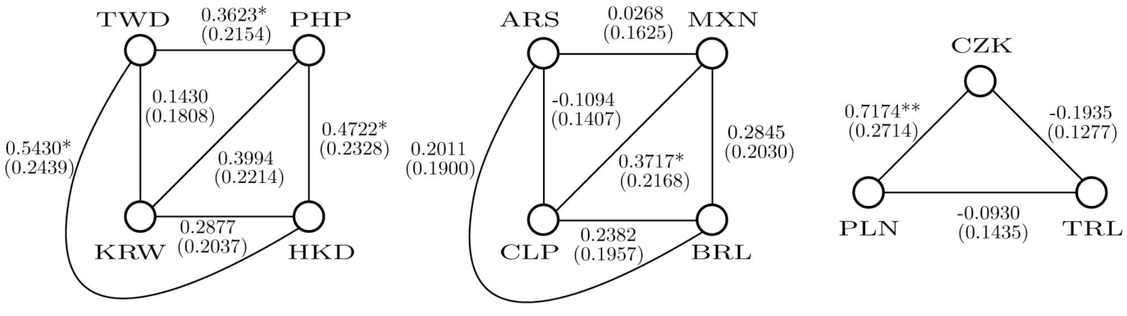
	PHP	KRW	TWD	HKD	MXN	BRL
Mean	0.0001	-0.0001	-0.0001	0.0000	0.0002	0.0032
Standard deviation	0.0096	0.0090	0.0061	0.0048	1.0018	1.0014
Skewness	-0.6606	-2.4162	-0.2596	-0.0627	-10.3679	-4.3679
Kurtosis	12.5937	41.0840	12.9869	7.6304	34.2589	82.6645
Tail index	0.3215	0.3043	0.2767	0.2202	0.3579	0.2061
	ARS	CLP	PLN	CZK	TRL	
Mean	0.0006	0.0001	0.0002	0.0000	0.0011	
Standard deviation	2.0082	0.0087	0.0053	0.0053	0.0091	
Skewness	-31.6155	-1.9462	0.4625	-1.2341	-1.9409	
Kurtosis	83.2000	32.5745	14.6754	34.9373	33.6778	
Tail index	0.3288	0.2690	0.3128	0.2396	0.2073	

Notes:
Descriptive statistics of logarithmic return of spot exchange rate for emerging market currencies against the US dollar.
Tail index of innovation terms for the filtered data is Hill's estimator in equation (7).

Dependence measures of daily data (Figures 5, 6, and 7)

In the sample period (June 30, 1993 - July 31, 2001), $\overline{\chi}$ of many currency pairs are positive but too small to calculate χ except CZK-PLN. Tail dependence is smaller than linear correlation in almost all pairs. This is a big difference from hourly data, and we may say that contagion occurs in a very short period in emerging market currencies. Thus, an analysis of daily return may not be sufficient to determine the risk of emerging currency markets.

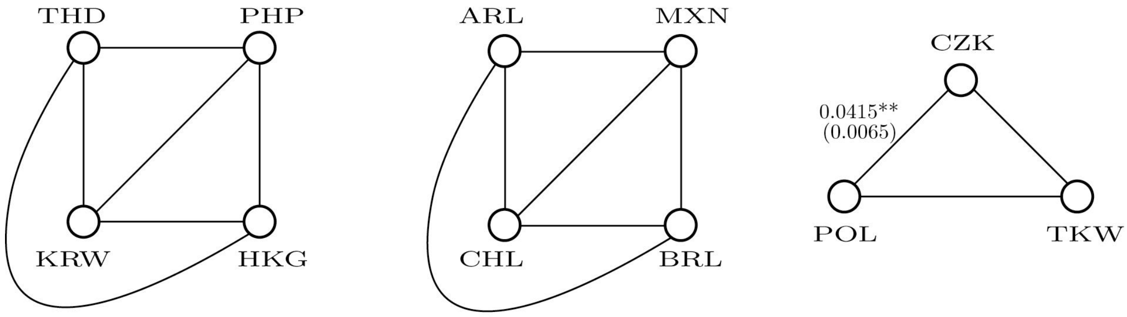
Figure 5: $\overline{\chi}$ of daily data



(a) Subgraph 1 (b) Subgraph 2 (c) Subgraph 3

Notes:
Values not in parentheses are $\overline{\chi}$ of logarithmic return of spot exchange rate (we use right tail of the distribution) for emerging market currencies against the US dollar.
Values in parentheses are standard deviation.
$\overline{\chi}$ is computed based on tail index estimation on Fréchet marginals.
* We can reject $\overline{\chi} = 0$ at a 90% confidence level.
** We cannot reject $\overline{\chi} = 1$ and we can reject $\overline{\chi} = 0$ at a 90% confidence level.

Figure 6: χ of daily data



(a) Subgraph 1 (b) Subgraph 2 (c) Subgraph 3

Notes:

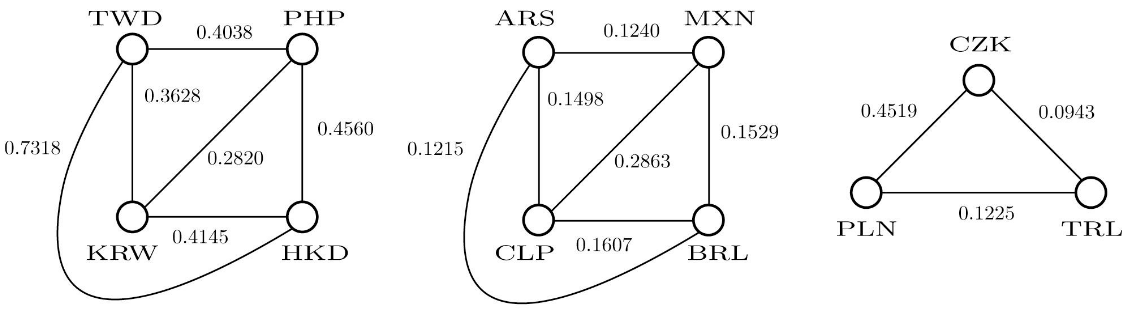
Values not in parentheses are χ of logarithmic return of spot exchange rate (we use right tail of the distribution) for emerging market currencies against the US dollar.

Values in parentheses are standard deviation.

χ is computed based on tail index estimation on Fréchet marginals.

** χ is statistically significant at a 90% confidence level.

Figure 7: Linear correlation



(a) Subgraph 1 (b) Subgraph 2 (c) Subgraph 3

Notes:

Values are linear correlation of logarithmic return of spot exchange rate for emerging market currencies against the US dollar.

3.4.3 Contagion between currencies in different subgraphs (Table 6)

We empirically analyze contagion (tail dependence) between currencies in a subgraph and those in other subgraphs using daily return series. Here, we use average *daily* return of currencies in each subgraph, since emerging market currencies are traded in a specific period of time in a day. For instance, Asian emerging market currencies are almost only traded in Asian time (GMT 0:00~8:00) and South American emerging market currencies are traded in US time (GMT 16:00~0:00). Therefore, it is difficult to see tail dependence between currencies in a subgraph and those of others in an hourly frequency. So, here, we decided to use only daily data.

If we test contagion between subgraphs using daily data, it is necessary to consider time differences among geographical regions. This is because subgraphs in this paper correspond to geographical regions. If we analyze contagion originating in the US time zone, we need to see US data at time t and European and Asian data at time $t+1$. In Table 6, 1=>2 means tail dependence between Asian currencies at t and South American currencies at t, and 2=>1 shows the tail dependence between South American currencies at t and Asian currencies at $t+1$. Also, 1=>3 means tail dependence between Asian currencies at t and European currencies at t. Here, we estimate $\bar{\chi}$ and linear correlation, in order to see interdependence of subgraphs in extreme. From Table 6, we cannot find any clear evidence that there was contagion between subgraphs.

Table 6: Dependence measure of inter-subgraphs

	1=>2	2=>3	3=>1	3=>2	2=>1	1=>3
$\bar{\chi}$	-0.0003	0.0636	-0.0920	0.1014	0.1800	0.0659
Standard deviation	0.1581	0.1503	0.1285	0.1741	0.1667	0.1685
Linear correlation	0.2740	0.0176	-0.1145	0.2888	-0.0426	0.1438

Notes:
Values are $\bar{\chi}$ and linear correlation of logarithm return of spot exchange rate for emerging market currency regions against the US dollar.
$\bar{\chi}$ measure is computed based on tail index estimation on Fréchet marginals.
Subgraph 1 consists of Hong Kong, Korea, Taiwan, and Philippines, subgraph 2 consists of Argentina, Chile, Mexico, and Brazil, and subgraph 3 consists of Turkey, Czech, and Poland.

4. Conclusion

In this paper, we studied contagion of emerging currency markets. First, we constructed graphs based on our survey of eight large currency brokers. Next, we measured tail dependence of each pair of currencies.

From the graph based on our survey, we found that broker risk-hedging behavior makes some complete subgraphs. The hedging behavior creates groups in which currencies are hedged with each other, but not with other groups. Within a complete subgraph, brokers tend to sell other proxy currencies available when a currency is under huge selling pressure.

Brokers do not use currencies in other subgraphs for risk-hedging purposes.

We empirically validated the graph structure based on our survey employing multivariate extreme value theory. First, we filtered the original data into i.i.d. data using several GARCH models in order to apply multivariate extreme value theory. And we measured tail dependence of the filtered data, which we define contagion. From the results, we found relatively strong tail dependence between some currency pairs in hourly data. We also found that interdependence among subgraphs was very weak, which is consistent with our survey.

We conclude that broker behavior can create contagion among emerging market currencies as we saw in the case of the Argentine peso and its neighbor currencies. Also, tail dependence in hourly data is stronger than that in daily data, and therefore currency contagion might be fast. Finally, our analysis reveals the important differences between observations in the tails versus the whole distribution when evaluating the risk of emerging currency markets.

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Appendix (Questionnaire for drawing Figure 1) [6]

We sent a questionnaire to large currency brokers in order to ascertain the microstructure of emerging currency markets. The questionnaire focuses on a broker behavior in many scenarios and market liquidity. In the paper, we use a part of the questionnaire for drawing graphs, which explain the network of emerging market currencies through broker behavior. We just show one of questions in the questionnaire.

If you cannot cover the following currencies in the market for liquidity reasons, what kind of currencies are you using as a proxy? Please circle some against each currency.

Argentine peso (currency board)
Brazil, Chile, Czech, Hong Kong, Korea, Mexico, Philippines, Poland, Taiwan, Thailand, Turkey

Brazilian real (managed floating)
Argentina, Chile, Czech, Hong Kong, Korea, Mexico, Philippines, Poland, Taiwan, Thailand, Turkey

Chilean peso (independent floating)
Argentina, Brazil, Czech, Hong Kong, Korea, Mexico, Philippines, Poland, Taiwan, Thailand, Turkey

Czech koruna (managed floating)
Argentina, Brazil, Chile, Hong Kong, Korea, Mexico, Philippines, Poland, Taiwan, Thailand, Turkey

Hong Kong dollar (managed floating)
Argentina, Brazil, Chile, Czech, Korea, Mexico, Philippines, Poland, Taiwan, Thailand, Turkey

Korean won (independent floating)
Argentina, Brazil, Chile, Czech, Hong Kong, Mexico, Philippines, Poland, Taiwan, Thailand, Turkey

Mexico peso (independent floating)
Argentina, Brazil, Chile, Czech, Hong Kong, Korea, Philippines, Poland, Taiwan, Thailand, Turkey

Philippine peso (independent floating)
Argentina, Brazil, Chile, Czech, Hong Kong, Korea, Mexico, Poland,

[6] We should have included other currencies such as USD or EUR for proxy currencies in the survey. Since some brokers include currencies omitted by our survey as proxy currencies in the answer to our survey, we directly interviewed brokers to ask additional questions on the point after the survey. The results are included in the calculation of Figure 1.

Taiwan, Thailand, Turkey

Polish zloty (independent floating)
Argentina, Brazil, Chile, Czech, Hong Kong, Korea, Mexico, Philippines, Taiwan, Thailand, Turkey

Taiwan dollar (independent floating)
Argentina, Brazil, Chile, Czech, Hong Kong, Korea, Mexico, Philippines, Poland, Thailand, Turkey

Thai baht (independent floating)
Argentina, Brazil, Chile, Czech, Hong Kong, Korea, Mexico, Philippines, Poland, Taiwan, Turkey

Turkish lira (independent floating)
Argentina, Brazil, Chile, Czech, Hong Kong, Korea, Mexico, Philippines, Poland, Taiwan, Thailand