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Price Discovery and Volatility Transmissions in the Asian Major Currencies

- Applications of Multivariate Rotated ARCH Model -

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I. Introduction

The globalization of modern financial market would be inevitable tendency. Not only developed countries but also developing countries intend to participate in these trends by deregulating the capital in-and-out flows beyond their national border. This increases the cross-border capital mobility, and as a consequence, the information and volatility from each country have been conveyed into currency and financial markets in other countries.

All information about the capital flows across borders is ultimately reflected in the FX rates in onshore and offshore currency markets. US dollar has been the key or base currency in the world and the payment and settlement medium in international commercial and financial trades after World War II. Thus, it is also the most important numeraire to evaluate the currency of other countries than US. Moreover, some countries choose the so-called dollarization scheme without local currency. None including euro, SDR and gold can have such roles and status in the world until now. However, the significance and value of US dollar has been deteriorated as the US economy growth slows down and its governmental fiscal deficit widens. Although it is still the key currency in the world, it is hard to deny that its power and influence has been significantly decreased since the global financial crisis which was triggered by US subprime mortgage distress.

Traditionally, Japanese yen has been the most influential internationalized currency after US dollar at least in the Asia region. Japan used to be the second largest economy in the world in terms of total GDP for the long time and therefore Japanese yen is considered as the second most important currency in the international commercial and capital trades. The so-called yen-carry trades means the capital trades and mobility that comes from yen financing in Japan.

In addition, Japan used to be the number one or number two trading partner for the most of the Asian countries, and therefore, it was natural that Japanese yen had become the most crucial regional currency except from US dollar. The recent enormous quantitative easing policy firmly driven by Abenomics can begin since Japanese government has confidence on his currency yen.

However, Chinese economy surged dramatically and replaced the Japan's position in the world economy. In 2010, China's GDP (USD 5.4742 trillion) surpassed Japan's. Then, for the most of the Asian countries, the scale of trades with China has become highly larger than that of Japan. Furthermore, recently China government tries to internationalize Chinese yuan gradually and encourages other Asian countries to use yuan for the payment and settlement on the trade with China.[1]

Therefore, we can guess that there is a relative powers shift from Japanese yen to Chinese yuan in the Asian currency market before and after the global financial crisis. Specifically, we would compare the effect of Japanese yen (JPY) and Chinese yuan (CNY) to discover the price and to transmit the volatility on the other major Asian currencies such as Korea won (KRW), Philippine peso (PHP), Thai baht (THB), Indonesian rupiah (IDR), Malaysian ringgit (MYR), and Singapore dollar (SGD).

II. Data

We use daily time-series data provided by Datastream to find out the FX rate denominated in the US dollar for Japanese yen, Chinese yuan, and other major Asian currencies (Korea won, Philippine peso, Thai baht, Indonesian rupiah, Malaysian ringgit, and Singapore dollar). We would like to include dollar as well but it is the numeraire for the all currencies in the sample and cannot be included due to the so-called "*n-th currency problem*". Instead we include the gold price against dollar as it indirectly reflects the relative dollar value changes. The London Bullion Market Association (LBMA) provides the gold prices against dollar as well as euro.

The sample period for our study in this paper is 1,898 trading days from August 2, 2005 to November 7, 2012. We intentionally exclude the period before August, 2005 since China used fixed FX rate that time. Moreover, China executed the pegged exchange rate system of yuan from July, 2008 to May, 2010 due to global financial crisis triggered by subprime mortgage crisis. So we separate the above entire period

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[1] For example, People's Bank of China and Bank of Korea entered into currency swap of 64 trillion Korean won and 360 billion Chinese yuan in 2011 and allowed continually payments with each local currency in trades between the two countries.

into before (Aug. 1, 2005-Jun. 30, 2008) and after (Jun. 1, 2010-Nov. 11, 2012) the financial crisis, since our purpose is to check the effect of Japanese yen and Chinese yuan on the other Asian currencies before and after the crisis.

Figure 1. The USD Denominated Price of Major Asian Currencies and Gold

The sample period is from 2005.8.1. to 2012.11.7. For normalization, USD denomination is used. The quantities for all currencies and gold corresponding to USD 100 at 2005.8.1. are measured by US dollar.

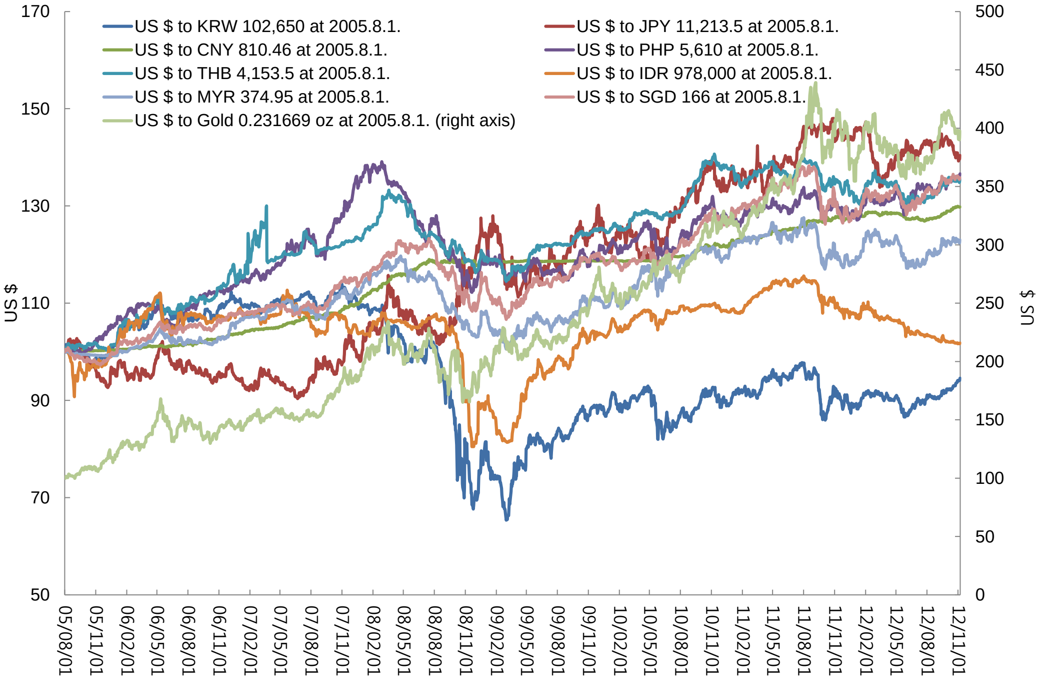
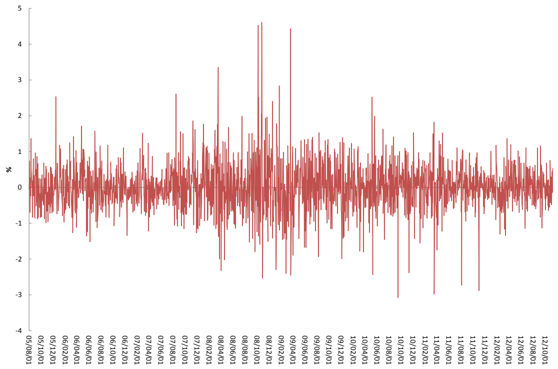


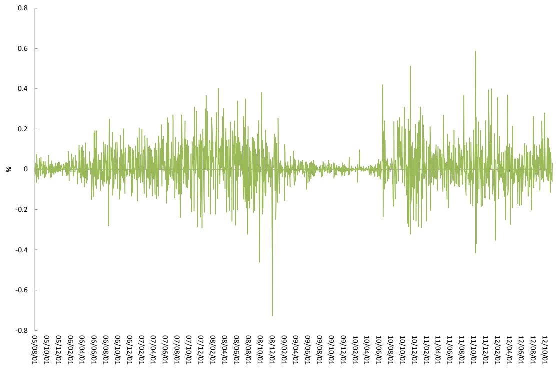
Figure 2. The Daily Growth Rate of US $ denominated Price of Major Asian Currencies and Gold

The sample period is from 2005.8.1. to 2012.11.7. Daily growth rate of US dollar price of each currency and gold are provided. Daily growth rate is log-difference of exchange rate multiplied by 100. So its unit is %.

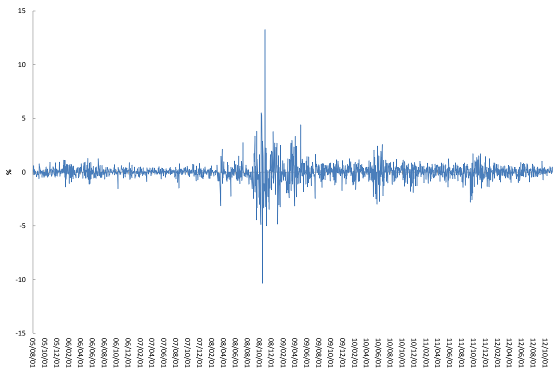
(a) Japan Yen



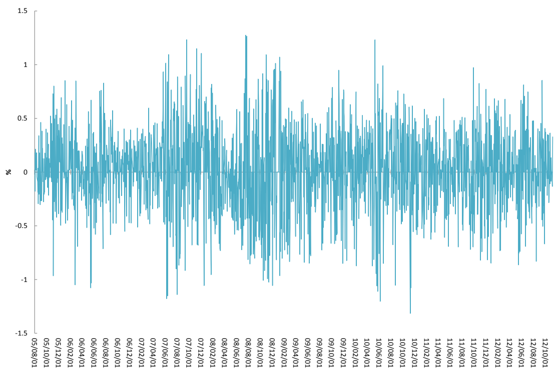
(b) China Yuan



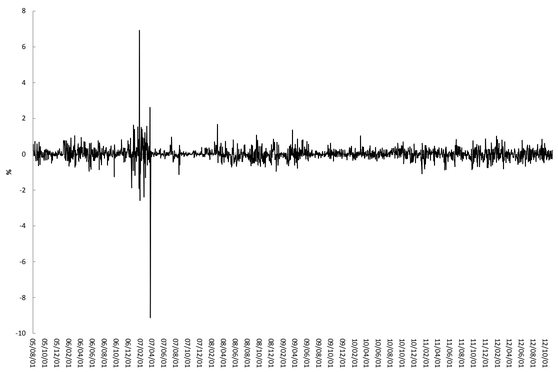
(c) Korea Won



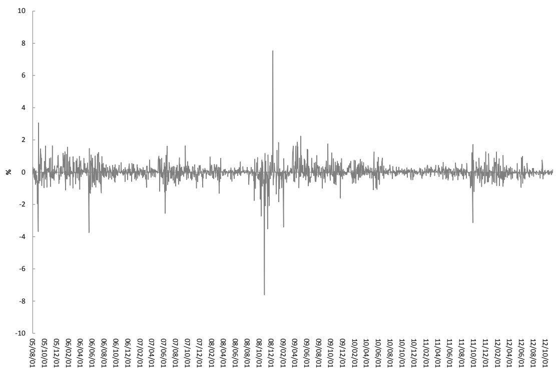
(d) Philippine peso



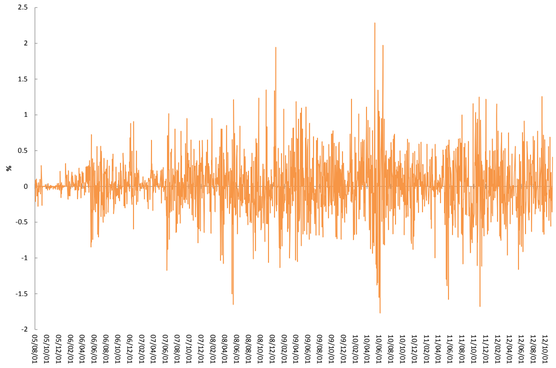
(e) Thai Baht



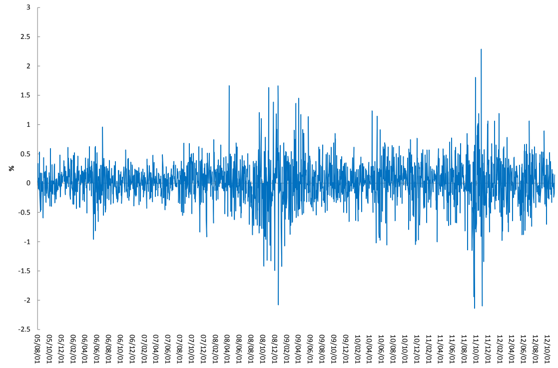
(f) Indonesian rupiah



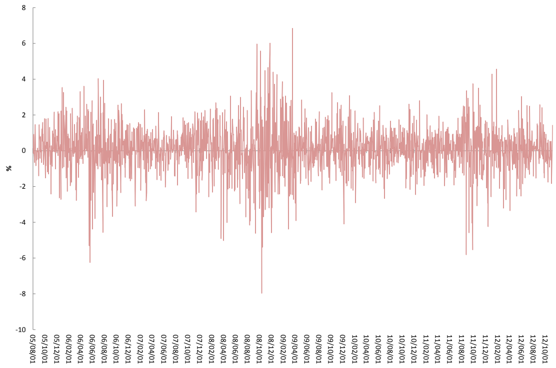
(g) Malaysian ringgit



(h) Singapore dollar



(i) Gold



III. Empirical methodologies

3.1 Information share methodology

We conduct information share analysis suggested by Hasbrouck(1995) among Gold, JPY, CNY, and other major Asian currencies including KRW, PHP, THB, IDR, MYR, and SGD. Using this methodology, we can estimate the contributions of information due to one currency into the price discovery of the other currency when their prices series are co-integrated. The estimation procedure is as follows. Assume the time-series vector

$$p_t = [\ln p_t^{Gold}, \ln p_t^{CNY}, \ln p_t^{JPY}, \ln p_t^{KRW}, \ln p_t^{PHP}, \ln p_t^{THB}, \ln p_t^{IDR}, \ln p_t^{MYR}, \ln p_t^{SGD}].$$

Here, each component p_t^{XYZ} is unit gold (ounce) or unit XYZ currency denominated by US dollar. CNY, JPY, KRW, PHP, THB, IDR, MYR and SGD denote Chinese yuan, Japanese yen, Korea won, Philippine peso, Thai baht, Indonesian rupiah, Malaysian ringgit, and Singapore dollar, respectively.

<u>Step 1</u>: estimating VAR(q) and decide the optimal lag q^*
Estimate VAR model in equation (1) for $p = 1,2,3,\cdots$ and find out q^* with the lowest AIC and SC.

$$p_t = \alpha + \beta_1 p_{t-1} + \beta_2 p_{t-2} + \cdots + \beta_q p_{t-q} + \varepsilon_t \ ,$$
$$\varepsilon_t = \left[\varepsilon_t^{Gold}, \varepsilon_t^{CNY}, \varepsilon_t^{JPY}, \varepsilon_t^{KRW}, \varepsilon_t^{PHP}, \varepsilon_t^{THB}, \varepsilon_t^{IDR}, \varepsilon_t^{MYR}, \varepsilon_t^{SGD}\right]' \sim (0, \Omega) \quad (1)$$

<u>Step 2</u>: Johansen's cointegration test
Equation (1) of VAR(q^*) can be converted to VECM($q^* - 1$) in the equation (2) in the below for Johansen cointegration test.

$$\Delta p_t = \alpha + \kappa\delta' p_{t-1} + \xi_1 \Delta p_{t-1} + \cdots + \xi_{q^*-1} \Delta p_{t-(q^*-1)} + \varepsilon_t \ ,$$
$$\varepsilon_t = \left[\varepsilon_t^{Gold}, \varepsilon_t^{CNY}, \varepsilon_t^{JPY}, \varepsilon_t^{KRW}, \varepsilon_t^{PHP}, \varepsilon_t^{THB}, \varepsilon_t^{IDR}, \varepsilon_t^{MYR}, \varepsilon_t^{SGD}\right]' \sim (0, \Omega) \quad (2)$$

<u>Step 3</u>: VECM($q^* - 1$) estimation
Use the equation (2) to estimate VECM($q^* - 1$)

<u>Step 4</u>: Estimate Variance-Covariance vector Ω and long-run impact matrix $\Psi(1)$
Ω can be estimated with VECM estimation of the equation (2), $\Psi(1)$ can calculated from a numerical simulation.

<u>Step 5</u>: Computation of information shares
The information share of j-th component into i-th component in the vector p_t can be calculated with the equation (3)

$$S_{ij} = \frac{\left([\widehat{\Psi}(1)L]_{ij}\right)^2}{[\widehat{\Psi}(1)\,\widehat{\Omega}\,\widehat{\Psi}(1)']_{ii}} \quad (3)$$

Here, L is the lower triangular matrix in the Cholesky decomposition. For given i, the summation S_{ij} over j will give us 100%.

Step 6: Permutation of ordering of variables

It is well known that the information shares are dependent on the ordering of variables due to the Choelsky decomposition. In terms of Structural VAR, Choelsky decomposition, which is often low triangular restriction, imposes that the prior the component in the multivariate vector locates, the more exogenous it is. Thus, we compute the information share for all permutations of the variable orderings. As we cannot guess the righteous ordering, we examine the average, minimum, and maximum in the information share estimates for all orderings. Since we have a vector with 9 0components, the number of all permutation is 9! (factorial) more than 360,000.

3.2 Volatility transmission with VAR(1)-MRARCH model

We use the multivariate Rotated GARCH model (MRARCH) to capture and to measure the volatility transmission process between different currencies and gold. When there are increased numbers of parameters due to the so-called 'curse of dimensionality 'in the multivariate GARCH, diagonal restriction has been often applied. In both VECH and BEKK model, diagonal restrictions have often been used. Such modeling would ignore the cross-effects between variances and covariances.

Above all, we choose to use BEKK model, because it guarantees the positive semi-definite in the variance-covariance matrices in maximizing the log-likelihood. In Full BEKK, no structural restrictions into parameters in coefficient matrices are imposed so the computation burden is so severe and the number of estimated parameters becomes substantially large. So it would be almost impossible that we estimate the Full-BEKK under the vector with 9 components. For example, under Full-BEKK(1,1) model, we should estimate as many as 207 parameters.[2] It is

[2] In general the number of parameters in Full BEKK(p,q) for $n \times 1$ vector is $\frac{n(n+1)}{2} + n^2(p+q)$.

computationally impossible work. However, we should the identify the transmission relationship between variances of 9 gold and Asian currencies.

So we decide to employ the MRARCH, recently proposed by Noureldin, Shephard, and Sheppard (2012). They impose the sophisticated and flexible restrictions on BEKK under space transform (rotation) based on spectral decomposition. That is, the raw return or return residual r_t can be transformed into e_t in orthogonal space by spectral decomposition. We call e_t as rotated return or return residual. Suppose that G_t is the variance-covariance matrix of e_t in the transformed orthogonal space. We make a natural and simple restrictions on the dynamics of e_t. First, we assume that the long-run unconditional variance of e_t is the n-dimesional identity I_n. This assumption can be acceptable since the rotated return e_t is located in the space of orthogonal bases.

Second, we can impose the three type restrictions into the coefficients representing the autoregressive dynamics of e_t. We choose the diagonal restriction on the BEKK for e_t. This can be estimable computationally since it is diagonal BEKK.

Eventually, we recover the original dynamics of r_t from diagonal-BEKK of the rotated return $\mathrm{e_t}$ based on the inverse transform. Then, we can get almost Full-BEKK. That is, no parameters in the coefficient matrices are zeros due to prior zero restrictions. The estimated BEKK, i.e., MRARCH is not Full-BEKK strictly but does not lose the major characteristics of Full-BEKK. Actually, MRARCH is the Full-BEKK with complex and sophisticated restrictions for us to recover the rich dynamics of the raw return r_t. So we can infer the cross-effects between the variances and covariances as well as autoregressive effects.

We specify the stochastic dynamics of FX rates as VAR(1)-MRARCH(1,1) as the follows:

$$r_t = \alpha + \beta r_{t-1} + \epsilon_t \,, \epsilon_t \sim (0, H_t)$$
$$var(\epsilon_t) = \overline{H} = P\Lambda P'$$
$$e_t = \overline{H}^{-\frac{1}{2}} \epsilon_t = P\Lambda^{-\frac{1}{2}} P'$$
$$var_{t-1}(e_t) \equiv G_t = (I_4 - AA' - BB') + Ae_{t-1}e'_{t-1}A' + BG'_{t-1}B'$$
$$E(G_t) = E(e_t e'_t) = I_4$$

(4)

In (4), $r_t = \begin{pmatrix} r_t^{Gold} \\ r_t^{CNY} \\ r_t^{JPY} \\ r_t^{KRW} \\ r_t^{PHP} \\ r_t^{THB} \\ r_t^{IDR} \\ r_t^{MYR} \\ r_t^{SGD} \end{pmatrix}$ and $r_t^{XYZ} = 100 \cdot (\ln p_t^{XYZ} - \ln p_{t-1}{}^{XYZ})(\%)$,

ϵ_t is the original residual, e_t is the rotated residual in orthogonal space, H_t is the variance-covariance of ϵ_t and G_t is the variance-covariance of e_t. $\bar{H}$ is the unconditional variance-covariance of ϵ_t and is decomposed into $P\Lambda P'$. Λ is the diagonal matrix with eigenvalues of $\bar{H}$. P is the eigenvector matrix of $\bar{H}$.

Moreover, we should apply tensor calculation to get the parameters representing the cross-effects of volatilities as the follows:

$$vec(H_t) = var(\bar{C}\bar{C}') + \bar{A}\otimes\bar{A}\, vec(\varepsilon_{t-1}\varepsilon_{t-1}') + \bar{B}\otimes\bar{B}' vec(H_{t-1}) \qquad (5)$$

These formulae are necessary to compute standard errors of impact coefficients based on the so-called delta-method. In our analysis, we use numerical gradients not analytical gradients.

IV. Empirical results

4.1 Information share analysis results

The empirical analysis results indicate that all the currencies and gold has relatively high information share from itself (note that the diagonal terms in the Table 1). When we compare the information share from Japanese yen and Chinese yuan to the other major Asian currencies, we found that Japanese yen overall has higher information share for price discovery compared to Chinese yuan. However, if we compare Panel A and Panel B in Table 1, the information shares from Japanese yen decreased after the global financial crisis whereas that of Chinese yuan increased.

Although China has become the second largest economy in the world, it is found that Chinese yuan's information share for the price discovery of other Asian currencies is still very weak and the information share from neighboring country is often relatively large. We suggest that is because China still has imposed the heavy regulation on the capital flows and onshore foreign exchange market. Moreover, China has executed the exclusive policy for the Chinese capital market such as the limit of foreign investor's shareholding.

This in turn restricts the yuan's ability or role to share information and to discover the other Asian currencies in the Asian foreign exchange markets, in spite of China's economy size and the status in the international economy. Nevertheless, we need to focus the increasing information role of yuan after the global financial crisis.

Table 1.Information Share Analysis with all orderings

This table provides the information share analysis based on Hasbrouck(1995) under all orderings of 9 components of (Gold, JPY, CNY, KRW, PHP, THB, IDR, MYR, SGD) in log price vector. Note that the number of the orderings is 9!= 362,880. Due to Cholesky decomposition, the information share results are dependent on the ordering of variables in log price vector. So this table shows the average, maximum, minimum in 362,880 orderings. With the lowest AIC, we take a VAR(2) so run VECM(1). Johansen Conintegration test implies that the cointegrating rank be 1. In this table, the columns represent the triggering shock of each currencies and gold and the rows is the subject variable of price discovery.

Panel A. Before the global financial crisis (2005.8.1.~2008.6.30, 761 days)

		GOLD	JPY	CNY	KRW	PHP	THB	IDR	MYR	SGD
GOLD	average	53.82	1.54	0.43	9.92	6.51	3.29	6.92	6.76	10.80
	max	74.08	5.68	2.13	22.98	22.57	5.09	23.69	26.93	36.95
	min	42.71	0.00	0.00	2.94	1.01	0.28	0.91	0.10	0.32
JPY	average	45.57	43.46	0.57	2.08	0.24	1.83	0.33	0.51	5.41
	max	60.61	59.09	2.29	7.15	1.87	4.68	1.92	2.89	19.69
	min	35.78	32.67	0.00	0.85	0.00	0.42	0.00	0.00	0.03
CNY	average	82.39	3.08	0.34	5.69	0.67	4.46	0.48	0.50	2.38
	max	90.55	7.71	1.46	10.92	4.52	7.40	4.10	4.51	9.72
	min	76.13	0.19	0.00	3.51	0.00	2.17	0.00	0.00	0.00
KRW	average	31.97	1.12	0.16	49.83	4.97	2.79	2.74	3.20	3.21
	max	41.93	4.99	1.42	69.53	20.10	4.56	15.44	19.83	22.59
	min	22.32	0.00	0.00	38.64	0.59	0.41	0.00	0.00	0.01
PHP	average	45.50	1.70	0.10	20.52	17.20	4.51	4.02	4.28	2.17
	max	54.55	5.91	1.26	38.86	40.96	7.18	20.91	25.39	20.95
	min	31.86	0.01	0.00	11.42	9.26	1.28	0.00	0.00	0.00
THB	average	43.87	0.95	0.22	15.75	2.50	29.15	2.72	2.18	2.65
	max	52.29	4.24	1.80	28.94	12.73	39.76	14.69	15.81	20.63
	min	31.47	0.00	0.00	9.05	0.19	25.45	0.03	0.00	0.00
IDR	average	41.50	1.07	0.18	3.07	7.72	3.52	29.09	6.14	7.71
	max	60.96	4.12	0.91	11.96	25.34	8.71	54.93	25.27	29.37
	min	32.59	0.00	0.00	0.01	1.05	1.52	17.44	0.00	0.00
MYR	average	40.36	1.78	0.92	6.89	11.55	1.83	8.48	16.58	11.62
	max	62.46	6.12	3.80	21.33	35.07	6.18	29.77	47.82	41.29
	min	29.79	0.00	0.00	0.74	2.50	0.42	0.81	3.57	0.20
SGD	average	76.67	6.40	0.37	0.71	0.63	3.88	1.30	1.91	8.12
	max	93.43	14.99	1.64	3.19	3.14	7.61	5.64	8.02	24.62
	min	66.27	1.67	0.00	0.00	0.00	2.36	0.00	0.00	0.18

Panel B. After the global financial crisis (2010.6.1.~2012.11.7, 637 days)

		GOLD	JPY	CNY	KRW	PHP	THB	IDR	MYR	SGD
GOLD	average	81.74	1.43	0.53	1.03	1.26	7.16	1.07	1.89	3.87
	max	99.76	3.85	3.10	6.64	7.26	22.35	5.49	10.27	15.24
	min	72.30	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
JPY	average	10.79	85.39	0.17	0.19	0.14	1.10	0.11	0.30	1.82
	max	19.28	93.52	0.85	1.12	0.78	3.92	0.68	1.47	5.56
	min	4.90	79.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CNY	average	55.70	7.44	12.18	2.39	1.93	6.88	1.19	3.03	9.26
	max	82.31	14.07	23.99	13.50	11.79	26.99	7.22	16.92	31.05

	min	42.84	3.18	8.57	0.00	0.00	0.00	0.00	0.00	0.99
	average	19.72	0.95	1.78	30.06	5.74	9.21	2.35	10.33	19.87
KRW	max	43.99	3.11	10.00	67.57	28.91	40.37	12.73	45.73	60.55
	min	9.87	0.00	0.01	16.92	0.00	0.17	0.00	0.00	4.58
	average	28.06	6.64	1.75	7.61	12.92	11.27	1.63	8.15	21.96
PHP	max	58.28	12.64	9.86	34.21	42.85	45.37	9.24	39.13	62.64
	min	14.69	2.53	0.01	0.09	3.09	0.30	0.00	0.00	6.83
	average	49.01	0.56	1.59	10.14	8.23	14.16	3.19	6.75	6.38
THB	max	78.13	1.92	8.94	35.53	33.18	48.53	16.23	33.90	31.37
	min	35.82	0.02	0.03	2.42	0.75	1.28	0.02	0.00	0.00
	average	18.11	0.92	2.21	12.56	6.32	12.51	25.48	10.45	11.44
IDR	max	43.51	2.74	12.09	47.62	33.65	50.38	56.86	48.88	45.64
	min	8.70	0.00	0.08	2.00	0.00	0.94	14.23	0.00	0.82
	average	25.29	2.81	2.32	8.82	6.43	14.26	2.62	18.07	19.38
MYR	max	55.97	6.58	12.33	39.33	33.11	54.50	15.17	61.65	63.26
	min	12.48	0.34	0.07	0.43	0.00	1.01	0.00	2.48	3.42
	average	27.93	4.04	1.82	9.89	6.70	11.06	2.09	11.85	24.63
SGD	max	58.69	8.84	10.33	39.96	32.72	46.25	12.60	49.13	68.69
	min	14.76	0.90	0.02	1.08	0.05	0.28	0.00	0.10	7.60

4.2 Volatility transmission analysis results

The VAR(1)-MRARCH(1,1) model estimation based on the equation (4)-(7) is conducted. First, we take the 9×1 vector of $r_t = (r_t^{Gold}, r_t^{CNY}, r_t^{JPY}, r_t^{KRW}, r_t^{PHP}, r_t^{THB}, r_t^{IDR}, r_t^{MYR}, r_t^{SGD})'$ with total 9 components. We analyze them under VAR(1)-MRARCH (1,1). The results are reported in the Table 2 (before the global financial crisis period) and Table 3(after the global financial crisis period)

We found that the lagged volatility of gold $\sigma_{G,t-1}^2$, Chinese yuan $\sigma_{C,t-1}^2$, and Japanese yen $\sigma_{J,t-1}^2$ all have some impacts on the volatility of the other Asian currencies. When we compare the magnitude of the impact, the impacts from Chinese yuan's volitility has increased after the global financial crisis that before.

Table 3. VAR(1)-MRARCH(1,1) Estimation Result I (before the global financial crisis)

Daily exchange rate data from Datastream and LBMA is used. The sample period is from Aug. 2, 2005 to June 31, 2008. We take the log difference of each currency and apply VAR(1) and extract residuals. MRARCH(1,1) model is applied to those residuals. Then, we calculate the coefficient for each component in vector and standard deviation of impact coefficient is derived by delta method. In MRARCH, the dynamics of conditional covariances as well as conditional variances are estimated. However, we provide the coefficient estimates for dynamics of conditional variances, since we are not interested in the covariance dynamics.

Panel A. Components in Matrix A

	$\epsilon^2_{G,t-1}$	$\epsilon^2_{J,t-1}$	$\epsilon^2_{C,t-1}$	$\epsilon^2_{K,t-1}$	$\epsilon^2_{P,t-1}$	$\epsilon^2_{T,t-1}$	$\epsilon^2_{I,t-1}$	$\epsilon^2_{M,t-1}$	$\epsilon^2_{S,t-1}$
$\sigma^2_{G,t}$	0.5824	0.0042	***0.0120	-0.0053	***0.0041	**0.0006	0.0013	**-0.0008	0.0001
	(0.4332)	(0.0029)	(0.0033)	(0.0032)	(0.0015)	(0.0003)	(0.0008)	(0.0004)	(0.0001)
$\sigma^2_{J,t}$	*0.0054	2.9318	**-0.0263	-1.3006	**-0.0235	**0.0098	1.3821	-0.3066	0.1629
	(0.0029)	(2.2287)	(0.0120)	(1.1889)	(0.0096)	(0.0049)	(0.9585)	(0.2593)	(0.1026)
$\sigma^2_{C,t}$	***0.0108	**0.0059	***5.1710	0.0098	***-0.1335	***-0.0214	***-0.0075	-0.0059	**0.0023
	(0.0028)	(0.0029)	(1.1883)	(0.0112)	(0.0371)	(0.0063)	(0.0016)	(0.0055)	(0.0009)
$\sigma^2_{K,t}$	0.0011	***-0.4990	**-0.0886	***1.2068	***-0.0635	***0.0352	**0.0951	***0.2112	***0.0502
	(0.0009)	(0.1905)	(0.0355)	(0.4402)	(0.0180)	(0.0137)	(0.0512)	(0.0548)	(0.0157)
$\sigma^2_{P,t}$	***0.0040	-0.0104	***0.2200	*-0.0587	***0.4363	***0.0649	-0.0038	**-0.0297	**0.0066
	(0.0013)	(0.0119)	(0.0653)	(0.0358)	(0.1061)	(0.0181)	(0.0064)	(0.0126)	(0.0028)
$\sigma^2_{T,t}$	**0.0015	0.0440	**0.0506	0.1496	**0.1048	***0.1550	0.0876	***0.1490	***0.0436
	(0.0007)	(0.0789)	(0.0225)	(0.0992)	(0.0482)	(0.0444)	(0.0916)	(0.0359)	(0.0144)
$\sigma^2_{I,t}$	**0.0047	0.7694	*-0.0667	0.0328	**-0.0225	**0.0165	*1.0593	-0.1468	**0.2070
	(0.0022)	(0.6910)	(0.0368)	(0.2676)	(0.0109)	(0.0081)	(0.6122)	(0.1559)	(0.0953)
$\sigma^2_{M,t}$	0.0010	**-0.1309	***-0.1316	0.2530	***-0.0461	**0.0592	***-0.0936	***0.3430	***0.0637
	(0.0008)	(0.0640)	(0.0437)	(0.1619)	(0.0157)	(0.0242)	(0.0346)	(0.0519)	(0.0115)
$\sigma^2_{S,t}$	**0.0040	0.2019	-0.0301	**0.1068	-0.0093	**0.0278	0.4608	0.1218	***0.2629
	(0.0017)	(0.2100)	(0.0437)	(0.0419)	(0.0125)	(0.0141)	(0.3060)	(0.0850)	(0.0847)

Panel B. Components in Matrix B

	$\sigma^2_{G,t-1}$	$\sigma^2_{J,t-1}$	$\sigma^2_{C,t-1}$	$\sigma^2_{K,t-1}$	$\sigma^2_{P,t-1}$	$\sigma^2_{T,t-1}$	$\sigma^2_{I,t-1}$	$\sigma^2_{M,t-1}$	$\sigma^2_{S,t-1}$
$\sigma^2_{G,t}$	***97.8530	*0.0004	***-0.0085	***-0.0099	***-0.0044	***0.0016	***-0.0067	***0.0814	***0.0277
	(0.3210)	(0.0002)	(0.0007)	(0.0029)	(0.0001)	(0.0000)	(0.0019)	(0.0004)	(0.0004)
$\sigma^2_{J,t}$	0.0001	***72.9013	***0.1180	***-26.5090	***-0.8790	***0.7053	***38.8003	***-7.0544	***5.1627
	(0.0001)	(3.3150)	(0.0242)	(1.6215)	(0.0278)	(0.0078)	(1.5431)	(0.3911)	(0.1763)
$\sigma^2_{C,t}$	***-0.0019	0.0152	***77.9770	***-0.3083	*0.2861	0.0111	***-0.2879	***-0.7337	***0.0976
	(0.0006)	(0.0107)	(4.8395)	(0.0208)	(0.1711)	(0.0298)	(0.0040)	(0.0075)	(0.0012)
$\sigma^2_{K,t}$	*-0.0023	***-13.4629	*-0.1089	***37.8498	***-2.6772	***2.1030	***4.7663	***7.9031	***2.2218
	(0.0012)	(0.3165)	(0.0651)	(0.8755)	(0.0412)	(0.0183)	(0.1313)	(0.1011)	(0.0374)
$\sigma^2_{P,t}$	***-0.0021	***-0.4359	***-0.8682	***-2.6700	***29.4724	***4.5691	***-0.6006	***-1.8087	***0.2592
	(0.0001)	(0.0307)	(0.2938)	(0.0804)	(0.1198)	(0.0219)	(0.0047)	(0.0203)	(0.0036)
$\sigma^2_{T,t}$	***0.0015	***0.6530	***-0.3469	***4.0438	***9.1748	***8.3568	***2.2501	***6.9673	***1.9384
	(0.0001)	(0.0860)	(0.0894)	(0.2328)	(0.0674)	(0.0565)	(0.1642)	(0.0418)	(0.0284)
$\sigma^2_{I,t}$	**-0.0016	***19.2975	***-0.2082	***4.8446	***-0.5671	***1.1806	***33.8082	***-2.9902	***7.6303
	(0.0008)	(1.0295)	(0.0319)	(0.2711)	(0.0322)	(0.0124)	(1.0732)	(0.2514)	(0.1771)
$\sigma^2_{M,t}$	***0.0427	***-3.5637	***-0.4651	***7.8286	***-1.7856	***3.5200	***-3.0850	***14.8806	***3.2838
	(0.0009)	(0.1081)	(0.0988)	(0.3163)	(0.0299)	(0.0341)	(0.0638)	(0.0844)	(0.0221)
$\sigma^2_{S,t}$	***0.0298	***5.1082	***0.1423	***4.4223	***0.5640	***1.9761	***15.1798	***6.5707	***11.2773
	(0.0008)	(0.3136)	(0.0303)	(0.0391)	(0.0294)	(0.0224)	(0.5584)	(0.1341)	(0.1504)

Table 4. VAR(1)-MRARCH(1,1) Estimation Result II (after the global financial crisis)

Daily exchange rate data from Datastream and LBMA is used. The sample period is from June 1, 2010 to Nov. 7, 2012. We take the log difference of each currency and apply VAR(1) and extract residuals. MRARCH(1,1) model is applied to those residuals. Then, we calculate the coefficient for each component in vector and standard deviation of impact coefficient is derived by delta method. In MRARCH, the dynamics of conditional covariances as well as conditional variances are estimated. However, we provide the coefficient estimates for dynamics of conditional variances, since we are not interested in the covariance dynamics.

Panel A. Components in Matrix A

	$\epsilon^2_{G,t-1}$	$\epsilon^2_{J,t-1}$	$\epsilon^2_{C,t-1}$	$\epsilon^2_{K,t-1}$	$\epsilon^2_{P,t-1}$	$\epsilon^2_{T,t-1}$	$\epsilon^2_{I,t-1}$	$\epsilon^2_{M,t-1}$	$\epsilon^2_{S,t-1}$
$\sigma^2_{G,t}$		0.0070	-0.0051	-0.0286	-0.0101	0.0096	-0.0495	***0.1009	*0.0873
	(1.0720)	(0.0115)	(0.0231)	(0.0255)	(0.0142)	(0.0125)	(0.0525)	(0.0378)	(0.0522)
$\sigma^2_{J,t}$	0.0021	0.6511	-0.0914	**0.7242	0.0385	0.0393	0.0749	0.0416	0.0022
	(0.0091)	(0.8627)	(0.0959)	(0.3699)	(0.0282)	(0.0670)	(0.3171)	(0.1429)	(0.0157)
$\sigma^2_{C,t}$	-0.0025	-0.0097	0.1109	-0.0322	0.2833	-0.0077	-0.0232	-0.0920	0.0058
	(0.0023)	(0.0511)	(4.4662)	(0.0320)	(1.3714)	(0.0250)	(0.0951)	(0.0698)	(0.1064)
$\sigma^2_{K,t}$	0.0061	0.2075	-0.0683	*2.5998	0.0211	-0.0038	***-0.7548	-0.2835	-0.0441
	(0.0148)	(0.1758)	(0.0837)	(1.4518)	(0.0175)	(0.0281)	(0.2900)	(0.7079)	(0.1496)
$\sigma^2_{P,t}$	0.0048	-0.0469	-1.0423	-0.0240	0.6147	*-0.0161	**-0.1276	-0.0940	-0.0114
	(0.0077)	(0.0382)	(2.4159)	(0.0551)	(1.0394)	(0.0091)	(0.0577)	(0.0823)	(0.0731)
$\sigma^2_{T,t}$	0.0134	*0.2674	-0.1819	***0.4125	0.1282	0.0305	0.0493	0.0381	0.0023
	(0.0218)	(0.1578)	(0.5160)	(0.1296)	(0.1458)	(0.1069)	(0.3509)	(0.2651)	(0.0321)
$\sigma^2_{I,t}$	0.0145	0.3676	-0.1317	-0.1955	***0.0659	0.0380	0.3828	***0.1781	0.0208
	(0.0355)	(0.2889)	(0.1318)	(0.2646)	(0.0251)	(0.0877)	(0.5310)	(0.0591)	(0.0888)
$\sigma^2_{M,t}$	*0.0426	*0.1171	-0.0569	***1.2753	0.0177	-0.0036	-0.3177	**1.8508	**-0.4259
	(0.0248)	(0.0697)	(0.1762)	(0.3476)	(0.0522)	(0.0250)	(0.2093)	(0.7650)	(0.1939)
$\sigma^2_{S,t}$	*0.1012	*0.2076	-0.0949	***-0.4516	0.0916	0.0368	0.4084	-0.4442	0.2009
	(0.0612)	(0.1192)	(0.3282)	(0.1342)	(0.0670)	(0.1076)	(0.2733)	(0.2846)	(0.2623)

Panel B. Components in Matrix B

	$\sigma^2_{G,t-1}$	$\sigma^2_{J,t-1}$	$\sigma^2_{C,t-1}$	$\sigma^2_{K,t-1}$	$\sigma^2_{P,t-1}$	$\sigma^2_{T,t-1}$	$\sigma^2_{I,t-1}$	$\sigma^2_{M,t-1}$	$\sigma^2_{S,t-1}$
$\sigma^2_{G,t}$		*0.0061	**-0.1309	***-0.0673	*0.0287	***0.0401	***-0.2347	***1.2913	***2.2514
	(1.6915)	(0.0033)	(0.0657)	(0.0179)	(0.0147)	(0.0015)	(0.0644)	(0.0329)	(0.0504)
$\sigma^2_{J,t}$	*0.0081	***24.8680	**2.4811	***6.1115	**-1.6435	***2.4229	***12.4414	***1.5288	***1.5561
	(0.0043)	(0.9580)	(1.1918)	(0.3267)	(0.7968)	(0.0791)	(0.5661)	(0.0722)	(0.0864)
$\sigma^2_{C,t}$	0.0322	-0.2394	31.4709	**-0.2644	10.7794	***1.0089	***-0.3703	0.5892	0.6681
	(0.0327)	(0.5158)	(25.1242)	(0.1111)	(8.8109)	(0.3120)	(0.0331)	(0.5117)	(0.5948)
$\sigma^2_{K,t}$	***-0.0399	***3.4478	0.3205	***43.5482	*-0.9101	***1.0735	***-8.1886	***9.6754	***-2.2641
	(0.0101)	(0.3005)	(0.3377)	(0.8530)	(0.5565)	(0.0374)	(0.2713)	(0.2587)	(0.0494)
$\sigma^2_{P,t}$	-0.0067	0.1525	11.2169	0.2807	10.4555	***0.9734	0.6302	0.4908	0.6051
	(0.0061)	(0.3415)	(9.2327)	(0.3312)	(8.4649)	(0.3081)	(0.8840)	(0.4290)	(0.5443)
$\sigma^2_{T,t}$	***0.0357	***2.3750	-2.2959	***1.8409	-2.1507	***5.4987	***7.2068	***2.7930	***5.4671
	(0.0075)	(0.2955)	(2.3415)	(0.1382)	(2.2296)	(0.1115)	(0.5547)	(0.1538)	(0.1834)
$\sigma^2_{I,t}$	***-0.1337	***5.8988	-0.0545	***-8.9232	*-2.0752	***3.5480	***19.7619	-0.1664	***4.5743
	(0.0348)	(0.5070)	(0.1477)	(0.1192)	(1.0893)	(0.0831)	(0.5705)	(0.1632)	(0.1536)
$\sigma^2_{M,t}$	***0.6618	***0.8178	-1.4455	***8.8917	-1.1859	***1.5719	***0.3883	***35.2225	***-6.6556
	(0.0210)	(0.1104)	(0.9128)	(0.5282)	(0.7778)	(0.0403)	(0.1092)	(0.8185)	(0.2308)
$\sigma^2_{S,t}$	***2.2189	***1.3992	*-2.9087	***-4.5772	*-2.5535	***5.1956	***8.6752	***-14.1891	***13.4465
	(0.0543)	(0.1874)	(1.6516)	(0.2730)	(1.4908)	(0.0807)	(0.6196)	(0.2202)	(0.1965)

To see the fitness of our model, we draw the time-series plots of the absolute residuals and estimated conditional standard deviations in VAR(1)-MRARCH(1,1) in the figures in Appedix.

V. Conclusion

Our research investigates the effect of gold, Japanese yen, and Chinese yuan on the Asian currency markets. Our focus is on comparing the impact of Japanese yen and Chinese yuan on the major Asian currencies in terms of the price discovery and volatility transmission.

We could not include US dollar in this study due to the 'n-th currency problem' (=because it is used as a kind of numeraire), but include US dollar price of gold instead. The study results show that the information shares of Chinese yuan is still very low on the Asian currencies. However, yuan's information share is increasing whereas yen's share is decreasing as of the global financial crisis. On the other hands, it is found that Chinese yuan has bigger role in volatility transmission to Asian currencies than Japanese yen especially after global financial crisis.

Overall, this research found that both JPY and CNY have very limited power to discover the price and to transmit the volatility because US dollar still has the dominant impact on currencies in the world including East Asia region. However, we expect to see the increase of the Chinese yuan's influence on Asian currencies and this study may be the first research to look into that possibility.

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Appendix

Figure A.1. The absolute residuals and estimated conditional standard deviation I (before the global financial crisis)

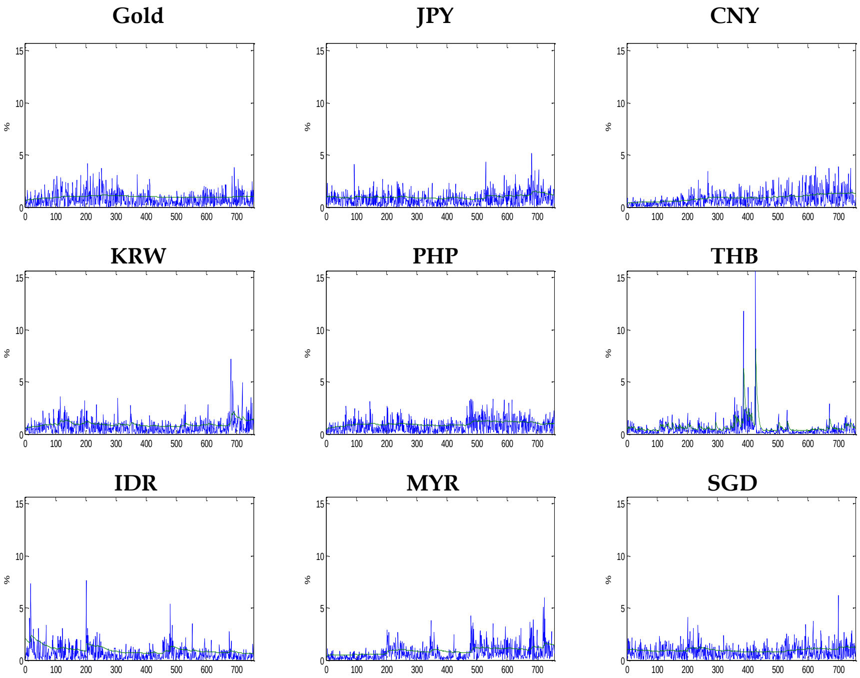

Figure A.2. The absolute residuals and estimated conditional standard deviation II (after the global financial crisis)