Local Currency Effect on Volatility Asymmetry in Asian Stock Markets

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***Abstract*—The aim of the paper is to study the effect of currency exchange rate changes on the stock market volatility asymmetry, based on the 14 country sample of Asian markets. We calculate time series of stock market volatility asymmetry using APARCH model and using both local currency returns and the USD returns to compare the results. We use standard statistical tests along with wavelet methods to compare the obtained time series estimates of the volatility asymmetry. We find that the effect from the exchange rates to the equity market volatility asymmetry is statistically not significant but short periods exist when currency rates can affect equity market volatility asymmetry.**

***Index Terms*—APARHC model, exchange rate effect, volatility asymmetry, wavelet models.**

I. Introduction

Volatility in equity markets appears to be asymmetric which is a well-documented empirical finding. Although even experimental setups have shown that volatility asymmetry (higher volatility when prices go down when compared to volatility when prices go up) exists in artificial markets, not that much attention has been turned to the exchange rate volatility. There are still a number of papers investigating the volatility asymmetry of exchange rates, generally with the results that for some currencies the asymmetry is present and for some it is not the clear case ([1] and [2]). Still, the asymmetric nature of volatility remains an important topic for asset pricing and volatility forecasting. The underestimation of volatility asymmetry can very easily lead to underestimation of risks [3].

Previous studies (e.g. [4]) have shown that asymmetry from the equity markets can affect the foreign exchange rates but not much support has been found for volatility transmission in the opposite direction [5]. Still, an important question remains whether possible volatility asymmetry from the currency markets can affect the volatility asymmetry in the equity markets and to what extent. Current paper adds to the literature providing a detailed comparison using a sample of Asian countries (as it contains both large and small developed and emerging markets) to test whether and to what extent can changes in foreign exchange rates affect volatility asymmetry in equity markets.

We approach the problem from the equity market side, using the methodology of [6] by adopting an APARCH model complemented with wavelet based jump detection and kernel weighting function to repeatedly estimate volatility asymmetry for 14 country stock markets to obtain time series of volatility asymmetry estimates. Repeating the same procedure with stock market returns measured in the local currency and in the US dollars, we can isolate the effect of currency exchange rates to the volatility asymmetry. This enables to compare whether currency exchange rates can contribute to the volatility asymmetry present in most of the sample countries.

We find that the effect from the exchange rates to the equity market volatility asymmetry is minimal. Standard statistical tests do not find significant effect for any of the 14 countries. Comparison of the obtained detailed volatility asymmetry time series enables to distinguish short periods when currency rates can affect equity market volatility asymmetry. But even advanced wavelet based semblance analysis of [7] does not enable to spot any significant effects from the currency rates and correlation of the asymmetries obtained in the returns measured in the local currency or in the USD, remain near 90% for most of the countries and the whole sample on average.

The rest of the paper is organized as follows. Section 2 gives an overview of the literature of volatility asymmetry of equity and currency markets. Section 3 describes the data and summarizes the methodology used in the study. Section 4 presents the results of comparing the obtained asymmetry data series and concluding remarks are brought in Section 5.

II. Related Literature

Volatility in equity markets tends to be asymmetric. [8] present an overview of the various studies documenting the effect and in a more recent work [6] show that asymmetric volatility exists in most of the stock markets. The causes of the volatility asymmetry still need further studying as the first studies (e.g. [9]) attempt to explain the asymmetry with leverage effect, meaning that a drop in the value of the stock increases financial leverage by reducing the value of equity, which makes the stock riskier and increases its volatility. Further studies like [10] find that leverage can only explain a small part of the movements in volatility.

Another well-known and tested hypothesis of the volatility asymmetry is explaining it by time-varying risk premiums as presented in the works of e.g. [11].

Other causes for the volatility asymmetry in the literature include proposing that that stop-loss orders and portfolio insurance can cause the effect [12]. Reference [8] finds that the volatility feedback effect can cause the effect.

More recent work like [13] show that volatility asymmetry exists even in experimental setups, which suggests that there could be behavioral factors influencing the asymmetry. Reference [14] goes one step further to test the behavioral

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factors and show that a higher level of economic development and market efficiency is coupled with a higher level of volatility asymmetry.

In the equity markets asymmetry is generally found to be larger for aggregate market index returns than for individual stocks [15].

There is no clear consensus about the volatility asymmetry in the foreign exchange markets. Early evidence in [16] doesn't find much support for that. Among papers finding support for exchange rate volatility are [17], [1], [5]. For example [2] find volatility asymmetry of AUD, GBP, and JPY against USD but no volatility asymmetry in EUR trade weighted indices against USD.

The causes for exchange rate volatility asymmetry can be a little different than for equity. According to [1] one of the possible explanations is the direction and size of central bank interventions that can cause volatility asymmetry. Other explanation that they propose is the base-currency effect in which the base currency is used for profit and loss calculation, making the variations in the bilateral rate to be a risk of the other currency. As [18] show that contrarian and herding investors can cause asymmetric volatility in equity markets, according to [2] this can be also the case for foreign exchange markets as similar trading patterns are present there.

In the asset market approach to the exchange rate determination [19] causality runs from equity markets to the exchange rates. In the goods market approach the causality is the opposite [20]. Among studies investigating the linkage between stock market and exchange rate volatility [21], [22] and [23] found evidence of the spillover effect from equity market, whereas [22] found an asymmetric effect from the stock market to the foreign exchange market. Reference [5] finds that the volatility of stock returns affects the volatility of exchange rates but no evidence of the volatility transmission in the opposite direction.

III. Methodology

A. Data

At first the volatility asymmetry is estimated by using the returns of MSCI indexes which are measured as the log difference of the price in the USD. Then all the procedures are repeated and the models are estimated once again with the returns measured as the log difference of the price in local currency of the MSCI index. Data is obtained from Thomson's Datastream for 14 Asian counties. The sample starts from 1980 for developed countries and from 1987 or later for emerging markets and expands till the end of 2008.

B. APARCH Methodology

The paper uses the same methodology as [6] where the asymmetric power GARCH (APARCH) model of [24] coupled with skewed Student's t-distribution is used to estimate volatility of all markets. As current study focuses on volatility estimation of equity markets, the APARCH model is chosen which has been shown by [25] and [26] to deliver relatively (compared to other models) very accurate VaR forecasts relying on volatility out of sample forecasting.

The main advantage of the APARCH model is that it nests various models among which the general GARCH model of [16] features a conditional variance equation, as well as the model of [27], which features a conditional standard deviation equation.

The choice of the model is the APARCH(1,1) model without constants and ARMA orders which enabled to obtain results with quite a small number of observations (1001 observations for each rolling time window) and relatively stable results. Another advantage of using the APARCH (1,1) model is an easier interpretation of the model as the APARCH equation becomes:

$$\sigma_t^{\delta} = a(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^{\delta} + \beta\sigma_{t-1}^{\delta} \quad (1)$$

where α, γ, β and δ are parameters to be estimated. The conditional standard deviation is given by σt and γ reflects volatility asymmetry where a positive value means that past shocks ε(t-1) have a larger impact on current conditional volatility when the shocks are negative compared to shocks being positive.

C. Outlier Detection

GARCH type models cannot properly handle jumps present in returns [28], so we use two different methods to automatically detect the jumps. The first method to detect jumps is based on wavelets, which are powerful for detecting jumps as demonstrated in [29]. We use a wavelet based model as proposed by [30], so that jump locations and sizes could be estimated.

The second outlier detection method of [31] uses local volatility in a predefined time window to test for jump components in returns. Jumps are captured studying the volatility condition prevailing at the time of the tested return. In times of high volatility, an abnormal return is bigger than an abnormal return in times of low volatility.

The average number of eliminated observations amounts to 1-2% for most countries and robustness checks (see [6]) show that volatility asymmetry estimations are not qualitatively affected by eliminating jumps.

D. Model Adjustments

As the focus of this study is on time dynamics and causes of asymmetric volatility, we are particularly interested in asymmetry measures in as small a time window as possible, thus choosing the observation window size of 1001 observations (trading days) to repeatedly estimate the volatility asymmetry. As 1001 observations is an arbitrary choice and to focus the measurement on an even smaller time span, we use the Gaussian kernel weighting function for the input data to the APARCH model with the size of 4 standard deviations. This improves the stability of APARCH estimations.

To compare asymmetric volatility in different countries, we estimate the time series of the APARCH model parameters for each country. As proxy for the volatility asymmetry, we use the time series of gamma from Equation 1. We also perform an adjustment and compute an adjusted gamma as done in [6]. This is done for both estimation procedures, i.e. stock market returns measured in USD and local currency.

We still use median values of the non-adjusted gamma for each country and also calculate volatility asymmetry measures using the whole sample of returns for each country. The resulting gamma estimate is referred to as "the whole period gamma".

To summarize the estimations done in the paper to measure volatility asymmetry, we use a rolling time window of 1001 observations for each country. We move the time window by a step of 5 observations and repeatedly estimate the used APARCH model to obtain a time series of volatility asymmetry estimates (gamma). Returns for the rolling time window APARCH estimation have gone through two outlier detection methods and Gaussian kernel weighting function. With the obtained time series of gamma, which still contains some noise, we calculate a base value of volatility asymmetry for each country (referred as "adjusted gamma") and also median value for the time series ("median gamma") as well as median values for every year of the observed time period. For further comparison we estimate the same APARCH model only once for each country with all data for the particular country to obtain another estimate of the base volatility asymmetry ("whole period gamma"). Our approach of obtaining time series of volatility asymmetry estimates has clear advantages of only computing a whole period asymmetry as the latter doesn't take into account time-varying characteristics of the volatility asymmetry.

IV. Results

A. Standard Tests for the Whole Sample

Using the described methodology, we obtain a time series containing about 1200 estimates for each country (having data starting from 1980) and with about 800 observations (for the countries having data starting from 1987). We repeat the procedure with returns in the local currency and with returns in the USD (results for the obtained volatility asymmetry estimates are presented in Table I). This enables us to run standard tests to see whether the obtained asymmetry estimates differ depending on the currency used to measure the stock market returns.

We compute t-statistics to test the difference of the obtained asymmetry measures for the whole sample. We do not find statistical difference in the results for any of the asymmetry measures (average gamma, median gamma and adjusted gamma) depending on the currency used. The presented t-stat p-values in Table I indicate that there is a very high probability of the differences being zero meaning that the results are quite far for being different depending on the currency used.

Furthermore, the correlation between the asymmetry measures in different currencies reaches 96% for average gamma and remains over 92% for all other measures (even when eliminating China and Hong Kong where the local currency is pegged to the USD). It should be noted that also other currencies (like Singapore dollar) of the sample can be partially pegged to the USD or a basket of currencies containing the USD but taking that into account and eliminating those counties from the tests does not change the results. We repeated the tests with using the whole sample and ran the same tests with eliminated countries where pegged currencies could start to affect the results. Such robustness checks showed that it still does not change the results nor conclusions that could be made from those results.

One could question the obtained time series estimates of the gamma (volatility asymmetry measure) as at certain times the obtained standard errors for the asymmetry measures can be quite high. Thus we use the same APARCH model and estimate it only once for each country with all data points available (still repeating that with both returns in the local currency and the USD) to get smaller standard errors. We also repeat the whole period gamma estimation twice, once with returns containing jumps (original data) and secondly with data used for obtained volatility asymmetry time series estimation that has jumps removed. Both t-tests and correlation of over 96% still shows that the results do not depend on the calculation method of the volatility asymmetry measures and confirms the previously noted finding.

We still have to face the potential critique that the differences between countries can be noteworthy which can produce relatively high standard errors. Thus t-tests of the whole sample might not convincingly enable to say that the asymmetry measures obtained with the local currency returns differ from the asymmetry measured obtained with returns measured in the USD. To address this potential problem, we still run some additional tests with individual countries.

B. Standard Tests for Individual Countries

As the t-tests run so far show results only for the whole sample, we calculate median gamma values for each country for every year of the sample period. This enables us to run t-test on individual countries. The results of such testing confirm the abovementioned finding as we do not find statistically significant difference in any of the countries in the sample, although the p-values for individual countries (ranging from 0.17 to 0.98 compared to p-values of around 0.8-0.95 for the whole sample) imply that on country level there is a higher probability for possible differences in the volatility asymmetry affected by currency exchange rates. But such a difference is still very far from statistically significant for a great majority of the sample (see Table II for individual country level test results).

We still run some additional robustness checks. As our first whole sample median gamma test showed no statistical difference, we only had one observation for each country representing the true median of the volatility asymmetry. This approach can under certain circumstances underestimate the variability of the volatility asymmetry. Thus for a robustness check, we use the previously calculated median gammas for each year of the sample for each country. Taking the average of the median gammas still gives us the same clear result of no statistical difference of the volatility asymmetry depending on the currency exchange rate changes.

C. Wavelet Based Analysis

So far all of our tests have used somehow aggregated data which can arise a question whether there in fact can be periods where currency exchange rates affect volatility asymmetry of the stock markets even if the average effect is very small. Traditional statistical methods lack very good methods to compare time series similar to higher frequency data containing noise. Our volatility asymmetry time series still contains noise despite using jump detection and input weighting for the APARCH model which significantly improved the stability of our obtained model estimates. In order not to start removing the noise, we use a wavelet based method of [7] to conduct semblance analysis of the obtained time series.

TABLE I: VOLATILITY ASYMMETRY MEASURES

	Returns measured in the local currency				
Country	**Average gamma**	**Median gamma**	**Adjusted gamma**	**WPG (jumps)**	**WPG (no jumps)**
Australia	0.278	0.281	0.422	0.161	0.132
China*	0.275	0.212	0.243	0.131	0.117
Hong Kong*	0.172	0.171	0.246	0.155	0.128
Indonesia	0.109	0.120	0.109	0.092	0.037
India	0.141	0.138	0.143	0.093	0.092
Japan	0.364	0.324	0.383	0.275	0.221
Korea	0.166	0.168	0.169	0.167	0.144
Sri Lanka	0.057	0.067	0.055	0.051	0.040
Malaysia	0.183	0.157	0.197	0.164	0.127
New Zealand	0.076	0.084	0.095	0.110	0.113
Pakistan	0.006	0.008	0.007	0.028	-0.003
Singapore	0.192	0.167	0.209	0.129	0.105
Thailand	0.104	0.074	0.077	0.129	0.098
Taiwan	0.224	0.208	0.233	0.167	0.144
	Returns measured in the USD				
Country	**Average gamma**	**Median gamma**	**Adjusted gamma**	**WPG (jumps)**	**WPG (no jumps)**
Australia	0.228	0.185	0.324	0.161	0.140
China*	0.277	0.215	0.246	0.130	0.116
Hong Kong*	0.171	0.162	0.248	0.157	0.125
Indonesia	0.110	0.109	0.111	0.084	0.038
India	0.159	0.143	0.179	0.104	0.104
Japan	0.287	0.269	0.350	0.232	0.197
Korea	0.179	0.173	0.179	0.170	0.149
Sri Lanka	0.067	0.083	0.071	0.070	0.056
Malaysia	0.159	0.138	0.161	0.165	0.119
New Zealand	0.105	0.121	0.107	0.129	0.108
Pakistan	-0.002	-0.002	-0.003	0.012	-0.003
Singapore	0.221	0.186	0.260	0.141	0.130
Thailand	0.122	0.079	0.098	0.132	0.110
Taiwan	0.220	0.218	0.229	0.158	0.147
T-stat p-values	0.919	0.813	0.953	0.982	0.875
Correlation	0.959	0.927	0.959	0.968	0.979

The table presents different volatility asymmetry measures for all countries in the sample. The upper panel presents the results of returns measured in the local currency and the lower panel with the returns measured in the USD. The last two rows present the p-values of some of the conducted t-tests on the whole sample and correlation of the volatility asymmetry measures presented in the upper pane and lower pane. (*China and Hong Kong are not included in the t-tests and in correlation calculations presented in the table because of closely pegged currencies to the USD. It should be noted that also other currencies (like Singapore dollar) of the sample can be partially pegged to the USD or a basket of currencies containing the USD, but taking that into account and eliminating those counties from the tests does not change the results.) WPG stands for the "whole period gamma".

Wavelet-based approaches provide the ability to account for temporal (or spatial) variability in spectral character [7]. Semblance analysis is calculated as a function of both scale (or wavelength) and time (or position) which enables the changing phase relationships of the two datasets to be visualized and analyzed. Although [7] propose the use of the semblance analysis for geophysical datasets, they also demonstrate the use of the method on financial data.

TABLE II: VOLATILITY ASYMMETRY CORRELATION AND T-TEST RESULTS FOR INDIVIDUAL COUNTRIES

Country	Correlation between median gamma	T-stat for testing average gamma difference	T-stat for testing median gamma difference
Australia	0.633	1.076	0.940
China	1.000	0.021	0.000
Hong Kong	0.991	0.034	0.044
Indonesia	0.936	0.020	0.285
India	0.707	0.458	0.761
Japan	0.716	1.367	1.510
Korea	0.909	0.200	0.432
Sri Lanka	0.924	0.147	0.386
Malaysia	0.959	0.414	0.489
New Zealand	0.556	0.504	1.201
Pakistan	0.979	0.164	0.072
Singapore	0.906	0.746	0.635
Thailand	0.972	0.348	0.296
Taiwan	0.937	0.064	0.095

The results of the semblance analysis (for Australia, Singapore and India) are brought in Figures 1-3, where the red color indicates a large positive amplitude and the dark blue indicates a large negative amplitude. The figures also present the obtained time series of volatility asymmetry (gamma) where the returns are both measured in the USD (the upper pane) and in the local currency (the third pane). The second and the fourth pane represent the results of the wavelet length analysis obtained from the input of the time series of the asymmetry measures (the asymmetry measures obtained from the returns measured in the USD and in the local currency, respectively).

The lower pane of the figures presents the results of the semblance analysis. The results of semblance analysis confirm the previous results that if differences exist in the asymmetry measures caused by the currency exchange rates, the differences are minimal and exist only for short periods of time. For most of the time even the time series of asymmetry measures follow the same pattern regardless of the currency exchange rate movements.

For example for Australia (see Figure 1), which showed the lowest correlation (0.633) between the median gamma measures depending on the currency used for calculations (see Table II for results for all countries), the semblance analysis reveals that there is a difference between the gamma only for the period around 1997 to 2005 with the peak around the burst of the internet bubble. But studying more closely the time series of the obtained volatility asymmetry estimates reveals that most of that difference comes from a slightly different asymmetry movement pattern and the average levels of the volatility asymmetry are not too different even for that period.

In terms of semblance analysis, most of the other countries follow the similar patterns of Singapore (see Figure 2) and India (see Figure 3). For brevity, only results of Australia, Singapore and India are presented in the paper; other results are available upon request.

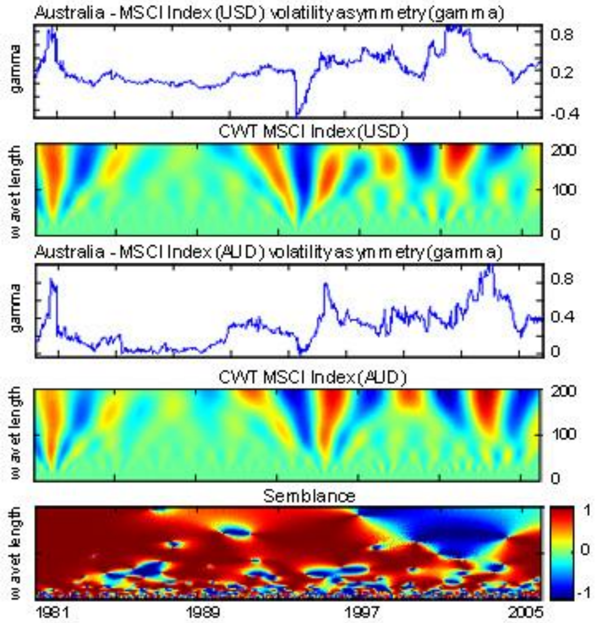

Fig. 1. Volatility asymmetry in Australia and semblance analysis results (CWT - continuous wavelet transform).

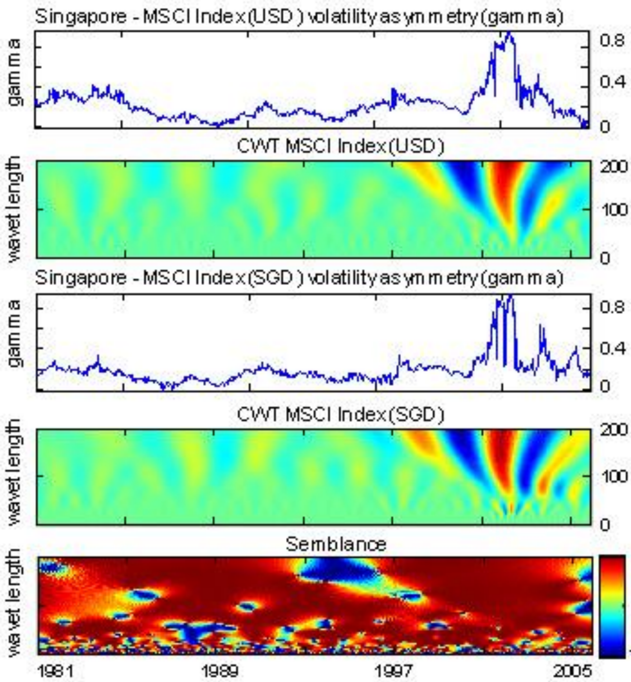

Fig. 2. Volatility asymmetry in Singapore and semblance analysis results (CWT - continuous wavelet transform).

Having a correlation of 0.906, the semblance analysis of the Singapore's volatility asymmetry reveals that there is also a very little difference in the movement of the asymmetry measures depending on the currency used for the calculations.

The results of India show that even for a correlation of 0.707 the semblance analysis actually finds minimal differences in the asymmetry measures. In the case of India, a lower than average correlation can be caused by the difference in the extreme levels of the volatility asymmetry depending on the currencies, but the semblance analysis reveals that this does not in fact mean that an overall difference exists, not even for shorter time periods.

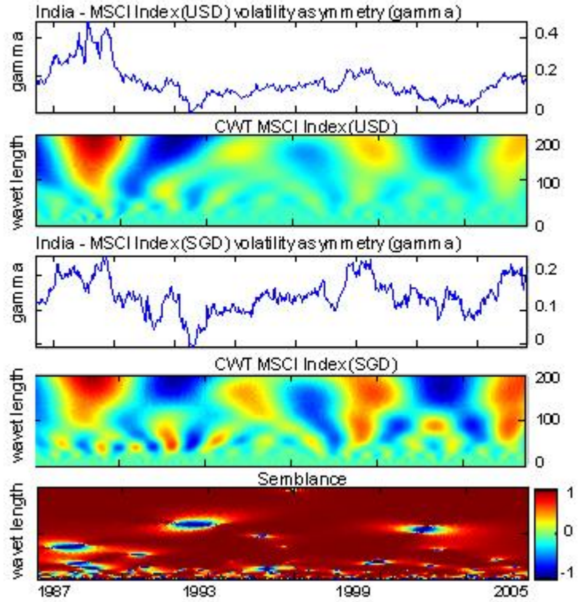

Fig. 3. Volatility asymmetry in India and semblance analysis results (CWT - continuous wavelet transform).

V. Conclusion

Estimating volatility asymmetry on 14 Asian stock markets with model input returns measured in the local currency or in the USD give us results to compare the obtained results to test whether currency exchange rate fluctuations have effect on volatility asymmetry of stock markets. The results are clear and all robustness checks confirm that the effect from the exchange rates to the equity market volatility asymmetry is minimal. Standard statistical tests do not find significant effect for any of the sample countries. Comparison of the obtained detailed volatility asymmetry time series enables to distinguish short periods when currency rates can affect equity market volatility asymmetry but even wavelet based semblance analysis does not enable to spot any significant effects from the currency rates. We conclude that volatility asymmetry of the sample stock markets is statistically not significantly nor economically significantly affected by currency exchange market. Current results and work could be extended by using even a larger sample of countries to conduct similar analysis on.

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