DISSERTATION
Number DBA07/2020

The Impact of the Introduction of FX Futures on the Volatility of the Underlying Asian Emerging Market Currencies

Submitted by

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Doctor of Business Administration in Finance Program

In partial fulfillment of the requirements

For the degree of Doctor of Business Administration in Finance

Sacred Heart University, Jack Welch College of Business and Technology

Fairfield, Connecticut

Date: July16, 2020

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Doctoral Dissertation Paper

The Impact of the Introduction of FX Futures on the Volatility of Underlying Asian Emerging Market Currencies

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Abstract: This paper examines the impact of the introduction of currency futures on the volatility of four Asian emerging market currencies: Chinese yuan, Indian rupee, South Korean won, and Thai baht. A GARCH(1,1) model is implemented to measure volatility in pre- and post- futures introduction periods along with an MCMC procedure to estimate the model and test the significance in changes in volatility between the periods. We find that for three of the four currencies, the persistence and long-run mean of volatility significantly decrease after futures were introduced, while the variance of variance decreases for all four currencies. The results suggest that the market for each currency becomes more efficient when futures are traded.

Keywords: currencies, futures, emerging market, volatility, GARCH, MCMC

This version: July 2, 2020

Dissertation Mentor: Walker K. Hughen, Ph.D.

1. Introduction

With high economic growth and increased volume in capital flows, the topic of emerging market stability has become ever popular. To help manage risks with foreign investment, including currency risk, derivatives have been introduced to these emerging market economies to put investors at ease. Derivatives serve many purposes in our financial systems such as risk management, speculation, reduced transaction costs, and regulatory arbitrage (McDonald, 2006). To this point, Kesara Manchusree, the Managing Director of the Thailand Futures Exchange (TFEX) stated at the time of introduction of currency futures: "this product will enhance trading opportunity and help managing foreign exchange rate risk" (Siddiqui, 2012). However, as emerging economies and markets are quite unstable and more susceptible to movements in currency, the introduction of new financial instruments is also met with much concern. Although introduced to help mitigate risks and further increase capital flows, futures, a quite transparent financial instrument, hold many unknowns when it comes to their impact on underlying assets.

Much research has been done regarding the impact futures have on underlying assets, but a single conclusion has not been reached. In particular, currency futures, have not been conclusively proven to impact underlying currency volatility in any particular way. One could theoretically argue that the introduction of derivative contracts, especially futures, would decrease the volatility of the underlying asset due to the improved completeness of information circulating through the market and the increase in market liquidity. Derivatives have many benefits for investors including lowering the costs of diversification and hedging, providing new and previously unattainable opportunities, reallocating risks, making markets more complete, and revealing more information to investors (Sill, 1997, p.15). However, one could also argue that the introduction of derivative contracts attracts uninformed investors to the market with their low transaction costs and minimal margin requirements, destabilizing the market with their incredibly leveraged investments. As stated by the IMF in 2002: "Also, due to their very nature (i.e. the fact they allow market participants to establish leveraged positions), derivative instruments tend to amplify volatility in asset markets" (p. 67). To date, empirical research has not been able to clarify as to which theoretical strain of literature holds. Empirical research has established varying conclusions: the introduction of derivative contracts may decrease, increase, or have no effect on the volatility of the underlying asset.

This paper extends previous research to examine the introduction of foreign exchange currency futures on four Asian emerging market currencies: the South Korean won (USD/KRW), the Indian rupee (USD/INR), the Thailand Baht (USD/THB) and the (deliverable) Chinese Yuan (USD/CNH). Further, this paper extends the scope of research to include evaluating and comparing underlying currency volatility (in pre- and post- futures introduction periods) using the GARCH model. Section 2 provides an overview of past empirical research regarding the effect of introducing future contracts on underlying assets. Section 3 describes the data sets used and methodology for calculating and comparing the volatility between the pre- and post-introduction periods. The results of our GARCH and MCMC model in determining changes in volatility between periods will be examined and discussed in Sections 4 and 5. Finally, Section 6 summarizes the main arguments and findings.

2. Literature Review

Since the growth in popularity of financial instruments called derivatives in the late 1900s, the impact of their introduction into markets has been a popular topic of interest. As derivatives serve many purposes in our financial systems such as risk management, speculation, reduced transaction costs, and regulatory arbitrage, it is no wonder the role of stabilization and, in turn, destabilization of underlying markets has become an ever-growing research topic (McDonald, 2006). Although a popular topic, there does not seem to be a consensus as to if the introduction of futures stabilizes, destabilizes, or has no effect on underlying markets. This is especially true for emerging markets and currency futures. The most popular of emerging markets studied is India, but even then, the results are not cohesive across studies. The following empirical works of literature examine the relationship between futures and underlying spot market volatility.

Okur, Cagil, and Kiran (2019) tested the impact of the introduction of stock index futures in Borsa Istanbul on the underlying spot markets. They gathered spot prices from both the BIST National 30 Index and the BIST National 100 Index for September 1, 2000, to June 30, 2010, and divided the data into four periods: pre-futures, post-futures, pre-crisis (2008 Global Financial Crisis) and post-crisis. An EGARCH(1,1) model with matched returns across the two indices was used to estimate volatility over the different periods. To test the impact of futures, a proxy variable, in this case the BIST National 100 Index, was used to "isolate price volatility specific to spot market related to the introduction of futures" (p. 67). They also included a dummy variable in the variance equation which took the value of 0 for pre-futures and pre-crisis periods and 1 otherwise. They then performed diagnostic testing on the squared residuals which indicated that there was no presence of ARCH effects left in the standardized residuals, confirming their use of an EGARCH model. To evaluate the impact of futures, they examined the results from the EGARCH(1,1) model of the four following parameters. First, the ARCH term (α_1) expresses the level of volatility or the level of response of the conditional variance to shocks. The larger this term, the larger the response. The symmetry variable (λ_1), which if positive implies that positive shocks/news generate less volatility than negative shocks and if negative implies that positive shocks generate more volatility than negative shocks. The GARCH term (β_1) expresses the persistence of conditional volatility in which a high β_1 denotes a persistence of volatility from old news. Finally, the dummy parameter (γ_1), which implies an overall increase (if positive) or decrease (if negative) of volatility due to the introduction of stock index futures. They found that the dummy parameter was negative and significant for all periods implying a decrease in volatility in the underlying spot market due to the introduction of futures. However, they also found that in the period post-futures trading, volatility persistence (β_1) increased. They believe this is due to a decrease in the ARCH parameter, or the "fall in the rate of flow of recent news" from the pre-futures to the post-futures period (p. 68).

Sakthivel, Chittedi, Sakyi, and Anand (2017) studied the effects of currency derivative trading on three spot exchange rates (GBP/INR, JPY/INR, and EURO/INR) for the 11 years between October 20, 2005, to October 30, 2016. Both a GARCH and GJR GARCH model were used to estimate volatility over both the pre- and post-introduction of currency futures periods. In the GARCH model, volatility is measured by the ARCH parameter which explains how previous news effects conditional volatility of the underlying spot. The GARCH parameter explains volatility persistence and a dummy variable is added to "explore the effect of currency futures trading on volatility of spot exchange rates" (p. 430). In the GJR GARCH model, a fourth parameter is added to evaluate symmetry. From the GARCH model, it was found that there was a reduction in the volatility of the spot exchange rates for JPY/INR and GBP/INR due to currency futures trading. This was deduced from the negative and statistically significant dummy variable. Contrastingly, they found an increase in volatility, or a positive and significant dummy variable, in the EURO/INR spot exchange rate. The GJR GARCH model returned a positive and significant coefficient of asymmetry in the presence of the dummy variable in the variance equation. Sakthivel et al suggest this combined negative and statistically significant dummy variables implies not only an asymmetric effect but that currency futures trading reduces volatility for JPY/INR and GBP/INR. Again, however, they find a positive and significant dummy variable for the EURO/INR spot exchange rate, suggesting an increase in volatility.

Singh and Tripathi (2016) examined the impact of the introduction of currency derivatives on exchange rate volatility of the Euro in terms of the Indian Rupee. Data was collected from the EURO/INR exchange rates for the sample period of April 2005 to March 2015. Using a GARCH(1,1) model, they found the presence of volatility over the entire data set. They then proceeded to implement a GARCH(1,1) model with a dummy variable – set equal to zero in the pre-derivative period and 1 in the post period. The results indicated a significant, negative impact on, or a decrease in, volatility in the post-derivative period. This was concluded due to the significant, negative dummy coefficient. Diagnostic testing on the GARCH model was done using Q statistics on the standardized residuals and an ARCH-LM test. The Q statistic results were insignificant and the ARCH-LM test showed no remaining ARCH effects in the residuals, confirming the use of the GARCH model.

Chiraz (2016) examined the relationship between futures on the CAC40 index and the French stock market (CAC40 Index) using the Markov-switching model over the period from January 3, 2000, to December 31, 2015. Through the use of a Markov-switching technique, Chiraz found four structural breaks in the data and consequently divided the data into five sub-periods to examine the changes in mean during those periods. Transition probabilities and expected durations are calculated through the use of EViews tools, and it was deduced that a high transition probability infers a strong effect of shocks by futures on the series price. A high transition probability was found in regime 1, which begins in 2000, but is found to be induced by multiple worldwide financial crises such as the dot-com bubble. The second regime, which spanned from January 4, 2004, to June 6, 2007, exhibited a lowered transition probability which implies a decrease in the "impact of futures on the variability of the underlying stock market" (p. 6). The third and fourth regimes are also low variability regimes, but the results are deemed insignificant. Finally, a large jump is seen in the switching transition probability and expected duration in the fifth regime, implying the effect of futures on the variability in CAC40 prices is more important in this regime. Although the effect is greater in the fifth regime, Chiraz states that "the effect of the impact of futures is significant but it is very small, the impact of the shock exists but is unsustainable" (p. 8). Chiraz concludes that the results are consistent with the hypothesis that the introduction of index futures stabilized the French stock market and that any high-variability periods are likely to be caused by other events, such as financial crises.

Oduncu (2011) explored the effect of the introduction of currency futures on the volatility of the underlying currency market in Turkey. A sample period of February 2002 to February 2008 was used – currency futures in Turkey were introduced in February of 2005. Oduncu analyzes volatility through the use of three models: a GARCH(1,1), a GARCH-M, and a GJR GARCH model. In each, a dummy variable that takes the value of 0 in the pre-futures period and 1 in the post-futures period, is included. The GARCH(1,1) model returned a negative and statistically significant dummy parameter which implies that the introduction of futures trading decreases the volatility of the underlying asset. The ARCH parameter was found to decrease from the pre-futures to the post-future period indicating that "in the presence of currency futures trading, 'old news' plays a smaller role in determining the volatility of the market" (p. 105). The GARCH-M and GJR GARCH modeled also returned negative and statistically significant dummy parameters but the GARCH-M model found an increase in the ARCH term while the GJR GARCH model found an increase in the asymmetric response of volatility to news.

Gulen and Mayhew (2000) investigated the differences in stock market volatility across 25 countries before and after the introduction of equity-index futures trading. To measure volatility in both pre-future and post-future introduction periods, a multiplicative dummy variable which takes the value of 0 in the pre-futures period and 1 in the post-futures period, is included in the GJR GARCH model. The GJR GARCH model returned a positive, statistically significant (5%

level) dummy parameter estimate for Japan and the USA. The results indicated a negative, statistically significant (5% level) dummy parameter for Australia, Austria, Belgium, Chile, Denmark, France, Germany, Hong Kong, Israel, Italy, Malaysia, the Netherlands, Norway, South Africa, Switzerland, and the UK. For the remaining 7 countries, no significance was found on the returned dummy parameter; in other words, no significant effect from futures introduction. To check the robustness of results, they repeated the analysis of the GJR GARCH model with the use of an additive dummy rather than a multiplicative dummy. They also ran a standard GARCH(1,1) model and an EGARCH model. They found that all of the models yielded similar results with the same basic conclusion that the introduction of futures decreases volatility, outside of the USA and Japan.

Jochum and Kodres (1998) studied the impact of the introduction of currency futures on the respective underlying currencies in Mexico, Brazil, and Hungary. To directly test the impact of futures introduction on the Mexican peso cash market, a SWARCH model is estimated to include a dummy variable which indicates the introduction of futures. The results yielded a statistically significant, negative dummy coefficient, as deduced by the returned standard error of the parameter. According to Jochum and Kodres, this indicates a reduction in the volatility of the Mexican peso due to futures introduction. Futures trading on both the Brazilian Bolsa and the Hungarian forint began before the sample period for this paper. So, to measure the impact of futures on the two currencies, the dummy variable in the SWARCH model used for the Mexican peso was replaced with a stationary measure of volume. The idea is that the level of trading activity serves as a proxy for the influence of the existing futures market. The volume dummy coefficient returned by the SWARCH model for both currencies was statistically insignificant and negative indicating no impact of the futures on the underlying spot currency.

3. Data and Methodology

3.1 Data Background

According to the IMF (2020), emerging market and developing economies make up 60.31% of global GDP. 58% (35.06% GDP contribution) of this is contributed by emerging and developing Asian economies (Figure 1). This high global contribution, along with their rapid growth, motivated the choosing and examination of Asian markets – specifically India, South Korea, China (Hong Kong), and Thailand – for this paper. The particular impact of currency futures effect on underlying currency volatility concerning multiple emerging economies is slim, but the implications are grand. As previously mentioned, the stability of currencies is especially important in emerging economies. “While the potentially destabilizing influence of futures markets has considerable interest in mature markets, the issue of excess fluctuations is even more important for emerging markets where the currencies are more vulnerable to sources of excess volatility and instability and the authorities tend to try to smooth out fluctuations” (Jochum & Kodres, 1998).

3.2 Data Description

The data used in this paper consists of daily closing spot exchange rates obtained from Bloomberg for the South Korean won (USD/KRW), the Indian rupee (USD/INR), the Thailand Baht (USD/THB) and the (deliverable) Chinese Yuan (USD/CNH). The beginning dates of the sample periods range from January 2, 1989, to August 23, 2010. All sample periods end November 8, 2019; thus, the shortest sample period in our study is a little over 20 years (USD/CNH) while the longest is almost 31 years (KRW). Futures contracts on the currencies began trading as early as 1999 and as late as 2012. As shown in Table 1, futures were introduced April 23, 1999 for USD/KRW; August 29, 2008 for USD/INR; June 5, 2012 for USD/THB; and September 17, 2012 for USD/CNH.

As explained below, the difference between the daily interest rate in the US and the considered country is used as a control variable in the implementation of the GARCH(1,1) model. However, South Korea did not adopt a policy rate until May of 1999, after intervention from the IMF following the 1997 Asian financial crisis; because futures did not begin trading until April 23, 1999, we were not able to include interest rate data for USD/KRW. Daily interest rates referenced for each country include the Effective Federal Funds Rate from Federal Reserve Economic Data (FRED) for the United States (USD), the HKBASE Index from Bloomberg for Hong Kong (CNH), the BISPDHIN Index from Bloomberg for India (INR) and the BTRRHALL Index from Bloomberg for Thailand (THB).

3.3 Methodology

The methods used in this paper include a unit root test (Augmented Dickey-Fuller) to check for stationarity of each data set, the GARCH(1,1) model to compute the volatility parameters in each pre- and post- period in the data sets and the Markov Chain Monte Carlo (MCMC) method to check for statistical significance of the changes in volatility parameters.

3.3.1 GARCH Model & MCMC Method

In 1986, Bollerslev proposed a generalization of the ARCH process introduced by Engle in 1982. The ARCH process, which models variance, allows for conditional variance, as a function of past errors, to change over time. The generalized autoregressive conditional heteroskedasticity (GARCH) process adds on the ARCH process by enabling lagged conditional variances. An important characteristic of the GARCH model is that it takes into consideration the phenomenon of volatility clustering. This is the idea that large swings or changes in volatility are followed by more large changes and small changes are followed by more small changes.

As referenced by Berkes et. al (2003), the GARCH(p,q) model is defined by the following equations:

$$R_t = \mu_{t-1} + \sigma_t \varepsilon_t \tag{1}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \sigma_{t-i}^2 \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{2}$$

where R_t is the return from time $t-1$ to t, μ_{t-1} is the conditional mean, and σ_t^2 is the conditional variance. To guarantee the conditional variance series remains positive the following conditions for the constants are imposed:

$$\omega > 0, \qquad \alpha_i \geq 0, \qquad \beta_j \geq 0. \tag{3}$$

The innovation sequence $\{\varepsilon_i\}_{i=-\infty}^{\infty}$ is assumed to be independent and identically distributed with zero mean and unit variance.

Following common practice and for tractability reasons, we focus on the GARCH(1,1) process. In this case, the conditional variance equation (2) may be rewritten:

$$\sigma_t^2 = \omega + \ \alpha\sigma_{t-1}^2 \varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 = \omega + (\alpha + \beta)\sigma_{t-1}^2 + \alpha\sigma_{t-1}^2(\varepsilon_{t-1}^2 - 1) \tag{4}$$

so that σ_t^2 is the sum of a constant term, an autoregressive term, and a zero-mean shock. In particular, $\rho := \alpha + \beta$ measures the degree of persistence of conditional variance and the variable $\kappa := 1 - \rho$ determines the speed at which conditional variance reverts to its long-run mean $V_L := \omega/\kappa$. This is made more obvious by rearranging (4) further to obtain:

$$\begin{aligned}\sigma_t^2 - \sigma_{t-1}^2 &= \omega + (\alpha + \beta - 1)\sigma_{t-1}^2 + \alpha\sigma_{t-1}^2(\varepsilon_{t-1}^2 - 1) \\ &= \kappa(V_L - \sigma_{t-1}^2) + \alpha\sigma_{t-1}^2(\varepsilon_{t-1}^2 - 1)\end{aligned} \tag{5}$$

Furthermore, the conditional variance of σ_t^2, also known as variance of variance, $VoV_{t-2} := Var_{t-2}(\sigma_t^2)$, is proportional to α^2:

$$VoV_{t-2} = Var_{t-2}(\sigma_t^2) = \alpha^2\sigma_{t-1}^4(E[\varepsilon_{t-1}^4] - 1) \tag{6}$$

In our empirical implementation, we follow common practice and assume the innovation terms are normally distributed so that the variance of variance is $VoV_t = 2\alpha^2\sigma_{t+1}^4$.

The aim of this study is to examine whether futures trading has an effect on the volatility of the underlying currency. One way to do this is to estimate the GARCH model separately on two periods, the period before futures introduction (the “pre-period”) and the period after futures introduction (the “post-period”), and then statistically compare the parameter estimates before and after futures were introduced. However, this method reduces the sample size which is likely to reduce the precision of the parameter estimates. Also, the two periods may have different lengths which might further complicate the statistical comparisons.

Instead, we propose to test whether the properties of the volatility series change after futures introduction by including dummy variables in the variance equation:

$$\sigma_t^2 = \omega + \omega_0 D_t + (\alpha + \alpha_0 D_t)\sigma_{t-1}^2\varepsilon_{t-1}^2 + (\beta + \beta_0 D_t)\sigma_{t-1}^2 \tag{7}$$

where D_t is a dummy variable that equals 0 in the pre-period and 1 in the post-period. A negative (or positive) ω_0, for example, indicates the constant term decreased (or increased) after futures were introduced. For a given currency, (7) is estimated using the entire sample period. We then examine and compare the persistence parameter ρ, the long-run mean V_L, and the variance of variance VoV (by comparing α^2) before and after futures introduction.

GARCH models are typically estimated by maximizing the log-likelihood function. With Gaussian innovation terms, the log-likelihood function is straightforward:

$$llf(\Theta) = -\left(\frac{T}{2}\right)\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\ln(\sigma_t^2) - \frac{1}{2}\sum_{t=1}^{T}\frac{(R_t - \mu_{t-1})^2}{\sigma_t^2} \tag{8}$$

where Θ is the parameter vector. In our case, there are six parameters in the conditional variance equation, and as explained below, we include two more in the mean equation (i.e., the conditional mean μ_t contains two additional parameters). Thus, the log-likelihood function must be maximized over an 8-dimensional space, which is large enough to cause potential problems in many optimization algorithms.

Instead, we use a Monte Carlo Markov Chain (MCMC) procedure to estimate the model. MCMC is an iterative procedure that produces a series of draws from the posterior distributions of the parameters. The procedure avoids many of the pitfalls of optimization algorithms. For each set of parameter draws, the log-likelihood function is computed and parameter point estimates are defined to be the set that produces the largest log-likelihood value. Furthermore, the procedure produces the entire distribution of the parameters, enabling straight-forward testing of statistically significant differences between the pre-period and post-period volatility series.

It remains to specify the conditional mean μ_t. Ideally, the conditional mean would include any exogenous variables that have been shown to affect exchange rates, to control for the factors besides futures trading that could affect volatility in our analysis. Such variables include inflation rates, interest rates, political stability, economic performance, etc. Many of these variables are not available at high frequency, while accurate estimates of volatility require daily or even higher frequency. The only variable in the above list that is available at daily frequency is interest rate. Thus, we include in the mean equation a constant and the interest rate differential ΔIR_t between the U.S. and the given country:

$$R_{t+1} = c + b\Delta IR_t + \sigma_{t+1}\varepsilon_{t+1} \tag{9}$$

This allows us to control for the impact of interest rates in our analysis, a variable that may also affect exchange rate volatility.

4. Results

Descriptive statistics for the returns of USD/KRW, USD/INR, USD/THB, and USD/CNH are given in Table 1. Descriptive statistics are taken for three distinct periods: overall (entire data set), pre-futures introduction, and post-futures introduction. The mean return of the THB is negative for both pre- and post- periods in our sample while the mean returns of KRW, INR, and CNH are positive. The return standard deviation is lower post-futures for KRW and THB but is higher for INR and CNH. All returns display little skewness, with the exception of KRW on the period before futures were introduced; on the other hand, all returns are highly leptokurtic with kurtosis ranging from about 12 for INR to over 126 for KRW. Interestingly, kurtosis decreases greatly after futures were introduced for all returns but CNH. For example, the kurtosis of KRW decreased from 119 before futures to 52 after futures were introduced, a decline of almost 60%. Similarly, the kurtosis of THB declined almost 60% and the kurtosis of INR declined about 50%. To confirm data stationarity, an Augmented Dickey-Fuller (ADF) test is conducted on the currency spot prices. The results from the ADF tests are reported in Table 3. While the INR, THB, and CNH are non-stationary at level form, the returns on all four currency data sets are stationary at 1% level of significance.

Although the impact of futures trading on unconditional return standard deviations is mixed – for KRW and THB the unconditional standard deviation is greater after futures were introduced but for INR and CNH it is the other way around, the kurtosis is greatly affected for all but CNH. This suggests that futures trading might impact conditional standard deviation. To examine whether this is the case, the GARCH(1,1) model (Eq. 7) with mean equation (Eq. 9) was estimated using the MCMC procedure described above. A total of 1.1 million draws were obtained and the first 100,000 draws were discarded to help negate the effects of the arbitrarily chosen initial values, and, furthermore, only every 10th draw was kept to help reduce the dependency on previous draws. This resulted in 100,000 posterior draws of each parameter. The point estimates are the parameter values that produce the largest likelihood function value (Eq. 8) for the posterior draws.[1]

The results are presented in **Error! Reference source not found.**, which shows for each currency the estimates of the conditional volatility parameters (ω, α, and β) on the pre-futures and post-futures periods and the estimates of the conditional mean parameters (c and b). As seen in the table, the constant term ω increases, the ARCH term α decreases, and the GARCH term β increases for all the currencies, with the exception of THB, after futures were introduced. For THB, the GARCH term decreases slightly after futures were introduced. Overall, the results suggest that today's conditional volatility is less sensitive to yesterday's news and is more sensitive to yesterday's variance for the post-futures period compared with the pre-futures period. Equation (4), however, makes clear that because the ARCH term measures the sensitivity to the squared shock, the correct measure of persistence of conditional variance is $\rho = \alpha + \beta$. If $\rho < 1$, then the long-run average variance, or unconditional variance, is given by $V_L = \omega/(1-\rho)$. Of course, if $\rho \geq 1$, then GARCH variance is non-stationary and the long-run mean V_L is not defined.

The point estimates of the persistence parameter ρ and the long-run mean volatility (annualized) $\sqrt{V_L}$ are presented in Table 5 for both the pre-futures and post-futures periods. Interestingly, for KRW and CNH the conditional variances are non-stationary in the pre-futures period while they are both stationary in the post-futures period. Similarly, the conditional

[1] We also used a standard optimization routine to find the optimal parameters. The results were almost identical—in fact, a tad worse--to the results of the MCMC procedure.

variance of THB is much less persistent after futures were introduced. On the other hand, the conditional variance of INR becomes slightly more persistent. Because conditional variance is non-stationary for KRW and CNH, the long-run mean volatility is not defined in the pre-futures period. For THB, the long-run mean volatility decreases from 6.8% before futures to 4.8% after futures were introduced. The odd one out is again INR, for which the long-run mean increases from 5.4% to 7.7% after futures were introduced.

To test whether the persistence parameter and long-run mean volatility (when defined) are significantly distinct over the two periods, the percentage of draws for which ρ (or $\sqrt{V_L}$) decreased after futures were introduced was computed. If the percentage of draws is greater than $P\%$, then we are at least $P\%$ confident that conditional variance is less persistent (or has lower long-run volatility) after futures began trading. In other words, we can reject, with confidence $P\%$, the null hypothesis that the persistence (or long-run mean) of conditional variance of the underlying currency return does not decrease after the introduction of currency futures.

With the data samples for KRW, THB, and CNH used in this study, we are at least 95% confident that conditional variance is less persistent after futures introduction. We are 99% confident that the long-run mean volatility of KRW is lower after futures introduction. In addition, the variance of variance parameter $2\alpha^2$ decreases for all four currencies. The decrease is marginal for THB and is not statistically significant, but is highly significant for KRW, INR, and CNH.

5. Discussion

We interpret these results as evidence to support the notion that the market for each currency becomes more efficient when futures are traded. Volatility and market efficiency are intertwined. The conditional variance persistence (ρ) determines how long it will take for the shock of news to dissipate in our markets. In an efficient market, we assume that all news and information is already considered and reflected in prices. The more efficient the market, the less time it should take for the shock to dissipate. In other words, the more efficient the underlying market, the lower the conditional variance persistence parameter. Similarly, a decrease in the long-run mean volatility ($\sqrt{V_L}$) implies an increase in market efficiency. In a high volatility environment, "prices will change by more than the value of the new information" implying an inefficient market (Engel and Morris, p. 26). The lower the long-run volatility, the less deviation from fundamental future values implied by an efficient market. A decrease in long-run volatility can also suggest an increase in the speed (κ) at which conditional variance reverts to its long-run mean; put differently, the speed at which any movement away from a base level of conditional variance is eliminated. In an efficient market, prices should react quickly and accurately to news shocks. The variance of variance can be thought of as the measure of sensitivity of the variance to shocks (Ishida & Engle, p.4). In an efficient market where all information is already reflected, the shocks of news should have slight impacts to variance. Therefore, the sensitivity to these shocks should also be slight. The more efficient the market, the less of a reaction to shocks.

[Segway into why India is different…]

Prior to 1991, India had a highly restrictive exchange control regime in which the rupee was not convertible for foreign investors. India initiated economic capital flow reforms in the early 1990s, but it has been a gradual and often interrupted process. In 2006, India began its 5-year process to shift to Fuller Capital Account Convertibility (FCAC) (Prabhakaran Nair & Prakash, p. 233). This enabled capital flows to be converted into foreign capital, albeit with multiple controls still in place. According to Arora, Rathinam, and Khan, "because of the increased openness of Indian economy in the past two decade, the financial crisis spilled over to India through financial as well as real channels" (p. 807).

In our results, we see the conditional variance of INR becomes slightly more persistent and the long-run mean volatility increases from 5.4% to 7.7% after futures while all other currencies saw a reduction. This significant difference in results may have been due to the timing of the introduction of currency futures in India. India introduced currency futures on August 29, 2008 – in the midst of the Global Financial Crisis. A large economic boom occurred in India in the years leading up to the Global Financial Crisis; as a result of the FCAC measures, Indian companies saw extreme growth and expansion. However, the under-developed stock market in India was still dominated by a few traded companies and a few major investors, including foreign institutional investors (FIIs). According to Ghosh and Chandrasekhar, these FIIs quickly realized they held extreme, manipulative power in the market; "This implicit manipulation of the market, if resorted to often enough, obviously generates a substantial increase in volatility" (p. 732). This increase in FII investment lead to an inflation in asset prices, an increase in underlying market volatility, and an appreciation of the rupee before the Global Financial Crisis. However, this four-year bull market did not last.

Because of the crisis, there was a large outflow of FII investment from India by investors looking to stabilize their investments. This created not only a large panic in Indian markets but also a sharp depreciation in the Indian rupee by more than 30% (Ghosh and Chandrasekhar, p. 732). The depreciation of the INR against the USD resulted from increased demand for USD by investors. The combination of long-term loss of investors with the significant impact of news on the underdeveloped market resulting in the sudden depreciation of the rupee could explain why the conditional variance persistence and the long-run mean volatility of the INR increased in the post-futures introduction period.

6. Conclusions

This paper aims to investigate the impact of currency futures introduction on the volatility of the underlying currency. More specifically, the paper empirically tests whether the introduction of currency futures shows a significant change in the underlying currency volatility of four Asian emerging markets: Hong Kong, India, South Korea, and Thailand.

The volatility in each pre- and post-futures introduction period was examined through the use of a GARCH(1,1) model that allows a regime shift upon futures introduction. From our data we find a statistically significant decrease in conditional variance persistence after futures introduction for KRW, THB, and CNH. We also find a statistically significant decrease in the long-run mean volatility of KRW; for THB and CNH the conditional variance is non-stationary in the pre-futures period but is stationary in the post-futures period. For all four currencies, we find a decrease in the variance of variance parameter – statistically significant for all but THB. The results indicated that the introduction of futures on each underlying currency market has made the market more efficient. The outlier from the results is the Indian rupee (USD/INR), which displays an increase in both conditional variance and long-run mean volatility but, as mentioned above, does display a statistically significant decrease in the volatility of volatility parameter.

The paper aims to add not only the general literature on the impact of derivative contracts on underlying assets but more specifically, to the set of studies on emerging markets and currency derivatives to help complete a more robust picture of the impact of derivatives on our societies.

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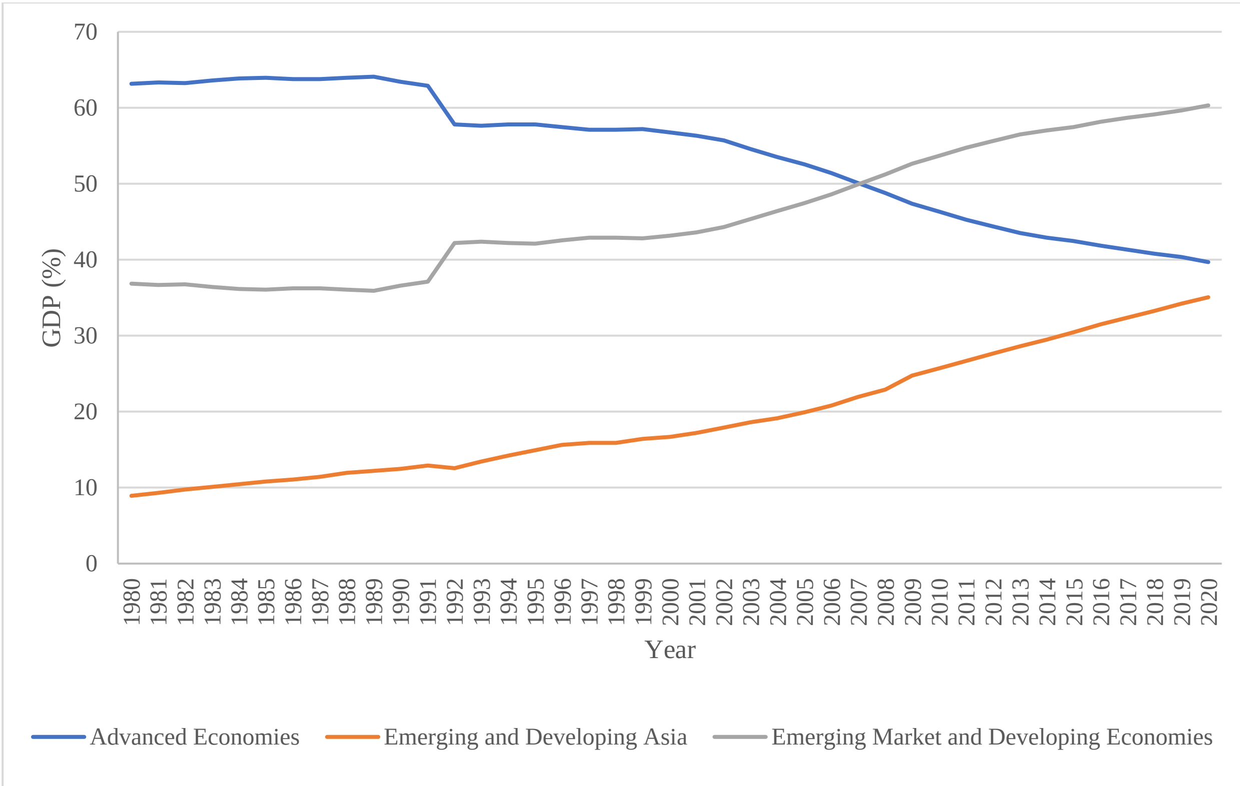

Figure 1. GDP vs. Year (for Advanced Economies, Emerging and Developing Asian Economies and Emerging Market and Developing Economies)

Table 1. Data Periods

Currency	**Data Period**	**Futures Date**	**Obs. Pre-**	**Obs. Post-**
USD/KRW	1/2/1989-11/8/2019	4/23/1999	2,689	5,260
USD/INR	1/1/1998-11/8/2019	8/29/2008	2,768	2,699
USD/THB	1/3/2000-11/8/2019	6/5/2012	3,241	1,866
USD/CNH	8/23/2010-11/8/2019	9/17/2012	538	1,864

The data period used for each currency, the date when futures were introduced, and the number of daily observations before and after the introduction of respective currency futures.

Table 2. Descriptive Statistics

Currency	Mean	Std. Dev.	Skewness	Kurtosis	J-B Test
			Overall		
USD/KRW	9.67E-05	0.007910	1.572125	126.7631	5077129
USD/INR	0.000117	0.003891	0.286652	12.39165	20170.49
USD/THB	-3.37E-05	0.003176	0.317830	13.22121	22321.36
USD/CNH	1.89E-05	0.002333	0.574222	17.39751	20886.79
			Pre-Futures		
USD/KRW	0.000257	0.010211	2.208437	118.8543	1505474
USD/INR	4.25E-05	0.002428	-0.005377	16.86234	22154.97
USD/THB	-4.36E-05	0.003325	0.504205	15.26325	20439.55
USD/CNH	-0.000114	0.001820	1.189505	14.98090	3338.388
			Post-Futures		
USD/KRW	1.60E-05	0.006424	-0.153780	52.38216	534480.1
USD/INR	0.000190	0.004961	0.247331	8.496426	3424.962
USD/THB	-1.51E-05	0.002900	-0.169525	6.321167	866.5322
USD/CNH	5.64E-05	0.002461	0.471992	16.82085	14904.78

Table 3. Unit Root Test Summary Results

Currency	ADF (Level)	ADF (1st Difference)
USD/KRW	-3.4561**	-12.9303***
USD/INR	-1.4550	-30.3720***
USD/THB	-1.9895	-70.1014***
USD/CNH	-1.0255	-48.5320***

*** indicates significance at a 1% level
** indicates significance at a 5% level

Table 4. GARCH(1,1) Model Estimates

	KRW	**INR**	**THB**	**CNH**
$c \times 10^5$	9.668	17.273*	-10.605***	74.965**
b		0.776	-0.349	51.687**
		Pre-Futures		
$\omega \times 10^7$	3.580***	3.020***	2.379***	1.183***
α	0.208***	0.255***	0.127***	0.238***
β	0.797***	0.719***	0.860***	0.763***
		Post-Futures		
$\omega \times 10^7$	3.699***	3.203***	5.908***	3.655***
α	0.075***	0.073***	0.116***	0.089***
β	0.913***	0.914***	0.819***	0.856***
llf	32549.3	23946.0	22038.3	11162.4
LR	113.3***	100.8***	14.0***	99.2***

*** indicates significance at 1% level ; ** indicates significance at 5% level
llf denotes the log-likelihood function
LR is the likelihood ratio statistic to test whether the regime switch variables are jointly significant.

Table 5. GARCH(1,1) Model Analytics

	KRW	**INR**	**THB**	**CNH**
		Pre-Futures		
persistence (ρ)	1.005	0.974	0.987	1.000
long-run mean $\left(\sqrt{V_L}\right)$	N/A	0.054	0.068	N/A
var of var $(2\alpha^2)$	0.087	0.130	0.032	0.113
		Post-Futures		
persistence (ρ)	0.989**	0.987	0.935***	0.945**
long-run mean $\left(\sqrt{V_L}\right)$	0.091	0.077	0.048***	0.041
var of var $(2\alpha^2)$	0.011***	0.011***	0.027	0.016***

*** indicates significant difference at 1% level between pre- and post-futures periods
** indicates significant difference at 5% level between pre- and post-futures periods