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Abstract

This paper estimates switching autoregressive conditional heteroskedasticity (SWARCH) time series models for weekly returns of nine Asian forward exchange rates. We find two regimes with different volatility levels, whereby each regime displays considerable persistence. Our analysis provides evidence that the knock-on effects from China's currency forwards markets upon other Asian countries have been modest, in that little evidence exists for co-dependence of volatility regimes.

Keywords: China, Renminbi, Asia, Forward Exchange Rates, Non-Deliverable Forward Market, SWARCH Models

JEL Classification: C22, F31, F36

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1. Introduction and Purpose of the Study

The financial turmoil in the Asia-Pacific region in the 1990s has sparked intense interest in the ongoing international financial integration and the co-movements between foreign exchange markets. Market participants have fretted that spillovers into other economies might amplify volatility in world financial markets. In particular, the impact of China's phenomenal economic growth is being felt around the world as the country establishes itself as a driver of global economic trends mainly in terms of exports and imports and FDI flows. With more than two decades of market-oriented reforms, China has become an international production hub which combines a vast supply of cheap labour with an economy that is unusually open by international standards. China's trade openness is illustrated by the fact that its total exports and imports expressed in terms of GDP reached 75 percent in 2004, while the equivalent figures for Brazil and India resided around the 25-30 percent mark. As a result global trade patterns and production structures in the rest of the world are forced to adjust to accommodate such sweeping changes.

As China is unusually open to trade, China's development is not just a driver of global growth, its also exerts a profound impact on other Asian economies. Whereas twenty years ago the rest of the world may not have been unduly concerned if China's growth faltered, today it would be a very different story. Advanced economies are concerned about a hollowing out of their manufacturing industries, and neighbouring Asian countries are even more exposed given their close geographical proximity. In recent years this development has been spurred by the unbundling and offshoring of production processes. Indeed, Greenaway *et al*. (2008) have demonstrated by means of a gravity modelling framework that China´s sustained export growth has displaced other Asian countries´ exports in third markets. They also note that trade links between China and Asian countries have strengthened considerably over the sample period 1990 – 2003.

On July 21, 2005, after more than a decade of pegging the renminbi to the U.S. dollar at an exchange rate of 8.28, the People´s Bank of China (PBOC) announced a revaluation of the currency and a reform of the exchange rate regime. As a result of this reform, the PBOC now manages the renminbi against an undisclosed basket of currencies of the main trading partners. Greater flexibility in China's exchange rate is viewed as an essential element of a global response to the existing macroeconomic imbalances in the world economy.[1]

In light of this, the Chinese currency's future path, as well as in co-movements across Asian currencies, has been under rigorous scrutiny not only from academic economists but also from institutional investors in recent times. Such scrutiny is all the more pertinent for those interested in the economic performance

1 The announcement and subsequent clarifications leave the Chinese central bank with considerable discretion over its renminbi target.

of China's Asian trading partners - not only are they weighted significantly in China's trade-weighted index, but China is also an important trade partner for them. As a consequence, the PBOC´s exchange rate policy is likely to influence the path of many Asian currencies. Indeed, Ho *et al*. (2005) and McKinnon (2005) have recently predicted an increasing orientation of East Asian countries´ exchange rate policies towards that of China in an effort to retain competitiveness against China. The sheer size of the Chinese economy will ensure that the renminbi plays an increasingly central role in East Asia and may lead to the renminbi acting as an anchor currency in East Asia – a view commonly referred to as the Chinese dominance hypothesis. Such a state of affairs raises the question of exactly how integrated are Asia´s exchange rate markets. Our analysis aims to shed light on this very issue.

An important feature of many Asian countries is that onshore forward exchange rate markets do not exist. We circumvent this problem by using both onshore and offshore non-deliverable forward (NDF) exchange rates to provide insights into the following four issues:

(1) Are the forward exchange rates under consideration characterised by regime switching and how many states can be identified?
(2) How common are low versus high volatility regimes and how persistent are the regimes?
(3) Is there evidence of temporal conformity of the low versus high volatility states across countries?
(4) Financial markets have steadily become more open to foreign investors and risk premia are increasingly determined globally. We therefore examine which countries show volatility co-movements and dependencies, especially in periods of market stress. Thus we delve into the question of how and to what extent the volatility of Asian currencies is affected by the renminbi exchange rate developments.

Th paper is laid out as follows: Section 2 describes the dataset used and establishes a set of stylised facts. Section 3 provides a brief sketch of the background of ARCH models whose conditional variance "jumps" between regimes. Section 4 presents the empirical results and discusses the performance of the various models. Section 5 investigates several potential determinants of the magnitude of co-movements across countries. Section 6 summarizes the main findings of this study.

2. Data Description and Preliminary Data Analysis

Our empirical investigation is built upon an analysis of forward exchange rates, but with a number of novel considerations included. We first present the dataset employed in our study, highlighting the main features of the markets for NDFs in Asian currencies. Unfortunately, several emerging market economies restrict the access of foreign firms and international investors to onshore financial markets and therefore forward markets either do not exist or are underdeveloped. Since the early 1990s, however, some international banks have been offering an offshore, over-the-counter market in NDFs for many emerging-market currencies, Chinese renminbi included.

In order to analyse comovements across Chinese and Asian forward exchange rates, we use weekly returns of U.S. dollar forward exchange rates for nine Asian countries which can be classified as follows: (1) China, (2) the "mature Tigers" (Hong Kong, Korea, Singapore and Taiwan), (3) the "new Tigers" (Indonesia, Malaysia, Philippines) and (4) Japan. The dataset therefore includes those countries which experienced the greatest extent of economic and financial turmoil during the Asian crisis 1997-98. Our dataset includes onshore and offshore forward exchange rates with three- and twelve- months maturities. Considering that the NDF markets began trading in full scale in 1997, our sample starts in 1998 and covers the period from 1 January 1998 to 21 February 2008 (530 weekly observations).[2] The country coverage is given in Table 1.

As with standard forward contracts, NDFs involve the fixing of exchange rates for conversion on a future date. However, unlike forward contracts, there is no delivery of underlying foreign currency. Instead, the net U.S. dollar is settled with a compensating payment made or due based upon the difference between the NDF contract rate and the exchange rate prevailing at maturity. Effectively, the NDF user is financially protected from exchange rate fluctuations by the compensating U.S. dollar payment paid or received based upon the NDF fixed rate even though there is no exchange of foreign currency. As distinct from standard deliverable forwards, NDFs trade offshore, i.e. outside the jurisdiction of the authorities of the corresponding currency.[3]

Figure 1 tracks the three- and twelve-month renminbi NDF exchange rates against the U.S. dollar over the sample period and therefore portrays the ebb and flows of economic expectations.

Given that it is centered on the old peg of 8.28 renminbi per dollar, the Figure shows that prior to mid-2002 the renminbi was under pressure to depreciate in the wake of the Asian financial crisis. Since late 2002 or early 2003, this entrenched negative sentiment towards the renminbi has been outweighed by expectations regarding longer-term appreciation of the reniminbi. Moreover, at the end of July 21, 2005, the day of the announcement of the PBOC, three-month NDF rates dropped below 8 renminbi per dollar, anticipating further appreciation of the renminbi-dollar exchange rate. Although it would be misleading to

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2 Following the SWARCH literature, our dataset comprises weekly return observations. The choice of weekly instead of daily data avoids timing pitfalls and mitigates the potential bias upon statistical inference induced by infrequent and/or nonsynchronous trading as suggested by Harvey (1995).

3 Active and growing NDF markets exist for several Asian currencies. An analysis of Asian NDF markets in general as well as the basic institutional features of the renminbi NDF market in particular is provided by Fung *et al*. (2004) and Ma *et al*. (2004). Ma *et al*. (2004) show that the Asian NDF markets have deepened over recent years. Turnover is highest on the Korean won market, the Taiwan dollar market and the Chinese renminbi, but the other more shallow markets have also deepened recently. Renminbi NDFs with the U.S. dollar, for example, have a daily trading volume of about U.S. dollar 150 to U.S. dollar 600 million. This suggests that the level of market liquidity is sufficient for fluctuations in NDF prices to serve as a meaningful indicator of the market's belief about the future path of the renminbi against the U.S dollar.

read NDF rates as a prediction of a currency's future path, they do provide valuable information about the sentiment of the participants in the market.[4]

In order to inspect the data in more detail, Figure 2 displays the various weekly return series for 3-months and 1-year maturity. A few general observations are in order: first, the graphs clearly demonstrate that volatility often increases substantially over a short period of time at the onset of a high-volatility period. These turbulent periods may indicate an overreaction to news, possibly due to a prevailing panic-like mood, or changes in agents´ expectations about the future. Second, as one would expect, in most countries the one-year contracts are characterised by higher volatility than the three-months contracts. Third, the existence of at least two regimes is clear from even a casual inspection of the graphs.

As a useful next step in our analysis, some stylised facts for each of the series are provided in Table 2 and Table 3. Over the entire sample period returns exhibit substantial non-normality, as can be seen from the skewness, kurtosis, and *JB* statistics. This departure from normality stems for the most part from excess kurtosis. Thus, the distributions are characterised more by fat tails than by asymmetry. Moreover, as indicated by the *LB* statistics, autocorrelation is low or insignificant, while the autocorrelation of the squared return series reveals strong volatility clustering. Also noteworthy is the fact that for many countries Hansen´s likelihood ratio *H*-statistic rejects the null hypothesis of no regime switching, indicating the existence of at least two regimes with different volatility levels.

These properties suggest using a flexible modelling framework which allows for serial correlation in the conditional variances as well as structural breaks. given the features of the data, we pursue the SWARCH avenue of investigation to add power to the analysis. We now consider this methodology in greater detail.

3. The SWARCH Modelling Framework

In this paper we model the volatility of exchange rates as a stochastic process whose conditional variance is subject to shifts in regime. In particular, we employ switching ARCH models, known as SWARCH models, pioneered by Hamilton and Susmel (1994) and Cai (1994) which allow statistical inference of breaks with minimal restrictions on the underlying data generating process. These contributions have paved the way for the introduction of a host of further models and have proved to be a catalyst for further research. Edwards and Susmel (2003) have extended the original model to the multivariate case while

4 The forward rate incorporates both expectations about the expected future spot rate, and a currency risk premium. Systematic forward rate prediction errors may arise from peso problems and rational learning about the environment. Using data from 1996 – 2004, Frankel and Poonawala (2006) have recently demonstrated that in emerging markets the forward discount bias is smaller than in advanced economies. Given the high riskiness of emerging currencies, this empirical finding indicates that the source of the forward discount bias may not be ascribed entirely to the risk premium.

Susmel (2000) has generalised the original SWARCH model by introducing the exponential SWARCH or E-SWARCH model.[5]

The SWARCH modelling framework combines the ARCH modelling framework with the Markov-switching model. ARCH effects are included because they are usually found in financial series and, if ignored, might cause inefficient estimation of transition probabilities. On the other hand, the omission of switching parameters may cause an upward bias in the measure of the persistence of shocks in single-regime ARCH models.[6] In sum, SWARCH models contain two channels of volatility persistence, namely persistence due to shocks and persistence due to regime switching in the parameters of the variance process.[7] More specifically, we postulate the following univariate SWARCH (k,q) model of returns, r_t:

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \varepsilon_t \qquad \varepsilon_t \mid I_{t-1} \sim D\ (0, h_t) \tag{1}$$

$$\frac{h_t}{\gamma_{s_t}} = \beta_0 + \sum_{i=1}^{q} \beta_i \frac{\varepsilon_{t-i}^2}{\gamma_{s_{t-i}}} \qquad i = 1, 2, ..., q \text{ and } s_t = 1, 2, ..., k \tag{2}$$

where q gives the order of the ARCH model, k is the number of regimes and the γ's are scale parameters that capture the change in regime. One of the γ's is unidentified and hence γ_1 for the regime with the lower volatility is arbitrarily normalised to 1. A sudden change to a turbulent regime with $\gamma_2 > 1$, will increase the constant and the weights on past news. The appropriate number of states remains an empirical question. Contrary to Kaufmann and Scheicher (2006), we do not restrict the investigation to the case of normally distributed error terms. As a conditional distribution, D, the normal and the Student t-test distributions are used, which we subsequently denote as N-SWARCH and t-SWARCH, respectively.

An important feature of (1) and (2) is that the parameters of the mean equation are constant across regimes, while the variances are state-dependent and changing across regimes. A particularly appealing feature of the model is that it allows us to date tranquil regimes versus periods of turmoil and therefore

[5] Alternatively, Kallberg *et al*. (2005) have used the non-parametric method of Bai *et al*. (1998) to draw statistical inference about regime breaks in six Asian (spot) currency and equity markets (Indonesia, Malaysia, the Philippines, South Korea, Taiwan and Thailand). Independent of this stream of research, Andreou and Ghysels (2002) and Otranto and Gallo (2002) have proposed various tests for structural breaks in the conditional variance dynamics, and these often indicate multiple structural breaks in asset returns.

[6] Lamoureux and Lastrapes (1990) have shown that high persistence in the conditional variance may be spurious in the presence of any structural change. In the SWARCH framework, a shock can be followed by a volatile period not only because of ARCH effects, but also because of the switch to the higher variance regime. This epitomises the “pressure-relieving” effect of the SWARCH set-up.

[7] Diebold (1986) appears to have been the first to argue along these lines. The SWARCH literature has led to a substantial literature with different methodologies, scope and results. Ramchand and Susmel (1998) have investigated international stock market comovements over time according to switching ARCH (SWARCH) processes. They found that the two-state SWARCH model has a higher explanatory power than the run-of-the -mill time-varying GARCH(1,1) approach. Other applications of the SWARCH methodology include Edwards and Susmel (2001, 2003) and Susmel (2000). A generalisation to SWGARCH models was developed by Gray (1996) and has subsequently been further developed by Haas *et al*. (2004).

avoids any ad-hoc partitioning of the sample path. The SWARCH model assumes that the unobservable realisation of the states is governed by a discrete-time, discrete state Markov stochastic process with fixed transition probabilities and state-dependent variances.[8] The probability law that causes the economy to switch between (latent) regimes is then given by the (hidden) *k*-state first-order Markov chain

$$\text{Prob}\left(s_t = j \mid s_t = i\right) = p_{ij} \tag{3}$$

The transition probability parameter p_{ij} represents the transition probability of going from state *i* to *j*. A large p_{ii} (i = 1, 2, ..., q) means that the model tends to stay longer in state *i*.
A by-product of the maximum-likelihood estimation of the model is that we can make inferences about the state of the return series under consideration at any given date. The filter probabilities denote the conditional probability that the state at date *t* is s_t. These probabilities are conditional on the values of *r* observed through date *t*. On the contrary, the smoothed probabilities are inferences about the state at date *t* based on data through the end of the sample. Therefore, smoothed probabilites represent the ex-post inference based upon the entire sample.[9] The empirical findings to emerge from this methodology are described in the next section.

4. Empirical Results

We now turn to the estimation results and discuss the features that arise from the SWARCH modelling framework. Maximum-likelihood estimation is straightforward using standard techniques for dealing with Markov switching.[10] All standard errors are computed from the heteroscedasticity-consistent variance-covariance matrix as proposed by White (1992). The estimation results for all countries under the various specifications are displayed in Tables 4 and 5.[11] The upper sections of the Tables display the parameters and the corresponding *t*-values. The lower sections present the regime-specific parameters, the transition probabilities and the *v* degrees of freedom parameter for the *t*-SWARCH models.

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8 There is no denying the attractions of the model, as many theories are naturally expressed in terms of regimes and the transition from one regime to another is often described by exogenous processes. A comprehensive review of the applications of Markov-switching models in econometrics can be found in Kim and Nelson (1999). For a brief textbook treatment see Tsay (2005), pp. 588-594.

9 Like nearest neighbourhood kernel estimates, the smoothed probabilities are relatively insensitive to observations far away from *t*. See Kim and Nelson (1999), chapter 4, for details.

10 However, maximum likelihood estimates may be plagued by the presence of multiple local maxima. Furthermore, one may encounter boundary problems when some transition probabilites p_{ij} become 0 or 1. In practice, parameters are set within a “reasonable” range and we have tested whether a global maximum of the likelihood has been reached or not by choosing starting values in a ± 10 percent interval around the provisional “reasonable” parameter values. When models had trouble converging, we simplified the model rather than continuing the numerical search toward poorly identified over-parameterised models.

11 We have also considered the inappropriateness of the two-regime MS framework to capture the parameter variability of the process parameters over the sample period. We experimented with three-state SWARCH (*k*=3) models. This finer partitioning, however, did not lead to interpretable and reasonable results for the third regime against the background of the evolution of the returns. Furthermore, the two-regime specification suffices to capture the main empirical non-linearities. Results are available from the authors upon request.

In practice, we never know the true data-generating process. To rank performance across models and to avoid over-parameterised and numerically unwieldy models, we have therefore resorted to the most commonly used model selection criteria (*AIC* and *BIC*) to determine the appropriate lag length q as well as the appropriate conditional distribution. In only in a couple of cases (Korea and Singapore) do the two criteria generate conflicting advice, i.e. no model clearly dominated the other. In these cases we have followed the *BIC* criterion since the *BIC* criterion selects the more parsimonious model.[12]

How should one interpret the estimation results? First, note that although switching in volatility is allowed for most countries the assumption of a *t*-distribution for the conditional residuals does result in a higher likelihood than the normal distribution. The *t*-SWARCH model also allows us to capture the tail properties of the data adequately.[13] Second, although there is no clear-cut “best” SWARCH model, we generally find two regimes with different volatility levels. In economic terms, the first regime (s = 1) pinpoints “normal” periods, while the second regime (s = 2) identifies periods with extraordinary shocks and captures the turbulent periods corresponding to the Asian crisis. Third, the SWARCH model turns out to be very powerful due to its ability to yield many significant parameter estimates, even when volatility regimes contain only a small number of observations. Fourth, since the “staying probabilities” p_{11} and p_{22} are high, the SWARCH model is characterised by long memory.

Next we report the *RCM* regime classification measure as proposed by Ahn and Bekaert (2002). The *RCM* statistic for two states is defined as

$$RCM = \frac{400}{T}\sum_{t=1}^{T} p_{1,t}\left(1 - p_{1,t}\right) \tag{4}$$

where the constant serves to normalise the measure to between 0 and 100. Good regime classification is associated with low *RCM* measures. A value of 0 means sharp (perfect) regime classification, while a measure of 100 implies that no information about the regimes is revealed. The no information case occurs when the probabilities hover around 0.5, boosting *RCM* towards 100. In a nutshell, the general pattern in Table 6 indicates that the SWARCH models deliver distinctive regime inference as the *RCM´*s are far from 100.

We now turn to a graphical enquiry of the estimated probabilities. In Figure 3, we plot the weekly returns forward exchange rates with 3 months maturity for each country in the top panel and the estimated (smoothed) probability that the economy in state 1 at time t in the bottom panel. The probability that the economy was in the high volatility state 2 at time t is the mirror imagine of the second (lower) panel. The

[12] As a further diagnostic check we have additionally tested whether the residuals appear to be white noise. We also did not find evidence of autocorrelation in the standardised squared residuals.

[13] This coincides with the results in Mittnik and Paolella (2000) who have found that for modelling Asian exchange rates, employing the *t*-distribution performs better compared to Gaussian residuals.

graphs indicate a pattern of dichotomous shifts between both regimes, suggesting that the model is well-suited. At first glance, a period of high volatility around the time of the Asian turmoil is observable in all countries. Later on, there is less evidence of common dynamics. For example, the markets of Hong Kong, Malaysia, Philippines and Taiwan display more regime switching behaviour and turbulence from high to low and back to high. In yet others (Korea, Japan and Singapore) volatility appears to be low over the whole sample, exception made for the Asian crisis period. Similar patterns are replicated for the 1-year forward exchange rate returns available in the Appendix. The “extra volatility” on the Chinese market in the aftermath of the reform of the exchange rate regime has not come entirely out of the blue and is not accidental either: an appreciating renminbi exchange rate was expected to help China to cool down its overheating economy.

Given the estimated probabilities, we are now in the position to assess the interactions across Asian countries. The low- and high-variance regimes are identified using Hamilton´s (1989) classification scheme in which an observation belongs to regime 1 or 2 whichever state’s conditional smoothed probability is higher than 0.5. Under this assumption, four different sets of correlations must be considered. (1) Chinese volatility low, other countries´ volatility low, (2) Chinese volatility low, other countries´ volatility high, (3) Chinese volatility high, other countries´ volatility low, and (4) Chinese volatility high, other countries´ volatility high. The results for these interrelations of volatility states when China is the “originator country” are given in Table 7 and 8.[14]

In short, the results in Table 7 and 8 show a wide dispersion of co-dependence of volatility regimes. Most of the coefficients are positive, and most of them are statistically significant. This indicates that several Asian countries show significant return synchronisation, i.e. shocks experienced in one market are indeed transmitted to other markets. The highest correlation coefficients are apparent for Hong Kong. On the other hand, inspection of the numbers reveals that the returns are not running neck-and-neck in the country pairs. Movements in the Indonesian rupee and the Malaysian ringgit, for example, are quite idiosyncratic. Restrictions on capital account transactions are still high in Asia and these market frictions may explain why the size of the cross-country correlation coefficients is less pronounced in a number of cases.

Taking this line of inquiry a step further we now investigate whether the Asian future markets are driven by contagion. Claessens *et al*. (20001) define market contagion as the spread of market disturbances from one country to the other. They place sources of market contagion into two categories. The first one is termed “fundamentals-based contagion” and includes spillovers arising from real and financial linkages. The second type comprises of “irrational” phenomena such as herding behaviour and financial panics, which intensify the transmission of shocks through geographically and fundamentally heterogeneous

[14] Despite their sound statistical background, SWARCH models are “black box” methods from an economic point of view. The volatility co-movements should therefore not be interpreted as causal relationships. The economies in question are characterised by a high degree of simultaneity and forward-looking behaviour, and are subject to changing policy regimes and policy rules. In the context of a reduced-form model, it is therefore difficult to infer a cause and effect relationship.

markets. Traditionally, tests for market contagion assess whether cross-market correlation coefficients increase in turbulent periods. The three countries that appear to have a stronger interdependence with China in the turbulent regime vs. the tranquil regime are the three “mature Tigers” - Hong Kong, Singapore, and Taiwan - while for the remaining counties there is no evidence for increasing synchronisation in the remaining correlations.[15] Prima facie, these findings appear to suggest that these three countries have experienced destabilising contagion. This view is not the consensus, however. One feature that must be taken into account to obtain consistent estimates of co-movements is the bias in cross-market correlations. As noted by Forbes and Rigobon (2002), tests for market contagion based on conventional methods assessing whether cross-market correlation coefficients increase in crises periods are somewhat shaky and biased towards acceptance. Cross-market correlation coefficients are conditional on market volatility and therefore conventional estimates of correlation between markets during high (turbulent) volatility periods tend to exhibit upward bias even if the unconditional correlation remains unchanged, thereby lending support to the contagion hypothesis. The authors have proposed a statistical methodology to account for the bias when testing for contagion from country *a* to country *b*. Let us suppose that the pair-wise correlation coefficients during the low-low volatility regime (*s* = 1) and the high-high volatility regime (*s* = 2) period are

$$\rho_1 = \frac{Cov(r_{1,a}\, r_{1,b})}{\sqrt{Var(r_{1,a})Var(r_{1,b})}} = \frac{\sigma_{1,a,b}}{\sqrt{\sigma_{1,a}^2\,\sigma_{1,b}^2}} \tag{5}$$

and

$$\rho_2 = \frac{Cov(r_{2,a}\, r_{2,b})}{\sqrt{Var(r_{2,a})Var(r_{2,b})}} = \frac{\sigma_{2,a,b}}{\sqrt{\sigma_{2,a}^2\,\sigma_{2,b}^2}} \tag{6}$$

respectively. If there is an increase in the volatility in the return of country *a*, i.e. $\sigma_{2,a}^2 > \sigma_{1,b}^2$, then $\rho_2 > \rho_1$, giving the false appearance of contagion. To adjust for this, Forbes and Rigobon (2002) show that the adjusted (unconditional) correlation is given by

$$v_2 = \frac{\rho_2}{\sqrt{1 + \left(\frac{\sigma_{2,a}^2 - \sigma_{1,a}^2}{\sigma_{1,a}^2}\right)\left(1 - \rho_2^2\right)}} \tag{7}$$

[15] Another plausible explanation and catalyst for the degree of interdependence between the “mature Tigers” future returns and the Chinese NDF market returns is financial integration. Most of the FDI into China is coming from Hong Kong and Taiwan. Zhang (2005) has analysed and identified various determinants of this dominant Hong Kong – Taiwan direct investment.

According to equation (7), the unconditional correlation (v_2) is the conditional correlation (ρ_2) scaled by a non-linear function of the percentage change in volatility $\left(\sigma^2_{2,a} - \sigma^2_{1,a} \big/ \sigma^2_{1,a}\right)$, country *a* in this case, over the high and low volatility periods.

Forbes and Rigobon (2002) demonstrate that whenever adjusted statistics are used, there is virtually no evidence of a significant increase in correlation coefficients during the Asian crisis. These results can be interpreted as evidence that there was no contagion. In Table 9 we ascertain the statistical significance of the increase in the co-movements during stress periods employing the measures presented above.

In synthesis, from the more efficient estimates displayed in Table 9 it is apparent that contagion was no relevant factor.

5. Country Characteristics and Cross-Country Comovements

The evidence of cross-country heterogeneity with respect to NDF market correlations with China discussed in Section 4 can seem bewildering at first glance: for some countries the conditional correlations are large, while for others they are close to zero. What factors help to explain the degree of heterogeneity in the magnitudes of the co-movements? And through which channels does the transmission process take place? Therefore, we additionally apply some eclectic tenets of economic analysis to explain these cross-country differences. First of all, we identify three possible sources of such differences: degree of trade openness, degree of financial openness, and exchange rate regime. We then choose a set of indicators to use as proxies for these possible explanations. In particular, we take bilateral exports with mainland China as our trade openness indicator, bilateral foreign direct investment (FDI) with mainland China as our financial openness indicators, and utilize both the *de jure* and the *de facto* exchange rate regime classifications. In Figure 4 and 5 we present a set of scatter diagrams, each plotting the co-dependence for state 1 and state 4 on the vertical axis and the values of the given indicator on the horizontal axis together with a (linear) regression fit line.

The obvious difficulty researchers face in analysing the co-movement of asset prices is the identification problem. Since future exchange rates are determined simultaneously, it is hard to trace the origin of exchange rate developments for a single country. The observed relationship between certain country characteristics and magnitudes of co-dependence could reflect causality from the former to the latter or vice versa. For example, countries enjoying better macroeconomic performance may systematically choose to adopt a certain exchange rate regime. In order to mitigate the reverse causality, or endogeneity problem, we have used indicators dated 1998.

The prime candidate expected to influence these cross-country co-movements is trade. Greater trade integration enhances financial market interdependence, as is apparent when a devaluation in one country temporarily increases its competitiveness, and thus also adversely affects its trading competitors.[16] Our findings appear to support this viewpoint: from the two plots in the upper left panel of Figure 4 and 5 it appears that trade openness can indeed be considered a plausible explanation for the degree of interdependence between Asian countries and Chinese NDF market returns, as higher export countries are also those with the higher correlation coefficients (Hong Kong, Korea, Singapore, Taiwan).

One would also expect financial integration impact the extent of linkage between Chinese and other Asian NDF markets. Financial openness can be quantified using a variety of measures: in Figure 4 and 5 we employ bilateral country-to-country FDI flows with mainland China as our measure of capital account openness. From the scatterplots in the upper right corners it appears that countries with greater exposure to bilateral capital flows experience stronger interdependence among NDF markets compared to countries where bilateral FDI inflows are of relatively smaller magnitude. Viewed as a whole, our results therefore suggest that the magnitude of co-movements between the renminbi and other Asian-currency NDF contracts is indeed related to the degree of real and financial integration.

A further issue worth exploring when analysing the determinants of cross-country differences in correlation coefficients is the type of exchange rate regime operating in each country. Empirical analysis seeking to uncover the link between countries' exchange rate regimes and their macroeconomic performance depend critically on how the regimes are classified. The official (*de jure*) IMF exchange regime classification categorizes member's exchange rate regimes based on their official reports to the IMF. The exchange rate regime declared by a country, however, often differs from its operational regime. In recognition of this problem, several authors have developed alternative systems of reclassifying exchange rate regimes. In particular, Levy-Yeyati and Sturzenegger (2003) defined *de facto* exchange rate regimes according to the behaviour of three classification variables: exchange rate volatility, the volatility of exchange rate changes, and the volatility of international reserves. They identify four exchange rate regime categories: the first and the second category corresponding to a pure and a dirty float, respectively, the third one to a crawling peg and the last category corresponding to a fix peg. An alternative classification was developed by Reinhart and Rogoff (2004) who incorporated data on parallel and dual exchange rate markets, arguing that market-determined exchange rates are better indicators of the underlying monetary policy than the official exchange rate. Their classification consists of six categories, ranging from currency board (category 1) to freely falling exchange rate regime (category 6).

From the two plots in the second row of Figure 4 and 5, it appears that the degree of flexibility of the exchange rate regime and the cross-country comovements appear to be negatively connected. In other

16 The role of trade as a catalyst of co-movements was originally highlighted in to the context of currency crises. See, for example, Glick and Rose (1999). Using a common factor model, Forbes and Chinn (1994) test the trade channel and other potential determinants of comovements also for non-crisis periods. They find that both trade and financial linkages have played important roles since the mid 1990s. Furthermore, their paper shows that regional spillovers can occur, emanating from the largest economy and spilling into smaller countries in the region.

words, the more flexible the exchange rate, the lower the correlation coefficient with China. In particular, this conclusion holds true for state 4.[17]

6. Conclusions and Further Comments

The evolution of forward exchange rate markets, which are considered a gauge of the anticipated direction of a change in the value of a currency, is closely monitored by international investors, multinational firms and portfolio managers seeking to manage their exposure to financial risk. In this paper we attempt to provide additional insights into the degree of volatility dependence across Asian forward exchange rates. The contribution of our paper to this ongoing debate can be regarded as twofold. First, we extend the existing literature by studying linkages across Asian forward exchange rates using the nonlinear SWARCH approach. Second, the paper gives new insights into exactly how synchronised various forward markets are. The results substantiate the claim that, thus far, the knock-on effects from renminbi future returns have been modest, that is to say that little evidence arises of temporal conformity of the low versus high volatility regimes across China and other Asian countries despite the rapid increase in intra-regional trade flows. This may indicate that the renminbi prospects of becoming a regional lead currency in the near future are limited. When testing for contagion during the 1997-1998 Asian crisis, the evidence and patterns tends to reject high volatility synchronisation. Such findings suggest that the degree of financial market integration currently existing in Asia is notably smaller than that which prevailed in Europe at the time of the ERM’s introduction.

[17] The scatterplots in Figure 4 and 5 report the results for three months maturity. Forward rates with one year maturity yield nearly identical results. The corresponding graphs are available upon request.

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Table 1. Country Coverage and U.S. Dollar Futures

COUNTRY	LOCAL CURRENCY	STANDARD FORWARD CONTRACTS	NDF CONTRACTS
China	Renminbi		√
Hong Kong	Hong Kong Dollar	√	
Indonesia	Rupiah		√
Japan	Yen	√	
Korea	Won		√
Malaysia	Ringgit		√
Philippines	Peso		√
Singapore	Singapore Dollar	√	
Taiwan	Taiwan Dollar		√

Notes: The table shows the data availability for all countries in the sample. √ indicates data availability. All data are currency option quotes in Hong Kong and the observations are recorded at the close of business (average of the closing bid and the offered rates).

Table 2. Univariate Statistics for Weekly Returns with Three Months Maturity

	China	*Hong Kong*	*Indonesia*	*Japan*	*Korea*	*Malaysia*	*Philip.*	*Sing.*	*Taiwan*
Mean	-0.040	-0.001	0.052	-0.038	-0.120	-0.051	0.025	-0.042	-0.018
SD	0.246	0.125	3.681	1.275	1.205	1.136	1.347	0.706	0.624
Sk	-0.905	-0.010	2.033	-1.453	-0. 409	-1.020	0.421	-0.525	-0.261
Ku	12.023	46.110	32.555	12.680	13.305	34.846	23.233	13.843	5.597
JB	1867.0	40654.2	19618.36	2252.02	2355.80	22446.0	9038.8	2561.4	154.68
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LB(6)	20.3164.	20.9534.	33.6989.	24.5809.	27.9561.	60.2319.	17.9530.	12.3801.	44.1017.
	(0.002)	(0.001)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)
$LB^2(6)$	84.1869.	69.1908.	207.7997.	20.6549.	323.6964.	593.1186.	245.2808.	153.6835.	82.3717.
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
H	3.826**	2.496*	1.772	3.494**	1.764	3.251**	1.183	2.960**	2.688*

Table 3. Univariate Statistics for Weekly Returns with One Year Maturity

	China	*Hong Kong*	*Ind.*	*Japan*	*Korea*	*Malaysia*	*Philip.*	*Sing.*	*Taiwan*
Mean	-0.076	-0.011	0.043	-0.033	-0.131	-0.058	0.042	-0.048	-0.027
SD	0.536	0.253	4.193	1.257	1.275	1.299	1.598	0.764	0.706
Sk	-0.223	1.113	3.230	-1.494	-0.382	-0.969	0.321	-0.084	-0.169
Ku	9.970	29.255	38.935	12.995	13.611	36.979	21.428	18.138	5.561
JB	1075.2	15187.1	29384.9	2399.29	2495.08	25530.9	7494.0	4314.9	147.09
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LB(6)	38.5774.	26.1782.	39.1358.	23.5425.	35.9008.	41.6820.	16.7946.	13.0237.	52.9628.
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.04)	(0.00)
LB²(6)	220.2063.	171.8065.	152.8119.	20.0709.	384.9011.	463.8107.	328.3470.	175.1043.	107.2359.
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
H	2.290	2.573	3.015*	3.691**	1.821	3.263**	1.392	2.664	2.420

Notes: Mean and SD are the sample mean and standard deviation; Sk (Ku) is the skewness (kurtosis); JB is the Jarque-Bera test for departure from normality based upon the skewness and the kurtosis measures combined and distributed $\chi^2(2)$; LB(k) is the Ljung-Box Q statistic for k order serial autocorrelation; LB²(k) is the Ljung-Box Q statistic for k order serial autocorrelation of the squared returns; the prob-values are given in parentheses; H is Hansen´s (1992) likelihood ratio test for regime switches. The LR test does not have the usual limiting chi-squared distribution because the switching probabilities are unidentified under the null. Hansen (1992) proposes a test that is able to provide an upper bound to the asymptotic distribution. We calculate Hansen´s test for all return series, using a Newey-West correction with a Bartlett kernel and a fixed bandwidth. A * (**) indicates significance at the 10 percent (5 percent) level.

Table 4. Univariate SWARCH(2, q) Models for Weekly Returns with 3 Months Maturity

	China		**Hong Kong**		**Indonesia**		**Japan**	
Mean Equation	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*
α_0	-0.003	-0.004	0.003	0.002	0.013	-0.006	-0.019	0.011
	(-1.30)	(-1.72)	(1.85)	(2.24)	(0.24)	(0.13)	(-0.40)	(0.23)
α_1	0.324	0.172	-0.008	0.060	0.279	0.233	0.227	0.214
	(8.88)	(3.66)	(-0.29)	(2.29)	(5.53)	(5.53)	(5.25)	(5.10)
Variance Equation								
β_0	0.0005	0.001	0.0006	0.003	0.777	1.146	1.099	1.12
	(4.13)	(2.23)	(13.80)	(0.44)	(9.59)	(3.06)	(16.51)	(11.87)
β_1	0.402	0.646			0.191	0.584		
	(5.42)	(2.03)			(3.14)	(2.01)		
β_2	0.425	0.304			0.164	0.302		
	(5.71)	(1.65)			(2.74)	(1.65)		
P_{11}	0.956	0.986	0.955	0.975	0.984	0.99	0.998	0.998
	(54.83)	(76.71)	(82.14)	(81.87)	(158.82)	(268.93)	(554.57)	(525.80)
P_{12}	0.021	0.005	0.133	0.048	0.06	0.003	0.005	0.005
	(2.59)	(1.24)	(3.97)	(2.49)	(3.08)	(0.97)	(0.70)	(0.61)
ν		2.780		2.123		2.89		10.44
		(5.46)		(6.98)		(5.98)		(2.58)
γ_2	58.30	37.167	72.198	35.798	49.44	23.54	4.497	3.471
	(4.07)	(3.44)	(10.49)	(4.62)	(7.98)	(3.84)	(5.94)	(4.18)
AIC	-0.91	**-1.07**	-3.06	**-3.32**	3.89	**3.80**	3.15	**3.14**
BIC	-0.84	**-0.99**	-3.01	**-3.27**	3.96	**3.87**	3.204	**3.199**

Table 4. (Continued) Univariate SWARCH(2, q) Models for Weekly Returns with 3 Months Maturity

Countries	**Korea**		**Malaysia**		**Philippines**		**Singapore**		**Taiwan**	
Mean Equation	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*
α_0	-0.044 (-1.29)	-0.058 (-1.84)	0.0003 (0.58)	0.0007 (1.06)	-0.034 (-1.12)	-0.032 (-1.11)	-0.025 (-1.12)	-0.027 (-1.26)	-0.009 (-0.43)	-0.011 (-0.54)
α_1	0.245 (5.29)	0.261 (6.59)	-0.176 (-17.62)	0.124 (4.96)	0.105 (2.28)	0.154 (3.35)	0.290 (6.30)	0.296 (6.49)	0.252 (5.41)	0.259 (5.66)
Variance Equation										
β_0	0.397 (9.71)	0.483 (7.01)	0.000 (10.29)	0.083 (16.04)	0.309 (11.41)	0.309 (6.27)	0.211 (11.95)	0.213 (9.72)	0.093 (7.31)	0.119 (5.03)
β_1	0.087 (1.78)	-0.019 (0.36)	1.566 (12.15)	605.44 (18.09)	0.270 (4.25)	0.0263 (2.94)	0.053 (0.98)	0.056 (0.95)	0.101 (1.67)	0.161 (1.79)
β_2	0.195 (2.64)	0.197 (1.87)								
P_{11}	0.998 (592.73)	0.998 (427.90)	0.949 (69.63)	0.995 (303.50)	0.990 (173.94)	0.989 (121.73)	0.998 (288.41)	0.998 (278.13)	0.932 (40.63)	0.976 (65.57)
P_{12}	0.005 (1.12)	0.007 (0.91)	0.163 (3.94)	0.004 (0.95)	0.025 (2.00)	0.0168 (1.04)	0.006 (0.72)	0.006 (0.53)	0.074 (2.64)	0.024 (1.62)
ν		5.86 (3.10)		2.001 (1162.80)		5.174 (4.25)		13.088 (1.51)		6.222 (2.80)
γ_2	12.995 (4.27)	25.596 (3.62)	6804.483 (7.08)	1851.11 (2.46)	9.686 (8.13)	6.876 (4.27)	12.039 (5.46)	10.892 (3.99)	5.869 (6.43)	4.241 (4.87)
AIC	2.54	**2.52**	-1.61	**-1.97**	2.59	**2.52**	1.592	**1.588**	1.59	**1.57**
BIC	2.61	**2.59**	-1.55	**-1.90**	2.65	**2.58**	**1.650**	1.654	1.65	**1.64**

Table 5. Univariate SWARCH(2, q) Models for Weekly Returns with 1 Year Maturity

	China		Hong Kong		Indonesia		Japan	
Mean Equation	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*
α_0	-0.036 (-2.82)	-0.029 (-1.50)	-0.005 (-1.70)	-0.004 (-1.48)	0.011 (0.83)	-0.075 (-1.59)	-0.015 (-0.30)	0.018 (0.37)
α_1	0.289 (5.45)	0.289 (6.23)	0.091 (2.43)	0.139 (3.17)	0.335 (7.39)	0.237 (5.81)	0.228 (4.75)	0.214 (4.78)
Variance Equation								
β_0	0.042 (10.35)	0.046 (5.52)	0.002 (9.08)	0.006 (2.29)	0.978 (11.44)	1.104 (2.81)	1.054 (14.50)	1.075 (10.13)
β_1	0.199 (3.23)	0.272 (2.42)	0.217 (2.99)	0.458 (1.67)	0.209 (3.33)	0.494 (2.10)		
β_2			0.197 (3.62)	0.470 (1.60)				
P_{11}	0.990 (224.20)	0.991 (157.94)	0.960 (83.05)	0.998 (391.97)	0.987 (165.53)	0.998 (191.83)	0.998 (374.16)	0.998 (272.70)
P_{12}	0.010 (1.85)	0.008 (1.29)	0.180 (3.24)	0.005 (0.82)	0.034 (2.84)	0.002 (1.09)	0.005 (0.86)	0.004 (0.76)
ν		4.025 (4.75)		2.668 (5.79)		3.077 (4.92)		10.091 (2.58)
γ_2	11.789 (7.92)	10.287 (5.00)	51.822 (5.48)	92.700 (2.84)	44.408 (9.99)	14.741 (4.48)	4.643 (9.03)	3.558 (4.77)
AIC	0.82	**0.76**	-1.47	**-1.61**	4.08	**3.96**	3.12	**3.10**
BIC	0.88	**0.83**	-1.41	**-1.54**	4.14	**4.03**	3.17	**3.16**

Table 5. (Continued) Univariate SWARCH(2, q) Models for Weekly Returns with 1 Year Maturity

	Korea		Malaysia		Philippines		Singapore		Taiwan	
Mean Equation	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*
α_0	-0.053	-0.060	0.002	0.006	-0.080	-0.078	-0.027	-0.030	-0.009	-0.014
	(-1.62)	(-1.83)	(-0.57)	(1.62)	(-2.14)	(-2.23)	(-1.18)	(-1.35)	(-0.37)	(-0.62)
α_1	0.244	0.242	0.062	0.124	0.171	0.191	0.262	0.269	0.284	0.279
	(5.11)	(5.23)	(4.35)	(2.97)	(3.54)	(3.91)	(5.54)	(5.76)	(6.06)	(6.07)
Variance Equation										
β_0	0.389	0.401	0.003	0.485	0.416	0.397	0.224	0.225	0.141	0.178
	(9.81)	(7.29)	(8.06)	(7.53)	(10.21)	(5.95)	(12.41)	(9.87)	(6.72)	(4.95)
β_1	0.133	0.121	0.974	94.609	0.333	0.380	0.065	0.072	0.109	0.148
	(2.46)	(1.79)	(9.21)	(4.53)	(5.04)	(3.46)	(1.22)	(1.18)	(1.78)	(1.77)
β_2	0.173	0.181								
	(2.57)	(2.09)								
P_{11}	0.998	0.998	0.871	0.994	0.988	0.987	0.998	0.998	0.932	0.974
	(274.52)	(261.07)	(45.44)	(238.63)	(142.16)	(108.46)	(357.94)	(319.56)	(34.79)	(54.36)
P_{12}	0.005	0.005	0.038	0.003	0.028	0.022	0.005	0.005	0.083	0.031
	(0.95)	(0.96)	(12.99)	(0.91)	(2.32)	(1.48)	(0.91)	(0.72)	(2.29)	(1.57)
ν		9.594		2.006		5.601		13.208		6.966
		(1.76)		(249.17)		(3.89)		(1.40)		(2.19)
γ_2	15.721	17.157	1129.47	33.591	8.385	6.238	13.277	12.144	4.826	3.678
	(3.97)	(3.55)	(161.29)	(3.39)	(8.01)	(4.24)	(5.19)	(4.17)	(5.69)	(4.68)
AIC	2.57	**2.56**	0.28	**-0.04**	2.93	**2.89**	1.671	**1.667**	1.86	**1.85**
BIC	**2.63**	2.65	0.34	**0.02**	2.99	**2.95**	**1.728**	1.733	1.914	**1.912**

Notes: t-values are given in parentheses. AIC = -2L + 2K and BIC = -2L + Klog(T), where L is the likelihood, K is the number of parameters estimated and T is the sample size. For each criteria, bold-type entries indicate the best model.

Table 6. The RCM Quality of Regime Classification Measures

COUNTRY	*RCM*-STATISTIC 3 MONTHS MATURITY	*RCM*-STATISTIC 1 YEAR MATURITY
China	8.51	8.45
Hong Kong	15.40	1.43
Indonesia	2.36	2.42
Japan	3.61	4.42
Korea	1.84	1.26
Malaysia	2.88	5.01
Philippines	12.70	20.32
Singapore	1.04	0.98
Taiwan	28.83	37.55

Table 7. Pair-Wise Co-Dependence of Volatility Regimes (Three Months Maturity)

	Correlation	# of Observations	Critical Value
China vs Hong Kong			
State 1: China low, Hong Kong low	0.10	189	0.15
State 2: China low, Hong Kong high	-	0	-
State 3: China high, Hong Kong low	0.42	170	0.15
State 4: China high, Hong Kong high	0.61	167	0.15
China vs Indonesia			
State 1: China low, Indonesia low	0.19	189	0.15
State 2: China low, Indonesia high	-	0	-
State 3: China high, Indonesia low	0.32	243	0.13
State 4: China high, Indonesia high	0.08	98	0.20
China vs Japan			
State 1: China low, Japan low	0.24	189	0.15
State 2: China low, Japan high	-	0	-
State 3: China high, Japan low	0.22	274	0.12
State 4: China high, Japan high	0.38	67	0.24
China vs Korea			
State 1: China low, Korea low	0.28	189	0.15
State 2: China low, Korea high	-	0	-
State 3: China high, Korea low	0.18	308	0.11
State 4: China high, Korea high	0.29	33	0.35
China vs Malaysia			
State 1: China low, Malaysia low	-0.11	189	0.15
State 2: China low, Malaysia high	-	0	-
State 3: China high, Malaysia low	0.33	180	0.15
State 4: China high, Malaysia high	0.28	161	0.16
China vs Philippines			
State 1: China low, Philippines low	0.02	123	0.18
State 2: China low, Philippines high	0.47	66	0.25
State 3: China high, Philippines low	0.16	233	0.13
State 4: China high, Philippines high	0.26	108	0.19
China vs Singapore			
State 1: China low, Singapore low	0.19	189	0.15
State 2: China low, Singapore high	-	0	-
State 3: China high, Singapore low	0.34	285	0.12
State 4: China high, Singapore high	0.47	45	0.30
China vs Taiwan			
State 1: China low, Taiwan low	0.38	118	0.18
State 2: China low, Taiwan high	0.46	71	0.24
State 3: China high, Taiwan low	0.26	166	0.16
State 4: China high, Taiwan high	0.40	175	0.15

Table 8. Pair-Wise Co-Dependence of Volatility Regimes (One Year Maturity)

	Correlation	# of Observations	Critical Value
China vs Hong Kong			
State 1: China low, Hong Kong low	0.37	332	0.11
State 2: China low, Hong Kong high	-	0	-
State 3: China high, Hong Kong low	0.49	139	0.17
State 4: China high, Hong Kong high	0.80	55	0.27
China vs Indonesia			
State 1: China low, Indonesia low	0.09	261	0.12
State 2: China low, Indonesia high	0.22	75	0.23
State 3: China high, Indonesia low	0.32	68	0.24
State 4: China high, Indonesia high	0.04	126	0.18
China vs Japan			
State 1: China low, Japan low	0.26	336	0.11
State 2: China low, Japan high	-	0	-
State 3: China high, Japan low	0.15	126	0.18
State 4: China high, Japan high	0.45	68	0.24
China vs Korea			
State 1: China low, Korea low	0.38	336	0.11
State 2: China low, Korea high	-	0	-
State 3: China high, Korea low	0.17	135	0.17
State 4: China high, Korea high	0.37	59	0.26
China vs Malaysia			
State 1: China low, Malaysia low	0.01	191	0.14
State 2: China low, Malaysia high	0.45	145	0.17
State 3: China high, Malaysia low	0.05	93	0.21
State 4: China high, Malaysia high	0.46	101	0.20
China vs Philippines			
State 1: China low, Philippines low	0.15	247	0.13
State 2: China low, Philippines high	0.31	89	0.21
State 3: China high, Philippines low	0.37	102	0.20
State 4: China high, Philippines high	0.48	92	0.21
China vs Singapore			
State 1: China low, Singapore low	0.28	325	0.11
State 2: China low, Singapore high	-	0	-
State 3: China high, Singapore low	0.36	149	0.16
State 4: China high, Singapore high	0.64	45	0.30
China vs Taiwan			
State 1: China low, Taiwan low	0.22	180	0.15
State 2: China low, Taiwan high	0.47	156	0.16
State 3: China high, Taiwan low	0.45	127	0.18
State 4: China high, Taiwan high	0.68	67	0.24

Notes: Cross-correlations exceeding $2/\sqrt{T}$ in absolute value are significant at the 5 percent level. The critical values in the 3rd column of Table 7 and 8 have been calculated accordingly.

Table 9. Adjusted (Unconditional) Correlations v_2

	3 MONTHS	1 YEAR
China vs Hong Kong	0.11	0.26
China vs Singapore	0.05	0.15
China vs Taiwan	0.06	0.18

Figure 1. The Movements of the Renminbi NDF´s against the U.S. Dollar
Weekly Data: 1/1/1998 to 21/2/2008

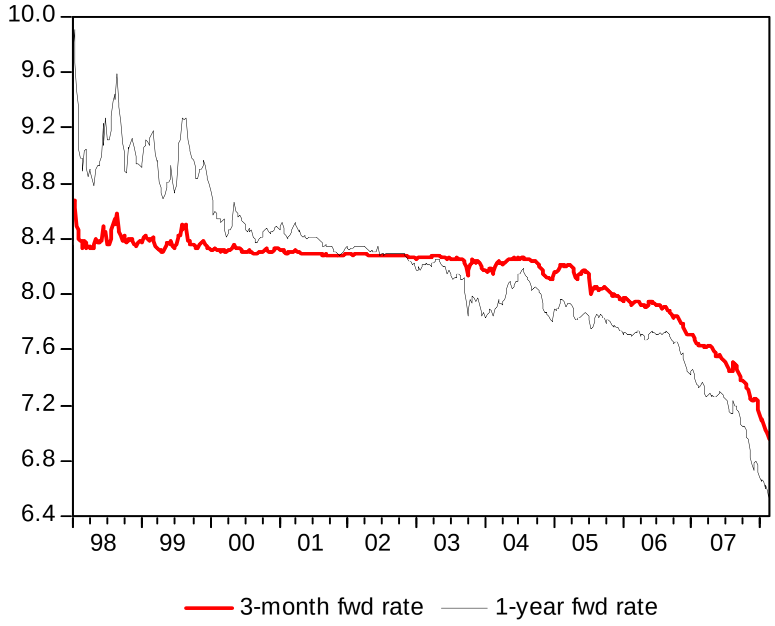
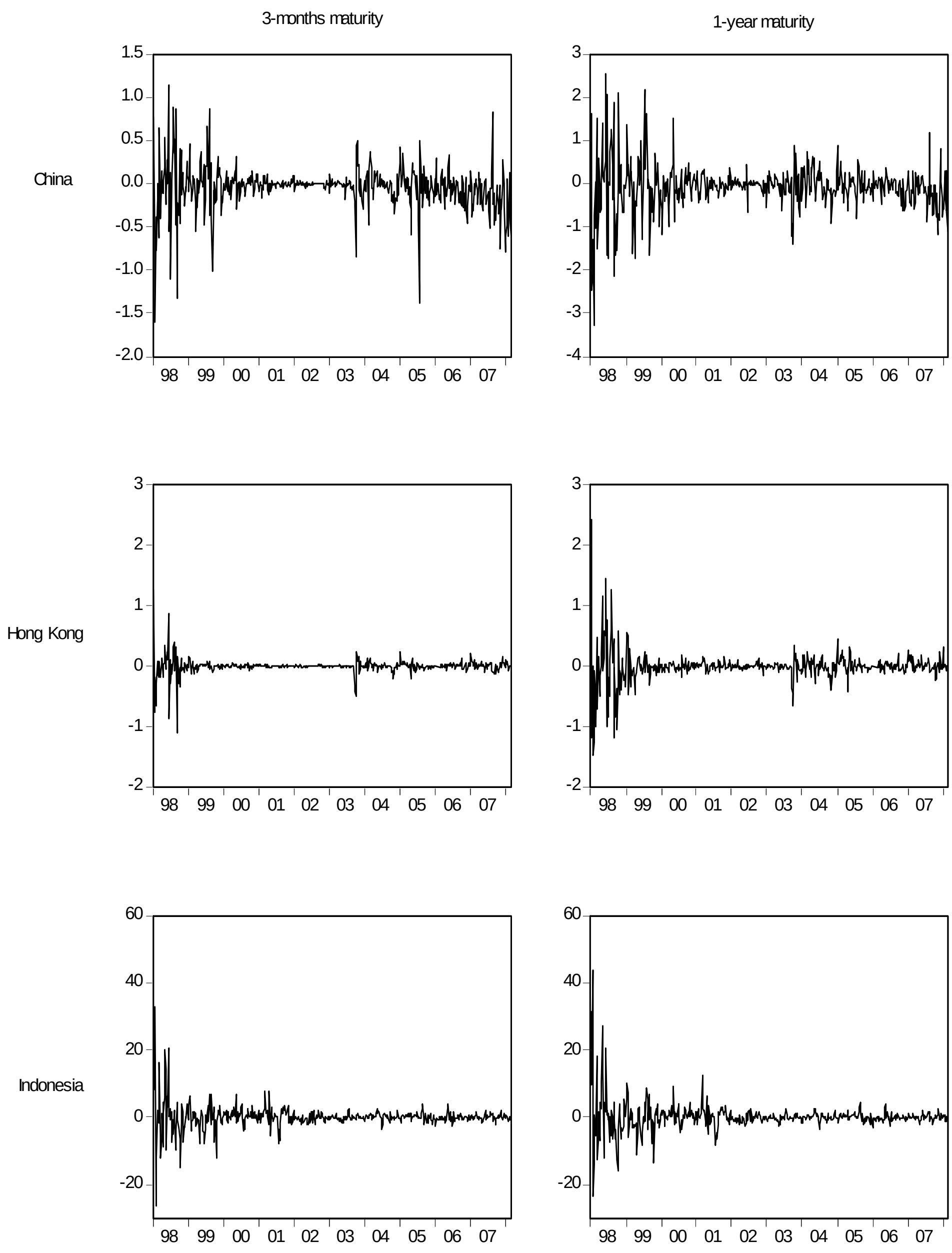
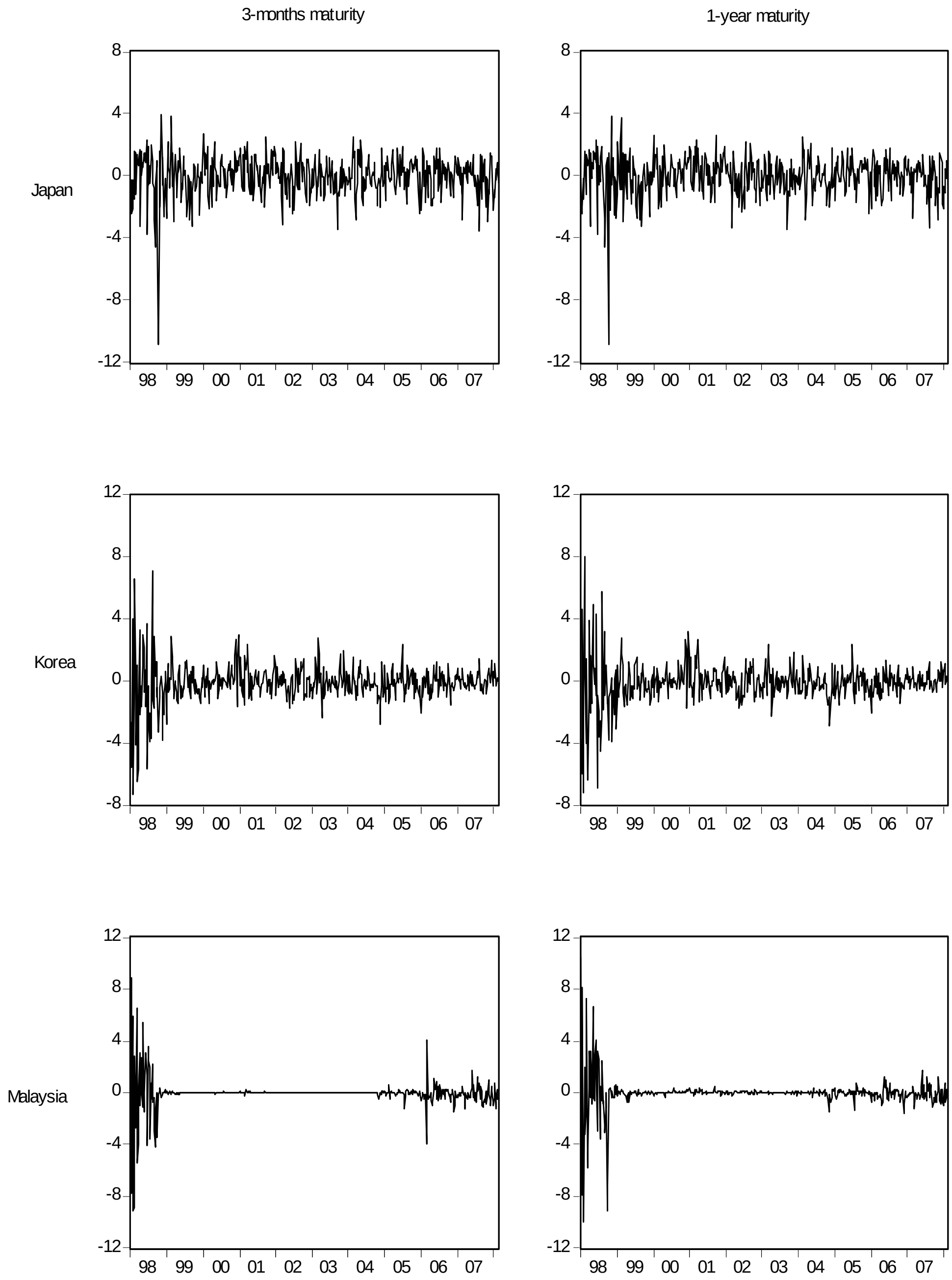


Figure 2. Weekly Returns of the 1-Year and 3 Months U.S. Dollar Futures by Country in % Period: 1/1/1998 to 21/2/2008




3-months maturity
1-year maturity
Japan
Korea
Malaysia
8
4
0
-4
-8
-12
12
98 99 00 01 02 03 04 05 06 07

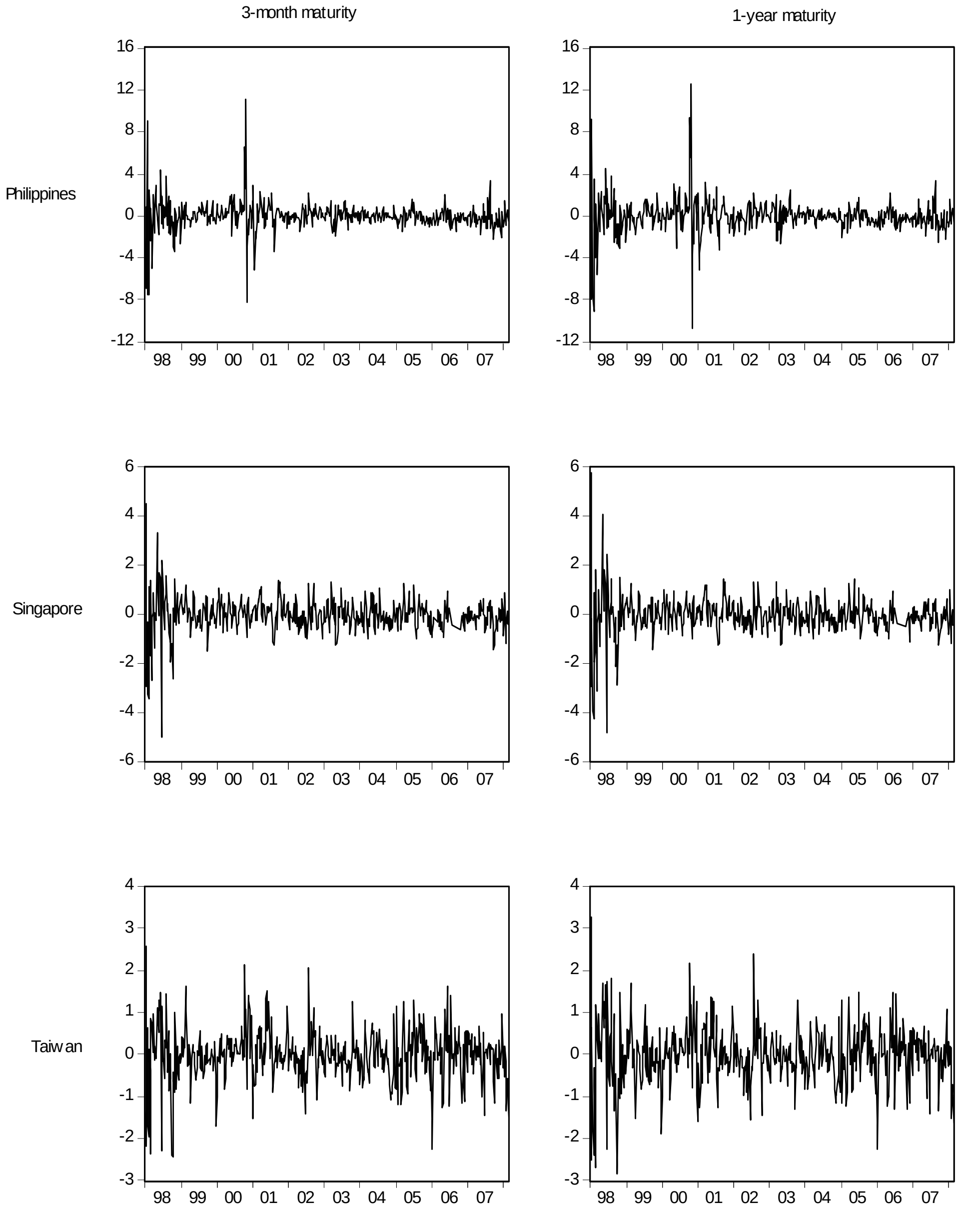
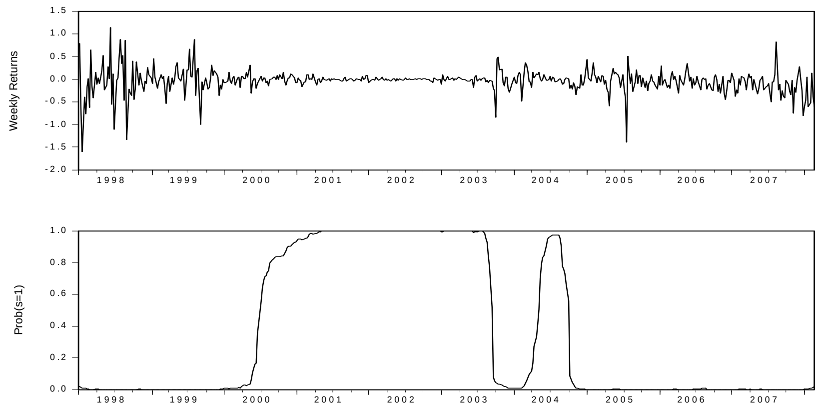
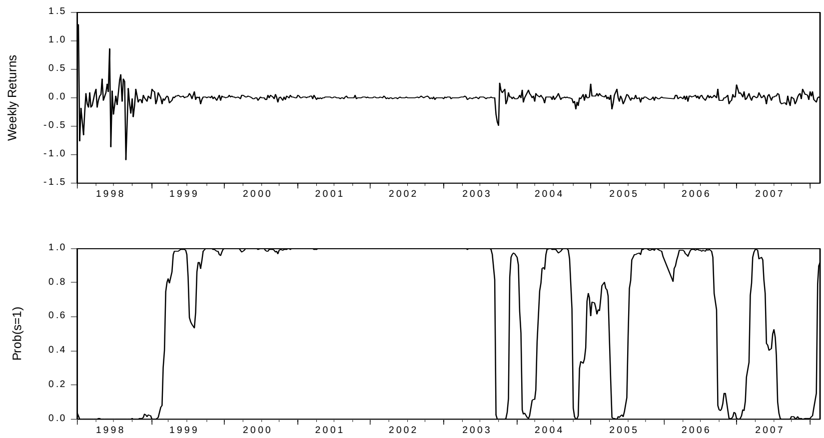

3-month maturity
1-year maturity
Philippines
Singapore
Taiwan
16
12
8
4
0
-4
-8
-12
6
4
2
0
-2
-4
-6
4
3
2
1
0
-1
-2
-3
98 99 00 01 02 03 04 05 06 07

Figure 3. Weekly Returns of U.S. Futures with 3 Months Maturity (Top Panel) and Smoothed 1st Regime Probabilities (Lower Panel)

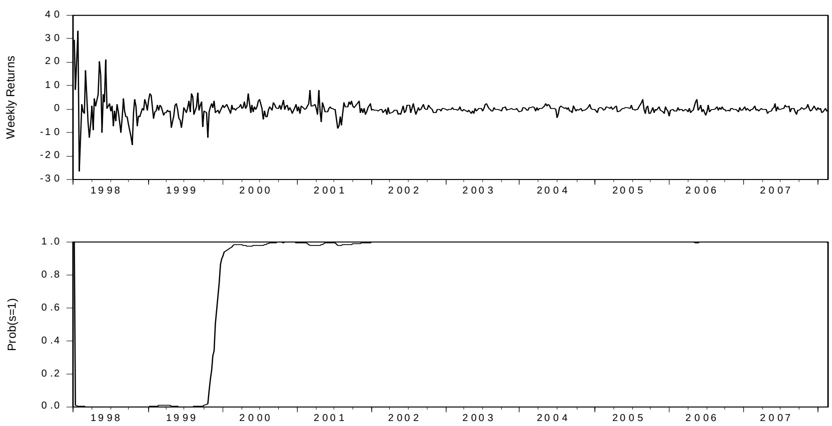
China



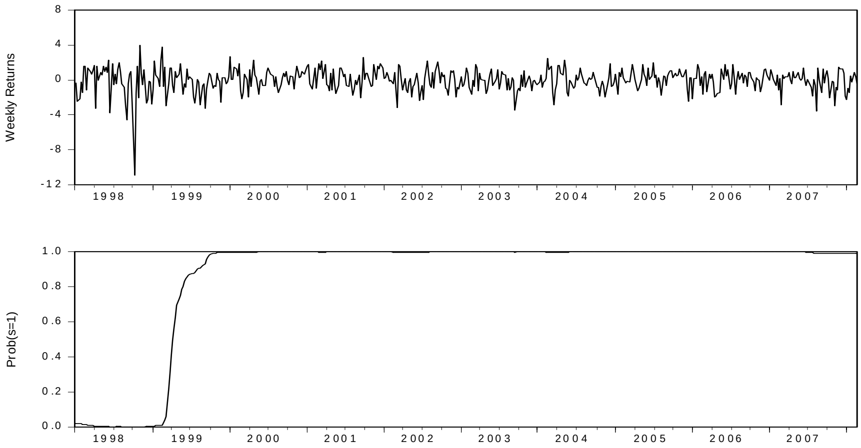
Hong Kong



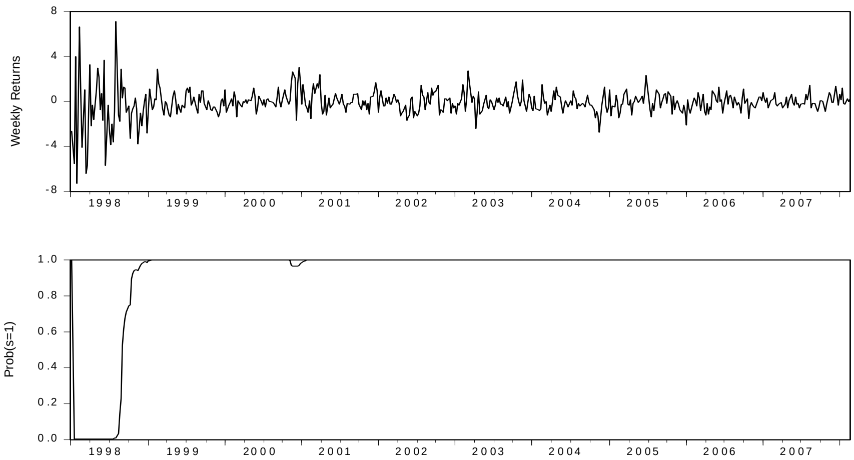
Indonesia



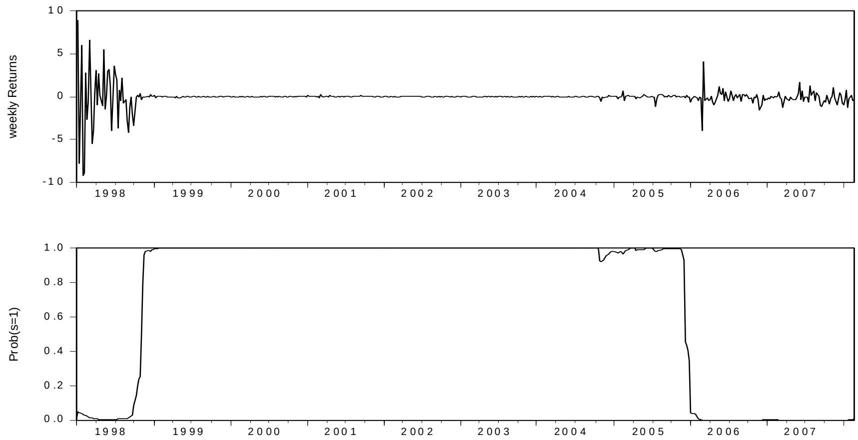
Japan



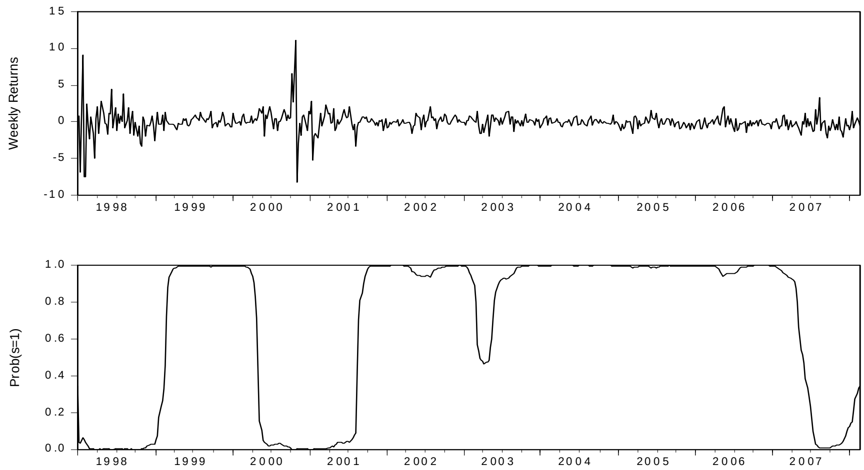
Korea



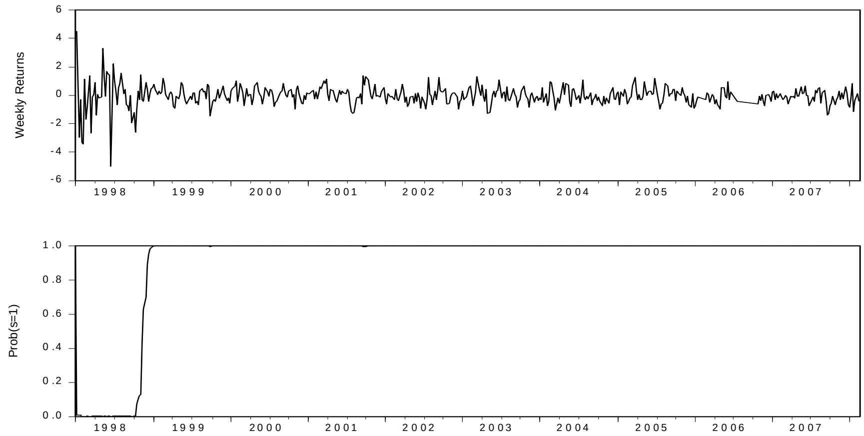
Malaysia



Philippines



Singapore



Taiwan

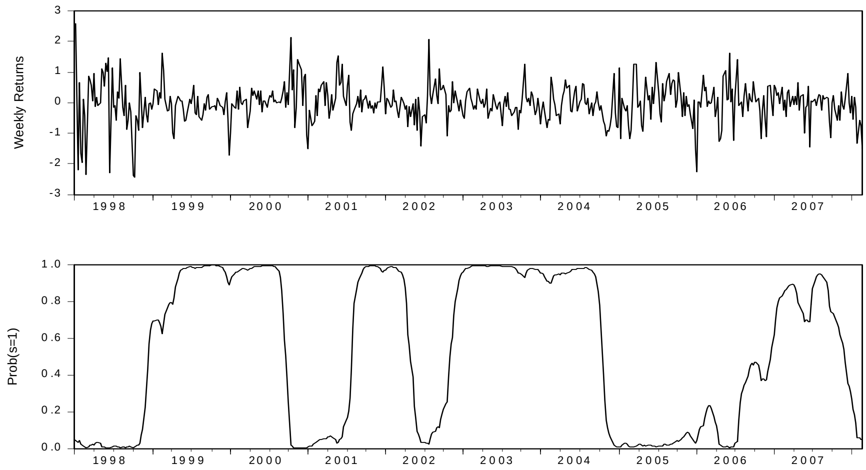
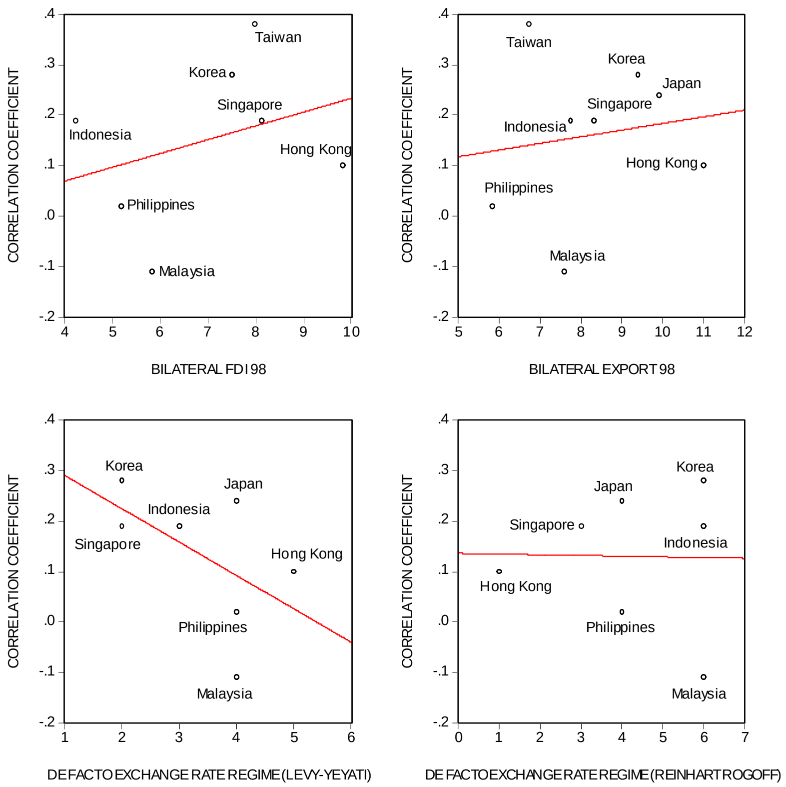
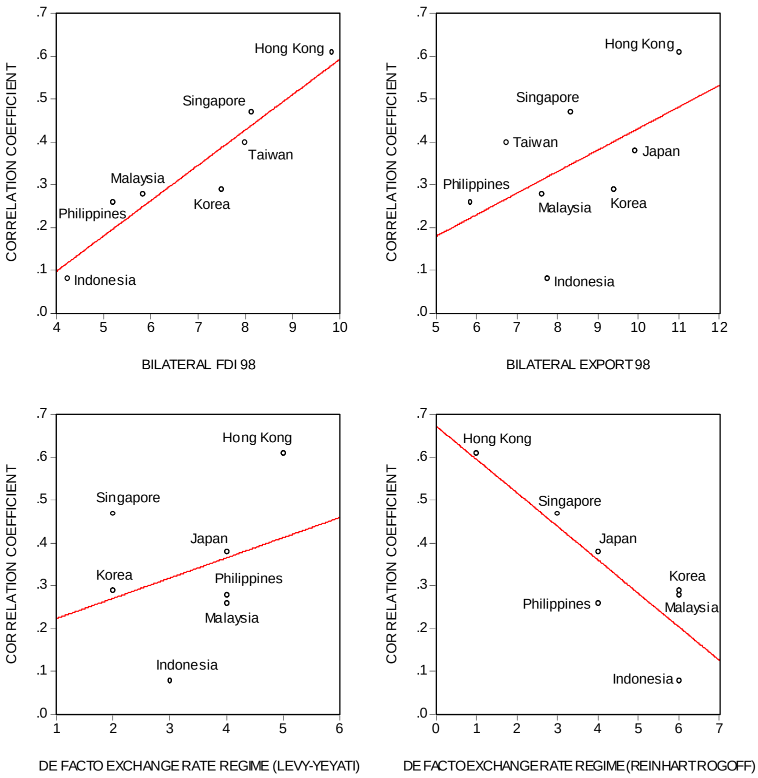


Figure 4. Economic Fundamentals and Co-Dependence with Mainland China in State 1 (Three Months Maturity)



Notes: The co-dependence measures are obtained from the SWARCH models. Bilateral export refers to exports into China from the reporting country, in millions of U.S. dollars. Bilateral FDI refers to the FDI flow into China from the reporting country, in millions of U.S. dollars. Data sources: IMF, DOT; National Bureau of Statistics of China. De facto exchange rate regime classifications were obtained from Levy-Yeyati and Sturzenegger (2003) and Reinhart and Rogoff (2004). Exchange rate regime classifications for Taiwan are not available.

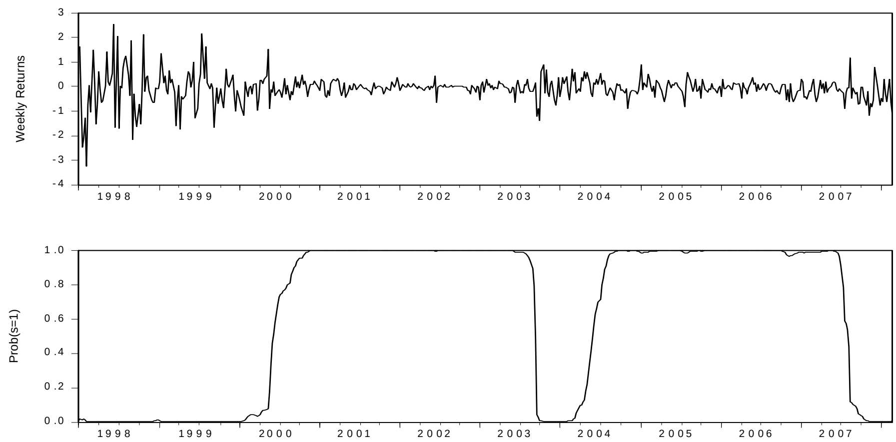
Figure 5. Economic Fundamentals and Co-Dependence with Mainland China in State 4 (Three Months Maturity)



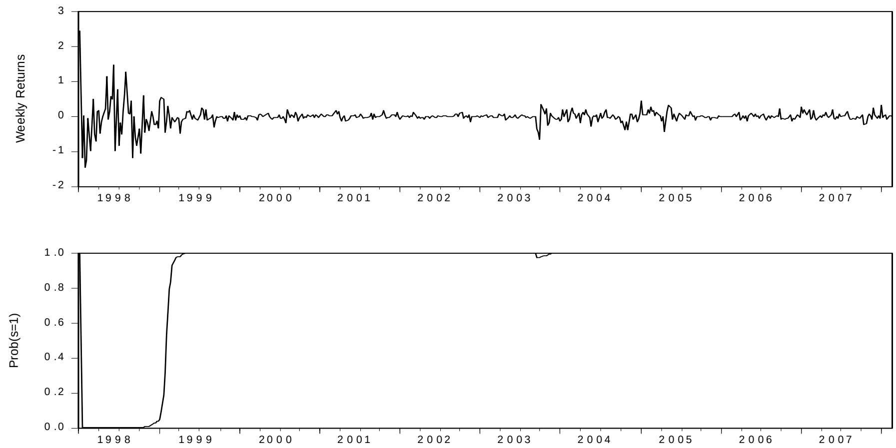
Notes: See Figure 4.

Appendix. Weekly Returns of U.S. Futures with 1 Year Maturity (Top Panel) and Smoothed 1st Regime Probabilities (Lower Panel)

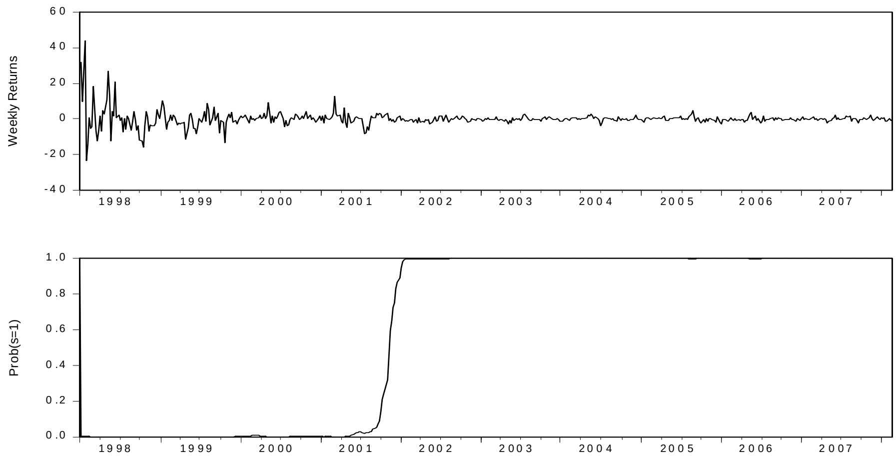
China



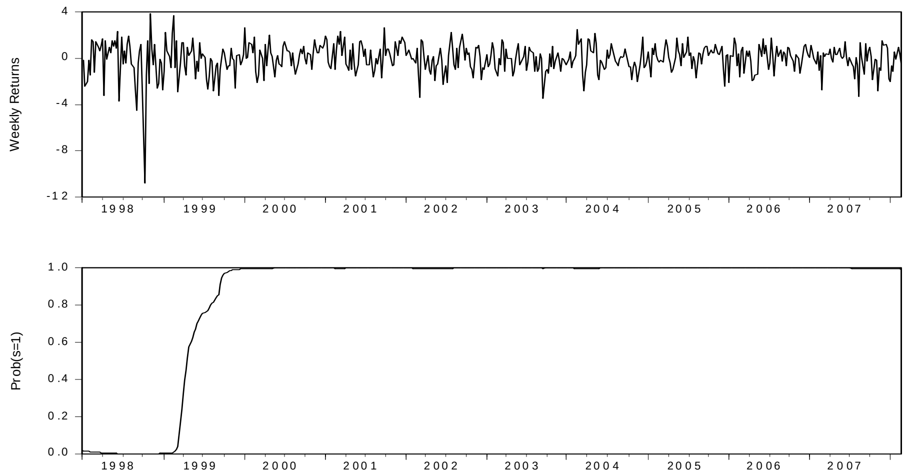
Hong Kong



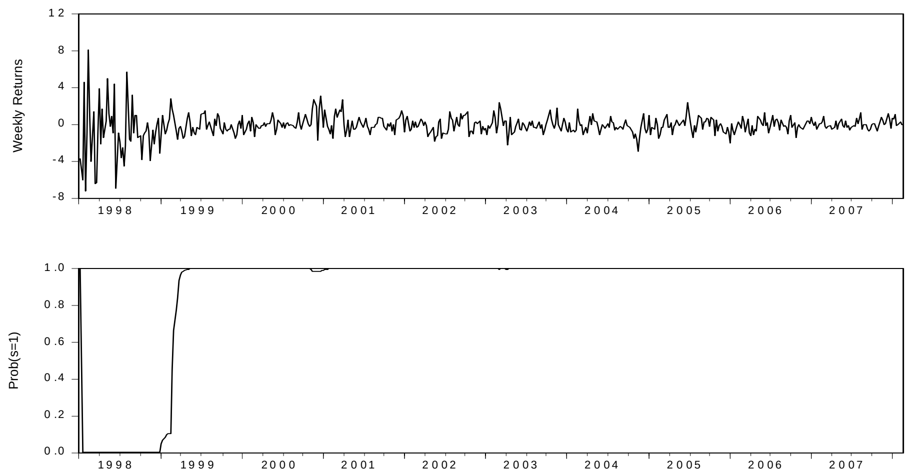
Indonesia



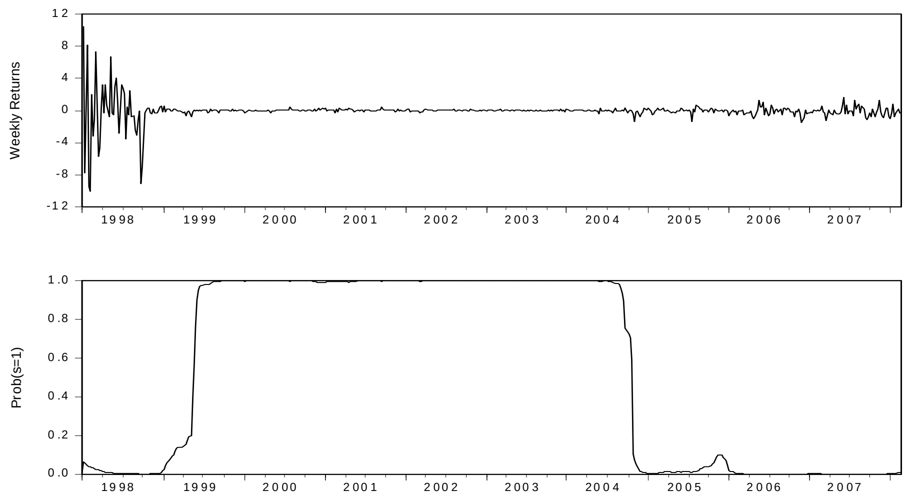
Japan



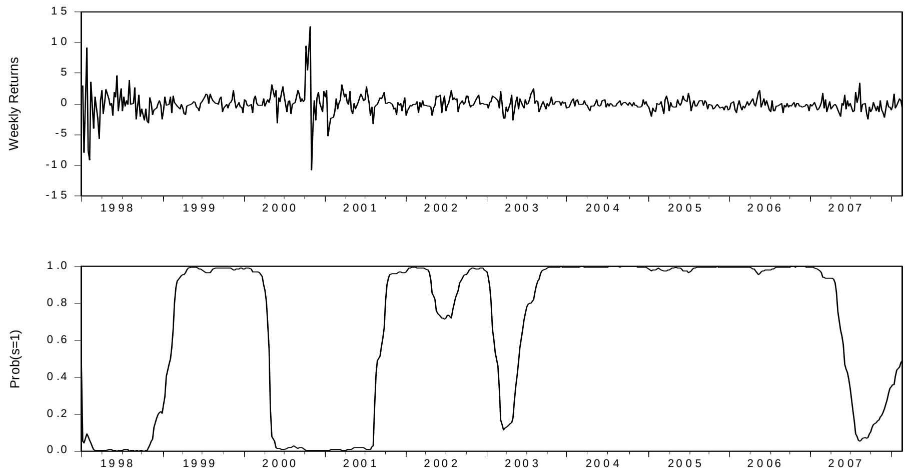
Korea



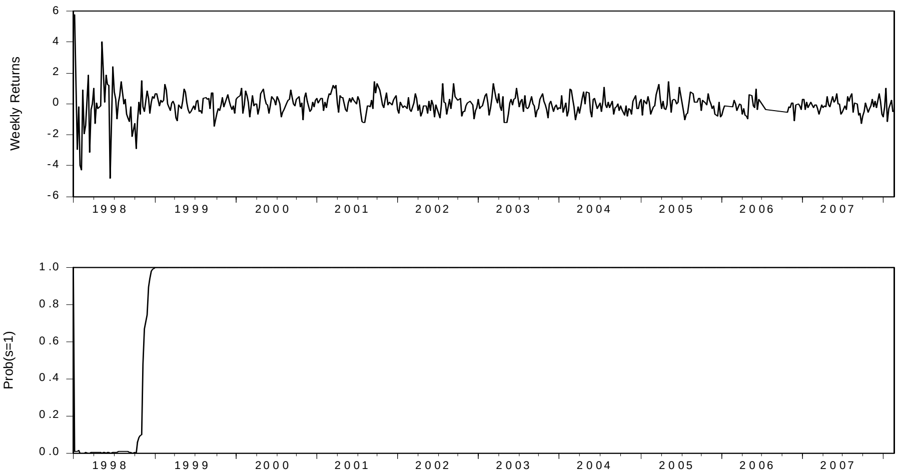
Malaysia



Philippines



Singapore



Taiwan