BOFIT Discussion Papers
17 • 2007

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Volatility dependence across Asia-Pacific on-shore and off-shore U.S. dollar futures markets

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Institute for Economies in Transition

BOFIT Discussion Papers
Editor-in-Chief Iikka Korhonen

BOFIT Discussion Papers 17/2007
20.8.2007

Roberta Colavecchio and Michael Funke: Volatility dependence across Asia-Pacific on-shore and off-shore U.S.dollar futures markets

ISBN 978-952-462-881-5
ISSN 1456-5889
(online)

Suomen Pankki
Helsinki 2007

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Abstract

This paper estimates switching autoregressive conditional heteroscedasticity (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 U.S. dollar future rates 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

Acknowledgement

We thank Michael Chui (BIS) who generously shared on-shore and off-shore forward exchange rate data for this research.

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Tiivistelmä

Tutkimuksessa arvioidaan, miten vaihtuvien tilojen autoregressiivisiä konditionaalisen heteroskedastisuuden (switching autoregressive conditional heteroscedasticity, SWARCH) mallit soveltuvat yhdeksän Aasian maan termiinikurssien viikkotuottoihin. Tuotoilla havaittiin olevan kaksi eri tilaa, joiden volatiliteetit poikkeavat toisistaan. Tilat ovat myös hyvin pitkäikäisiä ja vaihtuvat harvoin. Tulosten mukaan Kiinan renminbin termiinikurssin vaikutukset muihin Aasian valuuttoihin ovat olleet suhteellisen pieniä, koska ei löytynyt todisteita siitä, että valuuttojen volatiliteetit vaikuttaisivat juurikaan toisiinsa.

Asiasanat: Kiina, renminbi, Aasia, termiinikurssit, non-deliverable forward rates
SWARCH-mallit

1 Introduction

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. 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 its exports.[1] 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. China's impact upon the world economy therefore manifests itself as a substantial supply shock. 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. (2006) have demonstrated by means of 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. Asia has even overtaken the euro area with respect to the ratio of intra-regional trade to GDP.

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.[2] As a result of this reform, the PBOC now manages the renminbi against an undisclosed basket of currencies of the

[1] See Rodrik (2006) for a comprehensive analysis of China´s export success.

main trading partners.[3] 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.

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 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 on-shore forward exchange rate markets do not exist. We circumvent this problem by using both on-shore and off-shore 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

[2] The terms "renminbi" and "yuan" are generally used interchangeably to refer to China´s currency. The renminbi is the currency, and the yuan is the unit of account.

[3] The announcement and subsequent clarifications leave the Chinese central bank with considerable discretion over its renminbi target. After some initial revaluation against the U.S. dollar the exchange rate band is to be widened over time as domestic foreign exchange markets develop.

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.

This paper is organised 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 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. 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 diverse economic agents. Unfortunately, several emerging market economies restrict the access of foreign firms and international investors to on-shore financial markets and therefore forward markets either do not exist or are underdeveloped. The underdeveloped forward markets reflect the shallowness and narrowness of their domestic financial markets rendering them more vulnerable to swings in global capital flows. 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.[4]

In order to analyse comovements across Chinese and Asian forward exchange rates, we use weekly returns of U.S. dollar futures for nine Asian countries which can be classified into one of three groups: (1) China, (2) the "mature Tigers" (Hong Kong, Korea, Singapore and Taiwan), and (3) the "new Tigers" (Indonesia, Malaysia, Philippines, Thailand). The dataset therefore includes those countries which experienced the greatest extent

[4] Since August 2005, a Chinese on-shore interbank forward market exists with eight foreign currency pairs currently trading. Yet, to date this small and shallow market is still hampered by low liquidity with volume trivial and a lack of independent pricing. In fact, market participants in the onshore market largely base their quotes on the prices on the prices in the NDF market.

of economic and financial turmoil during the Asian crisis 1997-98 – a crisis which was entirely unpredicted. Our dataset includes on-shore and off-shore forward exchange rates with maturities from one month to eighteen months. Contracts with maturities longer than twelve months, however, are too thinly traded to serve as a reliable market indicator. 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 23 March 2005 (377 weekly observations).[5] All data are obtained from Citibank in Hong Kong. The country coverage is given in Table 1.

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		√
Korea	Won		√
Malaysia	Ringgit		√
Philippines	Peso	√	
Singapore	Singapore Dollar	√	
Taiwan	Taiwan Dollar		√
Thailand	Bhat	√	

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 provided by Citibank and the observations are recorded at the close of business (average of the closing bid and the offered rates).

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.

[5] 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).

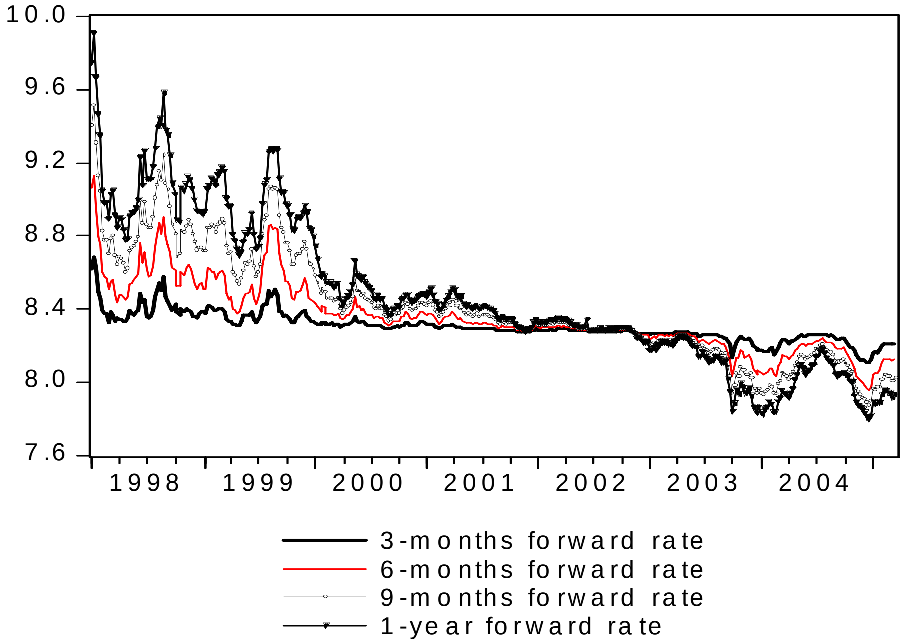
Active and growing NDF markets exist for several Asian currencies. These offshore markets offer international investors an otherwise unavailable hedging tool against local currency exposure. An analysis of Asian NDF markets in general as well as the basic institutional features of the renminbi NDF market 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. Figure 1 tracks the one-, three-, six-, 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.[6] 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 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. An NDF is a zero-sum game in which setting the NDF contract's exchange rate equal to the expected future spot rate minimises one participant's loss (and the other's gain). Hence, the parties will use all available information in forming their expectations.

[6] Even when a substantial revaluation of the renminbi is not the most likely prediction for the foreseeable future, the market price will nevertheless include compensation for the small probability of a substantial renminbi appreciation. This risk premium for the small probability of a large adjustment, i.e. the so-called peso problem, has caused the NDF rate to deviate on one side of the pegged exchange rate since the beginning of 2003.

Figure 1: The movements of the renminbi NDF´s against the U.S. dollar

weeklydata: 1/1/1998 to 23/3/2005

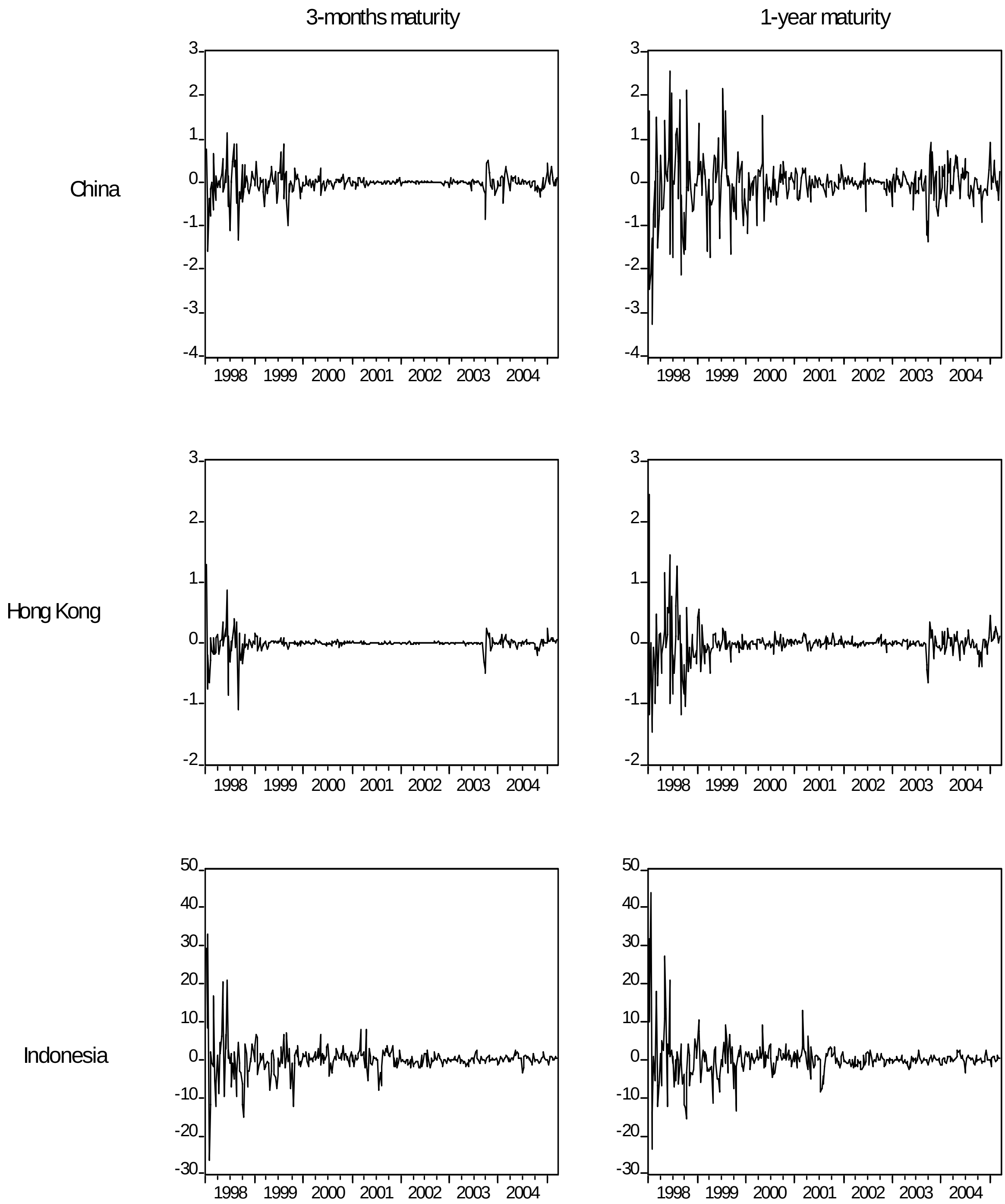


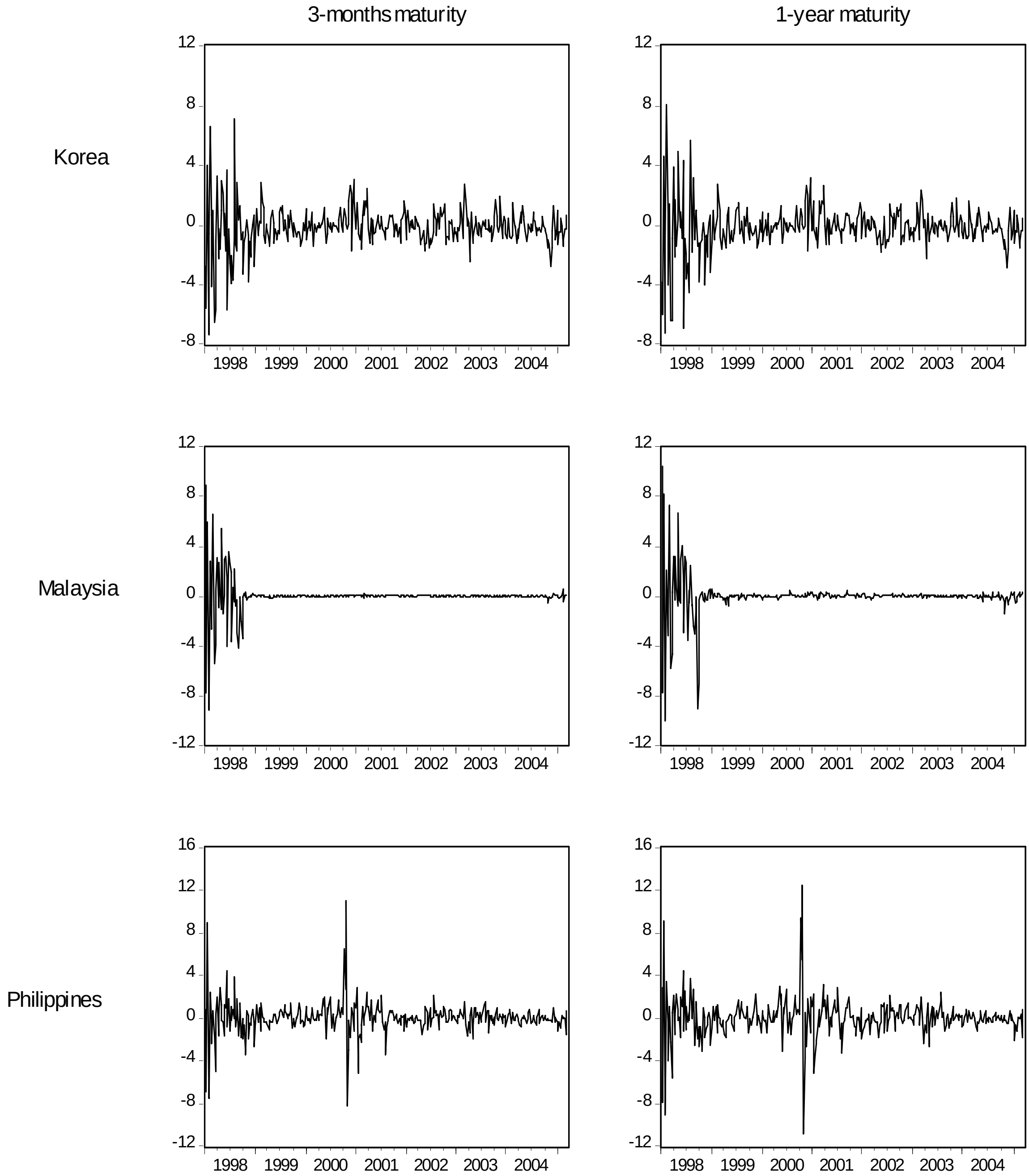
In order to inspect the data in more detail, Figure 2 displays the various weekly return series for 3-months and 1-year maturity. A few general observations are in order: First, the graphs clearly demonstrate that volatility often increases substantially over a short period of time at the onset of a 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.[7] 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. Finally, all the series appear to have fat-tailed distributions relative to the normal distribution with significant volatility clustering.

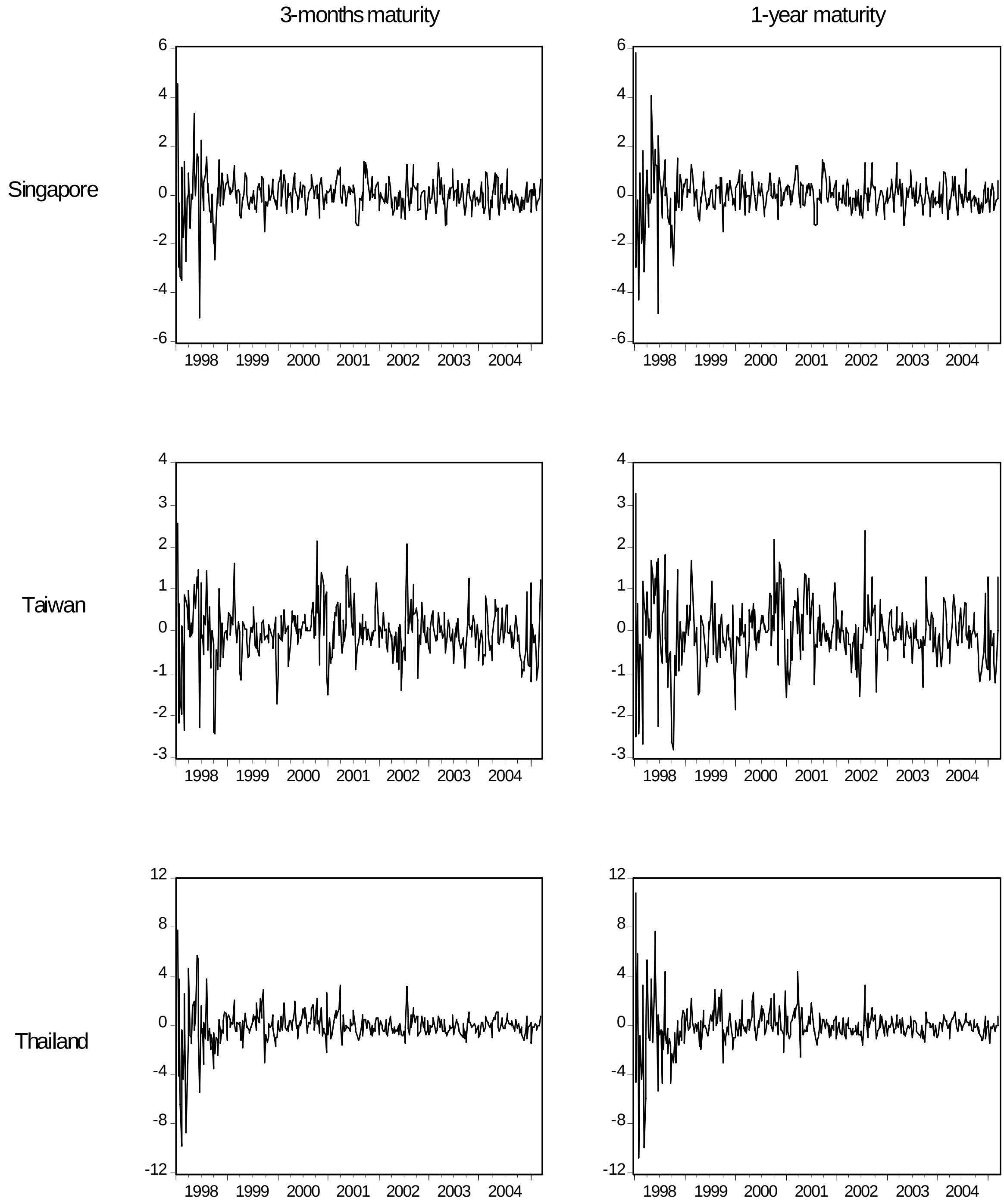
[7] The forward rate incorporates both expectations about the expected future spot rate, and a currency risk premium. Systematic forward rate prediction errors may arise from peso problems and rational learning about the environment. Using data from 1996 – 2004, Frankel and Poonawala (2006) have recently 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.

Figure 2 Weekly returns of the 1-year and 3 months U.S. dollar futures by country in %

Period: 1/1/1998 to 23/3/2005




3-months maturity
1-year maturity
Korea
Malaysia
Philippines
12
8
4
0
-4
-8
-12
16
1998
1999
2000
2001
2002
2003
2004



As a useful next step in our analysis, some stylised facts for each of the series are provided in Table 2 and Table 3.

Table 2 Univariate statistics for weekly returns with three months maturity

	China	*Hong Kong*	*Indonesia*	*Korea*	*Malaysia*	*Philippines*	*Singapore*	*Taiwan*	*Thailand*
Mean	-0.013	-0.002	0.080	-0.153	-0.028	0.042	-0.019	-0.023	-0.078
SD	0.243	0.144	4.316	1.371	1.281	1.516	0.775	0.635	1.409
Sk	-0.948	-0.004	1.749	-0.340	-1.062	0.274	-0.612	-0.160	-1.032
Ku	14.147	36.919	23.997	10.991	29.636	20.045	12.957	5.935	17.612
JB	2003.1 (0.00)	18024.4 (0.00)	7098.7 (0.00)	1007.5 (0.00)	11185.4 (0.00)	4556.6 (0.00)	1576.7 (0.00)	136.6 (0.00)	3411.6 (0.00)
LB(6)	17.906 (0.01)	18.864 (0.004)	25.158 (0.00)	21.049 (0.002)	49.574 (0.00)	14.396 (0.03)	8.095 (0.23)	35.206 (0.00)	17.883 (0.01)
$LB^2(6)$	87.912 (0.00)	48.26 (0.00)	142.816 (0.00)	220.13 (0.00)	433.445 (0.00)	172.89 (0.00)	109.49 (0.00)	75.887 (0.00)	209.86 (0.00)
H	2.582*	2.454*	1.076	1.556	3.112**	1.059	3.164**	2.240	3.136**

Table 3 Univariate statistics for weekly returns with one year maturity

	China	*Hong Kong*	*Indonesia*	*Korea*	*Malaysia*	*Philippines*	*Singapore*	*Taiwan*	*Thailand*
Mean	-0.055	-0.017	0.067	-0.170	-0.040	0.021	-0.027	-0.035	-0.097
SD	0.598	0.293	4.926	1.459	1.510	1.816	0.842	0.739	1.680
Sk	-0.292	1.049	2.791	-0.298	-0.906	0.196	-0.161	-0.051	-0.402
Ku	8.925	22.959	28.835	11.142	28.672	18.023	15.900	5.686	17.930
JB	555.4 (0.00)	6309.9 (0.00)	10944.6 (0.00)	1044.1 (0.00)	10376.9 (0.00)	3538.3 (0.00)	2608.5 (0.00)	113.167 (0.00)	3502.234 (0.00)
LB(6)	30.158 (0.00)	19.984 (0.00)	28.439 (0.00)	26.763 (0.00)	33.454 (0.00)	13.448 (0.04)	10.472 (0.11)	39.989 (0.00)	17.311 (0.001)
$LB^2(6)$	148.19 (0.00)	118.88 (0.00)	104.99 (0.00)	261.49 (0.00)	327.10 (0.00)	230.162 (0.00)	125.753 (0.00)	90.963 (0.00)	217.814 (0.00)
H	2.368	2.402	1.977	1.538	3.241**	0.999	2.771*	2.101	2.649*

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; $LB^2(k)$ 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. The calculations were carried out using *RATS* 6.2.

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. The graphs indicate at least two regimes with different volatility levels, whereby each regime displays a considerable persistence. Thereat the high volatility regime captures the periods of turbulence corresponding to the Asian crisis. Also noteworthy is the fact that for many countries Hansen´s likelihood ratio *H*-statistic rejects the null hypothesis of no regime switching.[8]

These properties suggest using a modelling framework which allows for serial correlation in the conditional variances. To assess possible time-variation as well as structural breaks, a flexible econometric modelling technique which takes into account both strong volatility clustering and structural breaks is certainly desirable. One drawback of such an approach is that the timing of regimes is notoriously difficult to estimate. Based on this economic reasoning, as well as on existing literature in this area, we pursue the SWARCH avenue of investigation to add power to the analysis. This methodological design permits conditional volatility to be both time- and state-dependent while the volatility regimes are identified and estimated endogenously. We now consider this methodology in greater detail.

3 The SWARCH modelling framework

A number of different empirical methodologies have been applied in the literature to study the degree of synchronisation of financial markets. The basic approach is to construct time-varying correlations on the basis of a GARCH specification. In this paper we use a more sophisticated approach by modelling 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 Susmel (2000) has generalised the original SWARCH model by introducing the exponential SWARCH or E-SWARCH model. A generalisation to SWGARCH models

[8] This view does not represent the consensus, though, as there is also some evidence for a single regime. A lack of statistical power of the *H*-tests may arise from one state being composed of only a few observations.

was developed by Gray (1996) and has subsequently been further developed by Haas et al. (2004).

Bollen et al. (2000) argue that different exchange rate policy regimes give rise to different exchange rate behaviour. Vigfusson (1997) has constructed a two-state Markov switching model for the Canada-U.S. exchange rate dynamics capturing chartists and fundamentalists in the market. Ahrens and Reitz (2004) have applied the Vigfusson´s (1997) model to German-U.S. data.[9]

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.[10] 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.[11] More specifically, we postulate the following univariate SWARCH (k,q) model of returns, r_t:

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

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

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

[9] 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.

[10] 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.

[11] 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).

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 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.[12] The probability law that causes the economy to switch between (latent) regimes is then given by the (hidden) *k*-state first-order Markov chain

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

The transition probability parameter p_{ij} represents the transition probability of going from state *i* to *j*. In the model, the transition probabilities are exogenous and constant, i.e. it is time itself and not the state of the economic environment that governs turning points.[13] A large p_{ii} ($i = 1, 2, ..., q$) means that the model tends to stay longer in state *i*.

A byproduct 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

[12] 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. Only a few attempts have been made to test the ability of regime-switching ARCH and GARCH models to forecast high-frequency data. The results are not always encouraging. For a recent paper and review of the literature, see Marcucci (2005). One must bear in mind, however, that the overall fit of exchange rate regressions using daily or weekly data is typically not high. This may help to explain why SWARCH or SWGARCH forecasts tend to yield unspectacular results.

[13] Recall that Hamilton (1989) has assumed state-independent variances. The baseline Markov-switching model has been extended to allow for time-varying transition probabilities by McCulloch and Tsay (1993) and Filardo (1994). Although the modelling approach is given exogenously – and thus it may be considered ad hoc – the two-state Markov chain allows agents´ sentiments to switch from one state to another in a manner reminiscent of Keynes´ “animal spirits”.

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.[14] 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.[15] 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 5.16 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.

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 few cases (Korea, Singapore and Taiwan) do the two criteria generate conflicting

[14] 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.

[15] 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.

[16] 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.

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.17

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.18 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" p11 and p22 are high, the SWARCH model is characterised by long memory. In fact, [1/(1-pii)] is the expected duration of the process to stay in state i. For 0.95 < p11 < 0.99, the low volatility state 1 would be expected to last on average for 20-100 weeks. The range of 0.90 – 0.99 for p22 implies that the high volatility state 2 typically lasts for 10-100 weeks.

[17] 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.
[18] 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.

Table 4 Univariate SWARCH(*2*, *q*) models for weekly returns with 3 months maturity

	China		**Hong Kong**		**Indonesia**		**Korea**	
Mean Equation	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*
α_0	-0.003 (-0.83)	-0.002 (-1.36)	0.003 (2.54)	0.002 (2.24)	0.050 (0.68)	0.015 (0.25)	-0.059 (-1.41)	-0.073 (-1.80)
α_1	0.161 (3.22)	0.087 (1.61)	0.030 (0.98)	0.102 (3.19)	0.296 (5.06)	0.263 (4.92)	0.240 (4.52)	0.29 (6.79)
Variance Equation								
β_0	0.0012 (6.53)	0.001 (0.87)	0.004 (12.72)	0.011 (0.083)	0.816 (7.18)	1.502 (1.80)	0.041 (7.51)	0.563 (5.89)
β_1	0.313 (4.15)	2.007 (0.87)			0.174 (2.72)	0.751 (1.33)	0.095 (1.58)	-0.016 (-0.38)
β_2	0.253 (3.55)	0.335 (0.78)			0.206 (2.663)	0.479 (1.264)	0.279 (2.784)	0.251 (1.759)
P_{11}	0.965 (65.31)	0.988 (65.05)	0.954 (70.99)	0.984 (108.16)	0.974 (91.24)	0.99 (268.93)	0.99 (354.85)	0.997 (290.76)
P_{12}	0.038 (2.62)	0.003 (1.02)	0.131 (3.36)	0.043 (1.88)	0.07 (2.94)	0.004 (0.95)	0.006 (1.01)	0.008 (0.84)
ν		2.313 (5.41)		2.027 (6.18)		2.60 (5.29)		5.51 (2.74)
γ_2	49.01 (5.69)	35.264 (2.69)	163.33 (8.93)	100.33 (3.82)	47.68 (6.57)	21.32 (3.17)	11.042 (3.62)	24.261 (2.98)
AIC	-1.28	**-1.47**	-3.33	**-3.58**	4.32	**4.21**	2.782	**2.760**
BIC	-1.19	**-1.37**	-3.27	**-3.51**	4.40	**4.30**	2.866	**2.854**

Table 4 Continued

	Malaysia		**Philippines**		**Singapore**		**Taiwan**		**Thailand**	
Mean Equation	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*
α_0	0.000 (0.04)	0.0008 (1.25)	0.025 (0.71)	0.028 (0.82)	-0.001 (-0.06)	-0.003 (-0.14)	-0.023 (-1.03)	-0.020 (-0.94)	-0.039 (-1.06)	-0.045 (-1.22)
α_1	0.004 (0.49)	0.152 (5.47)	0.069 (1.37)	0.158 (2.91)	0.299 (5.80)	0.305 (5.91)	0.261 (5.09)	0.298 (5.86)	0.305 (5.08)	0.271 (4.45)
Variance Equation										
β_0	0.000 (10.23)	0.057 (1.37)	0.217 (8.01)	0.284 (4.60)	0.223 (10.7)	0.224 (8.44)	0.093 (6.52)	0.112 (5.92)	0.319 (8.88)	0.428 (5.52)
β_1	1.275 (9.15)	380.90 (2.14)	0.334 (3.73)	0.0297 (2.53)	0.017 (0.33)	0.024 (0.43)	0.086 (1.29)	0.145 (1.83)	0.253 (3.13)	0.290 (2.13)
P_{11}	0.974 (100.47)	0.997 (439.88)	0.979 (77.40)	0.988 (95.48)	0.997 (288.41)	0.997 (212.38)	0.951 (42.27)	0.980 (97.07)	0.982 (108.04)	0.998 (293.71)
P_{12}	0.182 (3.17	0.007 (0.90)	0.033 (2.06)	0.0191 (1.20)	0.006 (0.82)	0.006 (0.57)	0.073 (1.88)	0.025 (1.59)	0.082 (1.98)	0.007 (0.69)
ν		2.002 (1538.78)		4.558 (3.81)		12.160 (1.41)		6.086 (3.16)		5.022 (3.01)
γ_2	17682.12 (4.39)	57152.50 (2.46)	12.740 (6.47)	9.036 (2.46)	12.143 (5.36)	10.925 (3.86)	7.772 (5.08)	5.617 (4.79)	17.457 (4.23)	20.934 (3.01)
AIC	-2.976	**-3.323**	2.698	**2.615**	1.705	**1.701**	1.517	**1.499**	2.576	**2.541**
BIC	-2.902	**-3.239**	2.771	**2.699**	**1.778**	1.784	1.590	**1.583**	2.649	**2.625**

Table 5 Univariate SWARCH(*2*, *q*) models for weekly returns with 1 year maturity

	China		**Hong Kong**		**Indonesia**		**Korea**	
Mean Equation	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*
α_0	-0.024 (-1.51)	-0.018 (-1.50)	-0.004 (-1.36)	-0.0037 (-1.09)	0.062 (0.75)	-0.011 (-0.15)	-0.076 (-1.82)	-0.086 (-2.03)
α_1	0.264 (3.86)	0.282 (5.42)	0.069 (1.53)	0.149 (2.71)	0.345 (6.51	0.285 (5.75)	0.245 (4.40)	0.255 (4.68)
Variance Equation								
β_0	0.042 (8.81)	0.048 (2.05)	0.002 (7.01)	0.004 (2.29)	1.326 (8.896)	1.496 (3.26)	0.420 (7.82)	0.440 (5.89)
β_1	0.157 (2.46)	0.332 (1.48)	0.429 (3.80)	0.673 (1.73)	0.148 (2.37)	0.368 (1.95)	0.143 (2.16)	0.138 (1.63)
β_2			0.238 (3.24)	0.514 (1.489)			0.223 (2.48)	0.219 (1.98)
P_{11}	0.988 (145.74)	0.989 (83.59)	0.969 (78.88)	0.997 (243.29)	0.975 (90.76)	0.986 (86.46)	0.998 (274.52)	0.998 (261.07)
P_{12}	0.016 (2.00)	0.009 (1.09)	0.106 (2.31)	0.006 (0.80)	0.054 (2.71)	0.023 (1.38)	0.005 (0.89)	0.005 (0.93)
ν		2.890 (4.21)		2.803 (4.78)		3.24 (4.96)		9.788 (1.32)
γ_2	13.615 (6.71)	12.093 (3.70)	66.456 (4.29)	110.90 (2.53)	39.575 (8.11)	20.828 (3.87)	13.572 (3.58)	15.089 (3.20)
AIC	1.007	**0.905**	-1.340	**-1.443**	4.57	**4.44**	2.834	**2.830**
BIC	1.081	**0.989**	-1.256	**-1.349**	4.64	**4.52**	**2.917**	2.924

Table 5 Continued

	Malaysia		**Philippines**		**Singapore**		**Taiwan**		**Thailand**	
Mean Equation	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*	*N-SWARCH*	*t-SWARCH*
α_0	0.012 (2.25)	0.008 (2.11)	-0.023 (-0.53)	-0.011 (-0.27)	-0.003 (-0.10)	-0.003 (-0.13)	-0.029 (-1.04)	-0.031 (-1.16)	-0.075 (-1.79)	-0.073 (-1.78)
α_1	0.195 (3.25)	0.095 (1.67)	0.171 (3.06)	0.197 (3.95)	0.302 (6.15)	0.305 (6.11)	0.323 (5.86)	0.315 (5.97)	0.278 (4.65)	0.243 (4.08)
Variance Equation										
β_0	0.009 (8.97)	0.504 (5.83)	0.353 (5.65)	0.379 (4.18)	0.232 (10.95)	0.233 (8.90)	0.145 (7.00)	0.164 (4.77)	0.392 (8.51)	0.595 (4.65)
β_1	0.483 (4.61)	83.48 (2.37)	0.428 (4.03)	0.478 (3.30)	0.004 (0.11)	0.012 (0.23)	0.161 (2.03)	0.160 (1.58)	0.293 (3.75)	0.260 (2.42)
P_{11}	0.989 (156.03)	0.998 (474.78)	0.983 (94.95)	0.984 (93.05)	0.998 (251.28)	0.997 (232.13)	0.973 (67.2)	0.980 (69.70)	0.983 (118.04)	0.997 (345.11)
P_{12}	0.065 (1.43)	0.007 (0.65)	0.026 (1.55)	0.023 (1.58)	0.007 (0.96)	0.006 (0.84)	0.031 (1.83)	0.024 (1.39)	0.070 (2.07)	0.008 (0.71)
ν		2.01 (0.00)		4.936 (3.56)		16.021 (1.06)		7.540 (1.69)		4.390 (3.29)
γ_2	849.67 (3.74)	2259.37 (2.03)	9.680 (4.69)	7.850 (4.19)	14.151 (5.28)	13.150 (4.49)	4.918 (5.59)	4.698 (4.25)	17.174 (4.24)	20.595 (3.05)
AIC	-0.343	**-0.641**	3.134	**3.075**	**1.755**	1.756	1.868	**1.859**	2.844	**2.818**
BIC	-0.270	**-0.557**	3.208	**3.159**	**1.829**	1.840	**1.941**	1.943	2.918	**2.902**

Notes: The Tables show the various maximum-likelihood parameter estimates and the corresponding *t*-values. *AIC* = -2*L* + 2*K* and *BIC* = -2*L* + *K*log(*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 for the particular criterion. The calculations were carried out using *RATS* 6.2.

Next we report a regime classification test for our models. To measure the quality of regime classification, we use 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 5 indicates that the SWARCH models deliver distinctive regime inference as the *RCM*´s are far from 100. In other words, the quality of regime classification measures in Table 6 provide some indication of the relevance of the regime switching approach.

Table 6 The *RCM* quality of regime classification measures

COUNTRY	*RCM*-STATISTIC 3 MONTHS MATURITY	*RCM*-STATISTIC 1 YEAR MATURITY
China	8.35	14.05
Hong Kong	7.26	2.95
Indonesia	3.64	14.63
Korea	1.76	1.92
Malaysia	0.93	0.78
Philippines	11.76	19.28
Singapore	1.53	1.37
Taiwan	18.04	23.79
Thailand	2.10	2.68

We now turn to a graphical enquiry of the estimated probabilities, i.e. we use the ability of the procedure to date regimes. In Figure 3, we plot the weekly returns of U.S. futures 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 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 Hong Kong, Philippines and Taiwanese markets display more regime switching behaviour and turbulence from high to low and back to high. In yet others (Korea, Malaysia and Singapore) volatility appears to be low throughout except during the Asian crisis. Similar patterns are replicated for the 1-year U.S. futures returns available in the Appendix. The “extra volatility” on the Chinese market at the end of the sample period has not come entirely out of the blue and is not accidental because an appreciating exchange rate was expected to help China to cool down its overheating economy.

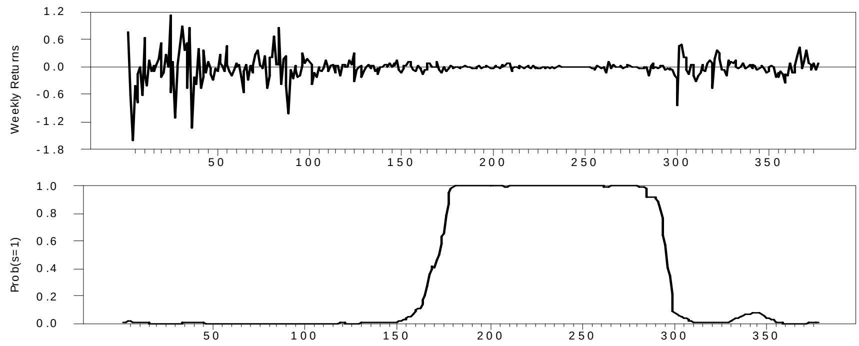
Given the estimated probabilities, we are now in a position to assess in greater depth the question whether the Asian countries have followed the “leader”, i.e. whether the renminbi NDF returns had some knock-on effects upon other Asian countries. In other words, we can calculate regime-dependent linkages of Asian on-shore and off-shore U.S. dollar futures, holding China as the dominant market. 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.[19] (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.[20]

[19] We have also considered bivariate SWARCH models but finding models converging to a well-defined global maximum proved troublesome. The poor performance of the bivariate SWARCH is due to the complicated likelihood function being a mixture of all possible state configurations. We therefore restrict ourselves to tractable univariate SWARCH models and a two-step procedure to obtain state-dependent linkages across countries.

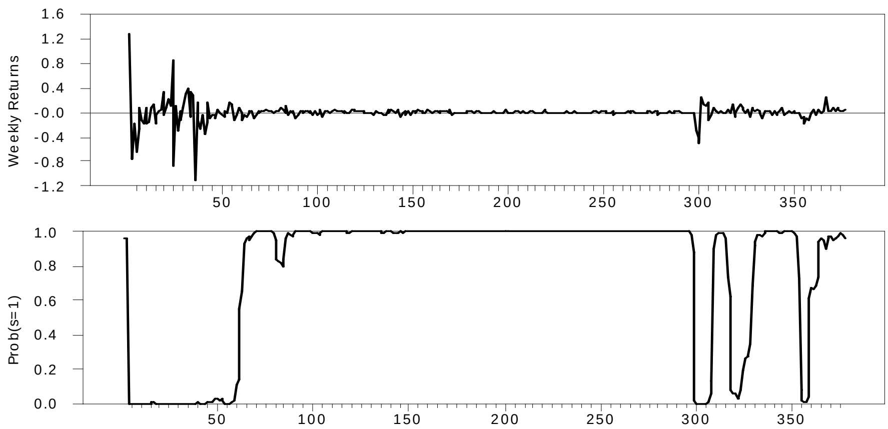
[20] A problem with the econometric approach is that the nonstructural data-based approach hard wires policy parameters and therefore does not lend itself to answering questions of interest to policymakers. Despite their sound statistical background, SWARCH models are “black box” methods from an economic point of view. The volatility co-movements should therefore not be interpreted as causal relationships.

Figure 3 Weekly returns of U.S. futures with 3 months maturity (top panel) and amoothed 1st regime probabilities (lower panel)

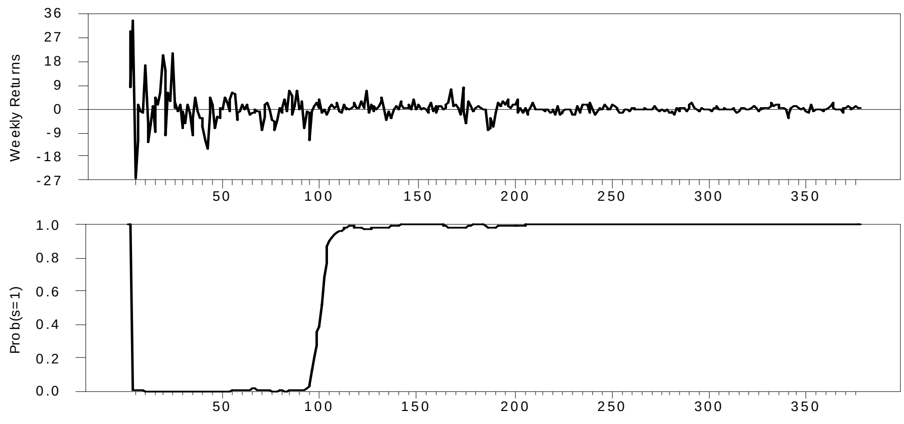
China



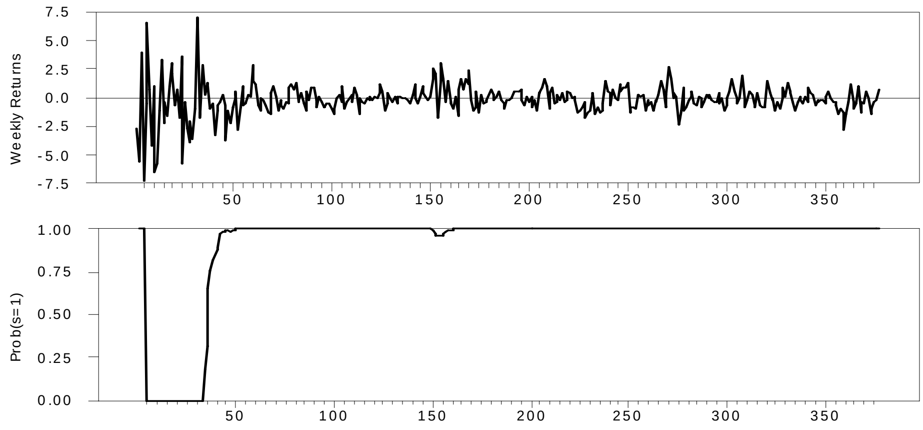
Hong Kong



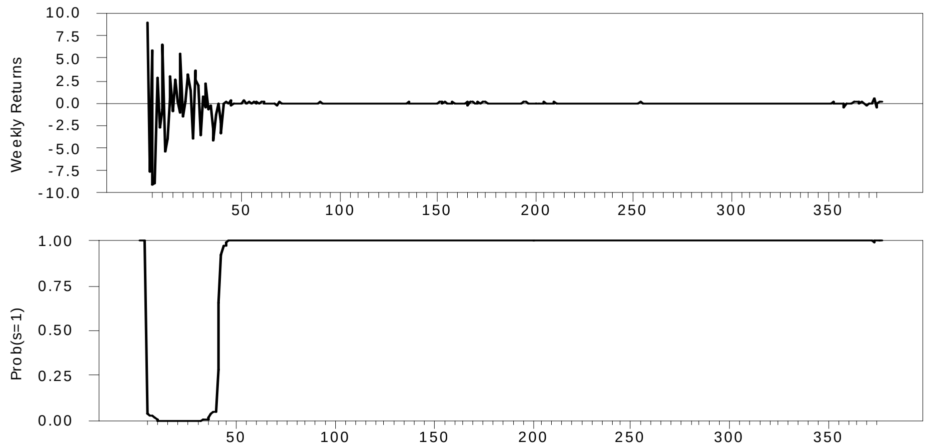
Indonesia



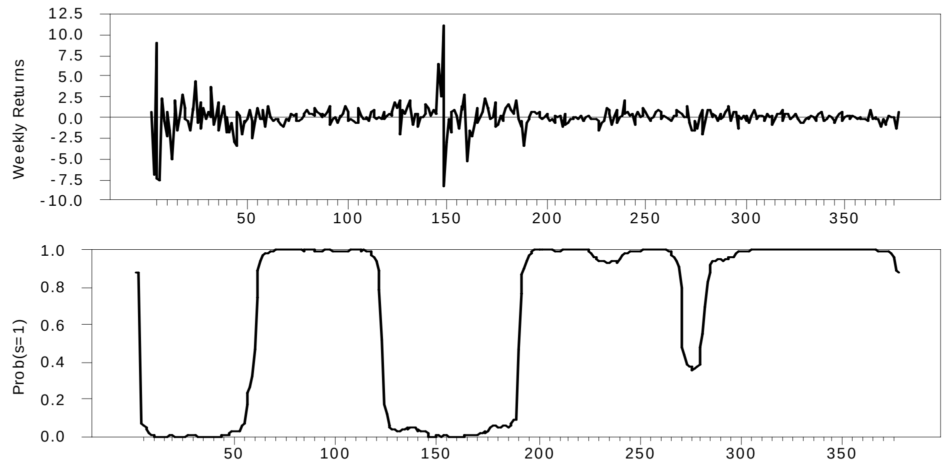
Korea



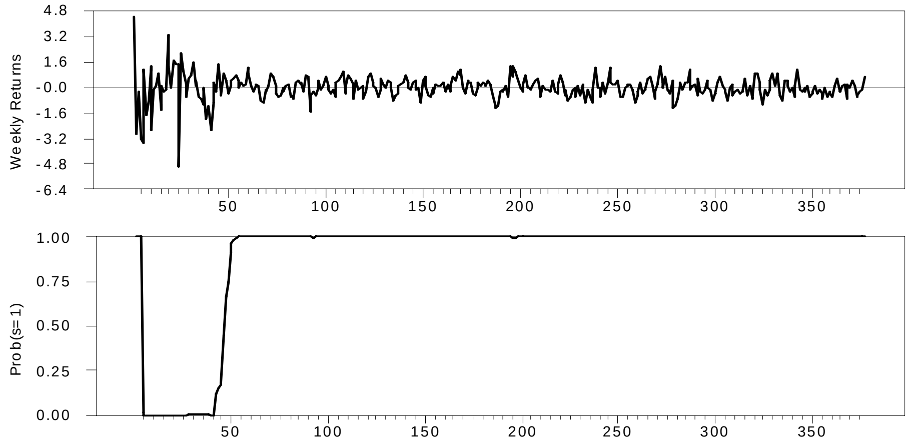
Malaysia



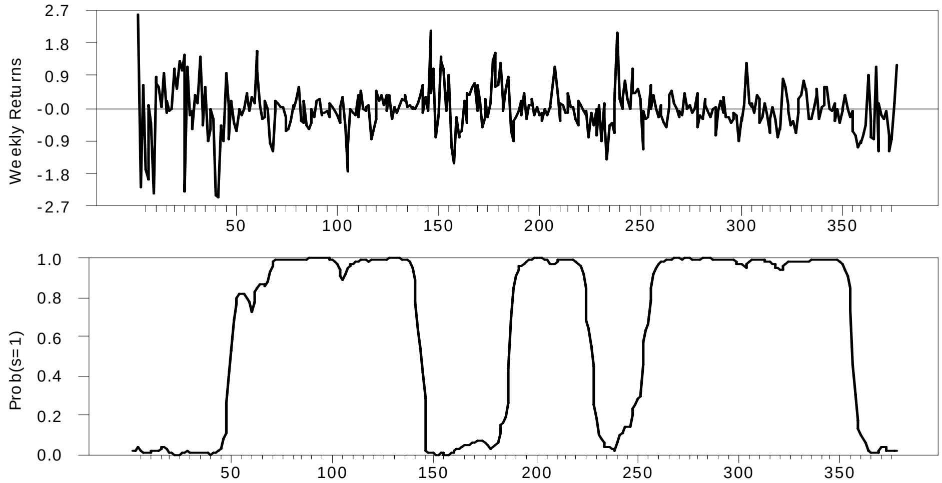
Philippines



Singapore



Taiwan



Thailand

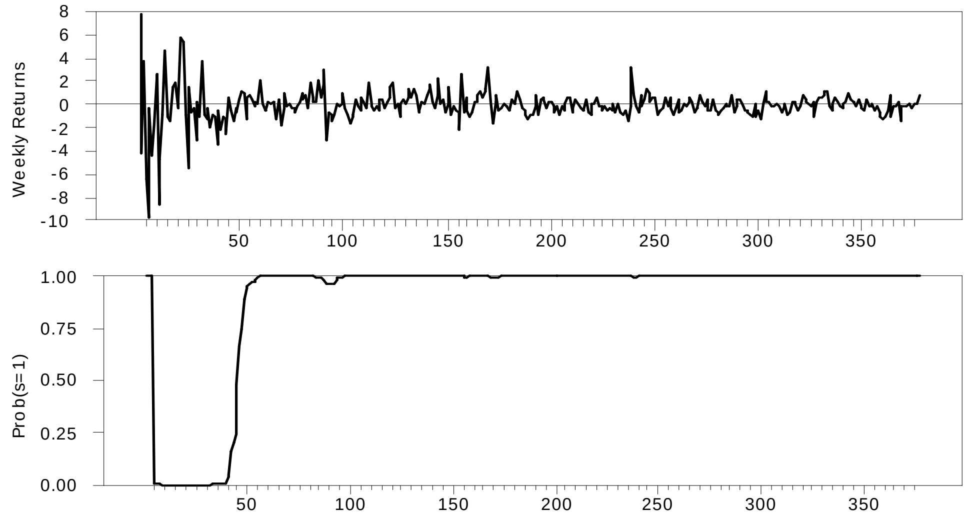


Table 7 Pair-wise co-dependence of volatility regimes (three months maturity)

	Correlation	# of Observations	Critical Value
China vs Hong Kong			
State 1: China low, Hong Kong low	0.25	124	0.18
State 2: China low, Hong Kong high	-	0	-
State 3: China high, Hong Kong low	0.48	169	0.15
State 4: China high, Hong Kong high	0.72	84	0.22
China vs Indonesia			
State 1: China low, Indonesia low	0.17	124	0.18
State 2: China low, Indonesia high		0	
State 3: China high, Indonesia low	0.35	156	0.16
State 4: China high, Indonesia high	0.10	97	0.20
China vs Korea			
State 1: China low, Korea low	0.25	124	0.18
State 2: China low, Korea high		0	
State 3: China high, Korea low	0.20	221	0.13
State 4: China high, Korea high	0.25	32	0.35
China vs Malaysia			
State 1: China low, Malaysia low	-0.15	124	0.18
State 2: China low, Malaysia high	-	0	-
State 3: China high, Malaysia low	0.32	216	0.14
State 4: China high, Malaysia high	0.19	37	0.33
China vs Philippines			
State 1: China low, Philippines low	-0.01	95	0.21
State 2: China low, Philippines high	0.13	29	0.37
State 3: China high, Philippines low	0.24	148	0.16
State 4: China high, Philippines high	0.17	105	0.20
China vs Singapore			
State 1: China low, Singapore low	0.15	124	0.18
State 2: China low, Singapore high	-	0	-
State 3: China high, Singapore low	0.27	210	0.14
State 4: China high, Singapore high	0.44	43	0.30
China vs Taiwan			
State 1: China low, Taiwan low	0.34	83	0.22
State 2: China low, Taiwan high	0.35	41	0.31
State 3: China high, Taiwan low	0.31	154	0.16
State 4: China high, Taiwan high	0.41	99	0.20
China vs Thailand			
State 1: China low, Thailand low	0.33	124	0.18
State 2: China low, Thailand high	-	0	-
State 3: China high, Thailand low	0.38	211	0.14
State 4: China high, Thailand high	0.33	42	0.31

Table 8 Pair-wise co-dependence of volatility regimes (one year maturity)

	Correlation	# of Observa-tions	Critical Value
China vs Hong Kong			
State 1: China low, Hong Kong low	0.69	196	0.14
State 2: China low, Hong Kong high	-	0	-
State 3: China high, Hong Kong low	0.63	127	0.18
State 4: China high, Hong Kong high	0.81	54	0.27
China vs Indonesia			
State 1: China low, Indonesia low	0.22	177	0.15
State 2: China low, Indonesia high	0.43	19	0.46
State 3: China high, Indonesia low	0.13	65	0.25
State 4: China high, Indonesia high	0.30	116	0.19
China vs Korea			
State 1: China low, Korea low	0.40	196	0.14
State 2: China low, Korea high	-	0	-
State 3: China high, Korea low	0.30	123	0.18
State 4: China high, Korea high	0.33	58	0.26
China vs Malaysia			
State 1: China low, Malaysia low	0.68	196	0.14
State 2: China low, Malaysia high	-	0	-
State 3: China high, Malaysia low	0.13	144	0.17
State 4: China high, Malaysia high	0.44	37	0.33
China vs Philippines			
State 1: China low, Philippines low	0.53	134	0.17
State 2: China low, Philippines high	0.38	62	0.25
State 3: China high, Philippines low	0.36	109	0.19
State 4: China high, Philippines high	0.41	72	0.24
China vs Singapore			
State 1: China low, Singapore low	0.56	196	0.14
State 2: China low, Singapore high	-	0	-
State 3: China high, Singapore low	0.29	138	0.17
State 4: China high, Singapore high	0.61	43	0.30
China vs Taiwan			
State 1: China low, Taiwan low	0.48	105	0.20
State 2: China low, Taiwan high	0.59	91	0.21
State 3: China high, Taiwan low	0.41	116	0.19
State 4: China high, Taiwan high	0.64	65	0.25
China vs Thailand			
State 1: China low, Thailand low	0.60	196	0.14
State 2: China low, Thailand high	-	0	-
State 3: China high, Thailand low	0.44	140	0.17
State 4: China high, Thailand high	0.45	41	0.31

Notes: Brandner and Neusser (1992) suggest the rule that cross-correlations between detrended series exceeding $2/\sqrt{T}$ in absolute value are significant at the 5 percent level. The critical values in the 3rd column of Table 6 and 7 have been calculated accordingly.

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 many 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, i.e. the evidence for the "dominance hypothesis" is not altogether compelling. 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. Furthermore, differences in market depth may reduce the speed with which information shocks spill over to some other countries.

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 heterogenous markets. Note that such events may still be rational at the individual level.21 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.22 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 correla-

[21] There is no generally agreed upon definition of contagion. For different definitions see the website http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/EXTPROGRAMS/EXTMACROECO/0,,contentMDK:20889756~pagePK:64168182~piPK:64168060~theSitePK:477872,00.html.

[22] A 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.

tions. 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 rigorous statistical methodology to account for the bias when testing for contagion from country a to country b.[23] 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

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

and

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

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

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

[23] Boyer et al. (1997) have proposed similar bias-correction procedures. Corsetti et al. (2005), however, have demonstrated that if return are not i.i.d., then the proposed bias-correction strategies tend to err in favour of the null hypothesis of no contagion. Bae et al. (2003) have developed a new approach to the measurement of market contagion. Instead of focussing on cross-market correlations, they evaluate contagion by assessing the coincidence of large positive and large negative returns across countries. In order to establish whether joint occurrences of large returns are larger than one would expect, they first calibrate the outcomes using monte Carlo simulations of the joint distribution of market returns with different assumptions about their dynamics (multivariate normal, multivariate Student-*t*, multivariate GARCH). They then develop an econometric model of co-exceedances. In their experiment, contagion is defined as the fraction of exceedance that is not explained in the regression model. Using daily stock returns, they conclude that contagion is more important in Latin America than in Asia.

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 $\left(\sigma^2_{2,a} - \sigma^2_{1,a} / \sigma^2_{1,a}\right)$, country a in this case, over the high and low volatility periods.[24]

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.

Table 9 Adjusted (unconditional) correlations v_2

	3 MONTHS	1 YEAR
China vs Hong Kong	0.09	0.34
China vs Singapore	0.04	0.18
China vs Taiwan	0.05	0.15

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

5 Conclusions and further comments

The degree of East Asian economic integration has been at the centre of a swathe of policy discussion and academic work in recent times. In this paper we attempt to provide additional insights into the degree of volatility dependence across Asian forward exchange rates. For this purpose, SWARCH models are estimated to capture the time-varying volatility dynamics of financial time series.

The contribution of our paper to this ongoing debate can be regarded as twofold. First, we extend the existing literature by studying forward exchange rates across Asian countries. Without doubt, the use of the SWARCH approach allows for extracting more insightful implications than a traditional GARCH framework and gives rise to a plausible interpretation of nonlinearities. Second, the paper gives new insights into exactly how synchronised various future markets are. The results substantiate the claim that, thus far, the

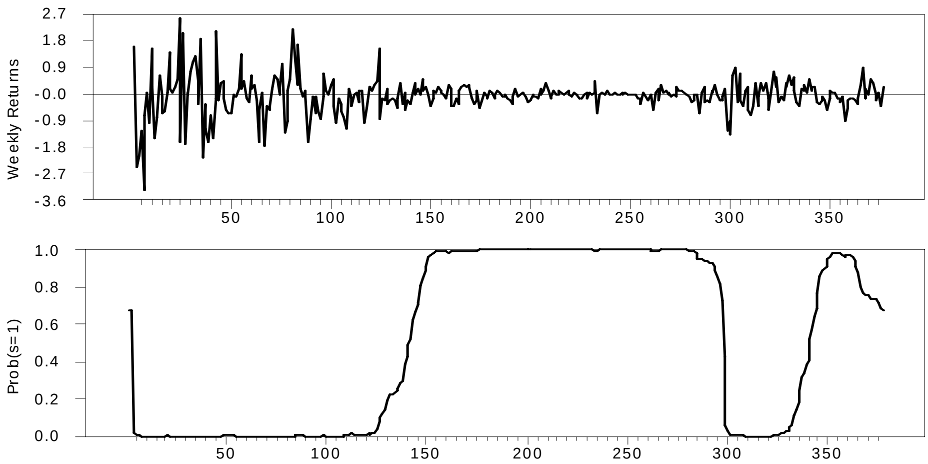
[24] A review of different modelling methodologies of contagion is provided by Dungey et al. (2004).

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.[25] This may indicate that the renminbi´s 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 sychronisation. 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.

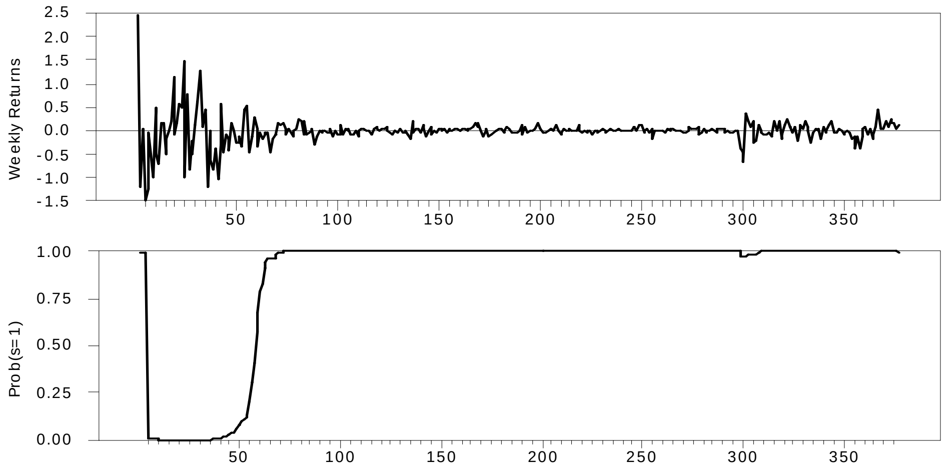
[25] This situation has not changed in recent times. Hong Kong, for example, has switched from simply maintaining the exchange rate at above HK dollar 7.80 per U.S. dollar to a trading band of 7.75 ≤ HK dollar ≤ 7.85 in May 2005. This added a ceiling to the floor by which it had traditionally managed the currency, in a move to discourage investors from using the HK dollar to speculate on a renminbi appreciation. This strategy was successful. While the renminbi appreciated against the U.S. $, the HK dollar is trading near the target at HK dollar 7.81 per U.S. dollar in January 2007, and there are no sign of an appreciation.

Appendix: Weekly returns of U.S. futures with 1 year maturity (top panel) and smoothed 1st regime probabilities (lower panel)

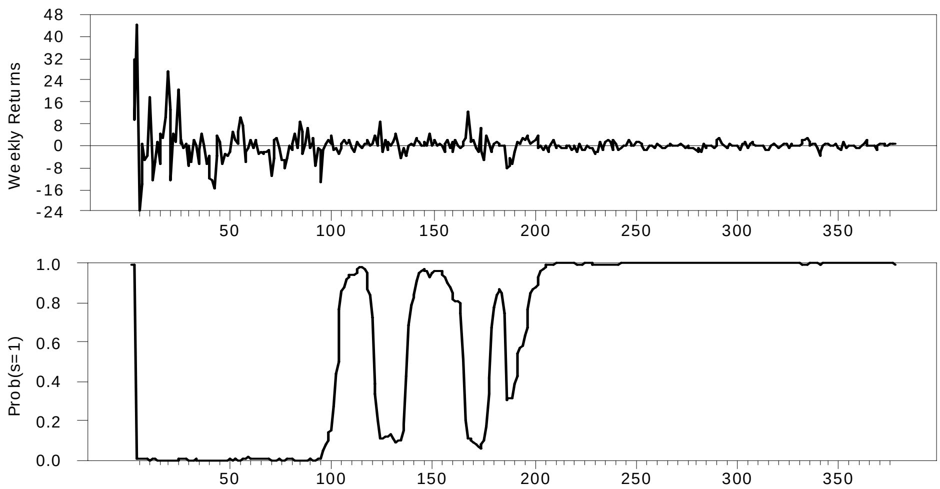
China



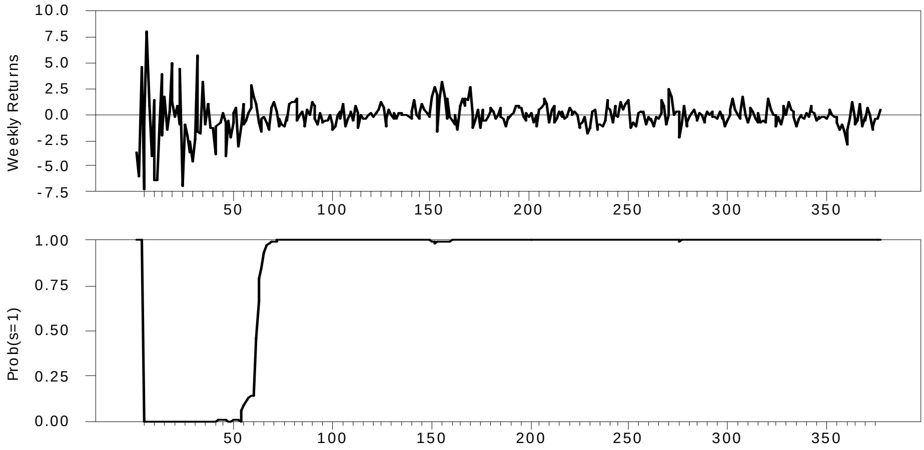
Hong Kong



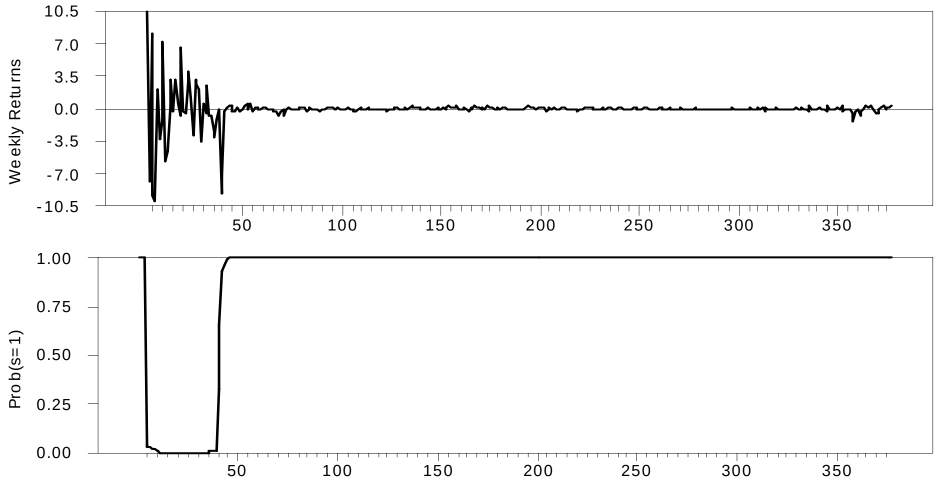
Indonesia



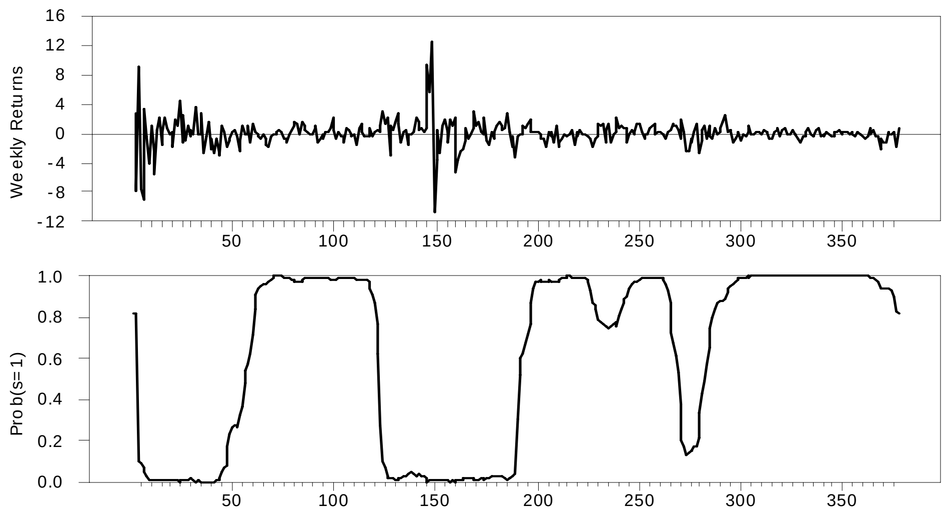
Korea



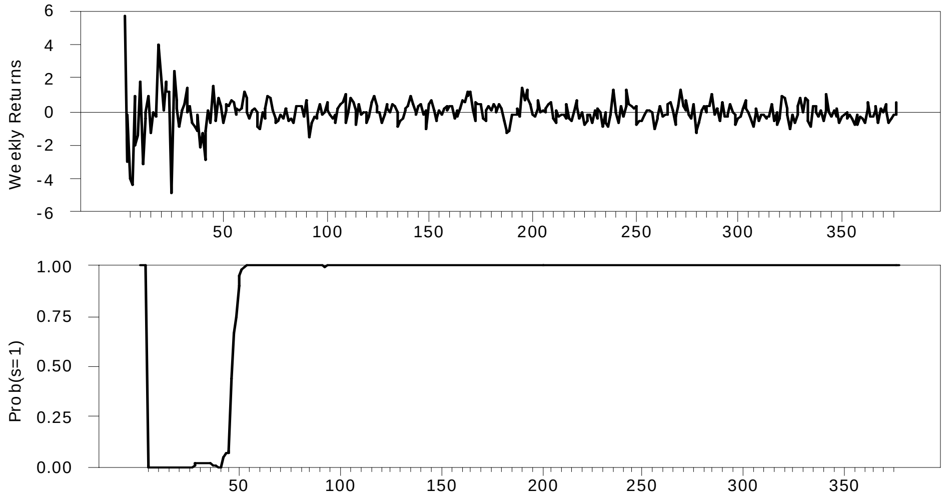
Malaysia



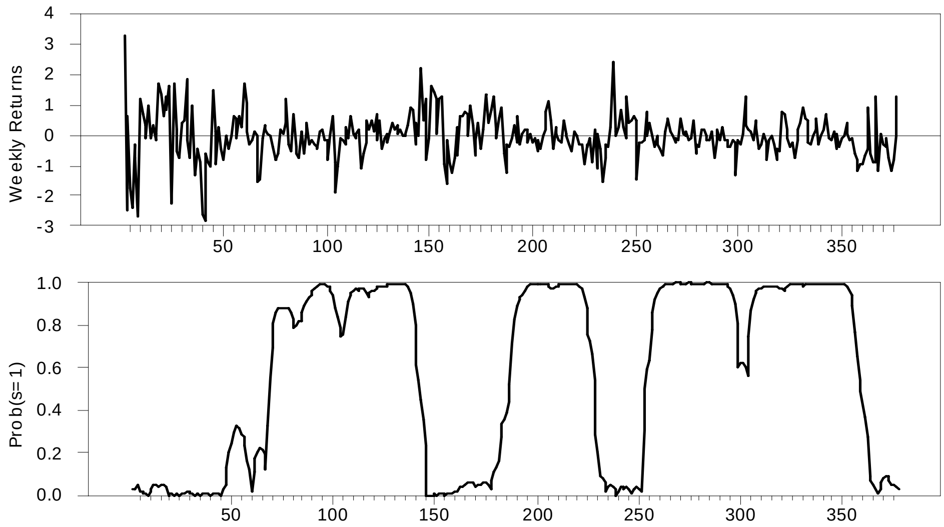
Philippines



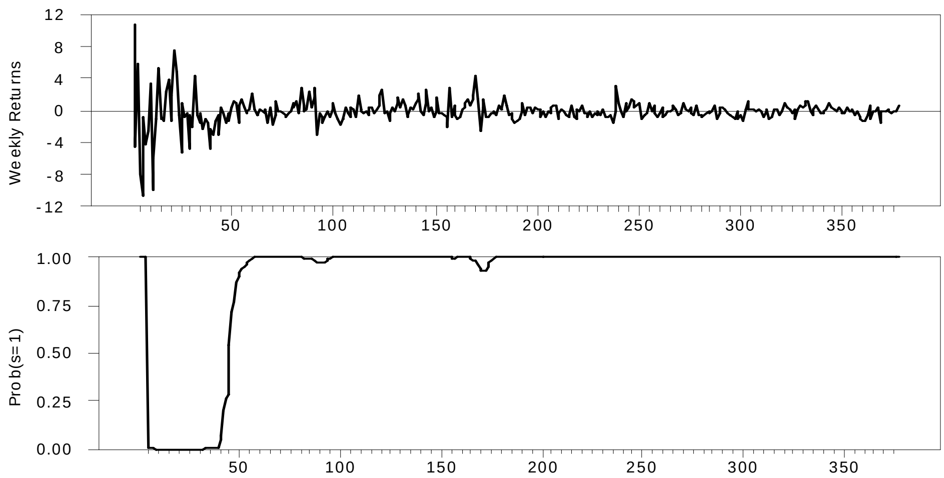
Singapore



Taiwan



Thailand



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