Regime Switching Analysis of ADR Home-Market Pass-Through

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Abstract

This paper takes a regime-switching approach to model and estimate the home market effect and US market effect on ADR returns. The regime switching model nests two regimes - "home market pass-through" and "pricing-to-US market" for ADRs, and treats the changes of these two regimes probabilistically, while taking into account the time-varying price of risks and time-varying covariance with the market. A proxy for home-market pass-through effect is developed for Japan, Germany, Argentina and China from 1998 to 2006. In pricing ADR index returns, Germany shows home-market pass-through regime dominance. Interestingly, Japan and China have a pricing-to-market regime dominance as well as the post-2003 Argentina. There is a frequent regime switching pattern for Argentina in the pre-2003 period.

JEL Classification: F21, F30, G15
Keywords: ADRs, Regime Switching, Conditional CAPM and International Finance.

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I. Research Description

Foreign firms usually list their stocks in US stock exchanges in the form of American Depository Receipts (ADRs). ADRs are issued by a US depository bank evidencing ownership of shares in a Non-US corporation. Investors bear all currency risks when holding ADRs and receiving dividends, and indirectly pay fees to the depository bank. Numerous research has been done rationalizing why firms cross-list in the past two decades (see surveys by Karolyi 1998, 2006). However, we still lack adequate knowledge of the pricing behavior of this particular group of cross-listed shares. This research addresses this issue and particularly the following questions: what determines the price movements of exchange-listed ADRs? And more specifically, how should we price ADRs? Do they move with their respective home stock markets or with the US stock markets?

To the extent that ADRs from a particular country share the same country-specific characteristics, they should be moved by the market fundamentals of their home country. We term this regime the home market systematic risk pass-through. Anecdotal evidence has shown that ADRs move with the US stock market as well, though seemingly incomprehensible theoretically. We term this regime pricing to US market's systematic risks, or simply pricing to market. The pricing to market effect may be due to US investors' demand for international diversification and non-overlapping trading hours across countries (Kim, Szakmary and Mathur 2000, Fang and Loo 2002). This "pricing-to-market" effect would also be time varying, depending on the performance of US economy and its covariance of the ADR returns.

Early research on ADRs has examined ADRs and their underlying assets in search of evidence for the law of one price (Officer and Hoffmeiser 1987, Kato, Linn and Schallheim 1991, Wahab, Lashgar and Cohn 1992, Park and Tavakkol 1994). The common theme from these papers is that in the absence of direct or indirect trading barriers, ADRs and their underlying shares are expected to be perfect substitutes and no arbitrage opportunities should be present. In other words, ADRs are expected to be priced the same as their home-market shares barring the effects of the appropriate exchange rates. Later studies have focused on the portfolio diversification effects of ADRs and found that ADRs from emerging markets bring diversification benefits for US investors and could be used as a proxy of their home markets (Jorion and Miller 1997, Bekaert and Urias 1999, Errunza, Hogan and Hung 1999). For example, Errunza, Hogan and Hung (1999) construct portfolios of US domestically traded securities using country funds, multinational corporations stocks and ADRs to examine whether they can mimic foreign stock market indices. They find that gains beyond those attainable through these home-made diversification portfolios are statistically and economically insignificant for 11 of the 16 markets they have studied.

More recent studies have revisited the hypothesis of ADRs as a perfect substitute of their underlying assets. Their results confront earlier studies, showing that there are ADRs perform differently from the underlying shares (Alaganar and Bhar 2001, Foerster and Karolyi 2000). They also provide explanations on these cross-country home-market pass-through variations, including the effects of transaction costs and order flow competition for ADRs from various countries. Among the few recent papers that touch upon the pricing factors of ADRs, US market risks and exchange rate risk are found to have an impact on ADRs price (Kim, Szakmary and Mathur 2000, Fang and Loo 2002). However, these empirical studies are subject to the "license fishing" critique, i.e., data-mining for significant factors. They lack a theoretical framework to explain why these factors are considered and how they affect ADR prices individually and jointly.

In this research, instead of searching for a "yes or no" answer to the question of pricing-to-market or home market pass-through for the ADR price movements, we recognize the uncertainties about the nature and timing of these two regimes. External shocks or changes of the predictable variables in either regime will have an effect on the ADR returns; therefore, one regime may appear to dominate the ADR returns in one period or another. They are not monotonic substitution of one for another, such as a gradual transition to a state of ADRs pricing to the US market. As these two regimes are endogenous to the pricing of ADRs, this research treats the changes of these two regimes probabilistically, using a regime-switching model to characterize the uncertainty nature. This regime-switching framework directly models the pricing of ADRs considering its intrinsic nature involving two markets. The research is important for our understanding of the status of international stock market integration and the benefits of international diversification, and has practical implications for asset management.

More specifically, this research adopts the standard regime-switching model by Hamilton (1988, 1989) to nest both the ADRs' home markets and the US market. In the home-market pass-through regime, ADRs are priced as their home-market asset using domestic Capital Asset Pricing Model (CAPM). In the pricing to market regime, ADRs are treated as US domestic assets and priced using CAPM in the US market. This regime-switching-GARCH model extends the domestic capital asset pricing model (CAPM) but not as idealized as the International Capital Asset Pricing Model (ICAPM), which assumes full integration of the world market. Besides modeling the time-varying conditional covariances and variances, the regime-switching-GARCH model also allows for differing prices of risks across countries as done by Bekaert and Harvey (1995). By using regime probabilities, it will capture the time-varying degree of home-market pass-through (or pricing-to-market), which has not been done on the pricing of ADRs. ADR indices data is used to capture the country-specific systematic risks, i.e., the home market risk pass-through of ADRs.

Section II of this paper discusses the theoretical framework in further detail and illustrates the benefits of the regime switching model in pricing ADRs. Section III briefly describes the empirical methodology. Data sources with summary statistics are reported in Section IV. Section V provides the empirical results and country-by-country findings. The final section summarizes the paper and points out further extensions of this research.

II. Theoretical Framework

The paradigm in asset pricing models in current research is mostly based on the Sharpe (1964) –Lintner (1965) and Black (1972) Capital Asset Pricing Models (CAPM).[1] Our base model starts with a conditional CAPM[2] in a completely integrated market with the absence of exchange rate risk:

$$E_{t-1}\left[R_{n,t}^{adr}\right] = \lambda_{t-1}\,\text{cov}_{t-1}\left[R_{n,t}^{adr}, R_t^m\right] \tag{1}$$

[1] The CAPMs are often called the beta-models, as they measure returns based on the exposure to risks. There is another strand of models, often referred to as consumption-based asset pricing models, in which prices equal to future payoffs times a simple discount factor. See Cochrane (2001) for details on consumption-based models.

[2] We choose conditional models over unconditional models because conditional models help capture the time variation in betas and risk premiums. Since this approach is fully parametric, one can recover any quantity that is a function of the first 2 conditional moments (De Santis and Gerard 1998).

where n=1, 2, …N countries, λ_{t-1} is the price of the market risk at time *t-1*, $\text{cov}_{t-1}\left[R_{n,t}^{adr}, R_t^m\right]$ is the expected conditional covariance of the ADR index return from country n with the market return for time t at time t-1.

One problem with this empirical CAPM is that, in the absence of a completely integrated world market, we do not know which market returns to use for ADRs from a particular country. Do ADRs reflect their home market risks or US market risks then? To incorporate this uncertainty nature of ADR home-market pass-through and pricing-to-market, we set an unobserved state variable S_t. S_t takes on the value of one when ADRs are pricing to the US market and a value of two when ADRs simply reflect complete pass-through of home market variations. At each point in time, there is a positive possibility of a regime switch that is captured by a regime-switching probability.

In the first regime where ADRs are pricing to the US market, ADR returns are determined by the price of US market risk times the exposure of ADR returns to the changes of US market returns. In this regime, ADRs are priced just like US domestic stocks listed on a particular US stock exchange. Equation (1) is then specified as:

$$E_{t-1}\left[R_{n,t}^{adr}\right] = \lambda_{t-1}^{us} \text{cov}_{t-1}\left[R_{n,t}^{adr}, R_{US,t}\right] \tag{2}$$

where *n=1, 2, …N* countries, λ_{t-1}^{us} is the price of US market risk at time *t-1*, $\text{cov}_{t-1}\left[R_{n,t}^{adr}, R_{US,t}\right]$ is the expected conditional covariance of the returns of the ADR from country n with US market return for time *t* at time *t-1*.

If there is complete home-market pass-though in the ADRs – Regime two, the returns for ADRs are determined by the home market price of risk times the ADRs' exposure to the changes in the home market returns.[3] The expectation equation is

$$E_{t-1}\left[R_{n,t}^{adr}\right]=\lambda_{n,t-1}\operatorname{cov}_{t-1}\left[R_{n,t}^{adr},R_{n,t}^{\$}\right] \tag{3}$$

where $\lambda_{n,t-1}$ is the market price of risk at time *t-1* for country *n* (home market price of risk). $\operatorname{cov}_{t-1}\left[R_{n,t}^{adr},R_{n,t}^{\$}\right]$ is the expected conditional covariance of ADR returns with home market returns (in US dollars) for time *t* at time *t-1*.

Given the information set $Z_{n,t-1}$ for country *n* at the time *t*, suppose the likelihood of regime one is responsible for $R_{n,t}^{adr}$ is $\phi_{n,t-1}$. Then the expected conditional mean return for time *t* at time *t-1*, will be equal to the sum of probability times the expected value of each regime:

$$E_{t-1}\left[R_{n,t}^{adr}\right]=\phi_{n,t-1}\lambda_{t-1}^{us}\operatorname{cov}_{t-1}\left[R_{n,t}^{adr},R_{US,t}\right]+(1-\phi_{n,t-1})\lambda_{n,t-1}\operatorname{cov}_{t-1}\left[R_{n,t}^{adr},R_{n,t}^{\$}\right] \tag{4}$$

The parameter $\phi_{n,t-1}$ falls in the interval [0, 1] and changes across time, expressed as

$$\phi_{n,t-1}=prob[S_t=1|Z_{n,t-1}]. \tag{5}$$

Equation (5) can be viewed as an approximation of probability of regime one being responsible for the ADR return at a particular time *t*. One benefit of using regime-switching models is that they allow us to infer the time-path of $\phi_{n,t}$ (ADRs pricing to the market), or $1-\phi_{n,t}$ (ADRs home market pass-through). We could imagine there is an "invisible hand" in the market, which is the collective decision of ADR sellers and buyers that determines $\phi_{n,t-1}$ given the information in both the home and the US markets.

[3] Following Bekaert and Harvey (1995), we measure home market returns in US dollars. Thus the home market returns pick up exchange rate risks as well as the home market risks in their respective home currencies. Home market factors used in the ensuing sections are measured in the same way..

To capture the time-varying characteristics of regime probability, we use the standard Hamilton (1988, 1989) method, in which S_t follows a two-state Markov process with constant transition (switching) probabilities. In the Hamilton regime-switching models, the change in regime is itself a random variable, the probability of S_t equal to a particular value i (i=1, 2) depends on the past only through the most recent value S_{t-1}.[4] Suppose the regime transition probabilities are the following (where the country subscript, n, has been suppressed):

$$\begin{aligned} \Pr(S_t = 1 \mid S_{t-1} = 1) = \mathrm{P} \\ \Pr(S_t = 2 \mid S_{t-1} = 2) = \mathrm{Q} \end{aligned} \tag{6}$$

Hence in this model, the regime switching probabilities are time-invariant, but the regime probabilities $\phi_{n,t}$ (ADRs pricing to market), or $1-\phi_{n,t}$ (ADRs home market pass-through) vary through time as new information changes the inference of the relative likelihood of the two regimes. Besides the time variation in regime probabilities, two other sources of time-variation in expected returns are incorporated in the model– the variation in the price of risk and the variation in the conditional risk measures (market betas).[5] Derivation of the likelihood function will be introduced in the methodology section. An alternative setup to this regime switching model is to adopt the International CAPM, using the world market

[4] See detailed discussions in Hamilton (1994), Chapter 22.

[5] This is similar to Bekaert and Harvey (1995). They apply regime-switching models to capture the time-varying world market integration. They treat market integration and segmentation as two regimes in determining the expected returns of foreign assets and find that a number of emerging markets exhibit time-varying integration. They interpret the probability of market integration regime as the degree of integration.

beta.[6] However, the world market beta from ICAPM is based on the assumption that the world capital market is fully integrated, which is far stronger than the assumption of integrated domestic market as in CAPM. Given the real world constraints, a weighted world market index cannot reflect the return in a perfectly integrated world. In the context of ADRs, we choose ADR pricing to the US market rather than pricing to the world market. Following Bekaert and Harvey (1995), we calculate the local market volatility in US dollar terms in this model. Therefore, the home market pass-through is the combination of the home market effect and the exchange rate fluctuations.

III. Methodology - Regime Switching GARCH

As the mean equation (4) involves the conditional covariance in both regimes, we assume that conditional covariance in different regimes follow a General Autoregressive Conditional Heteroskedasticity (GARCH) process.[7] This approach differs from Bekaert and Harvey (1995) who adopt the ARCH method. The GARCH-in-mean process suggests that a model that includes current and past conditional variances and covariances and past squared forecast errors is more efficient than an ARCH process. Hence an auxiliary assumption on the expected returns of the market equity portfolios is also added to complete our model as follows:

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[6] Patro (2000) found that the returns on ADRs have significant risk exposures to the returns on the world market portfolio and their respective home market portfolios.

[7] See Ng (1991). De Santis & Gerard (1998) also use diagonal multivariate GARCH process to test the conditional international CAPM. More recently, Carrieri, Errunza and Majerbi (2006) use GARCH (1,1) framework to model global equity returns.

$$
\begin{aligned}
y_{n,t} &= [R_{n,t}^{adr}, R_{i,t}]' \\
R_{n,t}^{adr} &= \phi_{n,t-1}\lambda_{t-1}^{us}\,\mathrm{cov}_{t-1}\left[R_{n,t}^{adr}, R_{US,t}\right] + (1-\phi_{n,t-1})\lambda_{n,t-1}\,\mathrm{cov}_{t-1}\left[R_{n,t}^{adr}, R_{n,t}^{\$}\right] + e_{n,t} \\
R_{i,t} &= \lambda_{i,t-1}\,\mathrm{var}_{t-1}[R_{i,t}] + e_{i,t}
\end{aligned}
\tag{7}
$$

Here i could be the US market portfolio in regime 1 or the home market portfolio in regime two. Let $e_t=[e_{n,t}, e_{i,t}]'$ and define e^1 and e^2 as the disturbance vector under regimes one and two respectively. Then we define the conditional variance processes under the two different regimes as

$$
\begin{aligned}
H_{1t} &= E[e^1 e^{1\prime} \mid Z_{n,t-1}] \\
H_{2t} &= E[e^2 e^{2\prime} \mid Z_{n,t-1}]
\end{aligned}
\tag{8}
$$

$\mathrm{cov}_{t-1}\left[R_{n,t}^{adr}, R_{US,t}\right]$ is the off-diagonal element of H_{1t} , and $\mathrm{cov}_{t-1}\left[R_{n,t}^{adr}, R_{n,t}^{\$}\right]$ is the off-diagonal element of H_{2t}, and the conditional variance dynamics are modeled as a diagonal GARCH(1,1) following the BEKK model (Engle and Kroner 1995) by assuming the variances in H_{1t} and H_{2t} only depend on past squared residuals and an autoregressive component while the covariances depend on the past cross-products of residuals and an autoregressive component. In addition, we assume the system is covariance-stationary for applying GARCH parameterization. This assumption is specified as follows:

$$
\begin{aligned}
H_{1t} &= C^1 C^{1\prime} + A^1 A^{1\prime} \otimes e_{t-1} e_{t-1}' + B^1 B^{1\prime} \otimes H_{1,t-1} \\
H_{2t} &= C^2 C^{2\prime} + A^2 A^{2\prime} \otimes e_{t-1} e_{t-1}' + B^2 B^{2\prime} \otimes H_{1,t-1}
\end{aligned}
\tag{9}
$$

where C^1, C^2, A^1, A^2, B^1, B^2 are 2×1 vectors of unknown parameters, and $\otimes$ represents element by element matrix multiplication. Compared with other multivariate GARCH forms, such as the BEW model that uses the VECH form,[8] the diagonal BEKK is less parameterized (Engle and Kroner 1995).

We also assume that the price of risk is time varying, and adopt the model used by Harvey (1991) and Bekaert and Harvey (1995)(see equation 17). According to Bekaert and Harvey (1995), the exponentiation ensures that the price of risk is positive.

$$\begin{aligned} \lambda_{t-1}^{us} &= \exp(\delta' Z_{t-1}^{*}) \\ \lambda_{n,t-1} &= \exp(\delta_n' Z_{n,t-1}^{*}) \end{aligned} \tag{10}$$

where Z_{t-1}^{*} represents a set of US macroeconomic variables (often called predictable variables) and $Z_{n,t-1}^{*}$ represents a set of local predictable variables for a particular country *n*. The US information set, Z_{t-1}, includes five variables: a constant, the US market dividend yield, the default spread of corporate bonds, changes of short-term Treasury bill rates, and changes of term spread of US Treasury securities.

For a particular country's information set, $Z_{n,t-1}^{*}$, we choose the following variables to proxy the state of the economy – a constant, short term rates, local market dividend yields, exchange rate changes, and changes of local stock market value. Compared with Bekaert and Harvey (1995), we add in the short-term rate, and use changes of local stock market value instead of the ratio of equity market capitalization to GDP. Changes of the short term rate will affect the yield curve of the country, which introduces more short-term fluctuations to the model. Since we use weekly data, there is no available data for GDP in this frequency, and we believe that changes of the local stock market value will capture the effect of the change of

[8] Bollerslev, Engle and Woolridge (1988) set up a multivariate GARCH model using column stacking operation (VECH), so the BEW representation is highly parameterized.

market size, which directly reflects the state of the economy and affects the degree of home-market pass-through.

Our empirical estimation follows the general Hamilton model (1994) that applies to a two-state regime switching environment, in which, as defined earlier, $\phi_{n,t} = \Pr(S_t = 1 \mid Z_{t-1})$. For convenience of notation, we express the log-return of ADR indices as y_t, which is presumed to be drawn from $N(\mu_{S_t}, \sigma^2_{S_t})$. The distribution of y_t conditional on available information is written as

$$f(y_t \mid S_t = i, Z_{t-1}) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left\{ \frac{-(y_t - \mu_i)^2}{2\sigma_i^2} \right\} \quad \text{i=1,2} \tag{11}$$

So the conditional probability density function is

$$f(y_t \mid Z_{t-1}) = \sum_{i=1}^{2} f(y_t, S_t = i \mid Z_{t-1}) = \sum_{i=1}^{2} f(y_t \mid S_t = i, Z_{t-1}) \Pr(S_t = i \mid Z_{t-1}) \tag{12}$$

By summarizing density functions over all possible values for i, we get the unconditional density function of y_t:

$$f(y_t;\theta) = \frac{\phi}{\sqrt{2\pi}\sigma_1} \exp\left\{ \frac{-(y_t - \mu_1)^2}{2\sigma_1^2} \right\} + \frac{(1-\phi)}{\sqrt{2\pi}\sigma_2} \exp\left\{ \frac{-(y_t - \mu_2)^2}{2\sigma_2^2} \right\} \tag{13}$$

Here θ is a vector of parameters that includes $\mu_1, \mu_2, \sigma_1^2, \sigma_2^2$, and ϕ. The log-likelihood for y_t is calculated as

$$\log L(\theta) = \sum_{t=1}^{T} \log f(y_t;\theta) \tag{14}$$

After we parameterize the conditional variance and covariance, the log-likelihood function in equation (14) is expressed in the following multivariate form that nests the regime switching model and GARCH process, which we call a hybrid ML function:

$$(15)\ \log L = \sum_{t=1}^{T}(\log[\frac{\phi_{n,t-1}}{\sqrt{2\pi}}|H_{1t}|^{-0.5}\exp\left\{\frac{-(e^{1}{}'(H_{1t})^{-1}e^{1})}{2}\right\}+\frac{(1-\phi_{n,t-1})}{\sqrt{2\pi}}|H_{2t}|^{-0.5}\exp\left\{\frac{-(e^{2}{}'(H_{2t})^{-1}e^{2})}{2}\right\}])$$

Therefore the parameters we need to estimate, to be expressed as a vector of parameters θ, are $\theta=[\delta',\delta_n',C^1,C^2,A^1,A^2,B^1,B^2,P,Q]'$. Under weak assumptions, the vector of parameters θ is asymptotically normally distributed with covariance matrix $H^{-1}PH^{-1}$ where H is the Hessian form and P is the outer product of information matrix.[9] This form is also called Quasi-Maximum likelihood (QML) approximation, which we use to calculate ML standard errors. The appendix at the end of the paper provides details about the inference of unobserved regime probabilities.

To estimate this model, we adopt the two-step procedure by Bekaert and Harvey (1995). First, we use the univariate non-linear GARCH (1,1) model to estimate the parameters related to country market returns alone. Particularly we estimate $C^1(2,2)$, $A^1(2,2)$, $B^1(2,2)$ and δ' using the US market returns and US information variables Z^*_{t-1} and $C^2(2,2)$, $A^2(2,2)$, $B^2(2,2)$ and δ_n' using the home market returns and predictable information variables $Z^*_{n,t-1}$. In step two, we plug them back to the whole model while estimating the rest of the parameters in the multivariate form, as represented by equation(7).

IV. Data

In this study, we use ADR price indices data developed by Bank of New York (BNY) for Japan, Germany, Argentina, and China.[10] Market indices are obtained from DataStream

[9] For further details, refer to Hamilton 1994, p145.

[10] There are 39 country-specific ADR indices in the BNY ADR database (www.adrbny.com). These indices track Depository Receipts traded on The New York Stock Exchange (NYSE), The American Stock Exchange (AMEX) and NASDAQ. They are capitalization-weighted, adjusted for free-float utilizing Dow Jones' current

global equity indices for calculating the market returns. These country equity indices are highly correlated with other indices from Morgan Stanley Capital International (MSCI) or Financial Times Stock Exchange (FTSE), so we believe it makes no difference using any of the equity market indices. Returns are calculated as log ratios and adjusted by the changes of exchange rates. As these countries' national stock markets open at different times from the US stock markets, we use weekly data to avoid non-synchronous trading problem.

The US default spread is calculated as the spread of Moody's seasoned corporate BAA bond yield over that for AAA bonds. The US short term rate is the yield of US 3-month Treasury bills. The US term spread is calculated using the yield of US Treasury securities at 10-year constant maturity minus that of 1-year US Treasury securities. These US predictable variables are all retrieved from the US Federal Reserve Board database, with weekly (Friday) frequency. The short-rates are middle rates for 3-month Euro-currency for Japan, Germany, 3-month interbank middle rate for Argentina and 3-month relending rate for China. All the series are retrieved from DataStream and matched weekly. There are 470 weekly (Friday) observations for each time series, covering the period of 1/2/1998 - 12/30/2006.[11] Table 1 provides summary statistics for the ADR returns and predictable variables for US, and Japan, Germany, Argentina, and China.

V. Empirical Results

Step one: Estimating market price of risks

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methodology , and calculated on a continuous basis throughout the trading day. BNY ADR indices for the four countries cover more than 80% of the total exchange-listed ADRs for each country.

[11] The start of our sample period is determined by data availability since the BNY ADR indices started in January 1998.

In step one, we first estimate $C^1(2,2)$, $A^1(2,2)$, $B^1(2,2)$ and δ' using the US market return and US macroeconomic variables, from the following equations

$$\begin{aligned} R_{US,t} &= \lambda_{t-1}^{us}\,\mathrm{var}_{t-1}[R_{US,t}] + e_{us,t} \\ \lambda_{t-1}^{us} &= \exp(\delta' Z_{t-1}) \end{aligned} \tag{16}$$

Here $\mathrm{var}_{t-1}[R_{US,t}]$ is the conditional variance. Using common notation for conditional variance h_t, and assuming that h_t follows a univariate GARCH (1, 1) process, we have

$$h_t = c + \alpha_1 e_{us,t-1}^2 + \alpha_2 h_{t-1} \tag{17}$$

where $c = (C^1(2,2))^2$, $\alpha 1 = (A^1(2,2))^2$ and $\alpha 2 = (B^1(2,2))^2$. Model parameters need to comply with the restrictions that $c > 0$ and $\alpha_1 + \alpha_2 < 1$ for the GARCH model to be valid. Assuming normal distributed residuals, we obtain the following form of Log Maximum Likelihood function,

$$\log L = \sum_{t=1}^{T} \log\left[\frac{1}{\sqrt{2\pi h_t}} \exp\left\{\frac{-(R_{US,t} - \lambda_{t-1}^{us}\,\mathrm{var}_{t-1}[R_{US,t}])^2}{2h_t}\right\}\right] \tag{18}$$

We also perform two model specification and diagnostics tests: test of constant price of risk and test of constant variance. The first test helps evaluate our specification of time-varying price of risk, while the second tests whether the GARCH specification is necessary. Since we have both restricted and unrestricted estimates, we use log-likelihood ratio tests. The likelihood ratio statistics is specified as

$$LR = -2(L^* - L) \tag{19}$$

where L^* is the log-likelihood value in the restricted model and L is the likelihood value from the unrestricted version. LR is approximately distributed as Chi-square with the degrees of freedom as the number of restrictions (Greene 2000).

During the estimation process, we obtain the maximized log likelihood value with every set of random starting values for model parameters. We use as many sets of random starting values as possible until there is no further improvement for the likelihood value and the model parameters converge. The starting value for conditional variance during the iterations is set at its steady state value, i.e., $h_t = c/(1-\alpha_1 - \alpha_2)$. Given the constrained maximum likelihood estimation, we calculate the covariance matrix following Kim and Nelson (1999, page 16), i.e., with constrained maximization, we adjust the model covariance with the gradient of constrained function. We save the estimated time series for the US price of risk and residuals for the second step estimation.

Table 2 provides the maximum likelihood estimates (MLE) of the US model. Panel A shows the estimates for the whole model, with the calculated error terms and standard t-ratios. The standard t-ratio shows the significance of coefficients c, α_1 and α_2. Panel B presents the restricted model of no time-varying price of risk, and likelihood ratio (LR) test against the null hypothesis of constant price of risk: H0: δ2=δ3=δ4=δ5=0. The LR statistics is 7.3886. The corresponding $\chi^2(4)$ probability is about 0.1. Panel C reports the restricted model of no GARCH effects: H0: α1= α2=0. With the LR statistics of 68.5648, the corresponding $\chi^2(2)$ probability is less than .05. These results support our assumptions of time-varying price of risk for the US market and a GARCH-in-mean model for modeling covariance. These findings are also evidenced in other studies such as Ng (1991) and Bekaert and Harvey (1995).

Similarly, we estimate Equation (16) for the other four national markets (namely, Argentina, China, Germany and Japan) independently using a simple conditional CAPM model. The results are presented in table 3. All models are tested with GARCH effects before estimation. Delta parameters are corresponding to home predictable variables in the order of a constant, changes of short rate,[12] changes of market value, market dividend yield, and changes of exchange rate. For each panel, the first row gives maximum likelihood estimates of parameters (MLE), and the second row gives the quasi- maximum likelihood (QML) errors, and the third row gives the t-ratio. Two likelihood ratio test statistics for model restrictions – constant delta, or the GARCH form are omitted here but available upon request.

Step two: Estimating MLE country by country.

In this step, we perform country-specific analysis using our regime-switching multivariate GARCH model (Equation(7)-(9)). As we discussed before, the local macroeconomic variables $Z^*_{n,t-1}$ monitor the price of risk in the ADR home markets.[13] We adopt the flow chart from Kim and Nelson (1999) for estimating regime switching models and add in the GARCH-in-mean steps in our model (see the appendix).[14] The initial iteration value for state probability is based on the unconditional ergodic probability (Hamilton 1994, p684). For the initial values of H_t and e_t (denoted as h_0, and e_0), we use the variance-covariance matrix of our sample ADR returns and market returns as the starting value for the e_0 (denoted as ee1 and ee2), while for h_0 we use the form of { H1= ee1 .*(i*i'-A1*A1'-B1*B1') and H2= ee2 .*(i*i'-A2*A2'-B2*B2') } where i represent vectors of 1's. As the time-varying price of risk and regime switching-GARCH models are highly non-linear, we pay special attention to

[12] We use the log differences to measure the changes of short rate, except for Japan where the negative short rates appear. So we use the first differences for Japan's short rate series.

[13] Here we also adjust local predictable variables by exchange rate changes, so as to keep consistency with the local market index returns measured in dollar terms.

[14] Authors acknowledge the insights from the programs provided by Kim and Nelson (1999).

the numerical optimization of our hybrid maximum likelihood function – we try at least 10 sets of starting values, choose the highest log-likelihood value and then we use the corresponding estimates as model starting values repeat the estimation process, so that we make sure the results converge.

Table 4 summarizes the estimation results from step 2. Estimates of regime transition probabilities are presented in the first row for each country, with the Quasi-Maximum Likelihood errors in the second row. They are all statistically significant except P for Germany. The third column provides the averages of the series of home-market pass-through (regime two probabilities), $(1-\phi_t)$, and the fourth column lists the likelihood values obtained in the optimization method. For the estimates of transition probabilities, P and Q are both high (>90%) for Argentina, which means that the probability of moving from regime one (two) in a period to regime one (two) in the next period is over 90%. This is an indication of regime persistence. That is, once one particular regime sets in, it tends to stay in the same regime.[15] We call this "inertia to change." As we assume constant P & Q through time for a particular country, Both regimes in Germany and Japan are also strong with regime transition probabilities about 70% and higher. China has a higher P value of 99%, with a lower Q value of 40%. It implies that, once regime one sets in, there is a 99% probability of staying in regime one and only a 1% of probability of moving from regime one to regime two. However, when regime two sets in, the probability of remaining in regime two is about 40% while the probability of switching to regime one is about 60%. Therefore, it shows a strong dominance

[15] As defined in the Markov-switching model – the regime probability in the next period depends on the regime probability of the last period, the regime switching probability and new information from the observable variable (ADR return in this case). See appendix.

of the pricing-to-market regime, Regime one, for Chinese ADRs. Figures 1-4 compares the time-varying pass-through for the four countries.

The home-market pass-through paths as shown in figures 1-4 have mainly three types of representations – home-market passthrough dominance (Germany), pricing-to-market dominance (Japan and China), and frequent regime switching (Argentina). Figure 1 depicts the time path of home market pass-through for Germany. We see that the regime probabilities for home-market passthrough dominate most of the time, but there are a few intermittent low regime two probabilities (high regime one probability). These few high pricing-to-US market regime probabilities happen around the time when US market returns (Figure 5) experience large fluctuations, such as the second half of 1998, first half of 2000 and 2001-2002.

The pricing behavior for Japanese ADRs is found significant different from that of German ADRs. As we can see from Figure 2, the regime probability of staying in regime two (home market pass-through) is kept very low. It indicates that the pricing-to-market regime dominates most of the time. We observe that there are two immediate jumps of the home-market passthrough regime probabilities in April 2000 and September 2001. Comparing Japanese ADR returns, the home market and US market index returns, we find that the two immediate jumps coincide with two large drops of US market returns -14% and -12% respectively. China shows a similar the time path of home-market passthrough to Japan – low regime probabilities for home-market passthrough (Figure 4). There are also a few immediate run-ups of high home-market passthrough regime probabilities. During these few short-lived high regime probabilities of home-market passthrough, the ADR index returns did not follow the US market returns but were priced to the home-market.

For Argentina, we see frequent regime switching patterns, especially during the period before April 2003 with an average pass-through probability of 54% (Figure 3). The two regimes almost equally share the probabilities of influencing the ADR index returns. When US market returns had the two largest drops in April 2000 and September 2001, the home market pass-through regime probability was almost 100%, which was consistent with the ADR behavior for Japan and China. Since April 2003 till the end of 2006, the pricing-to-market regime dominated (with an average of pass-through probability of only 1%). This pattern change captures the economic environment in Argentina. Argentina was tumbling through economic crisis from 1999 to 2002. As is seen in the time-path of passthrough probability, the regimes switch frequently between the home-market regime and pricing-to-market regime and two regimes are equally strong. During the post-2003 period, the Argentine economy started to recover, and its effects on their ADRs gave way to the influence of the US market. A smoothed time-path of home-market passthrough regime probability is presented in Figure 6. The smoothing algorithm is taken from Kim and Nelson (1999) by making inferences on the probability of Regime two using all the information in the sample. The smoothed graph clearly depicts the different characteristics of home-market passthrough probabilities before and after 2003.

Model specification and diagnostics

To make sure the model is specified correctly, we also perform a model specification test. We save the residuals $e_{n,t}$ from step 2 for each country, then check whether the ADR home-market macroeconomic variables and the US macroeconomic variables have explanatory power over these residuals. Table five shows the multivariate regression results. Regression estimates are presented in the first row while the White heteroskedasticity-consistent standard errors are listed in the second row in Italic form for each country. Among the four countries, China has the lowest R-squared value and we fail to find any joint explanatory power for China's residuals at 5% confidence level.[16] We find that the coefficients corresponding to the US predictable variables are all non-significant for all four countries except US term spread changes for Argentina. Two of local predictable variables – local market dividend yields and foreign exchange rate changes are insignificant for all four countries. Changes of local short rate are insignificant for all countries but Argentina.

However, there is still significant explanatory power for one home-market predictable variables – the market value changes for all four countries. This indicates that market value changes capture some risks that are omitted in the model, which could lead to a possible extension of the paper by adding this factor as an independent risk factor. As country predictable variables enter the model indirectly through the time-varying price of risks for the two markets, it is possible that they may still explain, to some extent, the residuals from our simple model. Therefore, we need to be cautious when interpreting the home-market passthrough measure in countries where there is evidence against the model specification.

VI. Summary and Future Research

In this paper we investigate whether ADR index returns are more reflective of their respective home market conditions (home-market pass-through) or driven by the US market (pricing to market). We employ a regime-switching model to nest these two regimes. We find different degrees of pass-through of ADRs in the four countries we have studied. In pricing ADR index returns, Germany shows strong home-market passthrough dominance. Japan and China have a pricing-to-market dominance (low home-market passthrough regime

[16] This information is not reported but available upon request.

probability), as well as Argentina for the post-2003 period. There is a frequent regime switching pattern for Argentina in the pre-2003 period with both regimes equally dividing the average probabilities.

There are a number of possible extensions of the paper. Firstly, as this paper only addresses four countries, we have a satellite result of how these two regimes affecting ADR returns. To have a complete view of this home-market pass-through of ADRs, we need to include more countries in future studies. Secondly, Kim, Szakmary and Mathur (2000) and Fang and Loo (2002) provide evidence that foreign exchange risk is another important factor in ADR pricing. One immediate extension of the paper is to include exchange rate directly in assessing home-market pass-through (regime two). As our paper only plugs in foreign exchange risk in estimating lambda – the price of risk, it will be interesting to see how foreign exchange will affect the home-market pass-through if we count in this risk. Thirdly, in this model, we assume the transition probabilities (P and Q) between the two regimes are constant, as in the standard Hamilton model. There are studies that extend the Hamilton model to allow for time-varying transition probabilities (e.g. Bekaert and Harvey 1995). Our model could be modified to allow of time-varying transition probabilities, which may provide a better fit of the data. Furthermore, using firm-specific ADR returns instead of ADR indices in the study will reveal firm-specific pass-through and allow cross-sectional analysis.

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Appendix Flowchart for the regime-switching - GARCH modeling process

$l(\theta)=0$ with $l(\theta)$ denotes the log-likelihood value

$\Pr(S_0)=\pi_j$ (steady-state probability)

And $\mathrm{h}_0, \mathrm{e}_0$

$\Downarrow$

$\Downarrow$

$$\Pr(S_t, S_{t-1} \mid Z_{t-1}) = \Pr(S_t \mid S_{t-1}) \Pr(S_{t-1} \mid Z_{t-1})$$

$\Downarrow$

$\mathrm{h}_1, \mathrm{e}_1$

$$f(y_t \mid Z_{t-1}) = \sum_{S_t} \sum_{S_{t-1}} f(y_t \mid S_t, S_{t-1}, Z_{t-1}) \Pr(S_t, S_{t-1} \mid Z_{t-1})$$

$\Downarrow$

$$l(\theta) = l(\theta) + \ln(f(y_t \mid Z_{t-1}))$$

$\Downarrow$

$$\Pr(S_t, S_{t-1} \mid Z_t) = \frac{f(y_t, S_t, S_{t-1} \mid Z_{t-1})}{f(y_t \mid Z_{t-1})} = \frac{f(y_t \mid S_t, S_{t-1}, Z_{t-1}) \Pr(S_t, S_{t-1} \mid Z_{t-1})}{f(y_t \mid Z_{t-1})}$$

$\Downarrow$

$$\Pr(S_t \mid Z_t) = \sum_{S_{t-1}} \Pr(S_t, S_{t-1} \mid Z_{t-1})$$

$\Downarrow$

t-1=t, h0=h1,e1=e0

$\Downarrow$

$$l(\theta) = \sum_{t=1}^{T} \ln(f(y_t \mid Z_{t-1})$$

Note: Based on the flowchart for regime switching by Kim and Nelson (1999), we add in the GARCH-in-mean effects. While we are updating information on the regime probability from Z_{t-1} to Z_t, we also update conditional variance and forecast error and iterate the process. Then we run the non-linear optimization for the log-likelihood function, and obtain model estimates.

Table 1: Summary Statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
ADR Indices (1 period log difference)							
Argentina	0.0014	0.0015	0.1702	-0.1830	0.0471	-0.1872	4.1908
China	0.0026	0.0049	0.2342	-0.2218	0.0475	0.2647	6.3143
Germany	0.0016	0.0033	0.2635	-0.1508	0.0409	0.3694	7.6181
Japan	0.0005	-0.0008	0.1046	-0.1249	0.0333	0.0907	3.2848
Market indices (1 period log difference)							
Argentina	-0.0007	0.0032	0.1600	-0.3365	0.0456	-0.8374	10.0125
China	0.0009	0.0000	0.1386	-0.0919	0.0307	0.7034	5.6079
Germany	0.0026	0.0033	0.6879	-0.1109	0.0428	8.6361	142.0160
Japan	0.0011	0.0009	0.1138	-0.1052	0.0316	0.1689	3.6369
Short Rate							
Argentina	0.1857	0.1018	1.1713	0.0064	0.2303	2.6451	9.5900
China	0.0393	0.0351	0.0991	0.0296	0.0152	3.0739	11.9862
Germany	0.0329	0.0314	0.7115	-0.0197	0.0352	15.3025	295.6897
Japan	0.0019	0.0004	0.1465	-0.0572	0.0169	1.7422	15.2514
Market Value (1 period log difference)							
Argentina	-0.0014	0.0029	0.3506	-0.3634	0.0542	-0.6436	14.8097
China	0.0060	0.0000	0.6081	-0.0919	0.0487	5.8471	63.8104
Germany	0.0030	0.0035	0.6879	-0.1282	0.0436	8.1142	131.5088
Japan	0.0015	0.0013	0.1138	-0.1031	0.0319	0.1914	3.6065
Market Dividend Yield							
Argentina	0.0242	0.0248	0.1640	-0.2978	0.0321	-3.6694	40.8867
China	0.0138	0.0121	0.0469	0.0068	0.0051	1.5925	6.8835
Germany	0.0207	0.0191	0.6930	-0.0247	0.0344	15.8953	311.4016
Japan	0.0093	0.0086	0.1508	-0.0543	0.0167	1.5338	14.3858
Exchange Rate (1 period log difference)							
Argentina	0.0024	0.0000	0.3441	-0.1181	0.0278	8.1409	98.3656
China	-0.0001	0.0000	0.0020	-0.0202	0.0010	-16.1898	313.6764
Germany	-0.0018	-0.0008	0.0409	-0.6796	0.0342	-16.6523	331.1253
Japan	-0.0002	0.0007	0.0636	-0.1396	0.0167	-1.5286	14.0354
US Predictable Variables							
Market Index returns	0.0009	0.0022	0.0893	-0.1441	0.0247	-0.6586	7.0603
3-Month T-bill	0.0339	0.0378	0.0622	0.0084	0.0171	-0.1355	1.5311
Term spread	0.0117	0.0069	0.0320	-0.0047	0.0117	0.3266	1.5175
Market dividend yield	0.0147	0.0154	0.0191	0.0095	0.0025	-0.3338	1.7964
US default spread	0.0089	0.0085	0.0145	0.0052	0.0021	0.7654	2.9511

Note: ADR price indices data are developed by Bank of New York. These ADR indices are capitalization-weighted and adjusted for free-float utilizing Dow Jones' current methodology (www.adrbny.com). Market indices of US, Japan, Germany, Argentina and China are from DataStream global equity indices. The short rates are middle rates for 3-month Euro-currency for Japan, Germany, 3-month interbank middle rate for Argentina and 3-month relending rate for China. US default spread is measured by the difference between Moody's seasoned BAA bond yield and the AAA bond yield; US short term rate is the yield of US 3-month Treasury bill. US Term spread is the yield of U.S. Treasury securities at 10-year constant maturity minus that of 1-year Treasury securities. Series for the market value and dividend yields for each country are aggregate market information based on local market indices, and converted to US dollar. All these series are retrieved from DataStream, matched weekly from January 2, 1998 to December 30, 2006.

Table 2. US price of risk

Panel A: GARCH (1,1)-in-mean model								
	c	α1	α2	δ1	δ2	δ3	δ4	δ5
ML Estimates	0.0000001	0.0419	0.9579	-18.0848	-6.6748	11.2440	4.3279	-0.0300
Standard Error	0.0000214	0.0685	0.1056	6.5171	9.5613	4.0784	12.7401	3.8080
T-ratio	0.0051553	0.6120	9.0746	-2.7750	-0.6981	2.7570	0.3397	-0.0079
Panel B: contant price of risk								
	c	α1	α2	δ				chi-squared
ML Estimates	0.0000011	0.0250	0.4745	2.7080				7.3886
Standard Error	0.0000020	0.0074	0.0075	1.8421				
T-ratio	0.5394	3.3659	63.2213	1.4701				
Panel C: contant variance model								
	c	δ1	δ2	δ3	δ4	δ5		chi-squared
ML Estimates	0.0242	-109.8320	-14.2307	71.0000	36.1213	-19.6003		68.5648
Standard Error	0.0009	475.9511	35.7087	299.0919	186.3547	89.2416		
T-ratio	25.9901	-0.2308	-0.3985	0.2374	0.1938	-0.2196		

Note: the above table provides results for the following model,

$$R_{US,t} = \lambda_{t-1}^{us} \operatorname{var}_{t-1}[R_{US,t}] + e_{us,t} \quad (19)$$
$$\lambda_{t-1}^{us} = \exp(\delta' Z_{t-1}^{*})$$

where $\operatorname{var}_{t-1}[R_{US,t}]$ is the conditional variance, which is estimated by GARCH (1,1)-in-Mean

$$h_t = c + \alpha_1 e_{us,t-1}^2 + \alpha_2 h_{t-1} \quad (20)$$

Delta parameters are corresponding to US state variables in the order of constant, changes of short rate, market dividend yield, changes of US term spread, the default spread. For each panel, the first row gives maximum likelihood estimates of parameters (MLE), and the second row gives the Quasi-maximum likelihood errors and the third row gives the t-ratio. Two likelihood ratio test statistics for model restrictions – constant delta, or the GARCH form.

Table 3. Home market price of risk

		c	α1	α2	δ1	δ2	δ3	δ4	δ5
Argentina	ML Estimates	0.00019726	0.2203	0.6890	1.8581	3.2226	21.5102	-450.0145	41.4178
	Standard Error	0.00019549	0.1911	0.2434	0.5381	3.1218	11.3715	233.6277	22.4244
	T-ratio	1.0090207	1.1527	2.8305	3.4533	1.0323	1.8916	-1.9262	1.8470
China	ML Estimates	0.00025415	0.1891	0.5467	-3.4389	-8.3410	-35.7926	182.5787	-153.4690
	Standard Error	0.00008649	0.0803	0.1192	1.6769	2.0112	25.1481	95.2277	134.3571
	T-ratio	2.93834655	2.3564	4.5857	-2.0507	-4.1472	-1.4233	1.9173	-1.1422
Germany	ML Estimates	0.000603	0.9459	0.0453	-4.5025	-47.2946	-2.0818	13.1754	68.2604
	Standard Error	0.00034876	0.1682	0.1572	1.5522	12.3289	0.9967	8.3514	57.1232
	T-ratio	1.72898462	5.6250	0.2879	-2.9008	-3.8361	-2.0887	1.5776	1.1950
Japan	ML Estimates	0.00000015	0.0158	0.9841	-2.0608	0.2790	-29.8122	223.7962	65.3793
	Standard Error	0.00000003	0.0054	0.0054	2.1783	3.2147	10.2920	119.4540	14.3919
	T-ratio	4.93347088	2.9291	183.2911	-0.9461	0.0868	-2.8966	1.8735	4.5428

Note: the above table provides results for the following model,

(19)
$$R^{\$}_{n,t} = \lambda_{n,t-1}\,\mathrm{var}_{t-1}[R^{\$}_{n,t}] + e_{h,t}$$
$$\lambda_{n,t-1} = \exp(\delta_n{}' Z^{*}_{n,t-1})$$

where $\mathrm{var}_{t-1}[R^{\$}_{n,t}]$ is the conditional variance for the home market portfolio (converted to US$) , which is estimated by GARCH (1,1)

(20) $h_t = c + \alpha_1 e^2_{us,t-1} + \alpha_2 h_{t-1}$

Delta parameters are corresponding to home predictable variables in the order of constant, changes of short rate, changes of market value, market dividend yield, changes of exchange rate. For each panel, the first row gives maximum likelihood estimates of parameters (MLE), and the second row gives the Quasi-maximum likelihood errors and the third row gives the t-ratio. Two likelihood ratio test statistics for model restrictions – constant delta, or the GARCH form are omitted here but available upon request.

Table 4. Step-two estimation of transition probability and home-market pass-though

	P	Q	Home market passthrough (1-Φ)	likelihood value
Japan	0.9019	0.7341	0.0045	2323.9620
	0.0053	0.515		
Germany	0.7297	0.6969	0.9226	2104.6524
	1.744	0.1471		
Argentina	0.9561	0.9054	0.2817	2397.8587
	0.0147	0.035		
China	0.9889	0.4018	0.0181	2389.1219
	0.0064	0.0472		

Note: The home-market pass-through is calculated by ($1-\phi_t$), which is the average over our sample period. For columns of P and Q, the first line of number gives the Maximum Likelihood estimates, and the number below is the Quasi-Maximum Likelihood errors.

Table 5. Multivariate regression of regime-switching residuals on predictable variables from the US market and home market.

	c	Local short rate	Local market value changes	Local Market Dividend Yield	Exchange rate changes	US short rate changes	US termspread changes	US Dividend Yield	US default spread	Adjusted R-squred
e_japan	0.0008	-0.1967	**0.9709**	1.2330	1.2859	1.3863	0.1911	-1.1030	0.4039	0.746988
	0.0062	*0.3542*	***0.0344***	*0.8871*	*0.8914*	*1.9551*	*1.3600*	*0.5955*	*0.4084*	
e_germany	-0.0058	-0.1002	**1.0407**	-0.4769	0.3330	-2.1153	-1.2552	1.0674	0.2362	0.567773
	0.0167	*0.2025*	***0.0795***	*0.4517*	*0.4503*	*2.9618*	*1.8613*	*0.9723*	*0.6912*	
e_argentina	-0.0092	**-0.0306**	**0.5527**	-0.0344	0.0420	4.2123	**4.6704**	-0.0031	1.9513	0.423656
	0.0182	***0.0143***	***0.0927***	*0.1552*	*0.2070*	*2.5031*	***2.3404***	*0.9750*	*1.1425*	
e_china	0.0067	-0.0025	**0.0897**	0.8119	-1.5751	3.2671	6.5105	-0.8415	-0.4748	0.011729
	0.0239	*0.2046*	***0.0408***	*0.4537*	*1.0902*	*3.6806*	*3.8337*	*1.2561*	*1.1676*	

Note: e_countryname represents the residuals from the regime-switching model for that country. C represents the constant term. Columns from the third to the sixth are four predictable variables from the home market converted to dollar equivalent. The last four variables are predictable variables from the US market as defined before. For each country, numbers in the first line are estimates for regression coefficients, and those in the second line are standard errors. The adjusted R-square values are from the multivariate LS regression.

Figure 1

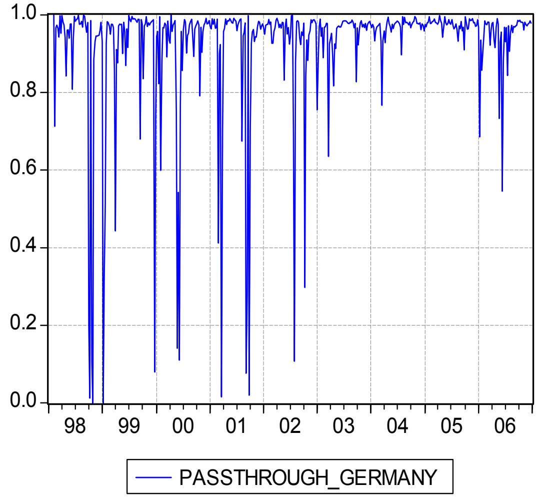


Figure 2

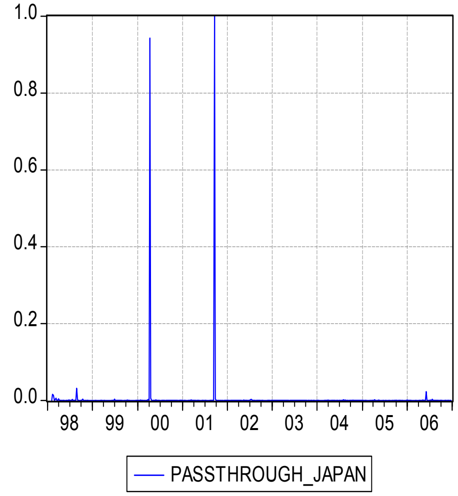


Figure 3

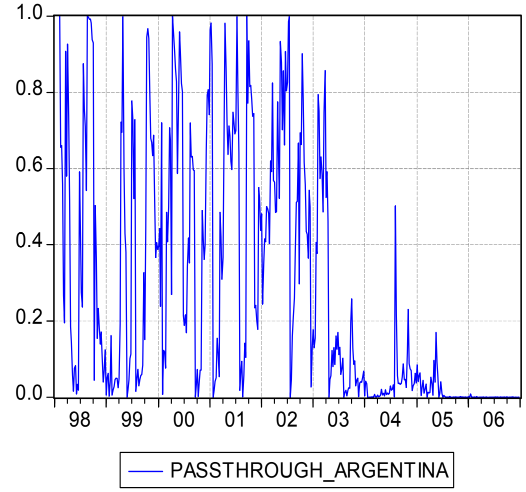


Figure 4

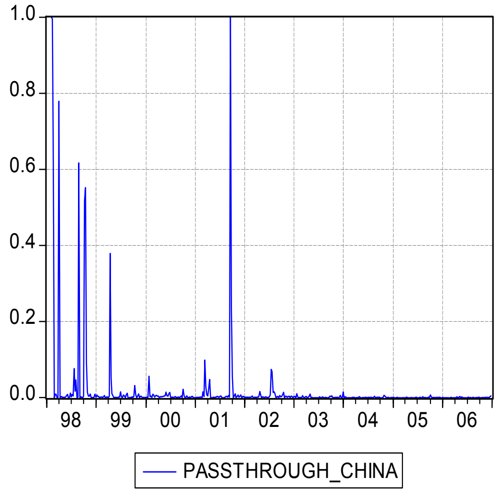


Figure 5

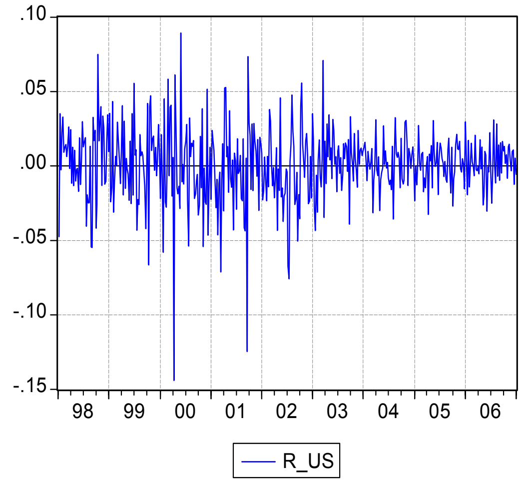
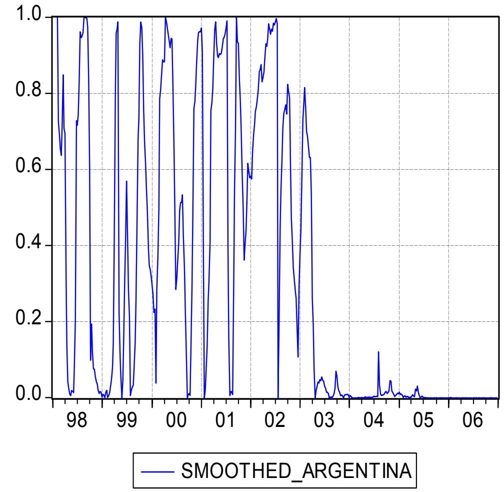


Figure 6



Note: PASSTHROUGH_countryname gives the time varying regime two probability we estimated, (1-phi), for that country. R_US represents the log returns of US total market price index. Smoothed_ARGENTINA is the smoothed series of PASSTHROUGH_ARGENTINA and is estimated based on the algorithm from Kim and Nelson (1999).