ESSAYS ON ADR PRICING

BY HUI HE

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ABSTRACT

This dissertation is an empirical research on pricing American Depository Receipts (ADRs). It addresses questions on the relationships of exchange-listed ADRs with the US market portfolio, home market portfolio and exchange rate changes. Furthermore, it touches upon the two-market puzzle for exchange-listed ADRs: Do they move more with the US market or home market, given that the global market is not fully integrated?

Three essays in this dissertation deal with ADR pricing from different perspectives. The first essay closely follows the recent studies using traditional factor pricing models. It intends to reconcile the mixed results in the literature with all of the country ADR portfolios available from 1998 to 2006. In this essay, three risk factors would be considered - the US market portfolio, home market portfolio and exchange rate changes. The second essay presents a two-state Capital Asset Pricing Model (CAPM) for ADRs assuming absence of exchange rate risk. It adopts the standard regime switching model by Hamilton (1988, 1989) to combine both the home market and the US market. This approach is new to ADR pricing literature. The third essay will expand the regime switching-CAPM model developed above, by adding expected exchange rate returns to the home market exposure. The proportions of the effect of currency returns on ADR index returns would be estimated as the pass-through of exchange rate risks to ADR index returns.

This study will provide evidence on the returns of exchange-listed ADRs with market risk factors and exchange rate factor. This is important to our understanding of the benefits of international diversification, and has practical implications for asset management.

"***ADRs are worth a closer look.***" (Wahab and Khandwala 1992)

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CHAPTER ONE: INTRODUCTION

I. Motivation for the Study

Foreign firms usually list their stocks on 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. Much research has been done rationalizing why firms cross-list in the past two decades (see surveys by Karolyi 1998, 2006). Researchers also try to quantify the relationships of ADRs with home market, US market and exchange rate changes and look for the price determinants of ADR returns. However, this research is still inconclusive given different factors included in the models and samples selected. We still lack adequate knowledge of the pricing behavior of this particular group of cross-listed shares. This research addresses this issue and in particular the following questions: what determines the price movements of exchange-listed ADRs? How should we price ADRs? Do they move with their respective home stock markets or with the US stock markets? Are exchange rates a significant risk factor for ADRs?

To the extent that ADRs from a particular country share the same country-specific characteristics, they should be impacted by the market fundamentals of their home country. This regime is named as the *home market systematic risk pass-through*. Anecdotal evidence has shown that ADRs move with the US stock market, though seemingly incomprehensible theoretically. I 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 or trading barriers such as 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 the US economy and the covariance of the ADR returns with a US market portfolio.

Early research on ADRs examines their underlying assets in search of evidence for the law of one price (Rosenthal 1983, Kato, Linn and Schallheim 1991, Wahab, Lashgar and Cohn 1992). The common hypothesis from this research 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. Although most of these studies concluded that arbitrage opportunities do not exist in general, they recognized that there are different risk-return characteristics of ADRs with their underlying shares. Studies of the portfolio diversification effects of ADRs provide further evidence of the close ties between ADRs and the home market. They find that ADRs from both industrial and emerging markets bring diversification benefits for US investors and can be used as a proxy of their home markets (Officer and Hoffmeiser 1987, Wahab and Khandwala 1993, Bekaert and Urias 1999, Errunza, Hogan and Hung 1999, etc). 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 studied.

More recent studies have revisited the hypothesis of no arbitrage in ADR markets, with new focus on the longer term performance of ADRs, and search for possible explanations for different home market pass-through effects across ADRs (Alaganar and Bhar 2001, Foerster and Karolyi 2000, Rabinovitch, Silva and Susmel 2003). These studies argue that arbitrage is costly due to the transaction costs cross-borders, and that market liquidity might significantly affect post-issuance ADR performance.

A group of recent empirical studies attempt to find the determinants of ADR returns in the context of multi-factor models (Patro 2000, Kim, Szakmary and Mathur 2000, Choi and Kim 2000, Alaganar and Bhar 2001, Fang and Loo 2002). Most of these factor pricing models find the home market is significantly influencing ADR returns, but the results on the US market and exchange rate risks are inconclusive and vary upon the country studies. For example, US market risk and exchange rate risk are found to have an impact on ADR prices (Kim, Szakmary and Mathur 2000, Fang and Loo 2002), but Patro (2000) finds that exchange rates are insignificant risk measures for ADR portfolio returns. 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 jointly, and the results from these studies are inconclusive due to different sample selected. As most of the studies are static models, they implicitly assume ADR risk exposures to these pricing factors are constant for the sample period.

In the area of ADR pricing, there is a demand to reconcile the inclusive results. At the same time, a model is in need that is based on asset pricing theory and allows time varying risk exposures of ADRs to market risks and exchange rate risks.

II. Basic Design of the Study

This dissertation is an empirical research on ADR pricing. It consists of three independent but closely related essays addressing the issue of ADR pricing.

The first essay intends to reconcile the mixed results in previous traditional factor pricing models. In this essay, the traditional approach will be used to estimate the risk sensitivities of ADRs to home market and US market factors and exchange rate changes for all country ADR portfolios available. It uses both regression and time series technique to look at the significance of sensitivities of ADRs to different risk factors. It directly contributes to the factor pricing literature on ADRs by (1) providing new evidence to the previous inconclusive findings using a large country scope (36 countries) and recent data (1998-2006); and (2) using an ADR country index which has not been used previously to evaluate the sensitivities of ADR country portfolios to different risk factors under the static model. The results from the traditional model would also be used to compare with the conditional Capital Asset Pricing Model (CAPM) in the regime switching model of the other two essays.

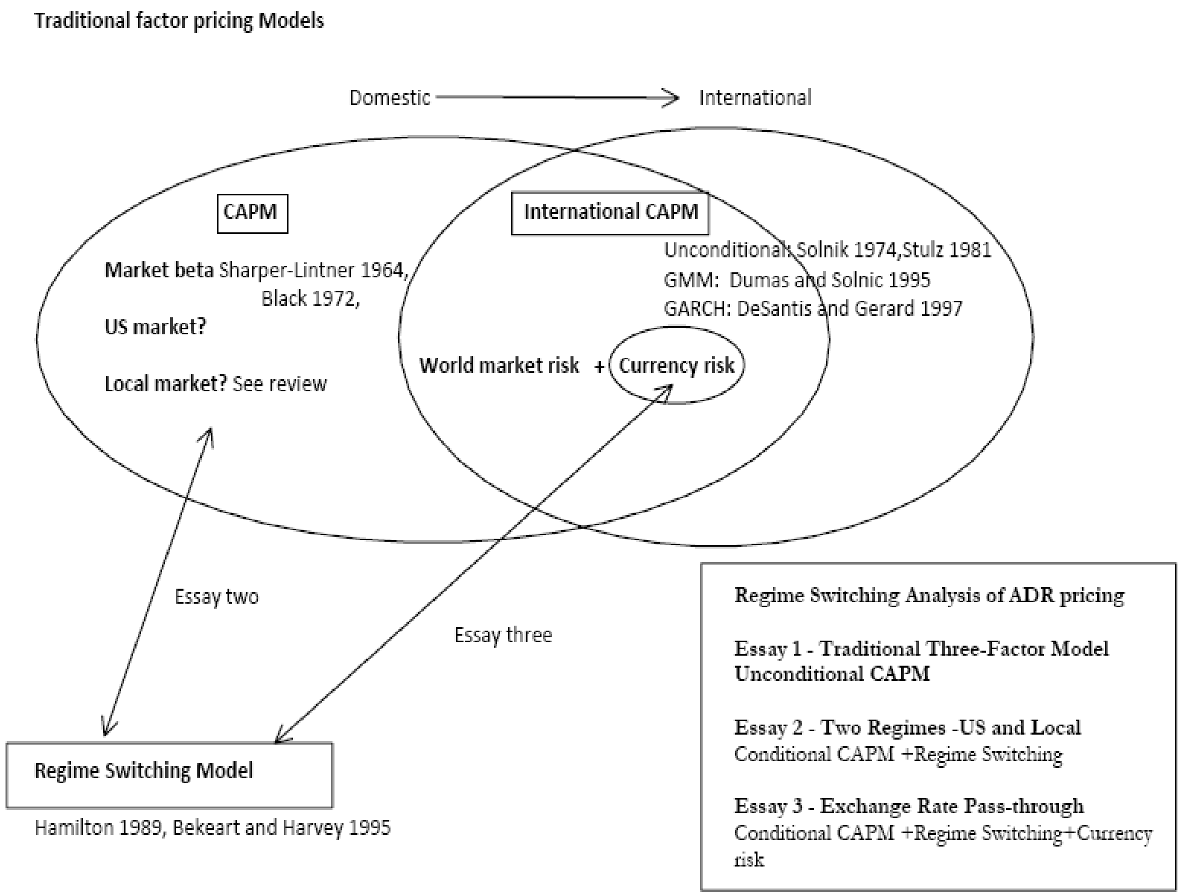
The second essay presents a two-state CAPM for ADRs. It adopts the standard regime switching model by Hamilton (1988, 1989) to nest both the home market and the US market. In a home market pass-through regime, ADRs are priced as their home market assets using conditional CAPM. In the pricing to market regime, ADRs are treated as US domestic assets and priced using CAPM in the US market. These two regimes are not a monotonic substitution of one another, such as the assumption that ADRs are gradually more priced to the 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-2-state CAPM extends the domestic capital asset pricing model but is not as idealized as International Capital Asset Pricing Model (ICAPM), which assumes full integration of the world market. It will also consider time-varying weight to covariance and variance factors, allowing 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 systematic risk pass-through, which has not been done on the pricing of ADRs. I use ADR indices to capture the country-specific systematic risks (i.e., the home market risk pass-through of ADRs).

The third essay will expand the regime-switching-CAPM model developed above, by explicitly adding exchange rate risk in the regime switching framework. Literature on International Capital Asset Pricing Models has shown that exchange rate risks play significant role in asset returns (Solnik and Dumas 1995, De Santis and Gerand 1998). With the regime switching framework, I expect to identify how much exchange rate risk affects ADR premiums and re-estimate the effect of home market on ADRs after separating home market performance with currency performance. The proportions of the effect of currency returns on ADR index return would be estimated as the pass-through of exchange rate risks to ADR index returns. This is also an extension of the regime switching model in Bekaert and Harvey (1995) which assumed absence of exchange rate risk.

Figure 1 summarizes the theoretical framework of this dissertation. Essay one is based on the traditional factor pricing model. Essay two is based on the conditional CAPM framework and combined with regime switching models. Currency risks are emphasized in ICAPM, which will be considered in the third essay. The three essays are relatively independent, and the model complexities gradually increase. Altogether they provide both static and dynamic analysis of ADR pricings.

Figure 1: Dissertation Design and Theoretical Framework



III. Intended Contributions

The surge in ADR investments in the past two decades has prompted great interests in the performance of ADRs. Although considerable research has been done on this subject, the research focuses on the motivation of cross-listings such as earlier studies on the market reactions and the "bonding hypothesis" in the current stage. The research on the performance of exchange-listed ADRs and their pricing factors is still in exploration stage – most of them are done "piecemeal", focusing a particular number of countries for a specific time period. Therefore, this study is intended to expand the scope of previous studies and provide systematic estimates with the most number of countries possible and with the latest data.

This study is intended to reconcile the conflicting evidence on the relationships of exchange-listed ADR returns with home market returns, US market returns and exchange rate risks. Therefore, this study will contribute to the traditional factor pricing model in the literature by consolidating the evidence of the risk exposures of ADRs to home market portfolio, US market portfolio and exchange rate changes.

Going beyond this traditional factor pricing model, a new technique, regime switching, will be applied to develop an empirical model for ADR pricing. In this regime switching framework, the weights of home market effects and US market effects are time-varying, which provides more dynamics rather than simply assuming the home market or US market factor as the market risk factor.

The effects of exchange rate risks are also modeled differently from previous factor pricing literature. Exchange rate risks are only considered in the home market pass-through regime when ADRs are treated as perfect substitute of underlying shares. That is to say, exchange rate risks should not be considered when US investors view ADR investment no different from other domestic investments if we want to model the investors' expectation on the future ADR returns. Therefore, the exchange rate risk in this model is derived from the return of investment on foreign currency. As to how much of this exchange rate risk is passed to investors' expectation on future ADR returns will depend on home market pass-through regime probability. This is also new in the literature.

The regime switching pricing model in essay two and essay three is tailor-made for ADRs, and is new to ADR pricing literature. 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.

The rest of the dissertation is organized as follows. Chapter 2 provides a background of ADRs, a survey of related ADR literature and a primer of regime switching model that will be used in this dissertation. Chapter 3 will be the first essay in this dissertation, which extends the traditional factor pricing models with a wide scope of data. Chapter 4 is the core of this dissertation. It develops a regime switching framework for the dissertation. Chapter 5 extends chapter 4 by separating exchange rate risk out of ADR covariance with home market. The three essays are relatively independent. Each contains sections on the research question, model (if specified), data, methodology and empirical estimation.

CHAPTER TWO: LITERATURE REVIEW

This section brings discusses the definition of ADRs, its' programs, benefits, buying and selling issues and a brief review of ADR research and related literature. A primer on regime switching models is also included at the end of the chapter.

I. The Background on ADRs

I.1. Definitions

Foreign firms usually list their stocks in the US stock exchanges in the form of American Depository Receipts (ADRs). Depositary Receipts (DRs) were created in 1927 by JP Morgan to aid US investors who wished to purchase shares of non-US corporations without going to a foreign market. A DR is issued by a US depositary bank evidencing ownership of shares in a non-US corporation. Each DR denotes Depositary Shares (DSs) representing a specific number of underlying shares on deposit with a custodian in the issuer's home market.[1] American Depositary Receipts (ADRs) are DRs that are publicly available to investors in the US. Investors bear all currency risk when holding ADRs and receiving dividends, and indirectly pay fees to the depositary bank (Foerster and Karolyi 1999).

ADRs may be unsponsored or sponsored. Unsponsored ADRs are issued by one or more depositaries in response to market demand, but without a formal agreement with the

[1] Note DRs are not limited to those listed or traded in the US markets. There are also global depositary receipts (GDRs), international depositary receipts (IDRs), and European depositary receipts (EDRs), which are generally traded or listed in one or more international markets.

company, which are now considered obsolete and are rarely established due to lack of control. Sponsored ADRs may be issued in different levels available in various trading markets and are issued by one depositary bank appointed by the company under a deposit agreement or service contract. Sponsored ADRs offer control over the facility, the flexibility to list on a US stock exchange and the ability to raise capital.

I.2. ADR programs

There are four types of ADRs. Level I ADRs are traded Over-the-Counter (OTC) through the OTC Bulletin Board and/or Pink Sheets. Level I ADR programs currently require minimal Securities and Exchange Commission (SEC) registration: the issuer seeks exemption from the SEC's traditional reporting requirements under Rule 12g3-2(b). With that exemption, the company agrees to send to the SEC summaries or copies of any public reporting documents required in its home market (including documents for regulatory agencies, stock exchanges or direct shareholder communications). The depositary, working with the issuer, also files the Form F-6 registration statement with the SEC in order to establish the program.

Level II ADRs are listed on a US exchange: the New York Stock Exchange (NYSE) or the American Stock Exchange (Amex), or quoted on the National Association of Securities Dealers Automated Quotations (NASDAQ) Stock Market. When a foreign company wants to set up a Level II program, it must file an F-6 registration statement with the SEC and is subject SEC regulation. In addition, the company is required to file a Form 20-F annually. Form 20-F is the basic equivalent of an annual report (Form 10-K) for a US company. In their filings, the company is required to follow GAAP standards. In addition, the company's annual reports and any interim financial statements are required to be submitted on a regular, timely basis to the SEC.

Level III ADRs are the most high-profile form of sponsored ADR program. They are issued as a public offering of securities on a US exchange. Level III ADR programs must comply with various SEC rules, including the full registration and reporting requirements of the SEC's Exchange Act. Besides the Form F-6 registration statement and Form 20-F registration statement like those for level II ADRs, Level III ADRs are also required to fill Form F-1 to register the equity securities underlying the ADRs that are offered publicly in the US for the first time, including a prospectus to inform potential investors about the company and the risks inherent in its businesses, the offering price for the securities, and the plan for distributing the shares. In addition, annual reports and any interim financial statements of this company are required to be submitted on a regular, timely basis to the SEC and to all registered public shareholders. Level III ADRs allow issuers to raise capital and greater visibility in the US market. Generally, companies that choose either a Level II or Level III program will attract a significant number of US investors.

Rule 144A, also known as RADRs, are capital raising issues privately placed with qualified institutional buyers (QIBs).[2] They are exempted from SEC registration and US reporting requirements. Table one presents a summary of these different types of ADRs programs.

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[2] More details on the ADR issuance process and types are available from *Depository Receipts Information Guide* by Citigroup Global Transaction Services (2005). wwss.citissb.com/adr/www/adr_info (accessed Nov. 14, 2006).

Table 1: Summary of ADR Programs

	Level I	Level II	Level III	144a
Description	Unlisted program in the US	Shares listed on a U.S. exchange	Shares offered and listed on a U.S. exchange	Private placement to qualified institutional buyers
Primary Exchange	OTC Pink Sheets	NYSE, AMEX, NASDAQ	NYSE, AMEX, NASDAQ	US private placement market
US Reporting requirements	Exempt under Rule 12g3-2(b)	Form 20-F*	Form 20-F*	Exempt under Rule 12g3-2(b)
SEC Registration	Register under Form F-6	Register under Form F-6	Register under Form F-1 and F-6	None
Time to Completion	10 Weeks	10 Weeks	14 Weeks	16 Days
Costs	$25K	$200-700K	$500K-2M	$250-500K

*Financial statements must be partially reconciled to U.S. GAAP

Source: JPMorgan, ADR research, http://www.adr.com/ and Bank of New York website, http://bnyadr.com/ (accessed May 23, 2007)

Besides the DRs issued in the US, there are DRs that go beyond the US equity markets to raise capital – Global Depositary Receipts (GDRs). GDRs generally combine two complementary structures: the Regulation S (Reg. S) depositary receipt and the ADR. Regulation S clarifies the conditions under which offers of securities outside the United States are exempt from SEC registration requirements. Regulation S depositary receipts are listed on European stock exchanges such as London or Luxembourg stock exchanges. Regulation S was adopted by the SEC in 1990 in conjunction with the adoption of Rule 144A.[3] This combined structure, Reg. S/Rule 144A DR, is most frequently-utilized, which raises capital in the European markets (typically London or Luxembourg) and through private placement with qualified institutional buyers in the US. The Reg. S DRs can also be combined with either Level I or Level II/III (exchange-listed) ADRs, depending upon the issuer's needs. In the recent years, capital raising using GDRs has increased relative to ADRs. According an ADR reference guide from JPMorgan, in 2004 to 2005, GDRs were used to

[3] DR glossary by Bank of New York, http://bnyadr.com/dr_edu_glossary.jsp#R (accessed July 31, 2007).

raise 40% of all capital from DR issuance, compared to 27% in the comparable 2001 to 2003 time frame.[4]

According to the statistics by JPMorgan, as of May 2007, there are about 1722 foreign firms from 72 countries cross-listed in the US markets. (www.adr.com). Among them, about 28% are direct listing on the US stock exchanges (Level II and III), and about half of companies choose Level I ADRs (over-the-counter), and about 22% are RADRs. As for ADR regional distribution (Table 2), developed Asia and Europe have the largest number of ADRs, emerging Asia, emerging Europe and Latin America also take more than 40% of total ADRs. It indicates that investors are not only buying those shares from more advanced economies but also interested in the risky investments in the emerging economies. As of May 15, 2007, according to JPMorgan ADR website (www.adr.com), the average daily trading share volume of ADRs is about 223 million, which is about 8.6 billion US dollars.

Table 2: ADR regional distribution by program types as of May 2007

LEVEL	DEV. ASIA	DEV. EUROPE	EMRG. ASIA	EMRG. EUROPE	LATIN AMERICA	MIDDLE EAST / AFRICA	Grand Total
144A	*12*	*48*	*162*	*90*	*51*	*28*	*391*
LEVEL I	*370*	*214*	*73*	*64*	*91*	*62*	*874*
LEVEL II	*51*	*131*	*21*	*1*	*45*	*15*	*264*
LEVEL III	*11*	*60*	*67*	*6*	*46*	*3*	*193*
Grand Total	**444**	**453**	**323**	**161**	**233**	**108**	**1722**

Source: JPMorgan, http://www.adr.com/ (accessed May 14, 2007)

I.3. Benefits of ADRs

[4] JPMorgan. http://www.adr.com/pdf/ADR_Reference_Guide.pdf (accessed July 31, 2007).

The benefits of ADR programs to issuers include an enlarged investor base, enhanced local market for shares, opportunity to raise new capital and a liquid secondary market in the United States, and international reputation (Foerster and Karolyi, 1999, Errunza and Miller, 2000). For companies that issue ADRs, the establishment of a Depositary Receipt program offers capital and commercial benefits: expanded market share through broadened and more diversified investor exposure with potentially greater liquidity, which may increase or stabilize the share price; enhanced visibility and image for the company's products, services and financial instruments in a marketplace outside its home country, flexible mechanism for raising capital and a vehicle or currency for mergers and acquisitions, etc. (www.bnyadr.com).

For investors, ADRs have a number of advantages: facilitating diversification into non-US securities, trading in accordance with practices of the investor's home market, providing enhanced accessibility of research, and price and trading information, allowing easy comparison to securities of similar companies trading in the investor's home market, permitting dividend payments in US dollars and corporate action notifications in English, elimination of global custodian safekeeping charges, potentially saving Depositary Receipt investors up to 10 to 40 basis points annually, etc..[5] ADRs also play a critical role in different types of cross border transactions such as privatizations and mergers and acquisitions for firms from both developed markets and emerging markets (Errunza and Miller, 2000).

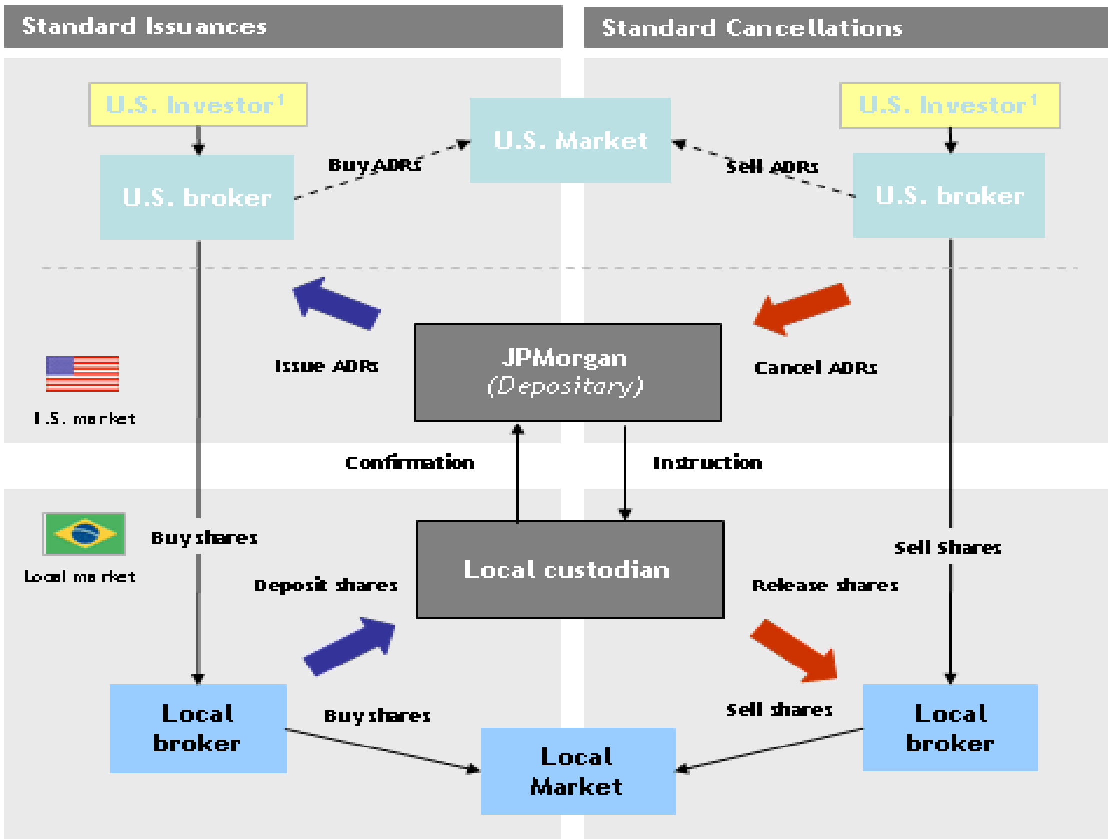
[5] *Depository Receipts Information Guide* by Citigroup Global Transaction Services (2005). wwss.citissb.com/adr/www/adr_info/InfoGuide05.pdf (accessed Nov. 14, 2006).

I.4. Dealing with ADRs - buying and selling[6]

ADRs are issued or created when investors decide to invest in a non-US company and contact their brokers to make a purchase. These brokers will contact the local broker in the company's home market to purchase the underlying ordinary shares and request that the shares be delivered to the depositary bank's custodian in that country. The broker who initiated the transaction will convert the US dollars received from the investor into the corresponding foreign currency and pay the local broker for the shares purchased. On the same day that the shares are delivered to the custodian bank, the custodian notifies the depositary bank. Upon such notification, ADRs are issued and delivered to the initiating broker, who then delivers the ADRs evidencing the shares to the investor. Besides a new issuance, brokers can also obtain ADRs by purchasing existing ADRs from the US market. In the United States, the depositary banks mainly include Bank of New York, Chase Mellon Bank, JPMorgan Chase, Citibank, Deutsche Bank AG, and Computershare Trust Co.. The left column of Figure 1 shows the standard issuance process for ADRs.

[6] Background information in this subsection is taken mainly from Bank of New York Mellon website, http://bnyadr.com/dr_edu_basics_and_benefits.jsp (accessed May 14, 2007)

Figure 1: Flowchart of standard ADR issuance and cancellation



Source: JPMorgan, http://www.adr.com/ (accessed July 17, 2007)

Once ADRs are issued, they are traded in the United States like other US securities. The purchase or sale of ADRs is simply the transfer of ADRs from different holders. This transfer process is known as an *intra-market* transaction. "An intra-market transaction is settled in the same manner as any other US security purchase: in US dollars on the third business day after the trade date and typically through The Depository Trust Company (DTC). Intra-market trading accounts for approximately 95 percent of all ADR trading in the market today. Accordingly, the most important role of a depositary bank is that of Stock Transfer Agent and Registrar."[7]

When investors want to sell their Depositary Receipts, they notify their broker. The broker can either sell the Depositary Receipts in the US market through an intra-market transaction or cancel the Depositary Receipts (release the custody of these shares back to the local market). This is depicted in the right column of Figure 1. In order to settle the trade, the US broker will surrender the Depositary Receipt to the depositary bank and the depositary bank will give instructions to the custodian to release the underlying shares and deliver them to the local broker who purchased the shares. The broker will arrange for the foreign currency to be converted into US dollars for payment to the Depositary Receipt holder. The currency risk due to the translation effect through the ADR issuance and cancellation is totally born with US investors. However, currency risk is not obvious for ADR trading in the US market as ADRs are denominated in US dollars.

I.5. Scope of ADRs in this study

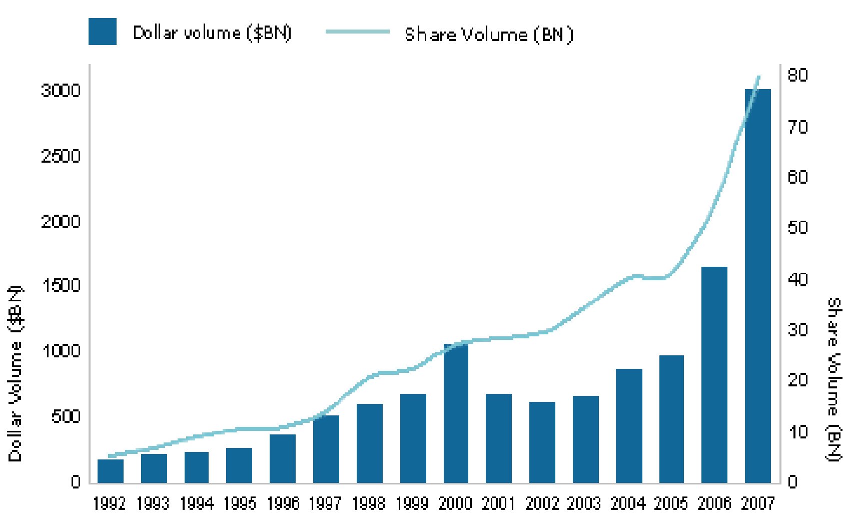
This study will focus on the intra-market transactions of exchange listed ADRs. As shown in Figure 1, this dissertation deals with the section above the dashed lines – buying and selling ADRs on the US market, more specifically on the AMEX, NASDAQ and NYSE. Table 3 gives a list of ADRs from countries and regions that will be covered in this research. There are 37 countries from Asia, Europe, Latin America and Middle East listed on US stock exchanges and most of them are listed on NYSE and NASDAQ. This study does not differentiate Level II and Level III programs; instead they are put together as exchange-listed

[7] http://bnyadr.com/dr_edu_basics_and_benefits.jsp (accessed July 17, 2007).

ADRs and ADR index data is used to represent each country. For the exchange listed ADRs, the trading volume increased to about 55 billion shares in 2006, which is worth over 1.6 trillion US dollars (see Figure 2).

Companies that have exchange-listed ADRs have to follow similar standard as a US company and these ADRs are traded like US ordinary shares. But is the US market actually affecting the price behavior of ADRs? What are the risk sources of ADRs? How should we price exchange-listed ADRs? These are questions that motivate the research of this special group of shares. Intuitively, these exchange-listed ADRs are like a group of "immigrants" to the US with close ties to their family in their home country, but they speak English in the US, are regulated by US laws and work with US investors. As these "immigrants" have "lived" in the US for quite a while, one may wonder whether they have become "Americanized" to some extent, and how different factors from home and the US jointly affect their "lives". This metaphor is simply used to illustrate the motivation for this research and does not present any other personal views from the author.

Figure 2: ADR Trading Volume: Exchange Listed ADRs



Source: J.P. Morgan, http://www.adr.com/ (accessed May 14, 2007

Table 3: Exchange-listed ADRs by country and region

ZONE	COUNTRY	AMEX	NASDAQ	NYSE	Grand Total
Asia	*Australia*		12	7	19
	China		24	22	46
	Hong Kong		7	6	13
	India		3	10	13
	Indonesia			2	2
	Japan		10	19	29
	Korea		7	8	15
	New Zealand			1	1
	Philippines		2	2	4
	Singapore		2		2
	Taiwan		4	5	9
Asia Total			**71**	**82**	**153**
Europe	*Austria*			1	1
	Belgium			1	1
	Denmark		2	1	3
	Finland			4	4
	France		8	18	26
	Germany		3	18	21
	Greece			3	3
	Hungary			1	1
	Ireland		6	5	11
	Italy		1	12	13
	Netherlands		7	14	21
	Norway		3	3	6
	Portugal			2	2
	Russia			6	6
	Spain		1	9	10
	Sweden		2		2
	Switzerland		1	10	11
	Turkey			1	1
	United Kingdom	2	16	47	65
Europe Total		**2**	**50**	**156**	**208**
Latin America	*Argentina*		3	14	17
	Brazil		1	34	35
	Chile			17	17
	Colombia			1	1
	México	2	3	18	23
	Perú			1	1
Latin America Total		**2**	**7**	**85**	**94**
Middle East	*Israel*		6	2	8
Middle East Total			**6**	**2**	**8**
Grand Total		**4**	**134**	**325**	**463**

Source: ADR directory from the Bank of New York, www.bnyadr.com (accessed May 14, 2007)

II. Literature review on ADRs pricing

II.1. An overview of areas of research on ADRs from 1980s to present

Much research has been done rationalizing why firms cross-list, especially in the past two decades, concomitant to the surge of the number of cross-listings since 1990s (see surveys by Karolyi 1998, 2006). In the first survey by Karolyi (1998), he documents the studies done on market behavior around listings and liquidity effects. These studies mostly concern themselves with the market behavior around the cross-listings, such as the share price reactions to the cross-listing decisions, and they examine the changes of cost of capital for cross-listed firms and liquidity effects from the price volatilities and trading volumes. As these studies focus on the changes pre and post listing, they mainly employ event study methodologies, using a market model as a benchmark to calculate cumulative returns.

Conventional wisdom for the motivation of cross-listing at that time is based on market segmentation hypothesis, which states firms cross list in order to overcome the market barriers. Karolyi (1998) summarizes the major findings from 1980s to 1990s on this area into the following points: (1) share prices react favorably to cross-border listings initially; (2) post-listing price performance up to one year is negative on average but variable depending on the home and listing market, its capitalizations and capital raising needs and other company-specific factors; (3) post-listing trading volume increases on average, and, for many issues, home market trading volume increases; (4) share liquidity improves overall, but depends on the increase in total trading volume, the listing location and the scope of foreign ownership restrictions in the home market; (5) exposure to domestic market risk is significantly reduced and is associated with only a small increase in global market risk and foreign exchange risk, which can result in a net reduction in the cost of capital of about 126 basis points; (6) ADRs represent an effective global diversification tool; and (7) stringent disclosure requirements are the greatest impediment to cross-border listings.

The arbitrage and diversification benefits of the ADR market is another important area of research from 1980s to 1990s (Officer and Hoffmeiser 1987, Wahab and Khandwala 1993, Kato, Linn, and Schallheim 1991 and Wahab, Lashgar, and Cohn 1992). The major conclusion is that although ADR prices might deviate from their underlying shares in the home market, the efficient arbitrage should force a realignment of the prices. Empirical studies do support the notion of efficiency, but each of them are small in scale, scope and quality of data (Karolyi 2006)[8]. This part of literature will be discussed in detail later, after the main areas of research are introduced.

From the late 1990s, a few new research initiatives emerged to better understand the motivations of cross-listings. The "bonding" hypothesis started from the agency conflict perspective, arguing that cross-listing is the way for bond managers not to take excessive private benefits given the high regulatory and legal requirements to list on the foreign exchange (see survey by Karolyi 2006). The information environment of cross-listed firms is also suggested to be one of the important reasons to cross-list, because the better the information flow, the more it serves as a signal for outside investors. "Spillover" effects of cross-listings are the stream of studies looking at the derivative effects of cross-listing to other firms in the same country or to the local market as a whole. The hypothesis is whether there is a more integrated local market, or a deteriorated local market due to the diversion of investment caused by overseas listings, and the results are mixed in these studies (Karolyi 2006).

[8] For the details on the name and general summary of the essays on different research areas, readers should consult Karolyi (2006).

The microstructure studies on price discovery in ADRs is another new research area. Here, researchers try to find the general rule in the price discovery of ADRs by looking at trade volume and market-makers at different exchanges. Yet, there is an important limitation of this micro-structure type of research – that is, "any inference about the relative importance of price discovery are necessarily a joint hypothesis with the dynamic model of price discovery", so that when the commonly-used dynamic error-correction model or Hasbrouck's common-trend model is misspecified, we may be incorrectly estimating the scope of influence of the new overseas' data (Karolyi 2006). Therefore, a group of static models emerge to analyze the price-determination, such as Patro (2000) and Fang and Loo (2002). They connect to the early literature on price parity and arbitrage between ADRs and the underlying shares.

II.2. ADR pricings - the home market and the US market

This section provides a review of selected studies on rationalizing how ADRs are related to the home market and how important the US factor is to the returns of ADRs.

II.2.1. Early Research on arbitrage in ADR markets

This group of research recognizes the intrinsic link between the relationships of ADRs with the underlying shares and examine whether or not the law of one price holds. The law of one price states that the price of identical goods are expected to be the same in competitive markets with no transaction costs and no barriers to trade (Lamont and Thaler 2003). Based on the law of one price, cross-listed shares represent the same assets, therefore should have identical prices if they are converted into the same currency. In case of ADRs, they should have the same prices with their underlying assets in the local markets, if there are no transaction costs and no barriers to trade. It is often argued that there should be no deviations of ADR prices from their underlying assets if arbitrage is possible. For example, if an ADR were selling at a premium, those who observed this situation could take this arbitrage opportunity, by buying the local shares, convert them to ADRs and then sell them for a profit. Therefore, in theory, ADR prices should closely follow the ordinary share prices in the home market if the firm has a local listing, with any deviations being corrected immediately.

The law of one price (or stock price parity) is confirmed by the early research on arbitrage and efficiency of the ADR market. They examine ADRs and their underlying assets and find that ADRs are similar to their respective underlying shares, and conclude that no arbitrage opportunities exist. However, they also find some mixed results for lower frequency returns data, as they are not near perfect substitutes for each other.

Rosenthal (1983) argues that ADRs certainly have similarities to the underlying shares, but international capital market imperfections could result in some differential pricing vis-à-vis the underlying shares. He examines the weak form efficiency of foreign equities for a group of 54 ADRs over the period 1974 through 1978 using weekly, biweekly and monthly rates of return. Serial correlation tests indicate that the null hypothesis of no linear dependence is not supported for weekly and biweekly returns, but is accepted for monthly returns. He concludes that the tests were reasonably consistent with a weak form efficient market for ADRs.

Similarly to Rosenthal (1983), Kato, Linn, and Schallheim (1991) directly compares the market prices of ADRs with their underlying foreign stocks (8 from Australia, 7 from

England and 8 from Japan) for differences and correlations. They use both the parametric T-test and non-parametric Rank-sum test on the prices of ADRs and their underlying shares (converted to US$). In their first differenced series, they find no significant differences between the prices of the two identical types of claims and conclude that no arbitrage opportunities exist between international capital markets encompassed by their study. Although they find the evidence to be supportive of the law of one price, they notice that the two returns are not near to being perfectly correlated. They explain this result by the overlapping time periods for the return calculations. Essentially, the timing differences can lead to spurious return correlation results.

However, based on the law of one price, Kato, Linn, and Schallheim (1991) implicitly assume that the ADR market is both integrated and efficient across countries, hence ADRs and their respective underlying shares have similar risks (Wahab, Lashgar, and Cohn 1992). Although ADRs are certificates of their underlying shares, there are possible differences in return volatilities of ADRs and their respective underlying shares due to market imperfections, differential trading frequency and market micro-structure effects, as argued by Wahab, Lashgar, and Cohn (1992).

Wahab, Lashgar, and Cohn (1992) treat ADRs and their underlying shares as different claims and tested null hypothesis of no arbitrage in ADR markets. They use the daily rate of returns of 31 pairs of ADRs and their underlying shares from 8 countries (UK, Japan, Germany, France, Sweden, Norway, Australia and South Africa) between 1/04/1988 to 5/31/1991. They establish long and short positions in identified portfolios of over and under-priced securities using both minimum-variance and an equally-weighted combination. They reject the null hypothesis of no arbitrage, and find annualized arbitrage returns between 1.23% and 4.44% were possible for some of the identified arbitrage portfolios.

They argue whether such a seemingly anomaly is of economic importance, and that it will depend on transaction costs faced by the potential arbitrageur.

Park and Tavakkol (1995) further investigate the risk and returns between Japanese ADRs and their underlying stocks. They analyze the weekly returns of a group of 21 pairs of ADRs and underlying shares from July 1977 to June 1987. They find that the exchange rate adjusted returns on ADRs were not significantly different from the returns on their corresponding securities, and that ADRs are more volatile than the underlying stocks, due to the impact of the currency market volatility and the covariance of the stock-currency returns. They compare ADRs and the underlying shares and find that ADRs are more responsive to the US market and less to the Japanese market; and that the exchange rate adjusted ADRs are less responsive to the movements in currency market than their underlying stocks.

II.2.2. Diversification with ADRs

Given the close relationship between the ADRs and their underlying shares, there has been research done on how ADRs providing foreign diversification benefits portfolios of US investors. Research in this area provides evidence that (1) by adding in ADRs, the US portfolio variance is greatly reduced given similar returns; and (2) ADRs can be used as a proxy to their home market portfolio and diversification can be achieved without physically investing in the foreign markets.

Officer and Hoffmeiser (1987) use a portfolio of 45 ADRs in comparison with a random sample of 45 domestic common stocks traded on NYSE or ASE over the same period with monthly returns from 1973 to 1983. They find significant lower systematic risk for ADRs than for comparable US firms. They test for mild segmentation by constructing portfolios containing both ADRs and US firms and find a 20% reduction in portfolio risk when including ADRs in a representative US stock portfolio without sacrificing any expected returns.

Extending the work by Officer and Hoffmeiser (1987), Wahab and Khandwala (1993) compare ADRs with their underlying assets from developed economies using daily returns from 1987 to 1990, with greater ADR representation from Asia and Europe. They create portfolios by adding in different number of ADRs or investment proportion of ADRs relative to the S&P 500 and use a three-way analysis of variance model. They find that ADRs provide similar expected returns to their underlying assets, but the variance of a portfolio containing seven foreign shares with a 50% investment is approximately 26% higher than the variance of a portfolio containing ADRs similarly constructed. They conclude that ADRs potentially provided better risk reduction benefits for US portfolio investors than their underlying shares. This result indicates that ADRs might have different risk-return characteristics from their underlying shares, which is consistent with the discussions of Wahab, Lashgar and Cohn (1992).

Officer and Hoffmeiser (1987) and Wahab and Khandwala (1993) look at the portfolio returns and variances when including ADRs to a US portfolio and show the diversification benefits of investing in ADRs. There are also studies that directly examined the relationship of ADRs with the US market (Webb, Officer and Boyd 1994).

Webb, Officer and Boyd (1994) examine the time structure of the relationship between US market daily returns and ADR returns from 1975 to 1989, and test whether the relationship varies according to the ADR country or region of origin. They use a regression model including three leads and three lags of US market index for each country. They find a strong, significant relationship between ADR and US market daily returns on a contemporaneous and one-day lagged basis, indicating a lead/lag relationship among equity markets with the US market acting as the lead market in equity pricing. They also create portfolios based on three regional groupings – UK, Europe and Japan, and find the same structural relationship, although the relationship is the strongest for the UK ADR portfolio. However, as this study only includes the US market and its leads or lags as explanatory variables, the model might be misspecified. The results could change if other risk factors such as the home market factor are added.

Karolyi and Stulz (1996) examine correlations between a portfolio of Japanese ADRs and a matched-sample portfolio of US stocks to explore the fundamental factors that affect the cross-country stock return correlations. The cross-country stock return correlations indicate the potential for international diversification. They construct overnight and intraday returns of these two portfolios. They find that US macroeconomic announcements, shocks to the Yen/dollar foreign exchange rate and Treasury bill returns, and industry effects have no measurable influence on US and Japanese return correlations. Instead, they find that large shocks to broad based market indices (Nikkei Stock Average and Standard and Poor's 500 stock indexes) positively impact both the magnitude and persistence of the return correlations. Their results show that correlations and covariances are high when markets move a lot. This suggests that covariances between countries change over time and it is more appropriate to model covariances as time varying.

During the late 1990s, further evidence on the diversification benefits of ADRs were provided by more rigorous empirical research on the relationship of ADRs with their respective home market portfolios from both industrial economies and emerging markets (Jiang 1998).

Jiang (1998) examines the effectiveness of ADRs as a convenient route towards international diversification with weekly data of 113 ADRs from 8 industrial countries (Australia, France, Japan, Netherlands, South Africa, Spain, Sweden and UK) during the period of January 1980 to September 1994. This article also tries to identify the dynamic relationships between ADR portfolios and the respective local market portfolios and the pricing factors that affect the returns of ADR portfolios. It shows that the portfolio with investment in the ADR portfolios perform better than those with investment in the US market and foreign market indices. The cointegration tests of ADR portfolios and national market indices indicate that only 3 out of 8 pairs of ADR portfolios and market indices are found to be cointegrated. The VAR analysis of ADR returns and home market returns show that although ADRs are affected by their respective market index portfolios, the impact of ADRs on local market portfolios is relatively stronger for countries with cointegrated ADR and market portfolios. Jiang (1998) also explores the pricing factors of weekly returns of ADR country portfolios with a GARCH (1,1) for each country and finds that ADR country portfolio returns are significantly associated with the US market returns, the orthogonal local market return and orthogonal currency return.

As it is often referred as "free lunch" to investment in emerging markets, Bekaert and Urias (1999) provide further evidence of the diversification benefits of three investment vehicles - closed-end mutual funds, open-end mutual funds, and ADRs from emerging markets. Using mean-variance spanning tests, they find that diversification benefits from emerging equity markets are sensitive to the time periods of the tests, and in some cases, to the particular investment vehicle. Their results show that direct exposure to emerging market indexes almost always gives benefits at least as strong as those from managed funds or ADR portfolios, and that closed-end funds, open-end funds, and ADRs provided statistically significant diversification benefits in the 1993-1996 test period. They also argue that as global capital market integration continues, the returns investors expect to earn in emerging markets are likely to fall and investors need to be more selective when "going forward" in emerging markets.

Errunza, Hogan and Hung (1999) expand the search to 17 countries, which includes seven developed economies and 10 emerging economies. They investigate the ability of investors to mimic returns on foreign market indices with domestically traded securities, such as MNCs, country funds and ADRs. They find that the increasing availability of assets that represent claims on foreign traded assets, such as ADRs, made it possible to exhaust most of the diversification benefits by holding domestically traded foreign assets. They provide evidence that gains beyond those attainable through home-made diversification have become statistically and economically insignificant for 11 of 16 markets (all seven of the developed markets plus four of the emerging markets: Argentina, Brazil, Korea and Mexico).

In sum, these studies on the diversification benefits of ADRs touch upon the relationships between ADRs and the underlying home market, or ADRs and the US market, though mostly imply that the relationships are persistent across countries and over time.

II.2.3. Second-wave research on arbitrage in ADR markets

Previous research on the arbitrage and efficiency of ADR markets tries to test whether or not the "law of one price" holds between ADRs and underlying shares, and the general consensus is that it does hold and that there are no arbitrage opportunities. However, they also find evidence that ADRs show different risk structure with the underlying shares and they are not perfect substitutes for their underlying shares. Recent research revisits the topic of the arbitrage and efficiency of ADR markets, with a new focus on the longer term performance of ADRs, and searches for possible explanations for differences of home market pass-through effects.

Foerster and Karolyi (2000) investigate the long-run return performance of non-US firms that raise equity capital in US markets. They find that overall a sample of 333 global equity offerings with US depositary receipt (ADR) tranches from 35 countries in Asia, Latin American and Europe under-perform against local market benchmarks of comparable firms by 8%-15% over the three years following issuance between 1982 and 1996. They perform univariate tests of return performance by firm attributes such as offering type, region and market type, accounting rating of the home country, issuance year, and privatization and IPO/SEO type. It shows that differences in long-run returns are related to the scope and magnitude of investment barriers that induce segmentation of capital markets around the world. They find that firms that issue equities on major public exchanges in the US modestly outperform their benchmarks, but those that come from emerging markets with low accounting standards significantly outperform their benchmarks. They also perform univariate tests of return performance by post-issuance liquidity and find that the monthly ADR turnover is dramatically higher at about 30%, versus about 8% in the home market. The results also show that inter-market competition for order flow in the post-issuance period affects long-run return performance and post-issuance buy-and-hold abnormal returns are most significantly and positively related to the offering's ability to generate a larger share of US trading volume.

Besides the investment barriers such as accounting ratings of the country that relates to the long-run performance of ADRs relative to benchmarks, Rabinovitch, Silva and Susmel (2003) specifically measure the transaction costs associated with arbitrage activities in

Chile and Argentina. They compare the distributions of ADR returns and the returns of the locally traded shares between Chile and Argentina. They find that while the mean returns are the same, before as well as after their translation into US dollars, the return standard deviations are significantly larger for the ADR returns than for the returns on locally traded stocks in Chile, while Argentinean ADRs and their respective underlying shares have the same distribution of the returns. In addition, they find that the estimated transaction costs associated with arbitrage activities are between 1% and 2% for Chilean ADRs and smaller – between 0.66% and 1.65% for the Argentinean ADRs. The speed with which local prices adjust to arbitrage activities is significantly higher in Argentina: the estimated daily return spread reversion caused by arbitrage activities is around 40% for Argentinean ADRs, while only 30% for Chilean ADRs, indicating the Argentinean market is more efficient. A possible explanation is that Argentina did not impose any restrictions on foreign investments, while Chile did. Therefore, arbitrage is costly given the direct or indirect investment barriers.

Foerster and Karolyi (2000) and Rabinovitch, Silva and Susmel (2003) extend the previous literature by specifically looking at possible factors that affect the differences of ADRs with local benchmarks, and point out that arbitrage is costly. Furthermore, arbitrage may not be possible or viable in some cases. A financial intermediary may have to pay extra costs to collect information in a foreign market and also transaction fees to buy foreign shares. Even in developed markets, arbitrage activity may also be impeded due to non-synchronous trading times (Kim, Szakmary and Mathur 2000). So when arbitrage fails to align the ADRs with their underlying foreign assets, it indicates that home market pass-through of ADRs is incomplete.

Besides that, differences in supply and demand in different markets might also lead to different prices of the same assets in segmented markets. Lamont and Thaler (2003) provide an example – Infosys, an Indian IT company trading in Bombay and also listed on NASDAQ. As of a March 7, 2000, Infosys had experienced a huge increase in value, and the enthusiasm of American investors appeared to be much greater than that of local investors. The Infosys ADR was trading at a 136 percent premium (ADR price is higher than its underlying assets).

Sometimes the over-enthusiasm of US investors might seem irrational, such as the Infosys example. This irrational-seeming behavior could be explained by asymmetric information and home bias. The US investors face information disadvantage about the foreign firms because of distance, differences in language and culture, and because of time zone differences (Kang and Stulz, 1997, Karolyi and Stulz 2002). Therefore, sometimes US investors buy ADRs without knowing anything about the foreign firms it represents, simply following other investors. This kind of herding behavior has nothing to do with the underlying asset, but affect the demand of ADRs. Furthermore, the demand shock in the US markets might also be transmitted back to the home market by ADRs, creating a feedback effect. So far I have not seen much research done on the herding effect or feedback effect of US demand on the ADR prices. This study will not directly test these effects. Instead it focuses on identifying the risk exposures of ADRs to the US market and home market in both static and dynamic settings, and look for explanations on how the innovations of these market risk factors affect ADR returns across countries.

In sum, the ADR research on arbitrage and efficiency of ADR markets and the diversification benefits of ADRs provide us evidence that ADRs present different risk-return characteristics with their underlying shares due to the investment barriers, costly arbitrage, different trading hours, etc. Some of them touch upon pricing factors of ADRs (Jiang 1998) which is closely related to the recent research on factor-pricing models for ADRs as discussed in the following section. A summary of literature in this section is appended at the end of the chapter (Appendix 1).

II.3. Existing literature on empirical models of ADR pricing

A group of recent empirical studies attempt to find the determinants of ADR returns in the context of multi-factor models (Patro 2000, Kim, Szakmary and Mathur 2000, Choi and Kim 2000, Alaganar and Bhar 2001, Fang and Loo 2002). Most of these factor pricing models are unconditional arbitrage pricing models, as they all find the home market is significantly influencing ADR returns. Thus the results on the US market and exchange rate risks are inconclusive and vary upon the country studies.

Patro (2000) provides an empirical analysis of 123 American depositary receipts (ADRs) from 16 countries from 1992 to 1997 using various factor pricing models with Seemingly Unrelated Regression (SUR). The research examines the relative importance of variations in returns of home and the world market portfolios, exchange rates and global risk factors and finds that the returns on ADRs have significant risk exposures to the returns on the world market portfolio and their respective home market portfolios. It also finds that ADRs do not have significant risk exposures to changes in their home currency's exchange rates. This research compares alternative asset pricing models and includes global risk factors such as world market return, changes in logarithm of the trade weighted value of the dollar, changes in 3-month T-bill yields and changes in oil prices. Their results show that in explaining variations in ADR returns, a multi-factor model with the world market return and the home market return as the risk factors performs better than models with just the world market return, the home market return or a set of global factors as the risk factors.

Choi and Kim (2000) add in firm-specific factor and industry factors. They examine the several major determinants of ADRs and their underlying stock returns for the period of 1990-1996. They consider a firm-specific factor (underlying stock returns), world market factor (world market returns), country factors (local and US market returns), industry factors (world, local and US industry factors) and exchange rates. They find that local factors (market or industry) explain ADRs and their underlying shares returns across countries and industries better than the world factor in their sample period, and the explanatory power of the exchange rates for ADRs are not as strong as expected. At the same time, they also find that the effect of local markets on the underlying stocks is greater than that on ADRs, which implies that the effect of international diversification of investing in ADRs may be less than that with direct investment in the underlying stocks.

Alaganar and Bhar (2001) investigate the following three hypothesis involving returns of the Australian stocks in US dollar, matching ADRs, Australian equity index and the US equity index - "H1: ADRs are priced efficiently in line with the underlying stocks and that risk-return characteristic of an ADR portfolio is similar to that of the foreign stocks," "H2: correlation coefficient between the US equity market and the ADR portfolio is similar to that between the US equity market and the underlying stocks," and "H3: There is a unidirectional causality and transfer of pricing information from the domestic market to ADR market." They examine 24 Australian ADRs during the period from January 1, 1988 to October 31, 1998. They find that the ADR market is priced efficiently that the "law of one price" holds, but the ADRs have an economically significant higher reward/risk ratio than underlying stocks, partly due to lower transaction costs. They also find that ADRs have a low correlation with the US market under high states of global and regional shocks. They test unidirectional information transmission from the underlying stocks to ADRs with a

Vector Autoregressive process (VAR). However, this study is restricted to ADRs from Australia, so the results have limited applications.

Kim, Szakmary and Mathur (2000) consider three pricing factors for ADRs: the price of the underlying shares in the local currency, the relevant exchange rate, and the US market index. They use daily prices of ADRs from Japan, UK, Sweden and Australia for a three-year period (1988-1991). This research applies both VAR with cointegrating constraints and SUR analysis. Their results show that while the price of the underlying shares is most important, the exchange rate and the US market also have an impact on ADR prices. An interesting result from this research is that the authors find that the ADRs appear to initially overreact to the innovations in the US S&P 500 index, but under-react to changes in underlying share prices and exchange rates. However, the overreaction to the US market is very short-term in nature, being reversed within a few days. They interpret the results essentially as being that, US investors initially attempt to price the ADRs partly with reference to their own market, rather than to the foreign market in which the underlying assets are held and traded. However, this research does not explain why US investors only "initially" attempt to price the ADRs referring to their own markets, and their model does not capture the time variation of the impacts of these three factors. And since they only used data from developed economies, it would be interesting to know whether their results apply to emerging markets and whether there are significant differences in cross-country results on these three factors.

Similarly, Fang and Loo (2002) examine the pricing of ADRs in an unconditional three factor pricing model using the US market as a factor instead of the world market factor. Different from previous studies, they also test how the sensitivities to these risk factors are priced and whether or not risk sensitivities vary across ADRs due to different firm characteristics. They find that ADR returns are more significantly affected by their home market returns than by US market returns for six countries (Australia, Chile, Japan, Mexico, Netherlands, and UK) for most of the ADR portfolios (2 portfolios created for each country). However, in the sample, they also find that one Australian, one Dutch, and one UK portfolio has significant sensitivities to US market movements. The results are also mixed after they divided the sample according to listed exchanges, listing years and market capitalization. Since they only have 6 countries in their sample, it would have been more convincing to increase the sample size. As more countries are included, it is plausible to find the significance of these cross-country differences on the ADRs' exposure to home market and US market risks.

In short, these empirical studies use data before 1998 with both daily and monthly frequencies. The largest number of countries included is 16 in Patro (2000). Except Kim, Szakmary and Mathur (2000), these studies usually created an ADR country portfolio using selected ADRs from that country. Exchange rates risk is mostly included except Alaganar and Bhar (2001). The home market portfolio was either created by selected stocks matching ADRs or by the local market index. These different constructions could possibly explain the different magnitude of home market effect on ADR returns among these studies.

The US market portfolio is used as one factor in these models except Patro (2000) which uses the world market portfolio instead. This study will use the US market portfolio as one pricing factor for ADRs instead of the world market portfolio. International Capital Asset pricing models use the world market portfolio saying the returns of an international asset should be measured by its covariance with the world market factor. It requires a strong assumption that the global market is integrated and international assets are truly priced in such a "world market". Therefore, in this study, I do not assume that ADRs are fully integrated into the global market. As those exchange-listed ADRs are traded in the US market like other US stocks, they should be priced considering the US market risk. Appendix 2 provides a summary of these empirical studies.

The methodology used in these studies include multiple regression analysis for each country (Choi and Kim 2000), seemingly unrelated regression for a system of country equations (Patro 2000, Kim, Szakmary and Mathur 2000), cross-sectional regression (Choi and Kim 2000, Fang and Loo 2002[9]), and vector auto regression with or without cointegrating constraints (Kim, Szakmary and Mathur 2000, Alaganar and Bhar 2001). The regression analysis is able to provide information on risk exposures of ADRs to different pricing factors, but it is sensitive to the sample selected and it also assumes that risk exposures to different risk factors are constant during the sample period. That is, it does not reflect that ADRs exposure to different risk factors might be time varying and subject to changes in the market conditions. The VAR technique with a system of price level variables (or returns of different portfolios) gives us lead and lag relationships and hence reveals the information transmission among the variables in the system, but it does not consider how volatilities of these variables might influence the return series, or in other words, the variances and covariances of ADRs returns with market portfolios are not considered in the ADR return determination.

II.4. ADR pricings - the exchange rate risk

[9] Note that the cross sectional regression analysis by Choi and Kim (2000) is different from that by Fang and Loo (2002). The former simply obtains means for each ADR time series as dependent series and uses the means of underlying returns and exchange rates as independent variables. The latter tries to find the risk premium using risk exposures (betas) as independent variables.

ADR investments, although denominated in US dollars, are investments on foreign assets. Therefore an investment on ADRs is both an investment in the performance of the foreign assets and an investment in the performance of the foreign currency in terms of domestic currency. In the ICAPM, exchange rate risk is priced (e.g. Solnik 1974, Stulz 1981 and Adler and Dumas 1983, see survey Stulz 1995). Purchasing power parity (PPP) does not hold if relative prices of goods differ across countries or if investors have different preferences over goods across countries (Stulz 1995). If PPP does not hold, there are two important implications for portfolio choice and asset pricing in equilibrium: (1) optimal portfolio differs across countries; (2) the expected return of any asset must include a market premium as well as a currency premium (Dumas and Solnik 1995, De Santis and Gerard 1998). The conditional ICAPM contains risk premia that are based on the covariances of assets with the exchange rates, in addition to the traditional risk premium based on the covariance with the market portfolio given deviation from PPP (Dumas and Solnik 1995).

Econometrically, to estimate the conditional asset pricing models with exchange rate premia, Dumas and Solnik (1995) uses a latent-variable approach and constrains market price of risks to be time varying, then uses a Generalized Method of Moment (GMM). DeSantis and Gerard (1998) specify the dynamics of the second moment and test the currency risk premium with a diagonal multivariate GARCH process.

The ADR literature on the diversification benefits of ADRs for portfolio investment focus on the low return correlations, but relatively little has been done on the role of exchange rate risk. Liang and Mougoue (1996) directly investigate the pricing of foreign exchange risk in ADRs with monthly returns of 41 ADRs traded on NYSE and 69 traded OTC from Japan, South Africa and UK during the period 1976 to 1990. They decompose exchange rate risks into two parts – part of US stock market risk that due to foreign exchange influence, the incremental foreign exchange rate risks that are not imbedded in the market returns. They construct equally-weighted ADR portfolios for each country and use a two-factor model which includes market returns (US market returns) and currency returns to estimate risk premium associated with foreign exchange risks. They find that ADRs' returns for the entire period and for the majority of the sub-periods investigated are exposed to currency risk and that such risk is systematic. When currency returns are orthogonalized against market returns, i.e., incremental exchange rate risk is steamed out, ADRs are exposed to this risk but the incremental foreign exchange risk does not command a risk premium. This evidence implies that the incremental foreign exchange risk is diversifiable or can be effectively hedged.

However, Liang and Mougoue (1996) assumes market integration in the model so they only include US market return as the market factor. The exchange rate risk they measure might pick up the home market effects. Although they orthogonalize exchange rate risk with regards to the US market returns, the incremental exchange rate risk might still pick up risks from home market risk. Therefore, model that excludes both US market and home market effects would be more appropriate to measure the exchange rate risk factor in ADR pricing.

Exchange rate risk is also touched upon in the factor models discussed in the previous section. Patro (2000) considers the exchange rate risk in addition to the world market and home market factors in the unconditional factor pricing models but finds that country specific exchange rates are insignificant risk measures for ADR portfolio returns. Contrary to Patro (2000), Kim, Szakmary and Mathur (2000) incorporate exchange rate risk with two-market factor (underlying shares in the local currency and US market index) and find that exchange rate risk has an impact on ADR prices. Fang and Loo (2002) find that the sensitivity of ADR returns to the unanticipated exchange rate movement (i.e., the beta to exchange rate) is significant and negative for most cases, i.e., ADR returns are substantially harmed by an unanticipated appreciation of the home currency, and vice versa, when the home currency is depreciated. They also find that although US investors are exposed to incremental risk from foreign market when investing in ADRs, they do not command a risk premium as the risk can be diversified or effectively hedged by ADR investors. It is still an unsettled question whether exchange rate risk is a significant risk factor for ADRs, and whether or not this risk factor is priced in ADR returns.

III. Summary and intended contributions to the literature

The surge in ADR investments in the past two decades has prompted great interests in the performance of ADRs. Although considerable research has been done on this subject, the research focuses on the motivation of cross-listings such as earlier studies on the market reactions and the "bonding hypothesis" in the current stage. The research on the performance of ADRs and its pricing factors is still in exploration stage – most of them are done "piecemeal", focusing a particular number of countries for a specific time period. Therefore, this study is intended to expand the scope of previous study and provide a systematic study with the most number of countries possible with the latest data.

At the same time of putting "piecemeal" together, this study is intended to reconcile the conflicting evidence on the relationships of ADR returns with home market returns, US market returns and exchange rate risks. Therefore, this study will contribute to the traditional factor pricing model in the literature by consolidating the evidence of the risk exposures of ADRs to home market portfolio, US market portfolio and exchange rate changes.

Going beyond this traditional factor pricing model, a new technique – regime switching, will be applied to develop a new empirical model for ADR pricing. This regime switching framework will not assume international market integration like International Capital Asset Pricing models. It is based on conditional asset pricing models and puts together ADR covariances with US market portfolio and home market portfolio using regime probabilities. In this regime switching model, the weight of home market effects and US market effects is time varying, which provides more dynamics rather than simply assuming the home market or US market factor as the market risk factor.

The effects of exchange rate risk are also modeled differently from previous factor pricing literature. Exchange rate risks are only considered when ADRs are treated as perfect substitute of underlying shares. That is to say, exchange rate risks should not be considered when US investors view ADR investment no different from other domestic investments if we want to model the investors' expectation on the future ADR returns. Therefore, the exchange rate risk in this model is derived from the return of investment on foreign currency. As to how much of this exchange rate risk is passed to investors' expectation on the future ADR returns will depend on regime probability of ADRs are treated the same as the home market shares and priced only to home market risks. This is also new in the literature.

This regime switching pricing model which will be developed in Chapter Four and Five, is tailor-made for ADRs, which is a new attempt at ADR pricing literature. Below is a primer for regime switching models, which intends to provide a background for these models – basic setup, applications and derivation of likelihood function.

IV. A Primer on Regime Switching Models

This section will provide a short introduction of the regime switching model which will be applied in this research. Basic model setups, assumptions and the development of likelihood function will be reviewed, as well as a brief description on the estimation process.

Regime switching models are often used to model economic time series that are non-linear. It defines different states (or regimes) of the world, and allows the development of a time series to develop depending on the regime that occurs at a particular time t. This "state" or "regime" may be characterized by certain properties of the series, such as the means or the variances and autocorrelations of the series. For example, as the financial research shows, the autocorrelations of stock returns are related to the level of volatilities of these returns, the larger autocorrelations during the periods of low volatility and smaller during the periods of high volatility (LeBaron 1992). In this example, the level of volatility could be treated as a regime-determining process.[10]

The available regime switching models differ in the way the regime evolves over time. One set of models assume that regimes can be characterized or determined by an observable variable. That is to say, the regimes that have occurred in the past and present are known with certainty. Another set of models assume that the regimes cannot actually be observed but is determined by an underlying unobservable stochastic process. For the latter set of models, one can never know for sure what regime this process is in at a particular time, but can only assign the probabilities to the occurrence of the different regimes. An important aspect of these models is that the time at which a structural change occurs is endogenous to the model. The two sets of models will be introduced below.

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[10] This example is also mentioned in Kim and Nelson (1999).

IV. 1. Regimes determined by observable variables

IV.1.a. serially unrelated series

Here we start with the basic regression as the following[11]

$$y_t = x_t\beta + e_t,\ e_t \sim i.i.d N(0,\sigma^2) \tag{1}$$

where x_t is a $1\times k$ vector of exogenous variables. To estimate the parameters in this model, the log likelihood function is given by

$$\ln L(\theta) = \sum_{t=1}^{T} \ln f(y_t) \quad , \tag{2}$$

with

$$f(y_t;\theta) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left\{ \frac{-(y_t - x_t\beta)^2}{2\sigma^2} \right\}, \tag{3}$$

which can be maximized with respect to β, σ^2.

Now let's add in switching. If the parameter changes happen to β, σ^2, we have the following setup,

$$y = x_t\beta_{S_t} + e_t,\ t = 1,2,...,T,\ \ e_t \sim i.i.d N(0,\sigma^2_{S_t}), \tag{4}$$

$$\beta_{S_t} = \beta_1(1-S_t) + \beta_2 S_t, \quad \sigma^2_{S_t} = \sigma_1^2(1-S_t) + \sigma_2^2 S_t, \tag{5}$$

$$S_t = 0 \text{ or } 1, (S_t = 0 \text{ in Regime 1 or 1 in Regime 2}), \tag{6}$$

where β_1, σ_1^2 are parameters under regime 1, and β_2, σ_2^2 are parameters under regime 2. If S_t is known for all sample period, then the above example is nothing more than a dummy

[11] Kim and Nelson (1999), pages 59-62.

variable model, where S_t equals 0 in regime 1 and 1 in regime 2. In this case, the log likelihood function is simply

$$\ln L(\theta) = \sum_{t=1}^{T} \ln f(y_t \mid S_t) \tag{7}$$

where

$$f(y_t;\theta) = \frac{1}{\sqrt{2\pi}\sigma_{S_t}} \exp\left\{ \frac{-(y_t - x_t\beta_{S_t})^2}{2\sigma_{S_t}^2} \right\}. \tag{8}$$

This log likelihood function is maximized with respect to $\beta_1, \beta_2, \sigma_1^2, \sigma_2^2$.

IV.1.b. serially correlated series

If in the above example, the independent variable x_t is its own lagged value y_{t-1}, then the series become serially correlated. If the model assumes that the regime that occurs at time t can be determined by an observable variable q_t, it is often called the Threshold Autoregressive (TAR) model (Tong 1978, 1990). In TAR model, there is a threshold value c and regimes are determined given q_t relative to c. When q_t happens to be a lagged value of the time series itself, such as $q_t = y_{t-1}$, it is a special case of TAR called Self-Exciting TAR (SETAR) model. The model could be expressed as

$$y_t = \begin{cases} \phi_{0,1} + \phi_{1,1} y_{t-1} + \varepsilon_t & \text{if } y_{t-1} \le c, \\ \phi_{0,2} + \phi_{1,2} y_{t-1} + \varepsilon_t & \text{if } y_{t-1} > c, \end{cases} \tag{9}$$

Or

$$y_t = (\phi_{0,1} + \phi_{1,1} y_{t-1})(1 - I[y_{t-1} > c]) + (\phi_{0,2} + \phi_{1,2} y_{t-1}) I[y_{t-1} > c] + \varepsilon_t \tag{10}$$

where $I[y_{t-1} > c]$ is an indictor function with $I[y_{t-1} > c]=1$ if $y_{t-1} > c$ and 0 otherwise. Franses and Van Dijk (2000) provided a detailed discussion on the serially correlated series, representations and estimation process. Here I will focus the second set of models which assumes that the regime is influenced by an unobserved random variable.

IV.2. Regimes determined by unobservable variables

This set of models assumes that the regime is determined by an unobservable random process, which is denoted as S_t. Let S_t be a random discrete variable, taking only two values 1 and 2. For models like this, as a role of thumb, Kim and Nelson (1999) summarize the following steps to derive the likelihood function.

We obtain the joint density function of y_t and the state variable S_t

$$f(y_t, S_t = i \mid Z_{t-1}) = f(y_t \mid S_t = i, Z_{t-1}) \Pr(S_t = i \mid Z_{t-1}). \qquad (11)$$

where f denotes the density function, and $\Pr(S_t = i \mid Z_{t-1})$ represents the probability of regime at time t equals to i given the past information set up to time t-1 Z_{t-1}. Then we get the marginal density of y_t by summing up all possible values of S_t,

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

This marginal density function would be viewed as a weighted average of conditional density function weighted by the regime probabilities $\Pr(S_t = 1 \mid Z_{t-1})$ and $\Pr(S_t = 2 \mid Z_{t-1})$.

The log likelihood function then is given by

$$\ln L(\theta) = \sum_{t=1}^{T} \ln(\sum_{i=1}^{2} f(y_t | S_t = i, Z_{t-1}) \Pr(S_t = i \mid Z_{t-1})) \qquad (13)$$

To calculate the above log likelihood function, we will need to calculate regime probabilities $\Pr(S_t = 1 | Z_{t-1})$ and $\Pr(S_t = 2 | Z_{t-1})$. Based on the a priori assumption on S_t, we have two cases – Independent Switching and Markov Switching[12].

IV.2.a. Independent switching

When S_t evolves independent of its own past values, the simplest form is to assume the series are serially unrelated and that S_t is distributed i.i.d. across different dates t. In this special case, the observable series y_t is simply a mixture of different distributions. Here is summary of the statistical theory of IID Mixture distributions[13].

Again suppose that the regime that a given process y_t is in at date t is indexed by an unobserved random variable S_t, where there are two possible regimes (S_t =1, 2). When the process is in regime 1, the observed variable y_t is pre presumed to be drawn from a $N(\mu_1, \sigma_1^2)$ distribution. If the process is in regime 2, then y_t is presumed to be drawn from a $N(\mu_2, \sigma_2^2)$ distribution.

The distribution of y_t conditional on available information may be written as

$$f(y_t | S_t = i; \theta) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left\{ \frac{-(y_t - \mu_i)^2}{2\sigma_i^2} \right\} \tag{14}$$

for i=1,2. Here θ is a vector of population parameters that includes $\mu_1, \mu_2, \sigma_1^2, \sigma_2^2$.

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[12] This part of discussion is based on Kim and Nelson (1999), page 61-64. Readers are encouraged to go to original source for in depth discussion.
[13] Again readers should refer to Hamilton (1994), page 685-688 for in depth analysis.

The unobserved regime { S_t } is presumed to be generated by a probability distribution for which the unconditional probability that S_t takes on value i is denoted as π_i, i.e., $P[S_t = i;\theta] = \pi_i$ for i=1,2. The regime probabilities are also included in θ, that is, $\theta \equiv (\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, \pi_1, \pi_2)'$. Thus the equation (12) as in the introduction of the unobserved regime process, will be specified as

$$f(y_t;\theta) = \sum_{i=1}^{2} P(y_t, S_t = i;\theta) = \frac{\pi_1}{\sqrt{2\pi}\sigma_1} \exp\left\{\frac{-(y_t - \mu_1)^2}{2\sigma_1^2}\right\} + \frac{\pi_2}{\sqrt{2\pi}\sigma_2} \exp\left\{\frac{-(y_t - \mu_2)^2}{2\sigma_2^2}\right\} \quad (15)$$

Although the regime S_t is unobserved, the relevant density function is based on the observed process y_t. Since the regime variable S_t is assumed to be i.i.d. distributed across different time period *t*, the log likelihood for y_t as in equation (13) can be maximized with respect to $\theta \equiv (\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, \pi_1, \pi_2)'$ as,

$$\ln L(\theta) = \sum_{t=1}^{T} \ln(f(y_t, \theta)) \quad (16)$$

Hamilton (1994, page 688) also derived the analytical solution for the maximum likelihood estimates and the EM algorithm for the maximization procedure, which will not be discussed here.

To make inference on unobserved regime, i.e., we want to make inference about which regime was more likely to have been responsible for producing time t observation of y_t. Based on the definition of conditional probability, we have

$$P[S_t = i \mid y_t;\theta] = \frac{P[S_t = i, y_t;\theta]}{f(y_t;\theta)} = \frac{\pi_i f(y_t \mid S_t = i;\theta)}{f(y_t;\theta)}. \quad (17)$$

Once one has estimated θ, it would be possible to calculate the conditional probability above. The magnitude in equation (17) will represent the probability that the unobserved regime i is responsible for observation y_t.

IV.2.b. Markov switching

If S_t evolves depending on its past values, the weight factor in log likelihood function (13) $\Pr(S_t = i \mid Z_{t-1})$ will change over time. The most popular model of this class, was advocated by Hamilton (1989, 1990), which describes the process S_t as a Markov-chain. Thus, this kind of regime switching model is also called the Markov switching model. The basic intuition for structuring Markov-switching models is "if the process has changed in the past, clearly it could also change again in the future, and this prospect should be taken into account in forming a forecast. Moreover, the change in regimes surely should not be regarded as the outcome of a perfectly foreseeable, deterministic event. Rather, the change in regime is itself a random variable."[14]

Suppose that the probability of S_t equals some particular value i depends on the past only through the most recent value S_{t-1}. Here we have

$$\Pr(S_t = i \mid S_{t-1} = j, S_{t-2} = k, ..) = \Pr(S_t = i \mid S_{t-1} = j) = p_{ji} \qquad (18)$$

This process is described as 2-state Markov Chain. The transition probability p_{ij} gives the probability that the state i will be followed by state j, and the sum of the probabilities transitioning from state i to all states should conform to 1. For example, in this two-state case, we have

[14] Hamilton (1994), page 677.

$$p_{j1} + p_{j2} = 1. \qquad (19)$$

Before we obtain the regime probabilities $\Pr(S_t = 1 | Z_{t-1})$ and $\Pr(S_t = 2 | Z_{t-1})$, let us specify the regime transition probabilities (or regime switching probabilities) as the following,

$$\begin{aligned}
\Pr(S_t = 1 | S_{t-1} = 1) &= p_{11} = p \\
\Pr(S_t = 2 | S_{t-1} = 1) &= p_{12} = 1 - p \\
\Pr(S_t = 1 | S_{t-1} = 2) &= p_{12} = 1 - q \\
\Pr(S_t = 2 | S_{t-1} = 2) &= p_{22} = q
\end{aligned} \qquad (20)$$

Using the theory of Ergodic Markov Chains, Hamilton (1994) shows that the unconditional probabilities that the process is in each of the regimes $\Pr(S_t = 1)$ and $\Pr(S_t = 2)$ for the two state Markov switching model as[15]

$$\begin{aligned}
\Pr(S_t = 1) &= \frac{1 - p_{22}}{2 - p_{11} - p_{22}} = \frac{1 - q}{2 - p - q} \\
\Pr(S_t = 2) &= \frac{1 - p_{11}}{2 - p_{11} - p_{22}} = \frac{1 - p}{2 - p - q}
\end{aligned} \qquad (21)$$

To obtain the maximum likelihood function, we will need to deal with the problem of unobserved S_t and derive the conditional regime probabilities $\Pr(S_t = i | Z_{t-1})$. Here we follow the two-step filter procedure as in Kim and Nelson (1999, page 63).

In step one, given the previous period regime probability $\Pr(S_{t-1} = j | Z_{t-1})$, j=1, 2 (two-regime model), at the beginning of time t or the t-th iteration, the current period regime probability $\Pr(S_t = i | Z_{t-1})$, i=1, 2, are calculated as

$$\Pr(S_t = j | Z_{t-1}) = \sum_{j=1}^{2} \Pr(S_t = i, S_{t-1} = j | Z_{t-1}) = \sum_{i=1}^{2} \Pr(S_t = i | S_{t-1} = j) \Pr(S_{t-1} = j | Z_{t-1}) \qquad (22)$$

In step two, once y_t is observed at time t, we will incorporate this new information by updating the probability as

[15] For a detailed derivation, please refer to Hamilton (1994), page 681-3.

$$\Pr(S_t = i \mid Z_t) = \Pr(S_t = i \mid Z_{t-1}, y_t) = \frac{f(y_t, S_t = i \mid Z_{t-1})}{f(y_t \mid Z_{t-1})}$$
$$= \frac{f(y_t \mid S_t = i, Z_{t-1}) \Pr(S_t = i \mid Z_{t-1})}{\sum_{i=1}^{2} f(y_t \mid S_t = i, Z_{t-1}) \Pr(S_t = i \mid Z_{t-1})} \tag{23}$$

These two steps may be iterated to get the regime probabilities $\Pr(S_t = i \mid Z_{t-1})$, t=1, 2,.., T. To start of the iteration process, we have $\Pr(S_0 \mid Z_0)$ equal to the steady state probabilities as in equation(21). Note the log likelihood function is calculated as by-product in the iteration process (equation(13)). The parameters will be estimated using the maximum likelihood technique.

If the observed data y_t is serially related, such as an autoregressive model of order one (AR (1)) process, the two-regime Markov Switching model can be written as

$$\begin{aligned} &\phi(L)(y_t - \mu_{S_t}) = e_t, \qquad e_t \sim N(0, \sigma^2_{S_t}), \\ &\Pr(S_t = i \mid S_{t-1} = j) = p_{ji}, \qquad i, j = 1, 2, \end{aligned} \tag{24}$$

Time series models of Markov-switching follow the similar procedure as we discussed above. The complication comes from the derivation regime probabilities and joint density functions given observations y_t follows different AR (1) process under two regimes. Figure 3 is a flowchart adopted from Kim and Nelson (1999, p67), on the AR (1) Hamilton's Markov switching model.

In this study (Chapter 4 and Chapter 5), the regimes are assumed to be determined by an unobserved random process which evolves as a Markov-chain. The regime switching model used in this study is the Markov switching model. In particular, there are only two regimes considered – regime one when ADRs are priced in the home market just like home market shares (named as home market pass-through regime), and regime two when ADRs are priced in the US market just like other US market shares (named as pricing-to-market regime). I follow the standard Hamilton model (1988, 1989) assuming constant regime switching probability as described above. One limitation of this model is that I assume constant regime switching probability at each point of time. Therefore I ignore the possibility of regime switching might be different at a different time of the market performance.

Figure 3. Flowchart of the iteration process of AR(1) Hamilton's Markov switching model.

Starting value set-up:

$l(\theta) = 0$ (Log likelihood value)

$\Pr(S_0) = \pi_j$ (Steady-State Probability)

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

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

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

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

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

t-1=t

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

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Appendix 1 –Literature Review on Arbitrage and Diversification on ADRs

Author	Issues/Research Question	Data	Methodology	Findings
Rosenthal (1983)	weak form efficiency of the American Depository Receipt market.	54 ADRs over the period 1974 through 1978 using weekly, biweekly and monthly rates of return.	Serial correlation tests Test for normality (Kolmogorov-Smirnov test)	Serial correlation tests indicated that the null hypothesis of no linear dependence was not supported for weekly and biweekly returns, but was accepted for monthly returns. However, it is not likely that significant excess returns could be earned from any price dependencies.
Officer and Hoffmeister (1987)	Diversification benefits of ADRs	Monthly returns 1973-1983 A portfolio of 45 ADRs	Portfolio approach – calculate portfolio risk	They found significant lower systematic risk for ADRs than for comparable US firms. They tested for mild segmentation by constructing portfolios containing both ADRs and US firms and found 20% reduction in portfolio risk using both ADRs and US stocks.
Kato, Linn and Schallheim (1991)	Differences and correlations of ADRs with their underlying stocks	8 from Australia, 7 from England and 8 from Japan. Daily data from 1981-1984.	Parametric T-test and non-parametric Rank-sum test on the price of ADRs and underlying shares (converted to US$) and their first differenced series	They found no significant differences between the prices of the two identical types of claims and concluded that no arbitrage opportunities exist between international capital markets encompassed by their study. Although they found the evidence to be supportive of the law of one price, they noticed that the two returns are not near to being perfectly correlated. They explained this result by the overlapping time periods for the return calculations and these timing differences can lead to spurious return correlation results.
Wahab, Lashgar, and Cohn (1992)	If we treat ADRs and underlying shares as different claims, are there arbitrage opportunities in ADR markets?	31 pairs of ADRs and their underlying shares (8 countries such as UK, Japan, Germany, France, Sweden, Norway, Australia and South Africa) between 1/04/1988 -5/31/1991. Daily rate of return (dollar numeraire).	Portfolio approach: They establish long and short positions in identified portfolios of over- and under-priced securities using both minimum-variance and an equally-weighted combination.	They rejected the null hypothesis of no arbitrage, and found annualized arbitrage returns between 1.23% and 4.44% were possible for some of the identified arbitrage portfolios. They argued that whether such a seeming anomaly is of economic importance will depend on transactions costs faced by the potential arbitrageur.

Author	Issues/Research Question	Data	Methodology	Findings
Wahab and Khandwala (1993)	Diversification benefits of ADRs	Daily returns 31 pairs of ADRs and underlying stock. 1988-1990.	Create portfolios given number of ADRs included or investment proportion in ADRs relative to S&P 500. Three-way analysis of variance model	They found that ADRs provide similar expected returns to their underlying assets, but the variance of a portfolio containing seven foreign shares with a 50% investment was approximately 26% higher than the variance of a portfolio containing ADRs similarly constructed. They conclude that ADRs potentially provided better risk reduction benefits for US portfolio investors than their underlying shares.
Park and Tavakkol (1995)	Risk and return' characteristics between Japanese ADRs and their underlying stocks	weekly returns of a group of 21 pairs of ADRs and underlying shares from July 1977 to June 1987	Compare weekly returns and variances for both individual pairs and portfolio level. Check exposures of ADRs and underlying shares to returns of US market index, Nikkei index and Yen-dollar rates.	They found that the exchange rate adjusted returns on ADRs were not significantly different from the returns on their corresponding securities, and that ADRs were more volatile than the underlying stocks, due to the impact of the currency market volatility and the covariance of the stock-currency returns. ADRs were more responsive to the US market and less to the Japanese market; the exchange rate adjusted ADRs, are less responsive to the movements in currency market than their underlying stocks.
Webb, Officer and Boyd (1995)	Time structure of the relationship between US market daily returns and ADR returns	A portfolio of 85 ADRs from 15 countries (UK, Europe, Japan, South Africa, etc). 1975 to 1989. Daily returns.	Regression model with 3 leads and 3 lags of US market index as well as the contemporaneous market risk. Country by country. $R_{n,t}^{adr} = \alpha_n + \sum_{j=-3}^{3} \beta_{j,n} R_{US,t+j} + e_{n,t}$	They found a strong significant relationship between ADR and US market daily returns on a contemporaneous and a one-day lagged basis, indicating a lead/lag relationship among equity markets with the US market acting as the lead market in equity pricing.
Karolyi and Stulz (1996)	The fundamental factors that affect the daily return comovements between Japanese and US stocks	Intraday and overnight returns for an equally-weighted portfolio of 8 Japanese ADRs and matching US stocks. 5/31/1988 -5/29/1992	Latent variable regression – regression returns on a set of information variables then using residuals to estimate conditional correlation between the Japanese ADRs portfolio with US stock portfolio.	They found that US macroeconomic announcements, shocks to the Yen/dollar foreign exchange rate and Treasury bill returns, and industry effects have no measurable influence on US and Japanese return correlations. Instead, they found that large shocks to broad based market indices (Nikkei Stock Average and Standard and Poor's 500 stock indexes) positively impact both the magnitude and persistence of the return correlations.

Author	Issues/Research Question	Data	Methodology	Findings
Jiang (1998)	Diversification effects of ADRs;	Jan 1980 to Sept. 1994. Weekly prices of 113 ADRs from 8 countries.	Cointegration and vector error correction model with ADR and national index portfolios. VAR. Regression with US market, home market factors and exchange rate factors with GARCH (1,1)	The portfolio with investment in the ADR portfolios performed better than that with investment in the US market and foreign market indices. Only 3 out of 8 pairs of ADR portfolios and market indices are cointegrated. Although ADR returns are significantly associated with the US market returns, they retain their exposure to local market and exchange rates.
Errunza, Hogan and Hung (1999)	They investigate the ability of investors to mimic returns on foreign market indices with domestically traded securities, such as MNCs, country funds and ADRs.	A sample of 30 MNCs, CFs and ADRs (26 total from 8 countries). Monthly returns. 1976 - 1993.	Mean-varying spanning test between diversification portfolios with ADRs and market indices. Bivariate GARCH for conditional covariance	They find that the increasing availability of assets that represent claims on foreign traded assets, such as ADRs, makes it possible to exhaust most of the diversification benefits by holding domestically traded foreign assets. They provide evidence that gains beyond those attainable through home-made diversification have become statistically and economically insignificant for 11 of 16 markets (all seven of the developed markets plus four of the emerging markets: Argentina, Brazil, Korea and Mexico).
Bekaert and Urias (1999)	They look at three investment vehicles - closed-end mutual funds, open-end mutual funds, and ADRs.	1990-1993 and 1993-1996. ADRs from 5 emerging markets that traded on a US exchange. Close-end funds (publicly traded US and UK emerging market funds up to 1992). Open-end funds	Unconditional and conditional mean-variance spanning tests.	Based on mean-variance spanning tests, they find that diversification benefits from emerging equity markets are sensitive to the time periods of the tests and, in some cases, to the particular investment vehicle. However direct exposures to emerging market indexes almost always gives benefits at least as strong as those from managed funds or ADR portfolios.
Foerster and Karolyi (2000)	How investment barriers affect securities returns in different markets. Liquidity and post-issuance share price performance.	333 global equity offerings with ADR tranches from 35 countries between 1982 and 1996. Monthly.	Holding period returns compared with bench market returns and matched-firm returned. Univariate tests of return performance by firm attributes (offering type, region and market type, etc). Multivariate regression tests.	They find that overall a sample of 333 global equity offerings with US depositary receipt (ADR) under-perform local market benchmarks of comparable firms by 8%-15% over the three years following issuance between 1982 and 1996. They show that differences in long-run returns are related to the scope and magnitude of investment barriers that induce segmentation of capital markets around the world.

Rabinovitch, Silva and Susmel (2003)	Returns on ADRs from Chile and Argentina. Arbitrage in emerging markets considering the transaction costs.	Daily returns of ADR and underlying shares that locally traded (6 from Argentina, 14 from Chile). 1993-2001	Non-parametric tests of return distributions. Non-liner Threshold Autoregressive model	The return distributions of the Chilean ADRs are significantly different from the distributions of the returns on the respective underlying Chilean shares. While Argentinean ADRs and their respective underlying shares have the same distribution of the returns. In addition, they find that the transaction costs for Chilean ADRs are higher than Argentina ADRs. Possible explanation is that Argentina did not impose any restrictions on foreign investments, while Chile did.

Appendix 2 – Summary of Empirical factor pricing models for ADRs in 2000s

Author	Issues/Research Question	Data	Methodology	Findings
Patro (2000)	What are the significant sources of risk for the variations of ADR returns? I.e. the relative importance of variations in returns of home and the world market portfolios, exchange rates and global risk factors.	123 American depositary receipts (ADRs) from 16 countries between 8/1992 and 8/1997. Monthly returns. Equally weighted ADR portfolios.	$R_{n,t}^{adr} = \alpha_n + \sum_{k=1}^{K} \beta_{n,k} R_{k,t} + e_{n,t}$ (n represents country, k represents the risk factors) Seemingly-Unrelated Regression (SUR) (for 16 countries)	The research finds that the returns on ADRs have significant risk exposures to the returns on the world market portfolio and their respective home market portfolios. Country specific exchange rates or global risk factors such as the changes in the trade weighted value of the dollar, changes in treasury yields or changes in crude oil prices are not significant risk measures in ADR returns.
Choi and Kim (2000)	Price determinants of ADRs and underlying stock returns	1990-1996. 156 ADRs from 13 countries	Cross-sectional regressions on different pricing factors using sample averages and standard deviations as proxies for risks.	They found that local factors (market or industry) explain ADRs and their underlying shares returns across countries and industries better than the world factor in their sample period, and the explanatory power of the exchange rates for ADRs was not as strong as expected. At the same time, they found little explanatory power of US factor.

Alaganar and Bhar (2001)	H1: ADRs portfolio returns= portfolio returns of the underlying stocks; H2: Corr (US portfolio, ADR portfolio) =Corr (US Portfolio, portfolio of the underlying stocks); H3: A unidirectional causality and transfer of pricing information from the domestic market to ADR market.	24 Australian ADRs during the period from 1/1/1988 to 10/31/1998. Daily, monthly. ADR portfolios	H1: matched pair t-test; H2: Monte-Carlo simulations; H3: VAR (returns of ADR portfolio, the underlying stocks portfolio, Australian index, US index.)	They find that the ADR market is priced efficiently that the "law of one price" holds, but the ADRs have an economically significant higher reward/risk ratio than underlying stocks, partly due to lower transaction costs. They also find that ADRs have a low correlation with the US market under high states of global and regional shocks. They test unidirectional information transmission from the underlying stocks to ADRs, which help to offset the strong information flow from the aggregate US market to the foreign market.
Kim, Szakmary and Mathur (2000)	It studies the dynamics of international transmission between ADRs and their underlying securities by considering three pricing factors for ADRs: the price of the underlying shares in the local currency, the relevant exchange rate, and the US market index.	56 ADRs from Japan, UK, the Netherlands, Sweden and Australia for a three-year period (1988-1991). Daily prices.	Three-factor model: VAR with cointegration constraints on factor prices. Seemingly-Unrelated Regression (SUR): regression of returns on contemporaneous and lagged factors.	Their results show that while the price of the underlying shares is most important, the exchange rate and the US market also have an impact on ADR prices. An interesting result from this research is that the authors find that the ADRs appear to initially overreact to the innovations in US S&P 500 index but under-react to changes in underlying share prices and exchange rates, but the overreaction to the US market is very short-term in nature, being reversed within a few days.
Fang and Loo (2002)	Are ADRs affected more so by US market factors or by their respective home market movements? Do US investors require ex ante risk premium for bearing such exposures? Do the risk sensitivities vary across ADRs due to different firm characteristics?	133 ADRs from 6 countries (Australia, Chile, Japan, Mexico, Netherlands, and UK) over sample period 1/1995 – 12/1999. Monthly returns.	Three-factor model: $R_{ikt} = \alpha_{ik} + \beta_{im} R_{mt} + \beta_{ik} R_{kt} + \beta_{ike} R_{ket} + e_{ikt}$ $E[R_{ik}] = \lambda_{0k} + \lambda_m \beta_{im} + \lambda_k \beta_{ik} + \lambda_{ke} \beta_{ike}$	They find that ADR returns are more significantly affected by their home market returns than by US market returns for six countries. While US investors are exposed to incremental risk from foreign equity market, they do not command a risk premium. The findings suggest that (1) markets are segmented and ADR listing does not integrate world capital market and (2) ADRs behave more like a foreign security and ADR is an effective tool of global risk diversification for US investors.

CHAPTER THREE: TRADITIONAL FACTOR PRICING MODELS

I. Introduction

This chapter follows the traditional model on ADR factor pricing models. It uses both the regression and time series technique to look at the significance of sensitivities of ADRs to different risk factors. It directly contributes to the factor pricing literature on ADRs by (1) providing new evidence to the previous inconclusive findings using a wide of range of country scope and most current data; and (2) an evaluation of sensitivities of ADR country portfolios to different risk factors under the static model. The traditional model will also provide results from static models to compare with the conditional CAPM in the regime switching model in chapter four.

II. ADR pricing factors

II.1. Home market, US market and exchange rate risks

The paradigm in international asset pricing models in the current state of research is mostly based on the Sharpe (1964) –Lintner (1965) and Black (1972) Capital Asset Pricing Models (CAPM). These models are popularly used by researchers and practitioners, and CAPM indicated betas are often used as a benchmark for risk sensitivities of an asset to the market portfolio. By definition, ADRs are certificates of shares of non-US companies. These foreign shares will be affected by the companies' performance in the home market. If we assume this foreign market is integrated within its own boundary, according to CAPM, the returns of these local shares shall be based on its covariance with the market portfolio in that country. Therefore, ADRs as certificates of these foreign companies' shares shall face a home market risk.

It is often argued that ADR prices should closely follow the ordinary share prices in the home market if the firm has a local listing, with any deviations being corrected immediately. For example, if an ADR were selling at a premium, those who observed this situation could take this arbitrage opportunity – buy the local shares and convert them to ADRs then sell them for a profit. Early research on ADRs has examined ADRs and their underlying assets in search of evidence to support the law of one price (Rosenthal 1983, Kato, Linn, and Schallheim, 1991, Wahab, Lashgar, and Cohn, 1992).

Another stream of ADR research that focuses on the diversification benefits of ADRs provides empirical evidence of the high correlation of ADRs and their home market. Officer and Hoffmeiser (1987) and Wahab and Khandwala (1993) compare ADRs with their underlying assets from developed economies and find that ADRs provide similar expected returns to their underlying assets and a risk reduction for US portfolio investors. Expanding the country scope, Jorion and Miller (1997) find that while emerging market country portfolio returns of ADRs are highly correlated with the IFC composite emerging market index but relatively low with S&P 500 index. They also find that ADRs could be used to replicate the emerging market IFC index. Errunza, Hogan and Hung (1999) expand the search to 17 countries, which includes seven developed economies and 10 emerging economies. They investigate the ability of investors to mimic returns on foreign market indices with domestically traded securities, such as MNCs, country funds and ADRs. They find that the increasing availability of assets that represent claims on foreign traded assets, such as ADRs, makes it possible to exhaust most of the diversification benefits by holding domestically traded foreign assets. They provide evidence that gains beyond those attainable through home-made diversification have become statistically and economically insignificant for 11 of 16 markets (all seven of the developed markets plus four of the emerging markets: Argentina, Brazil, Korea and Mexico). Alaganar and Bhar (2001) investigate the relative advantages of ADRs, the underlying Australian stocks and the Australian equity index for a US investor seeking international diversification. They find that ADRs have significantly higher reward-to-risk than underlying stocks, partly due to lower transactions costs. In short, these studies present mixed results as to how similar ADRs to their underlying assets in different markets.

The mixed results lead to further research on the differences of home market pass-through effects and possible explanations. Foerster and Karolyi (2000) find that overall a sample of 333 global equity offerings with US depositary receipt (ADR) under-perform local market benchmarks of comparable firms by 8%-15% over the three years following issuance between 1982 and 1996. They show that differences in long-run returns are related to the scope and magnitude of investment barriers that induce segmentation of capital markets around the world, and that inter-market competition for order flow in the post-issuance period affects long-run return performance. Similarly, Rabinovitch, Silva and Susmel (2003) focus the investigation on Chile and Argentina, comparing the distributions of ADR returns and the returns of the locally traded shares between Chile and Argentina. They find that the return distributions of the Chilean ADRs are significantly different from the distributions of the returns on the respective underlying Chilean shares. While the mean returns are the same, the return's standard deviations are significantly different. In contrast, the hypothesis that the distributions of the returns on the Argentinean ADRs and the returns on their respective underlying shares are the same cannot be rejected. In addition, they find that the transaction costs for Chilean ADRs are between 100 and 200 basis points, higher than Argentina ADRs which are between 66 to 165 basis points. Possible explanation is that Argentina did not impose any restrictions on foreign investments, while Chile did.

Furthermore, arbitrage may not be possible or viable in some cases. A financial intermediary may have to pay extra cost to collect information in a foreign market and also transaction fees to buy foreign shares. Even in developed markets, arbitrage activity may also be impeded due to non-synchronous trading times (Kim, Szakmary and Mathur 2000). So when arbitrage fails to align the ADRs with their underlying foreign assets, it indicates that home market pass-through of ADRs is incomplete. If one ADR price is higher than its underlying assets, it trades at a premium. Lamont and Thaler (2003) provide an example – Infosys, an Indian IT company trading in Bombay and also listed on NASDAQ. As of March 7, 2000, Infosys had experienced a huge increase in value, and the enthusiasm of American investors appeared to be much greater than that of local investors. The Infosys ADR was trading at a 136 percent premium.

Thus, the questions become: why would US investors buy ADRs at a premium? How is US market risk priced in ADR returns? The rational explanation for the first question would be that, in segmented markets, for the same asset to have different prices in different markets, it reflects differences in supply and demand (Lamont and Thaler, 2003). Sometimes the over-enthusiasm of US investors might seem irrational, such as the Infosys example. This irrational-seeming behavior could be explained by asymmetric information and home bias. The US investors face information disadvantage about the foreign firms because of distance, differences in language and culture, and because of time zone differences (Kang and Stulz, 1997, Karolyi and Stulz 2002). Therefore, sometimes US investors buy ADRs without knowing anything about the foreign firms it represents, simply following other investors. This kind of herding behavior has nothing to do with the underlying asset, but affect the demand of ADRs. Furthermore, the demand shock in the US markets might also be transmitted back to the home market by ADRs, creating a feedback effect. So far I have not seen much research done on herding effect or feedback effect of US demand on the ADR prices. This research will not directly test the feedback effects; instead I focus on identifying the risk exposures of ADRs to the US market and home market in both static and dynamic settings, and look for explanations on how the innovations of these market risk factors affect ADR returns across countries.

Besides the influences from the home market factor and US market factor, is there an exchange rate risk in the ADR pricing?

ADR investments, although denominated in US dollars, are investments on foreign assets. Therefore an investment on ADR is both an investment in the performance of the foreign assets and an investment in the performance of the foreign currency in terms of domestic currency. In the international asset pricing models, exchange rate risk is priced (e.g. Solnik 1974, Stulz 1981 and Adler and Dumas 1983, see survey Stulz 1995). Purchasing power parity (PPP) does not hold if relative prices of goods differ across countries or if investors have different preferences over goods across countries (Stulz 1995). If PPP does not hold, there are two important implications for portfolio choice and asset pricing in equilibrium: (1) optimal portfolio differs across countries; and (2) the expected return of any asset must include a market premium as well as a currency premium (Dumas and Solnik 1995, De Santis and Gerard 1998). The Conditional International Asset Pricing Models contains risk premia that are based on the covariances of assets with the exchange rates, in addition to the traditional risk premium based on the covariance with the market portfolio given deviation from PPP (Dumas and Solnik 1995). Econometrically, to estimate the Conditional Asset Pricing Models with exchange rate premia, Dumas and Solnik (1995) uses a latent-variable approach and constrains market price of risks to be time varying then uses a Generalized Method of Moment (GMM). DeSantis and Gerard (1998) specify the dynamics of the second moment and test the currency risk premium with a diagonal multivariate GARCH process.

II.2. Related empirical studies

A group of recent empirical studies attempt to find the determinants of ADR returns in the context of multi-factor models (Patro 2000, Kim, Szakmary and Mathur 2000, Choi and Kim 2000, Alaganar and Bhar 2001, Fang and Loo 2002). Most of these factor pricing models are unconditional arbitrage pricing models, as they all find the home market is significantly influencing ADR returns, with results on the US market and exchange rate risks being inconclusive and varying upon the country studies. A summary of these studies is also provided in the appendix.

Patro (2000) provides an empirical analysis of 123 American Depositary Receipts (ADRs) from 16 countries using various factor pricing models with Seemingly Unrelated Regression (SUR). The research finds that the returns on ADRs have significant risk exposures to the returns on the world market portfolio and their respective home market portfolios. It also finds that ADRs do not have significant risk exposures to changes in their home currency's exchange rates. This research compares alternative asset pricing models and shows that in explaining variations in ADR returns, a multi-factor model with the world market return and the home market return as the risk factors performs better than models with just the world market return, the home market return or a set of global factors[16] as the risk factors. Choi and Kim (2000) add in firm-specific factors and industry factors. They examine the several major determinants of ADRs and their underlying stock returns for the period of 1990-1996. They find that local factors (market or industry) explain ADRs and their underlying shares returns across countries and industries better than the world factor in their sample period, and the explanatory power of the exchange rates for ADRs is not as strong as expected. Through an Australian ADR portfolio equally weighted with 24 Australian ADRs, Alaganar and Bhar (2001) find that the ADR market is priced efficiently that the "law of one price" holds, but the ADRs have an economically significant higher reward/risk ratio than underlying stocks, partly due to lower transaction costs. They also find that ADRs have a low correlation with the US market under high states of global and regional shocks. However, this study is restricted to ADRs from Australian, so the results have limited applications.

Different from Patro (2000), Kim, Szakmary and Mathur (2000) incorporate exchange rate risk with two market factor (underlying shares in the local currency and US market index), and find that while the price of the underlying shares is most important, the exchange rate and the US market also have an impact on ADR prices. Similarly, Fang and Loo (2002) examine the pricing of ADRs in an unconditional three factor pricing model using the US market, home market and unanticipated exchange rate movement. They find that ADR returns are more significantly affected by their home market returns than by US market returns for six countries (Australia, Chile, Japan, Mexico, Netherlands, and UK) for most of the ADR portfolios (2 portfolios created for each country). However, in the sample, they also find that one Australian, one Dutch, and one UK portfolios have significant

[16] The global risk factors that are used in Patro (2000) include world market return, changes in logarithm of the trade weighted value of the dollar, changes in 3-month T-bill yields and changes in oil prices.

sensitivities to US market movements. The results are also mixed after they divide the sample according to listed exchanges, listing years and market capitalization. Since they only have 6 countries in their sample, it would be interesting to increase the sample size, to see that as more countries are included, the significance of these cross-country differences on the ADRs' exposure to home market and US market risks becomes more prominent.

As for the sensitivity of ADR returns to the unanticipated exchange rate movement (i.e., the beta to exchange rate), Fang and Loo (2002) find it significant and negative for most cases, i.e., ADR returns are substantially harmed by an unanticipated appreciation of the home currency, and vice versa, when the home currency depreciated. They find that although US investors are exposed to incremental risk from foreign market when investing in ADRs, they do not command a risk premium as the risk can be diversified or effectively hedged by ADR investors. This is consistent with Liang and Mougoue (1996). However, Patro (2000) finds that ADRs do not have significant risk exposures to changes in their home currency's exchange rates. It is still an unsettled question whether exchange rate risk is a significant risk factor for ADRs, and whether or not this risk factor is priced in ADR returns.

In sum, the research on the performance of exchange-listed ADRs and its pricing factors is still in exploration stage – most of them are done "piecemeal", focusing a particular number of countries for a specific time period. Therefore, this study is intended to expand the scope of previous study and provide systematic estimates with the most number of countries possible and with the latest data.

III. Data

In this study, I use ADR price indices data developed by Bank of New York (BNY).[17] Market indices are obtained from DataStream global equity indices for calculating the market returns and they are denominated in the local currency. These country equity indices are highly correlated with other indices from Morgan Stanley Capital International (MSCI) or Financial Times Stock Exchange (FTSE), so I believe it makes no difference using any of the equity market indices. The advantage of DataStream global equity indices is that it covers more countries than MSCI or FTSE. Matching ADR country indices and DataStream global equity indices, there are 36 countries data available.[18] Returns are calculated as log ratios. Exchange rates are WM/Reuters Closing Spot Rates retrieved from DataStream. Exchange rates are expressed in terms of national currency per US dollar.

Both daily data and weekly data will be used in this research. With daily frequency, information transmission among ADR trading would be explored and compare with the previous studies using daily returns. There are 2823 daily price observations from 1/28/1998 to 12/29/2006 for each country. As these countries' national stock markets open at different times from the US stock markets, weekly series will help to avoid non-synchronous trading problems. There are 466 weekly price observations for this period. Table 1 reports the

[17] 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 methodology, and calculated on a continuous basis throughout the trading day. BNY ADR indices cover both Level II and Level III ADRs.

[18] Luxemburg ADR index stopped from July 2007 due to the only ADR from Luxemburg being de-listed. Therefore, it is excluded from this study.

summary statistics for the weekly price data for the local market indices, ADR country indices and exchange rates.

IV. Methodology

IV.1. Cointegration tests on price indices

As it is known that price level data are non-stationary, the cointegration analysis would be applied if unit roots are detected. Cointegration tests help to detect any long-run trend that might be lost in the first-differencing of the variables, such as returns data. If cointegrating relationships are found, the VAR tests on returns data would need to consider such restraints. Therefore cointegration tests are the necessary step before VAR analysis. In the three-factor model by Kim, Szakmary and Mathur (2000), they detect the unit roots and cointegration relationships on the daily price series of four variables: ADRs, corresponding foreign shares, the value of foreign currencies against the US dollar and the S&P 500 index. Instead of using individual ADR series, I use ADR indices from each country to capture general country portfolio characteristics, and the corresponding country market price indices, and the value of foreign exchange rates in both weekly and daily series.

I use Johansen (1988, 1991) trace test and maximum eigenvalue test to see rank of cointegration, i.e., the cointegrating relationships in price indices of ADR, home market, US market and exchange rates (foreign currency per US dollar) for a particular country. More specifically, I define a vector of ΔY_t as the changes (first differences) in the four variables for a country. If Y_t, are integrated of order one and cointegrated then their evolution may be described by a vector error correction model (VECM):

$$\Delta Y_t = \Pi Y_{t-1} + \Phi_1^* \Delta Y_{t-1} + ... + \Phi_p^* \Delta Y_{t-p} + z_t \qquad (25)$$

with the associated vectors of real innovations, $z_1,....z_T$, assumed to be $IIN_n(0,\Lambda)$. The estimated rank of Π in (1), which I denote r, gives us the number of cointegrating relationships. Π may be considered the "long-run impact matrix", to distinguish these effects from the short run autocorrelation terms Φ_s, $s = 1,2...p$. If none of the eigenvalues of Π are significantly different from zero, then *r=0*. There is no cointegration. At the other extreme, if all of the eigenvalues of Π are significantly different from zero (and less than unity), then the rank of Π is equal to the number of series (*r*=n) and I have a stationary process with no long term expected changes in real returns. Of most interest, is the case where $0 < r < n$, so that the vector of total returns on debt, Y_t, is non-stationary, and there are r cointegrating relationships among the elements of Y_t. These cointegrating relationships will need to be taken into account in the VAR analysis.

IV.2. VAR

Accounting for cointegrating relationships if found, a Vector Autoregressive (VAR) test will be performed for a four-variable system for each country - the returns of ADR indices, returns of home market price indices and US market index, and the log ratios of exchange rates (which cannot be interpreted as the returns for currencies). By modeling these four variables in one VAR system, it helps to capture the dynamic relationships among these variables over time. Analyzing the time series jointly also helps to improve the forecast using the covariance matrix of VAR – as additional information from the related series could contribute to the estimation.

Different from Kim, Szakmary and Mathur (2000), VAR analysis in this research will use the returns data more specifically, which is calculated as the log ratios of price levels. Alaganar and Bhar (2001) also did VAR tests on self-constructed Australian ADR portfolio returns, underlying shares portfolio returns, Australian index and US index, but they have not included the exchange rate. This chapter will extend these two studies by using a wider country scope (36 countries altogether) and use both daily and weekly frequencies. Furthermore, this VAR analysis will provide evidence from the most recent data.

Here let us use R to represent returns, which equals the first differencing of price levels in logarithm form. The VAR system with order p can be written as

$$R_t = \sum_{j=1}^{p} \Phi_j R_{t-j} + \varepsilon_t \tag{26}$$

where $R_t = (R_t^{adr}, R_{n,t}, R_{US,t}, R_{EX,t})'$; ε_t is a vector of white noise process with $\varepsilon_t = (\varepsilon_t^{adr}, \varepsilon_{n,t}, \varepsilon_{US,t}, \varepsilon_{EX,t})'$ with properties that $E(\varepsilon_t) = 0, E(\varepsilon_t \varepsilon_t') = \Sigma$ and $E(\varepsilon_t \varepsilon_s') = 0$ for $t \neq s$; and Φ_j is the 4×4 coefficient matrix. Order of VAR system will be based on the information criteria such as AIC (i.e., I choose the order with the lowest of AIC) and analysis on the schematic representations of Cross-correlation and Partial Autocorrelation Matrices. If there is a cointegrating constraint, VECM will be used as in equation(25), which could be rewritten using returns as

$$R_t = \Pi(\log(p_{t-1})) + \sum_{j=1}^{p} \Phi_j^* R_{t-j} + z_t \tag{27}$$

Here the first term on the right hand side captures the cointegrating relationship of the logged price level (p_{t-1}).

IV.2.1. Impulse Responses

Under the VAR system, Impulse response function (IRF) will be calculated for each country and it will help to find the impacts of a shock in one variable on another variable over selected lag period and the significance of each impulse response. To capture such impulse response functions, I transform the VAR (p) to an infinite order moving average representation given our returns series are stationary, which is expressed as

$$R_t = \frac{1}{\Phi(B)}\varepsilon_t = \Psi(B)\varepsilon_t \tag{28}$$

where $\Phi(B) = 1 - \Phi_1 B - \Phi_2 B^2 - ... - \Phi_p B^p$, and $\Psi(B)$ represents the impulse responses of innovations ε_t on variables in return series R_t. It will be interesting to see the signs and magnitude of the responses of ADR returns on the shocks (impulses) from other variables, and how it changes over time. If the market is efficient, the impulse responses will be expected to happen right away, or within few lags.

In order to further the tests on the effects of components of the standardized shock process on the vector process R_t, I also standardize the white noise innovation process. Given positive-definite residual covariance matrix Σ, there is a lower triangular matrix P, such that $\Sigma = PP'$.[19] The transformed MA representation is expressed as

$$R_t = \Psi^*(B)u_t \tag{29}$$

where $\Psi^*(B) = \sum_{j=0}^{\infty} \Psi^*_j B^j$, and $\Psi^*_j = \Psi_j P$ and $u_t = P^{-1}\varepsilon_t$. To put it more intuitively, the impulse responses are standardized by the residual covariances. Ψ^*_j is also called the

[19] This is abstract from more detailed discussion on Impulse Response Function from SAS online documentation for VARMAX procedure for SAS 9.1.3. http://support.sas.com/onlinedoc/913/docMainpage.jsp (accessed July 14, 2007)

orthogonal impulse response. Thus the magnitudes of impulse responses from different innovation series to the vector process R_t are transformed into comparable terms.

IV.2.2. Prediction error variance analysis

The objective for this step is to find the contributions of innovations in variables R_t to the prediction error covariance in the n-step-ahead forecast. In the VAR analysis for weekly data, I perform the decomposition of 4-step-ahead prediction error covariance, i.e., one-month-ahead forecast errors. To compare with the results in Kim, Szakmary and Mathur (2000), the VAR test for daily data will do a 5-day-ahead forecast error covariance analysis (one-week-ahead forecast errors). Under the stationarity assumption, the 4-step-ahead of equation (29) is $R_{t+n|t} = \sum_{j=4}^{\infty} \Psi_j \varepsilon_{t+n-j}$. The prediction error of the 4-step-ahead forecast is $e_{t+n|t} = R_{t+n} - R_{t+n|t}$, which is normally distributed as with zero mean and covariance matrix equals

$$\Sigma(n) = \mathrm{cov}(e_{t+n|t}) = \sum_{j=0}^{n-1} \Psi_j \Sigma \Psi'_j = \sum_{j=0}^{n-1} \Psi^*_j \Psi^{*'}_j \tag{30}$$

where $\Psi^*_j = \Psi_j P$ and P is a lower triangle matrix obtained from $\Sigma = PP'$. Then the prediction error covariances are decomposed through dividing elements of Ψ^*_j by mean square errors. Thus I obtain the proportions of how much the components of standardized innovations of one variable contribute to the prediction error of another variable or the variable itself.

IV.3. Seemingly Unrelated Regressions (SUR)

The previous time series analysis of VAR system is done on a country-by-country basis. To model all 37 countries together in one VAR system will make the model cumbersome and lead to great inefficiencies to estimate. Instead I explore this by modeling all these countries together in a SUR system. SUR takes into account the contemporaneous correlations by viewing the regression equations as a system of equations and then estimate the parameters of this system efficiently. For each country, the regression model is expressed as,

$$R_{n,t}^{adr} = \alpha_n + \beta_{1,n} R_{n,t} + \beta_{2,n} R_{US,t} + \beta_{3,n} R_{EX,t} + e_{n,t} \tag{31}$$

Here $R_{n,t}^{adr}$ is the return on ADR index from country n at time t. $R_{n,t}$ and $R_{US,t}$ are returns of country n market index and US market index at time t. $R_{EX,t}$ is the log ratio of exchange rates of national currency per US dollar at time t, which can be interpreted as returns of US dollar. Home market returns and US returns are both important factors for ADR pricing, I would expect $\beta_{1,n}$ and $\beta_{2,n}$ to be positive and significant. As ADR returns are translation of home share returns, I would expect that when US dollar returns will have a negative impact on ADR returns, therefore my hypothesis on $\beta_{3,n}$ would be negative.

Patro (2000) does similar SUR tests looking for significant sources of risk for the variations of ADR returns such as the returns of home and world market portfolios, exchange rates and global risk factors using daily data. There are a couple of differences and improvements on Patro (2000). First, I use the US market portfolio return instead of world market portfolio as in Patro (2000). The reasoning lies in that among the world market portfolio, US market portfolio has disproportionate influence on these exchange-listed

ADRs than other countries. Using US market portfolio better captures how the trading market performance affects ADR returns. Secondly, on the data of ADR portfolios, Patro (2000) selects 123 ADRs from 16 countries and form equally weighted ADR portfolios, while I use 37 country ADR indices created by Bank of New York, which contains all exchange-listed ADRs and are capitalization weighted. This is much broader coverage than Patro (2000). Thirdly, Patro (2000) uses monthly returns from August 1992 to August 1997. I use both daily and weekly returns from 1998 to 2006, which provide the new evidence on the recent performance in higher frequencies.

Contemporaneous Correlation Test

SUR improves OLS estimation when there is contemporaneous correlation. To ensure there is contemporaneous correlation, Breusch-Pagan (BP) Lagrange Multiplier test will be done. For this test, the null hypothesis is that all cross-equation correlations among residuals are zero. The test statistics will be the sum of squared cross-correlations ($\hat{\rho}_{ij}$, i and j represent equation numbers) times total time period (T), which is approximately chi-squared distribution with the degree of freedom equations the total number of cross-equation correlations.

SUR with lagged series

Kim, Szakmary and Mathur (2000) do the regression tests on returns of both contemporaneous and lagged factors (up to lag 2), for 56 firms from 5 countries then obtain the average for each country. They found significant of lagged variables. Here I modify equation (31) to include lag one and lag two of each risk factor, expressed as

$$R_{n,t}^{adr} = \alpha_n + \sum_{j=0}^{2} \beta_{1,j,n} R_{n,t-j} + \sum_{j=0}^{2} \beta_{2,j,n} R_{US,t-j} + \sum_{j=0}^{2} \beta_{3,j,n} R_{EX,t-j} + e_{n,t} \tag{32}$$

which is equivalent to one equation for ADR returns in the VAR process of order two. Betas measure the sensitivities (or risk exposures) of ADR returns to risk factors.

V. Empirical results

V.1. Unit-roots and Cointegration Tests

After plotting the correlogram of the time series for ADR price indices, market price indices and exchange rate (foreign currency against US dollar), I observe non-stationary for all of them for the period 1998:1 – 2006:12. As a formal test for stationarity, I perform the commonly-used Augmented Dickey-Fuller unit root tests on the 112 time series for ADR price indices, market price indices and exchange rate (foreign currency against US dollar from 37 countries and US market price index for both daily and weekly frequencies. Table 2 reports the Augmented Dickey-fuller tau statistics for weekly series and corresponding probability for three situations: zero mean, single mean, and mean with trend. The null hypothesis is $\rho = 0$.

$$\Delta Y_t = \rho Y_{t-1} + \phi_1^* \Delta Y_{t-1} + \varepsilon_t \tag{33}$$

$$\Delta Y_t = \alpha + \rho Y_{t-1} + \phi_1^* \Delta Y_{t-1} + \varepsilon_t \tag{34}$$

$$\Delta Y_t = \alpha + \beta t + \rho Y_{t-1} + \phi_1^* \Delta Y_{t-1} + \varepsilon_t \tag{35}$$

With zero mean (33) and single mean (34) and a trend(35), the null hypothesis of unit root is not rejected for any of market price indices. For ADR price indices and the exchange rate series, the null hypothesis of unit root is not rejected in at least one of the Augmented DF tests for all 37 countries. To further our discussion, I also test unit roots for the first differenced series, but I fail to find unit-roots in the first differenced time series. Similar results are obtained as to daily price series, which will not be reported here.

After confirming unit roots, I perform the cointegration tests for all 37 countries. I assume no separate drift in the Vector Error Correction Model-VECM (p). I perform both Johansen trace test and maximum eigenvalue test to the following. The lag length is chosen based on Akaike Information Criterion (AIC) when the model includes as many lags as the observations allowed.[20] As noted in Kasa (1992), the trace statistics takes account of all the n-r of the smallest eigenvalues; it will tend to be greater than the maximum eigenvalue statistics when the eigenvalues are evenly distributed. However, when eigenvalues are clustered close to one or zero, maximum eigenvalue statistics will tend to give better test results. So the decision on the final rank of the test may become a judgment based on considerations of the two statistics along with an inspection of eigenvalues. As eigenvalues for each country all clusters to below 0.1, I choose maximum eigenvalue statistics. For weekly time series, I fail to find any cointegrating relationships for 30 countries. For the other 7 countries (Austria, China, Hungary, Mexico, New Zealand, Peru and Turkey), only one cointegrating relationship is found for each country at 5% significance level. For daily time series, I fail to find any cointegrating relationships for 25 countries. Also only one

[20] As argued by Fraser and Oyefeso (2005), evidence shows that the rank test is not very sensitive to over parameterization arising from a misspecified short-run structure, and the most useful strategy is to select the lag length based on AIC. Simulations run by Schwert (1989) show that in small and moderately large samples (from t=25 to 1000), including enough lags in the autoregression is important to minimize size distortions (see Hayashi's Econometrics, page 594).

cointegrating relationship is found for 12 countries (Brazil, Chile, China, Greece, Hungary, Korea, New Zealand, Peru, Philippines, Singapore, Spain, and Taiwan).

I also perform cointegration tests on data in logarithm forms. The first-differencing of the logarithm form of weekly price data will give weekly return data, therefore the VAR analysis later could be interpreted as return series. For logged series, I fail to find any cointegrating relationship for 26 countries and I find only one cointegrating relationship for 9 countries (Argentina, Austria, China, Columbia, Finland, Hungary, India, Peru and Russia), and two cointegrating relationships for one country – Turkey. Therefore for the ten countries I find cointegrating relationships, I model them with a vector error correction model (VECM) which is equivalent to a VAR on the returns with constraints concerning price levels in logarithm form. For the daily frequencies in logarithm forms, I find one cointegrating relationships for 21 countries and two cointegrating relationships for only Turkey. These countries VAR process are modeled with cointegrating constraints. Cointegrating test results will not be reported but available upon request.

V.2. VAR

After checking for the cointegrating relationships for these four non-stationary logged price series of each country, we perform the Vector Autoregressive tests separately for each country, using cointegrating constraints when necessary. The order of VAR model is chosen based on AIC and is four or five for most countries studied.

V.2.1. The impulse responses

For the impulse responses, I mainly focus on the impact that a shock in one variable has on ADR returns. Table 3a reports the orthogonalized impulse response by variable for each country as well as the corresponding t-ratios for the weekly data. For the impulses from home market returns, US market returns, and exchange rate changes, the responses of ADR returns mostly happen immediately at lag 0, i.e., the impacts of shocks from these variables are absorbed approximately in the same week except 6 countries out of 36 (Argentina, Austria, Finland, Hungary, India, Norway, Peru and Russia). The responses drop after lag 0 and diminish in the higher lags. The responses to shocks from the home market are all significant at lag 0 for all 36 countries. Specifically, the impulse responses to home market are all positive and over 1%, except China which is about 0.5%. The impulse responses to the exchange rate changes (per US dollar) are also mostly significant at lag 0 except Peru, and negative for 35 countries (except Peru). These are consistent with literature that home market will positively affect the ADR returns, while dollar appreciation will negatively affect ADR returns. The magnitude of the impulse responses to exchange rate changes is smaller compared to that of the home market returns.

However, the response of ADR returns to the shocks from US market is only statistically significant for China, Belgium, India, Philippines and Spain at lag 0, with both positive and negative responses. Comparing to the responses to the home market return, impulse responses to US market returns are quite small, less than 1% for all countries. Interestingly, for 17 countries or regions (China, Japan, Germany, Belgium, Columbia, Denmark, Indonesia, Ireland, Israel, Korea, New Zealand, Philippines, Portugal, Singapore, Spain, Sweden, Switzerland, Taiwan), the ADR response to the impulses in the US market returns are significant at lag 1, and even up to lag four or more (Japan, Germany, Belgium, Denmark, Indonesia, Ireland, Israel, New Zealand, Philippines, Portugal, Singapore, Spain, Sweden, Switzerland, Taiwan).

Table 3b reports the impulse responses obtained using daily data. Similar to the weekly data, the responses of the daily ADR returns to the innovations of the home market returns are all positive and significant at lag 0 for all 36 countries, and those to the innovations of the exchange rate changes are all negative and significant at lag 0 except Greece. The magnitude of the impulse responses to exchange rate changes is also smaller compared to that of the home market returns. The responses of the daily ADR returns to the innovations of US market returns are small relative to impulse responses to the home market returns and exchange rate changes in general.

However, different from the weekly frequency, the significant responses to the impulses of home market returns and exchange rate changes tend to last over the same calendar day. There are 22 countries that have significant responses to the innovations of home market returns and exchange rate changes that last to higher lags. Now recall the results of weekly data that only 6 countries from these 22 countries that have significant impulses responses last over a week. It implies that responses of ADR returns to the innovation of the home market and exchange rate risk factors stay over the same calendar day for about two third of the countries studied and stay significant over to the future days, but mostly diminishes after a week. Another observation to the impulse responses of daily ADR returns to the US market shocks, is that there is significant response at lag 2 or higher for 20 countries. It is interesting to see that although ADRs are traded in the United States, they are mostly affected by the information from US markets from the previous calendar day. It might come from the fact that US stock exchanges open later than most of the countries studied; the information from the US market will affect the next day trading of the home ADR home markets and then to the ADR returns over the time lag.

V.2.2. Prediction error variance analysis

For n-period-ahead forecast, the decomposition of forecast error variances helps us to find the contributions of innovations in one variable to the prediction error covariance in the n-step-ahead forecast of ADR returns, as in equation (30). The results for the weekly series are reported in Table 4a. Among 21 countries out of 36, the innovations of home market returns contribute to more than 50% of the prediction error variance of ADR returns. If I take the average of 36 countries, 49% of prediction error variance of ADR returns could be explained by the innovations of home market returns. However, innovations of US market returns contribute less than 1% on average, and those of exchange rates contribute about 7.7% of prediction error variance of the ADR returns. The results are consistent with impulse response analysis above, that is, the innovations from the home market returns contribute the most to the ADR forecast, while innovations of the US market returns contribute the least, and innovations of the exchange rates also contribute to the ADR forecast but relatively small.

Another result from this analysis is that there are three countries – China, Greece and Spain, in which the total contribution of innovations of home market, US market and exchange rates are less than 12%, meaning, over 88% prediction error variances are not explained by these three pricing factors. It indicates that ADR index returns from these three countries are influenced greatly by factors other than the market factor and exchange rates.

The results for 5-day-ahead prediction error variance using daily series are almost the same (Table 4b). Home market innovations contribute the most to the prediction error variance of ADR returns with an average of 32%, while innovations of exchange rate changes contribute about 5% on average and the innovations of the US market returns contribute less than .5%. Altogether, these daily innovations from the three pricing factors to ADRs contribute less than the weekly series.

Table 5a and Table 5b report the decomposition of forecast error variances for the whole VAR system for Australia, Argentina, China, Japan and Germany using weekly returns and daily returns respectively. The number in the cell reports the contribution of the innovations of the column variable to the forecast error in the row variable. The diagonal elements for each country give the degree of exogeneity of each return series. US market index, home market index and local currency returns show strong exogeneity of all other return series. Alaganar and Bhar (2001) perform VAR analysis and reports the 10-day forecast error variance explained by innovations by each variable for Australia (with daily returns of ADR portfolio, US index, Australian index, underlying stocks portfolio as a Vector). Alaganar and Bhar (2001) find that the innovations of Australian index contribute about 43% to prediction error variance of ADR portfolio, the innovations of underlying shares contributes about 14%, and innovations of US index contribute about 15%. Kim, Szakmary and Mathur (2000) also estimate VAR system for Australia (daily price for individual ADRs, exchange rates, underlying stocks and S&P 500 index), then get an average for the country as a whole. They find that exchange rate innovations contribute about 9% to prediction error variance of ADRs, and innovations of underlying shares contribute about 59%, and innovations of S&P 500 index contribute about 5%. Comparing with these two studies, the VAR system for Australia I estimate gives a higher contribution of innovations of the exchange rate to the prediction errors – about 28% to ADRs for weekly returns and about 21% for daily returns. I also find a lower contribution of innovations in US market index – about 0.45% of prediction error variance of ADRs for weekly returns and about 0.67% for daily returns. The contribution of home market shocks to Australia ADR returns is about 52% for weekly returns and about 27% for daily returns. The different results for Australia may be due to different sample period, as these two studies use data before 1997, while this research uses data after and it chooses a much larger sample size – with 36 countries and nine year's daily returns. In addition, Alaganar and Bhar (2001) did not consider exchange rate risk, while Kim, Szakmary and Mathur (2000) use individual ADRs and their underlying stocks then average them out for a particular country. This research directly uses an ADR portfolio created capitalization-weighted for all exchange-listed ADRs from that country, and the home market index, therefore it controls for that individual ADR specific risks and focus on the effect of home market shocks to ADR performance in general.

V.3. Seemingly Unrelated Regression (SUR)

Table 6 gives the SUR estimation with weekly series for all 36 countries together with three pricing factors – US market return, home market return, the dollar return (log ratio of exchange rates in terms of national currency per US dollar). Numbers with (***) represent statistical significance at 5% level, and those with (*) represent statistical significance at 10% level. The beta coefficients for home market returns are all positive and significant, which implies that home market returns have significant positive effects on the ADR portfolio returns. The sensitivities to the exchange rate changes (betas to dollar returns) are significant for all except China, India (Russia is significant at 10% level), and the coefficients are mostly negative, which indicates that as dollar returns increases, the ADR portfolio return will decrease. The beta coefficients to the US market returns are mostly insignificant and small in magnitude (significant for Ireland and Singapore and Taiwan). Sigma reports the root mean square error of the model, which is an estimate of the standard deviation of the error term.

As a diagnostic check, Breusch Pagen Lagrange Multiplier test for contemporaneous correlation is also performed. The test statistics equals time period (T) times the sum of squared cross-correlations ($\hat{\rho}_{ij}$), i.e., $T\sum\sum_{i<j}\hat{\rho}_{ij}$ =465×431.7264 =200752.776, which is far larger the significant Chi-squared statistics with 630 degree of freedom ($\chi^2_{(630)}$=689.5).

Table 7 reports the Seemingly Unrelated Regression with lagged variables, as in equation(32) using weekly returns. Consistent with the previous SUR without lagged variables, the beta coefficients to home market risk at lag 0 are significant and positive for all countries, and those to exchange rate risks are mostly significant and negative (insignificant for China and India, significant but positive for Peru). The beta coefficients to the US market risk are only significant for Ireland and Taiwan. Contrary to Kim, Szakmary and Mathur (2000), I only find significant beta coefficients to home market risk at lag one for 12 countries out of 36 at 10% level. The beta coefficients to the exchange rate risk at lag one is significant for 8 countries out of 36 at 5% level. For lag two home market and exchange rate beta coefficients, there are less countries that show statistically significance. The coefficients are also much less in magnitude than those in lag 0. This is consistent with previous VAR impulse response results – that most of the responses happen at lag 0 and diminishes at higher lags.

On the other hand, the beta coefficients to the US market risk show different pattern from home market risk and exchange rate risk factors. Although they are insignificant for most of countries at lag 0, they are significant for 4 countries – Argentina, Colombia, Mexico and UK at lag 1 and for other 8 countries at lag 2. The magnitude of these coefficients is larger at lag 1 for 8 emerging markets (Argentina, Brazil, China, Colombia, Korea, Mexico, Peru, Turkey) and 8 developed markets (Austria, Belgium, Denmark, Greece, Italy, Portugal, Sweden and UK). This is also consistent with VAR impulse response analysis which there is also less significant effects from the innovations of US market returns at lag 0, but for some countries, the responses become significant at lag 1 or higher.

In short, the Seemingly Unrelated Regression shows that ADR portfolios are more sensitive to home market risks than US market risks, and that the exchange rate change is also a significant risk factor. The SUR is also consistent with previous VAR analysis. Compared with previous studies, the exchange rate risk sensitivities are found to be higher in the weekly data in this research than the daily data in Kim, Szakmary and Mathur (2000), and US market risk sensitivities are found to be lower than Kim, Szakmary and Mathur (2000) and Alaganar and Bhar (2001) for Australia.

VI. Summary

This essay is based on the previous literature on ADR pricing using three pricing factor – US market, home market and exchange rate risk. It uses the both regression and time series technique to look at the significance of sensitivities of ADRs to different risk factors, and compare with the results in the previous literature.

The time series analysis shows that the responses of the ADR returns to the innovations of the home market returns are all positive and significant at lag 0 for all 36 countries, and those to the innovations of the exchange rate changes are all negative and significant at lag 0 with exceptions. The magnitude of the impulse responses to exchange rate changes is also smaller compared to that of the home market returns. The results also show that responses of ADR returns to the innovation of the home market and exchange rate risk factors stay over the same calendar day for about two third of the countries studied and stay significant over to the future days, but mostly diminish after a week. The responses of the daily ADR returns to the innovations of US market returns are small relative to impulse responses to the home market returns and exchange rate changes in general. However, there is significant response to US market shocks at lag 2 or higher for more than half of the countries studied. It is interesting to see that although ADRs are traded in the United States, they are mostly affected by the information from US markets from the previous calendar day. It might come from the fact that US stock exchanges open later than most of the countries studied; the information from the US market will affect the next day trading of the home ADR home markets and then to the ADR returns over the time lag.

For the prediction error variance analysis, home market innovations contribute the most to the prediction error variance of ADR returns with an average of 32% for daily series, while innovations of exchange rate changes contribute about 5% on average and the innovations of the US market returns contribute less than .5%. The weekly innovations from the home market, exchange rate and US market shocks to ADRs contribute about 50%, 7.7% and .68% respectively after taking average of the 36 countries.

The Seemingly Unrelated Regression shows that ADR portfolios are more sensitive to home market risks than US market risks, and that the exchange rate change is also a significant risk factor. The SUR is also consistent with previous VAR analysis. Compared with previous studies, the exchange rate risk sensitivities are found to be higher in this research than the daily data in Kim, Szakmary and Mathur (2000), and US market risk sensitivities are found to be lower than Kim, Szakmary and Mathur (2000) and Alaganar and Bhar (2001) for Australia.

This chapter provides the most new evidence to the factor pricing literature on ADRs with a systematic testing for 36 countries. Home market risk is found to be most significant pricing factors. Exchange rate is also found to be a significant pricing factor, and the dollar appreciation is found to be negatively affecting ADR returns. US market risk is found to be insignificant in the regression model, but found to be significant in affecting the next period ADR returns for some countries.

However, although this chapter gives an evaluation of sensitivities of ADR country portfolios to different risk factors, it is based on an unconditional model. The unconditional models look at the first moment, without considering the time-varying exposures of financial assets to the market risk. For example, the effect of the US market shocks on ADR returns may change over time. Therefore, a model is needed that combines the pricing factors and considers time-varying covariance of the financial assets with market portfolios.

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Appendix : Cointegration tests

First we start with a VAR(p) specification for the $n \times 1$ vector of I(1) variables, Y_t.

$$Y_t = \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + ... + \Phi_p Y_{t-p} + a_t \qquad t = 1,...,T \qquad (1)$$

where $a_1,....a_T$ are $IIN_p(0,\Lambda)$. Equation (1) can be rewritten as Vector Error Correction Model using differenced terms $\Delta = 1 - L$ where L is the lag operator,

$$\Delta Y_t = \Pi Y_{t-1} + \Phi_1^* Y_{t-1} + ... + \Phi_{p-1}^* Y_{t-p+1} + a_t \qquad (2)$$

where $\Pi = \Phi_1 + \Phi_2 + ... + \Phi_p - I_n$ and $\Phi_i^* = -\sum_{j=i+1}^{p} \Phi_j$, i=1, 2,…,p-1.

The rank of Π (r) determines the number of cointegrating relationships (the linear combinations of Y_t that is integrated of order 0 - stationary). Π is also called the "long-run impact matrix". When all eigenvalues of Π are equal to zero, the rank r is zero. There is no cointegration in this situation. If all n eigenvalues of Π are different than 0 and less than unity, the rank of Π is n and we have a stationary process. If $0 < r < n$, i.e., the matrix Π does not have the full rank, then there are r cointegrating relationships between Y_t, or $n - r$ common stochastic trends. Π can be factored into the multiplication of two $n \times r$ matrices $\Pi = \alpha\beta'$. We define α the adjustment matrix and the r columns of β cointegrating vectors (the linearly independent combinations of Y_t that are stationary. Since the decomposition of α, β is not unique, the specific elements of α and β is not so much of interest, but rather their dimensionality and structure of the space spanned by their respective columns (Kasa 1992). To determine the rank r, Johansen fully specify the data generating process and incorporate the estimation into a Maximum likelihood framework. Plug in α and β, then we get

$$\Delta Y_t = c + \alpha\beta' Y_{t-1} + \sum_{i=1}^{p-1} \Phi_i^* Y_{t-i} + a_t \qquad (3)$$

To conduct the rank test and maximum eigenvalue test to get r, we first concentrate out the short-run dynamics (i.e., eliminating the parameters with differenced terms) by regressing ΔY_t and Y_{t-1} on ($\Delta Y_{t-1},....\Delta Y_{t-p+1}$). This gives us residuals R_{ot} and R_{1t} and the residual product matrices.

$$S_{ij} = T^{-1} \sum_{t=1}^{T} R_{it} R_{jt} \text{ , } i,j=0,1 \qquad (4)$$

Then we get the concentrated model

$$R_{ot} = \alpha\beta' R_{01} + a_t \qquad (5)$$

Also here $a_1,....a_T$ are $IIN_p(0,\Lambda)$. Thus the problem of estimating α and β boils down to a nonlinear optimization problem (Johansen 1988) and is found by solving the eigenvalue problem

$$| \lambda S_{11} - S_{10} S_{00}^{-1} S_{01} | = 0 \qquad (6)$$

We get the eigenvalues $\hat{\lambda}_1 > \hat{\lambda}_2 > ... > \hat{\lambda}_n$ and corresponding eigenvectors $\hat{V} = (\hat{V}_{1,...,}\hat{V}_n)$ where $\hat{V}$ is normalized by $\hat{V}' S_{11} \hat{V} = I$. The maximum likelihood estimators are given by $\hat{\beta} = (\hat{V}_{1,...,}\hat{V}_r)$, $\hat{\alpha} = S_{01}\hat{\beta}$ and the $\hat{\Lambda} = S_{00} - \hat{\alpha}\hat{\alpha}'$. Here the r eigenvectors corresponding to the largest r eigenvalues. The intuition behind is that eigenvalues λ_i measures how strongly the linear combination $\hat{V}_i ' Y_{t-1}$ is correlated with the stationary part of the process. If $\hat{V}_i ' Y_{t-1}$ is non-stationary, the correlation will be zero, which means the corresponding eigenvalues will be zero. So asymptotically under the null hypothesis, there will be $(n-r)$ λ_i's equal to zero.

Finally the maximum likelihood function becomes

$$L_{\max}^{-2/T} = |\hat{\Lambda}| = |S_{00}| \prod_{i=1}^{r} (1-\hat{\lambda}_i) \qquad (7)$$

Johansen (1998, 1991) proposes two likelihood ratio tests based on the expression (7). The first test statistics for the null hypothesis that here are at most r distinct cointegration vectors is

$$Trace(r) = -T \sum_{i=r+1}^{n} \ln(1-\hat{\lambda}_i) \qquad (8)$$

For λ_i's that are less than 1, the statistic will be a positive number and we will reject the null for high positive values. Another test is called maximum eigenvalue test, which is based on the null hypothesis of at most r distinct cointegration vectors against the alternative hypothesis of $r+1$ distinct cointegration vectors. The test statistics is

$$\lambda_{\max}(r, r+1) = -T \ln(1-\hat{\lambda}_{r+1}) \qquad (9)$$

As noted in Kasa (1992), trace statistics takes account of all the n-r of the smallest eigenvalues; it will tend to be greater than the maximum eigenvalue statistics when the eigenvalues are evenly distributed. However, when eigenvalues are clustered close to one or zero, maximum eigenvalue statistics will tend to give better test results. So the final rank of the test should be a judgment based on considerations of the two statistics along with the inspection of eigenvalues.

Table 1. Summary statistics (weekly original series)

COUNTRY	Variable	Observations	Mean	StdDev	Variable	Mean	StdDev	Variable	Obs.	Mean	StdDev
ARGENTINA	**TOTMKAR**	466	4586431	1868590	**ARGPES**	2.12736	1.03215	**BNYARGN**	466	70.0043	41.62269
AUSTRALIA	**TOTMKAU**	466	1175	239.6139	**AUSTDO**	0.64736	0.08959	**BNYAUST**	466	148.9483	46.6658
AUSTRIA	**TOTMKOE**	466	720.2174	341.91208	**AUSTSC**	12.83092	1.74056	**BNYOEST**	314	204.18931	93.64205
BELGIUM	**TOTMKBG**	466	845.60197	174.81555	**BELGLU**	37.61596	5.10241	**BNYBELG**	466	14.29656	7.45066
BRAZIL	**TOTMKBR**	466	365.59899	189.50548	**BRACRU**	2.30874	0.63201	**BNYBRAZ**	466	118.86192	67.67273
CHILE	**TOTMKCL**	466	1295	384.41225	**CHILPE**	581.45489	80.90394	**BNYCHIL**	466	98.84449	28.34211
CHINA	**TOTMKCA**	466	1464	252.76591	**CHIYUA**	8.23357	0.10521	**BNYCHIN**	466	164.94105	61.88744
COLOMBIA	**TOTMKCB**	466	461.31034	363.05975	**COLUPE**	2260	426.69851	**BNYCOLM**	466	55.62106	52.34772
DENMARK	**TOTMKDK**	466	2899	749.91458	**DANISH**	6.94222	0.94223	**BNYDENM**	466	139.70743	43.63231
FINLAND	**TOTMKFN**	466	610.19129	251.4122	**FINMAR**	5.54393	0.75203	**BNYFINL**	466	289.77606	149.09584
FRANCE	**TOTMKFR**	466	1857	394.28271	**FRENFR**	6.11629	0.82978	**BNYFRAN**	466	136.56427	32.97688
GERMANY	**TOTMKBD**	466	640.10901	143.66865	**DMARKE**	1.82373	0.2474	**BNYGERM**	466	157.69211	53.32762
GREECE	**TOTMKGR**	466	1708	558.7665	**GREDRA**	314.67439	43.18446	**BNYGREE**	366	138.87282	261.33788
HUNGARY	**TOTMKHN**	466	722.26489	276.57534	**HUNFOR**	235.2612	33.22667	**BNYHUNG**	466	92.94204	26.12797
INDIA	**TOTMKIN**	466	650.08717	351.16884	**INDRUP**	45.17031	2.20345	**BNYINDI**	401	526.96023	278.39318
INDONESIA	**TOTMKID**	466	113.27131	44.35117	**INDORU**	9155	1199	**BNYINDO**	466	112.46489	61.72026
IRELAND	**TOTMKIR**	466	2608	501.84299	**IPUNTE**	1.38739	0.18166	**BNYEIRE**	466	121.07111	23.80671
ISRAEL	**TOTMKIS**	466	225.10167	68.34798	**ISRSHE**	4.33309	0.29713	**BNYISRA**	466	160.63095	55.40769
ITALY	**TOTMKIT**	466	2414	457.3654	**ITALIR**	1805	244.99275	**BNYITAL**	466	127.98486	25.77903
JAPAN	**TOTMKJP**	466	383.14725	80.63284	**JAPAYE**	116.48021	8.94153	**BNYJAPN**	466	97.05915	23.72974
KOREA	**TOTMKKO**	466	218.18202	78.41641	**KORSWO**	1171	129.31131	**BNYKORE**	466	159.99033	48.75477
LUXEMBOURG	**TOTMKLX**	466	381.95219	104.74389	**LUXFRN**	37.61596	5.10241	**BNYLUXM**	443	41.24777	33.78759
MEXICO	**TOTMKMX**	466	7495	3667	**MEXPES**	10.13512	0.84294	**BNYMEXC**	466	142.56975	65.93741
NETHERLANDS	**TOTMKNL**	466	1083	232.58764	**GUILDE**	2.05495	0.27873	**BNYNETH**	466	112.91479	22.38519
NEW ZEALAND	**TOTMKNZ**	466	202.33633	37.8183	**NZDOLL**	0.55669	0.09877	**BNYNEWZ**	466	76.30148	17.56286
NORWAY	**TOTMKNW**	466	1003	369.51961	**NORKRO**	7.53019	0.95875	**BNYNORW**	466	118.01917	60.25872

PERU	**TOTMKPE**	466	250.39489	85.14147	**PERUSO**	3.36935	0.18046	**BNYPERU**	466	90.04219	33.66115
PHILIPPINES	**TOTMKPH**	466	643.77247	160.70084	**PHILPE**	49.32627	6.12126	**BNYPHIL**	466	97.89721	48.75296
PORTUGAL	**TOTMKPT**	466	185.15399	37.50103	**PORTES**	186.92672	25.35967	**BNYPORT**	466	82.21107	18.00239
RUSSIA	**TOTMKRS**	466	1267	1182	**CISRUB**	26.70711	6.11791	**BNYRUSS**	466	262.83295	217.23434
SINGAPORE	**TOTMKSG**	466	272.78251	61.01512	**SINGDO**	1.70572	0.06856	**BNYSING**	366	23.83822	13.3623
SPAIN	**TOTMKES**	466	378.63088	77.39978	**SPANPE**	155.12032	21.05039	**BNYSPAN**	366	188.56296	216.73436
SWEDEN	**TOTMKSD**	466	1974	542.70877	**SWEKRO**	8.41235	1.09742	**BNYSWED**	466	97.1399	33.92
SWITZERLAND	**TOTMKSW**	466	765.93187	129.89275	**SWISSF**	1.44085	0.18053	**BNYSWIT**	466	129.11248	24.72566
TAIWAN	**TOTMKTA**	466	252.42788	56.57657	**TAIWDO**	33.07693	1.25792	**BNYTAIW**	466	177.4287	72.7729
TURKEY	**TOTMKTK**	466	259215	172969	**TURKLI**	1.18811	0.41793	**BNYTURK**	321	37.51676	20.9073
UK	**TOTMKUK**	466	3581	534.37778	**USBRITP**	0.6113	0.05943	**BNYUKAD**	466	111.97648	18.34903

Note: For each country, there are three variables – local market index (DataStream total market index), exchange rate (National currency per US dollar) and ADR index developed by Bank of New York. The first column gives the country name. The variables on the second column with the name "TOTMK**" represent the DataStream total market indices. The variables on the ninth column with the name "BNY****" represent the ADR indices developed by Bank of New York. The variables on the sixth column give the respective exchange rates for that country in terms of national currency per US dollar, obtained from WMR/Reuters closing rate. The summary statistics reported here are the original weekly price indices of the local market and ADRs, and the weekly exchange rates. The summary statistics for daily series, as well as the first differences of the log series, are also available but not reported here due to space limits.

Table 2: Unit roots for all countries (using original price level data)

Variable	Type	Tau	Prob<Tau	Variable	Type	Tau	Prob<Tau	Variable	Type	Tau	Prob<Tau
TOTMKAR	Zero Mean	1.25	0.9462	BNYARGN	Zero Mean	2.03	0.9901	ARGPES	Zero Mean	1.09	0.9284
	Single Mean	0.31	0.9785		Single Mean	1.54	0.9994		Single Mean	-0.78	0.8245
	Trend	-1.78	0.7153		Trend	-0.98	0.9438		Trend	-1.01	0.9409
TOTMKAU	Zero Mean	2.8	0.9989	BNYAUST	Zero Mean	1.86	0.9851	AUSTDO	Zero Mean	0.46	0.8127
	Single Mean	1.26	0.9985		Single Mean	0.4	0.9827		Single Mean	-0.67	0.8515
	Trend	-0.23	0.9923		Trend	-2.91	0.1611		Trend	-1.95	0.6274
TOTMKOE	Zero Mean	3.74	0.9999	BNYOEST	Zero Mean	2.42	0.9964	AUSTSC	Zero Mean	-0.66	0.4328
	Single Mean	2.68	0.9999		Single Mean	0.28	0.977		Single Mean	-0.66	0.8537
	Trend	-0.11	0.9947		Trend	-3.2	0.0858		Trend	-1.6	0.7939
TOTMKBG	Zero Mean	1.38	0.9587	BNYBELG	Zero Mean	-1.38	0.155	BELGLU	Zero Mean	-0.66	0.4318
	Single Mean	0.1	0.9657		Single Mean	-0.98	0.762		Single Mean	-0.66	0.8537
	Trend	-0.28	0.9909		Trend	-0.98	0.9444		Trend	-1.59	0.7948
TOTMKBR	Zero Mean	3.23	0.9997	BNYBRAZ	Zero Mean	2.3	0.9951	BRACRU	Zero Mean	0.22	0.7507
	Single Mean	1.82	0.9998		Single Mean	1.38	0.999		Single Mean	-1.88	0.3396
	Trend	-0.45	0.9853		Trend	-1.58	0.7996		Trend	-1.05	0.9345
TOTMKCL	Zero Mean	2.65	0.9982	BNYCHIL	Zero Mean	0.91	0.9031	CHILPE	Zero Mean	0.28	0.7679
	Single Mean	1.42	0.9991		Single Mean	0.08	0.9637		Single Mean	-1.56	0.503
	Trend	-0.97	0.946		Trend	-1.2	0.9086		Trend	-0.99	0.9436
TOTMKCA	Zero Mean	0.41	0.8006	BNYCHIN	Zero Mean	1.14	0.9351	CHIYUA	Zero Mean	-2.44	0.0143
	Single Mean	-1.09	0.7207		Single Mean	-0.02	0.9557		Single Mean	3.95	0.9999
	Trend	-0.5	0.9835		Trend	-0.6	0.9783		Trend	2.17	0.9999
TOTMKCB	Zero Mean	3.12	0.9996	BNYCOLM	Zero Mean	1.2	0.9417	COLUPE	Zero Mean	1.08	0.9276
	Single Mean	2.04	0.9999		Single Mean	0.69	0.9918		Single Mean	-2.41	0.1403
	Trend	-0.76	0.9677		Trend	-1.31	0.8841		Trend	-0.55	0.981
TOTMKDK	Zero Mean	1.96	0.9884	BNYDENM	Zero Mean	2.27	0.9947	DANISH	Zero Mean	-0.66	0.4321
	Single Mean	0.74	0.9929		Single Mean	1.48	0.9993		Single Mean	-0.66	0.8541
	Trend	-0.63	0.9766		Trend	0.23	0.9982		Trend	-1.59	0.7976
TOTMKFN	Zero Mean	-0.15	0.6305	BNYFINL	Zero Mean	-0.59	0.4619	FINMAR	Zero Mean	-0.65	0.4364

	Single Mean	-1.82	0.3711		Single Mean	-1.96	0.3056		Single Mean	-0.66	0.8534
	Trend	-1.9	0.6515		Trend	-2.33	0.4172		Trend	-1.61	0.7898
TOTMKFR	Zero Mean	0.94	0.9086	BNYFRAN	Zero Mean	0.57	0.84	FRENFR	Zero Mean	-0.65	0.4336
	Single Mean	-1.11	0.7123		Single Mean	-1.19	0.6821		Single Mean	-0.66	0.8537
	Trend	-1.15	0.9188		Trend	-1.16	0.9164		Trend	-1.6	0.7935
TOTMKBD	Zero Mean	0.28	0.7669	BNYGERM	Zero Mean	0.07	0.7047	DMARKE	Zero Mean	-0.66	0.4328
	Single Mean	-1.18	0.6857		Single Mean	-1.62	0.4737		Single Mean	-0.66	0.8537
	Trend	-1.05	0.9349		Trend	-1.65	0.7698		Trend	-1.6	0.7939
TOTMKGR	Zero Mean	0.45	0.81	BNYGREE	Zero Mean	-3.44	0.0006	GREDRA	Zero Mean	-0.38	0.5481
	Single Mean	-1.51	0.5267		Single Mean	-3.42	0.0112		Single Mean	-0.87	0.7972
	Trend	-1.55	0.81		Trend	-3.08	0.1129		Trend	-1.8	0.7029
TOTMKHN	Zero Mean	1.33	0.9543	BNYHUNG	Zero Mean	-0.36	0.5537	HUNFOR	Zero Mean	-0.32	0.5684
	Single Mean	0.21	0.9731		Single Mean	-1.96	0.3053		Single Mean	-0.99	0.7582
	Trend	-1.22	0.9053		Trend	-1.97	0.6142		Trend	-2	0.6008
TOTMKIN	Zero Mean	2.58	0.9978	BNYINDI	Zero Mean	0.01	0.6875	INDRUP	Zero Mean	1.08	0.9271
	Single Mean	1.41	0.9991		Single Mean	-1.71	0.4233		Single Mean	-3.2	0.0212
	Trend	-0.4	0.9874		Trend	-1.87	0.6695		Trend	-2.33	0.4146
TOTMKID	Zero Mean	1.47	0.965	BNYINDO	Zero Mean	2.27	0.9947	INDORU	Zero Mean	-0.48	0.5071
	Single Mean	0.94	0.996		Single Mean	1.85	0.9998		Single Mean	-2.86	0.0511
	Trend	-0.33	0.9897		Trend	-0.14	0.9942		Trend	-2.87	0.1746
TOTMKIR	Zero Mean	1.41	0.9612	BNYEIRE	Zero Mean	1.25	0.9469	IPUNTE	Zero Mean	0.64	0.8544
	Single Mean	0.32	0.9791		Single Mean	0.22	0.9737		Single Mean	-0.49	0.8908
	Trend	-0.56	0.9805		Trend	-0.51	0.9828		Trend	-1.59	0.7964
TOTMKIS	Zero Mean	1.61	0.9739	BNYISRA	Zero Mean	0.52	0.8281	ISRSHE	Zero Mean	0.59	0.8438
	Single Mean	-0.55	0.8787		Single Mean	-1.11	0.7127		Single Mean	-2.55	0.1051
	Trend	-1.57	0.8034		Trend	-2.33	0.4189		Trend	-1.76	0.7222
TOTMKIT	Zero Mean	0.49	0.8216	BNYITAL	Zero Mean	1.33	0.9541	ITALIR	Zero Mean	-0.65	0.4358
	Single Mean	-1.41	0.5763		Single Mean	-0.17	0.9392		Single Mean	-0.66	0.8533
	Trend	-1.4	0.8591		Trend	-1.23	0.9032		Trend	-1.59	0.7942
TOTMKJP	Zero Mean	0.52	0.8267	BNYJAPN	Zero Mean	0.05	0.6989	JAPAYE	Zero Mean	-0.29	0.58
	Single Mean	-0.73	0.8376		Single Mean	-1.15	0.6959		Single Mean	-2.3	0.1713
	Trend	-0.79	0.9649		Trend	-1.05	0.9345		Trend	-2.29	0.4375

TOTMKKO	Zero Mean	1.31	0.9527	BNYKORE	Zero Mean	0.6	0.846	KORSWO	Zero Mean	-1.84	0.0634
	Single Mean	-0.41	0.9045		Single Mean	-1.09	0.7219		Single Mean	-2.48	0.1213
	Trend	-1.58	0.7996		Trend	-1.5	0.8274		Trend	-2.99	0.1356
TOTMKLX	Zero Mean	0.24	0.7569	BNYLUXM	Zero Mean	-2	0.0439	LUXFRN	Zero Mean	-0.66	0.4318
	Single Mean	-1.07	0.7284		Single Mean	-1.92	0.3239		Single Mean	-0.66	0.8537
	Trend	-0.96	0.9468		Trend	-2.03	0.5812		Trend	-1.59	0.7948
TOTMKMX	Zero Mean	4.33	0.9999	BNYMEXC	Zero Mean	2.54	0.9975	MEXPES	Zero Mean	0.81	0.8873
	Single Mean	3.57	0.9999		Single Mean	1.72	0.9997		Single Mean	-2.06	0.2601
	Trend	1.2	0.9999		Trend	-0.18	0.9932		Trend	-2.51	0.325
TOTMKNL	Zero Mean	0.13	0.725	BNYNETH	Zero Mean	0.45	0.8108	GUILDE	Zero Mean	-0.66	0.4324
	Single Mean	-1.26	0.6521		Single Mean	-1.14	0.7021		Single Mean	-0.66	0.8536
	Trend	-1.21	0.9056		Trend	-0.99	0.9432		Trend	-1.6	0.7937
TOTMKNZ	Zero Mean	1.75	0.9809	BNYNEWZ	Zero Mean	-0.8	0.3683	NZDOLL	Zero Mean	0.54	0.8321
	Single Mean	0.76	0.9934		Single Mean	-1.91	0.3282		Single Mean	-0.44	0.8993
	Trend	-1.63	0.7793		Trend	-1.97	0.6171		Trend	-2.06	0.5657
TOTMKNW	Zero Mean	2.13	0.9923	BNYNORW	Zero Mean	2.46	0.9969	NORKRO	Zero Mean	-0.65	0.4355
	Single Mean	1.35	0.9989		Single Mean	1.75	0.9997		Single Mean	-0.78	0.8232
	Trend	-0.24	0.9921		Trend	-0.42	0.9868		Trend	-2.01	0.5965
TOTMKPE	Zero Mean	2.81	0.9989	BNYPERU	Zero Mean	-0.1	0.6478	PERUSO	Zero Mean	0.82	0.8887
	Single Mean	2.24	0.9999		Single Mean	-1.28	0.6398		Single Mean	-3.22	0.0197
	Trend	-0.44	0.9858		Trend	-2.57	0.2926		Trend	-2.7	0.2384
TOTMKPH	Zero Mean	0.87	0.8975	BNYPHIL	Zero Mean	2.05	0.9907	PHILPE	Zero Mean	0.7	0.8668
	Single Mean	0.08	0.964		Single Mean	1.59	0.9995		Single Mean	-1.42	0.572
	Trend	-0.28	0.991		Trend	0.29	0.9985		Trend	-0.09	0.9949
TOTMKPT	Zero Mean	0.19	0.742	BNYPORT	Zero Mean	-0.12	0.6432	PORTES	Zero Mean	-0.65	0.4349
	Single Mean	-0.99	0.7591		Single Mean	-1.32	0.6241		Single Mean	-0.66	0.8529
	Trend	-0.57	0.9797		Trend	-0.81	0.9629		Trend	-1.6	0.7919
TOTMKRS	Zero Mean	3.58	0.9999	BNYRUSS	Zero Mean	3.45	0.9999	CISRUB	Zero Mean	0.99	0.9151
	Single Mean	2.65	0.9999		Single Mean	2.5	0.9999		Single Mean	-4.42	0.0004
	Trend	-0.22	0.9926		Trend	0.08	0.9971		Trend	-2.9	0.1645
TOTMKSG	Zero Mean	1.34	0.9553	BNYSING	Zero Mean	-2.62	0.0087	SINGDO	Zero Mean	-0.52	0.489
	Single Mean	0.23	0.9741		Single Mean	-3.07	0.0306		Single Mean	-1.14	0.7032

	Trend	-0.69	0.9729		Trend	-2.68	0.2448		Trend	-1.72	0.7408
TOTMKES	Zero Mean	1.51	0.9677	BNYSPAN	Zero Mean	-3.49	0.0005	SPANPE	Zero Mean	-0.64	0.4387
	Single Mean	0.34	0.9803		Single Mean	-3.76	0.0039		Single Mean	-0.67	0.8526
	Trend	-0.19	0.9932		Trend	-3.28	0.0722		Trend	-1.61	0.7888
TOTMKSD	Zero Mean	0.78	0.8818	BNYSWED	Zero Mean	-0.81	0.3655	SWEKRO	Zero Mean	-0.54	0.4827
	Single Mean	-0.79	0.821		Single Mean	-1.87	0.3474		Single Mean	-0.83	0.808
	Trend	-0.86	0.9583		Trend	-2.88	0.1708		Trend	-1.52	0.8227
TOTMKSW	Zero Mean	0.67	0.8599	BNYSWIT	Zero Mean	1	0.9165	SWISSF	Zero Mean	-0.61	0.4512
	Single Mean	-0.68	0.8497		Single Mean	-0.53	0.8816		Single Mean	-0.96	0.7673
	Trend	-0.67	0.9741		Trend	-1.48	0.8356		Trend	-2.06	0.5667
TOTMKTA	Zero Mean	-0.52	0.4886	BNYTAIW	Zero Mean	-0.51	0.4959	TAIWDO	Zero Mean	-0.09	0.6514
	Single Mean	-1.92	0.324		Single Mean	-2.09	0.2492		Single Mean	-1.85	0.3572
	Trend	-1.73	0.7367		Trend	-2.14	0.5219		Trend	-1.83	0.689
TOTMKTK	Zero Mean	1.51	0.9684	BNYTURK	Zero Mean	-1.67	0.0895	TURKLI	Zero Mean	0.77	0.8802
	Single Mean	-0.11	0.9467		Single Mean	-2.54	0.1078		Single Mean	-2.05	0.2646
	Trend	-1.67	0.7618		Trend	-4.82	0.0005		Trend	-1.31	0.8827
TOTMKUK	Zero Mean	0.39	0.7949	BNYUKAD	Zero Mean	0.66	0.8585	USBRITP	Zero Mean	-0.74	0.395
	Single Mean	-1.07	0.7279		Single Mean	-0.77	0.8252		Single Mean	-0.61	0.8648
	Trend	-0.92	0.9524		Trend	-0.76	0.967		Trend	-2.19	0.4915
TOTMKUS	Zero Mean	0.65	0.8558								
	Single Mean	-1.69	0.4354								
	Trend	-1.69	0.7537								

Table 3a: Impulse Response by variable and their respective ratios by country (weekly returns)

Orthogonalized Impulse Response by Variable						T-ratio			
		Home	US	EX	ADR	Home	US	EX	ADR
ARGENTINA	**0**	**0.03342**	**-0.00090**	**-0.01390**	**0.02763**	**13.53036**	**-0.37610**	**-9.20530**	**11.18623**
	1	0.04179	0.00333	-0.01649	0.02824	20.09135	1.64851	-7.81517	7.67391
	2	0.04546	0.00131	-0.01659	0.03068	5.60543	0.30465	-2.85542	5.39192
	3	0.04474	-0.00097	-0.01701	0.03037	2.79276	-0.21272	-2.49048	5.74102
	4	0.04214	-0.00259	-0.01708	0.03041	1.72634	-0.30579	-1.76264	5.19829
	5	0.04279	-0.00367	-0.01891	0.03069	1.17587	-0.31665	-1.28552	4.67123
	6	0.04243	-0.00349	-0.01913	0.03070	0.77925	-0.22473	-1.10514	3.05169
	7	0.04187	-0.00363	-0.01944	0.03056	0.56330	-0.17587	-0.97297	2.24541
	8	0.04149	-0.00402	-0.01946	0.03068	0.43160	-0.15539	-0.82249	1.68757
AUSTRALIA	0	0.01877	-0.00053	-0.01395	0.01136	17.70755	-0.22108	10.98425	5.79592
	1	0.00103	0.00003	0.00007	-0.00066	.	0.03205	.	-0.76022
	2	0.00235	0.00028	0.00060	0.00123	1.03982	0.20086	.	.
	3	0.00139	-0.00167	0.00060	0.00074	.	.	.	.
	4	-0.00171	-0.00130	-0.00154	-0.00343	-0.31319	-0.97744	0.53472	-1.89503
	5	0.00007	0.00001	0.00034	0.00079	.	0.02170	.	.
	6	-0.00022	-0.00038	-0.00000	0.00030	.	-0.46681	0.00077	.
	7	-0.00172	0.00029	0.00019	-0.00121	-0.64662	0.18479	-0.13444	-0.90977
	8	-0.00075	0.00019	0.00021	-0.00002	-0.26462	0.17463	-0.10729	-0.02290
CHINA	**0**	**0.00493**	**-0.00461**	**-0.00222**	**0.04524**	**3.57246**	**-3.24648**	**-4.63950**	**29.56863**
	1	0.00884	-0.00412	-0.00317	0.04526	4.05505	-2.19149	-1.48131	16.82528
	2	0.01089	-0.00143	-0.00366	0.04583	1.27967	-0.20113	-1.54430	7.53783
	3	0.01199	-0.00408	-0.00707	0.04732	0.83964	-0.57546	-2.20249	6.78910
	4	0.01000	-0.00546	-0.00439	0.04998	0.46992	-0.44068	-0.70240	6.09512
	5	0.00961	-0.00491	-0.00414	0.05056	0.32609	-0.21592	-0.44325	3.94692
	6	0.00929	-0.00485	-0.00410	0.05248	0.27957	-0.13280	-0.26333	3.03002
	7	0.00884	-0.00447	-0.00356	0.05150	0.18486	-0.06965	-0.14133	1.62358
	8	0.00808	-0.00424	-0.00362	0.05127	0.15647	-0.03949	-0.09444	1.48997
JAPAN	**0**	**0.02747**	**0.00062**	**-0.01212**	**0.01500**	**14.01531**	**0.22008**	**-8.35862**	**6.07287**
	1	-0.00193	-0.00064	0.00234	-0.00233	-25.06494	-5.78374	20.76677	-8.04169
	2	0.00076	0.00073	-0.00064	-0.00059	12.71895	8.37113	-6.43993	-4.06262
	3	-0.00031	-0.00117	-0.00112	-0.00174	-3.40884	-8.66602	-6.76002	-7.71413
	4	0.00062	-0.00055	-0.00028	0.00098	15.79389	-9.49965	-4.34435	8.46471
	5	-0.00008	-0.00002	0.00005	-0.00050	-2.84259	-0.51612	1.12617	-14.88965
	6	0.00016	0.00006	0.00027	0.00032	12.16592	2.90890	10.16579	8.66344
	7	-0.00048	0.00001	-0.00019	-0.00056	-28.20841	0.27044	-5.90724	-9.74081
	8	-0.00039	0.00004	-0.00002	-0.00020	-345.04425	18.26407	-3.69637	-5.89727
GERMANY	**0**	**0.03268**	**-0.00081**	**-0.01179**	**0.02213**	**16.42211**	**-0.40892**	**-11.44660**	**8.74704**
	1	0.00000	0.00251	-0.00084	0.00121	0.06989	21.40908	-5.66478	3.75310
	2	0.00006	0.00065	0.00149	-0.00099	1.36060	10.07506	17.84645	-7.06777
	3	0.00090	-0.00045	-0.00147	0.00248	10.10696	-3.52391	-11.22909	15.18119
	4	-0.00117	-0.00023	0.00132	0.00162	-8.82486	-1.25057	7.21154	10.29421
	5	0.00240	-0.00029	-0.00009	0.00013	32.74662	-2.74725	-0.90131	0.74562
	6	0.00130	0.00019	-0.00029	0.00033	48.11251	4.81482	-7.53519	3.48854
	7	-0.00055	0.00023	0.00017	0.00015	-20.05698	5.83894	4.26892	3.03974

	8	-0.00037	-0.00015	0.00010	0.00016	-17.67163	-4.88355	3.23697	4.64727
AUSTRIA	0	0.01219	-0.00002	-0.01223	0.02921	12.65455	-0.01233	-15.14307	18.37107
	1	0.01746	0.00079	-0.01029	0.02327	8.95385	0.42683	-5.35938	9.53689
	2	0.01929	0.00107	-0.00863	0.02360	4.65942	0.28158	-2.15212	5.57920
	3	0.01648	-0.00001	-0.01044	0.02373	5.19874	-0.00212	-3.40065	7.02071
	4	0.01712	0.00017	-0.01403	0.02627	4.00937	0.04628	-3.54293	6.42298
	5	0.01855	0.00072	-0.01312	0.02622	3.98925	0.18524	-3.05828	6.05543
	6	0.01828	0.00049	-0.01355	0.02571	3.80833	0.12378	-3.06561	5.79054
	7	0.01771	0.00102	-0.01434	0.02564	3.72059	0.25758	-3.25909	5.78781
	8	0.01829	0.00141	-0.01514	0.02609	3.73265	0.34729	-3.35698	5.75938
BELGIUM	0	0.02180	0.00297	-0.00417	0.06118	19.29204	2.04828	-6.12461	26.83333
	1	0.00241	-0.00166	-0.00161	-0.00167	21.62017	-10.30288	-9.50975	-8.84206
	2	0.00248	0.00034	0.00186	0.00206	53.98346	5.16002	17.59032	12.22334
	3	0.00255	-0.00274	-0.00135	0.00152	32.57953	-20.02192	-8.01996	6.30339
	4	0.00262	-0.00183	-0.00286	0.00899	1073.77049	-26.55252	-21.44732	24.18422
	5	-0.00083	0.00016	0.00011	-0.00056	-38.54225	5.13506	3.70685	-12.23079
	6	0.00044	-0.00032	0.00030	0.00049	58.99191	-20.50097	12.90056	12.47536
	7	-0.00096	-0.00021	-0.00064	0.00006	-33.94307	-5.12043	-12.47381	0.96386
	8	-0.00118	-0.00001	-0.00044	0.00115	-23.52003	-0.10519	-5.80773	16.25671
BRAZIL	0	0.04701	0.00094	-0.01740	0.01955	16.32292	0.27416	-7.37288	4.00615
	1	0.00063	-0.00034	0.00093	-0.00491	1.68831	-0.64632	1.53809	-12.83190
	2	0.00476	-0.00103	0.00089	-0.00177	16.34840	-2.50255	2.05220	-4.07402
	3	0.00319	-0.00659	-0.00027	0.00051	43.20152	-27.73919	-0.79342	0.44303
	4	0.00096	-0.00001	-0.00134	0.00142	11.79128	-0.06592	-11.46671	7.06116
	5	0.00093	-0.00042	0.00039	-0.00010	22.28633	-6.89904	6.45778	-0.88029
	6	-0.00091	-0.00021	0.00011	-0.00048	-191.96211	-24.16985	6.12978	-4.84723
	7	-0.00367	0.00037	0.00065	-0.00192	-179.37439	11.06348	10.57319	-4.99701
	8	-0.00031	-0.00018	-0.00030	0.00053	-6.17324	-2.46892	-3.89101	8.43223
CHILE	0	0.02536	0.00069	-0.01006	0.01366	16.57516	0.22955	-8.04800	6.07111
	1	0.00648	0.00001	-0.00316	0.00080	41.42958	0.03446	-12.71886	1.37375
	2	0.00227	0.00112	-0.00007	0.00095	127.02854	24.89442	-1.17940	3.89286
	3	0.00178	-0.00414	-0.00014	-0.00321	7.13398	-11.04884	-0.33088	-5.01179
	4	-0.00032	-0.00159	-0.00250	-0.00209	-3.05448	-10.10743	-11.17968	-4.74310
	5	-0.00060	-0.00019	-0.00020	-0.00006	-35.22137	-7.74043	-7.73280	-0.94923
	6	0.00126	0.00007	-0.00013	0.00041	72.83237	2.67616	-5.19454	4.02623
	7	-0.00114	0.00061	0.00085	-0.00107	-40.83095	13.37298	16.72914	-6.87440
	8	-0.00112	0.00024	0.00070	-0.00025	-55.09100	7.99733	18.83967	-2.16224
COLOMBIA	0	0.02170	0.00033	-0.01218	0.05250	16.95313	0.20521	-18.37104	24.76415
	1	0.03005	0.01003	-0.01486	0.05115	11.12963	3.84291	-5.40364	14.09091
	2	0.03617	0.01276	-0.01838	0.05253	3.95301	2.23860	-2.87188	7.97117
	3	0.04143	0.01192	-0.02199	0.04928	2.72208	2.09859	-3.53537	8.15894
	4	0.03975	0.01059	-0.02337	0.05273	1.73127	1.06862	-2.97707	7.29322
	5	0.04227	0.01020	-0.02612	0.05322	1.22486	0.70883	-2.90222	5.63771
	6	0.04274	0.01050	-0.02687	0.05332	0.80870	0.46854	-2.63949	2.67671
	7	0.04324	0.01129	-0.02712	0.05155	0.58236	0.35548	-2.36443	1.69072
	8	0.04325	0.01062	-0.02737	0.05036	0.42911	0.24285	-2.17050	1.12436
DENMARK	0	0.02292	-0.00102	-0.01111	0.02862	18.33600	-0.56354	-13.18288	16.93491
	1	-0.00081	0.00208	0.00274	-0.00170	-119.34412	32.86459	22.88291	-7.08570

	2	0.00030	-0.00068	-0.00006	-0.00210	4.28473	-6.90929	-0.56392	-20.97064
	3	0.00046	0.00061	0.00094	-0.00179	7.58511	6.87261	10.23080	-18.32327
	4	-0.00199	-0.00040	-0.00046	-0.00204	-291.78886	-24.30505	-9.25236	-14.22693
	5	0.00137	-0.00014	0.00008	0.00067	51.52313	-3.65830	1.86869	8.40233
	6	-0.00019	-0.00005	-0.00007	0.00010	-21.70998	-3.74014	-5.55232	8.33140
	7	0.00025	0.00008	0.00012	0.00024	257.17180	27.74386	13.72189	12.26606
	8	0.00004	-0.00004	-0.00008	0.00006	374.89609	-35.97321	-30.29719	9.81639
FINLAND	0	0.05228	-0.00335	-0.01027	0.02237	12.21495	-1.08065	-6.75658	4.53753
	1	0.05190	-0.00119	-0.01028	0.02377	18.02083	-0.58621	-3.80741	4.25986
	2	0.05247	-0.00035	-0.00843	0.02023	7.87838	-0.06554	-0.97344	0.85431
	3	0.05296	-0.00482	-0.01030	0.01962	0.56007	-0.19112	-0.69035	0.17830
	4	0.05218	-0.00767	-0.00510	0.01422	0.12679	-0.07444	-0.09853	0.05033
	5	0.05280	-0.00725	-0.00486	0.01583	0.03747	-0.03229	-0.03648	0.02734
	6	0.05106	-0.00622	-0.00495	0.01667	0.02104	-0.00688	-0.01082	0.00448
	7	0.04586	-0.00541	-0.00451	0.01531	0.00401	-0.00113	-0.00212	0.00125
	8	0.04065	-0.00444	-0.00431	0.01483	0.00079	-0.00037	-0.00085	0.00060
FRANCE	0	0.02487	-0.00132	-0.01114	0.01278	11.25339	-0.55462	-8.70313	5.46154
	1	0.00233	0.00116	-0.00126	-0.00443	5.74344	2.01925	-2.30461	-10.15985
	2	-0.00162	0.00079	0.00181	0.00319	-5.42314	1.85882	4.47278	9.02226
	3	0.00127	-0.00130	-0.00109	-0.00202	6.45588	-4.60944	-3.98115	-6.72750
	4	-0.00038	0.00023	-0.00061	0.00171	-2.89011	1.26155	-3.37624	12.45357
	5	0.00074	-0.00016	0.00037	0.00025	241.11148	-24.85236	15.70633	3.19641
	6	0.00145	-0.00005	-0.00047	-0.00002	27.01192	-0.69863	-6.44217	-0.17138
	7	-0.00171	0.00021	0.00031	-0.00039	-55.55556	4.86597	6.76115	-2.63949
	8	0.00027	-0.00005	-0.00002	0.00027	25.13352	-3.29776	-1.13758	9.97459
GREECE	0	0.02661	-0.00264	-0.01051	0.14034	16.84177	-1.42703	-13.11815	25.89299
	1	0.00190	0.00703	-0.00600	0.00225	0.25606	0.93484	-0.80000	0.29723
	2	0.00047	-0.00008	-0.00032	0.00030	0.37200	-0.07358	-0.45133	0.35169
	3	0.00007	0.00007	-0.00003	0.00005	0.35300	0.60438	-0.29787	0.51766
	4	0.00001	0.00000	-0.00001	0.00000	0.29220	0.17592	-0.37938	0.24875
	5	0.00000	0.00000	0.00000	0.00000	0.27993	0.35987	-0.25707	0.34320
	6	0.00000	0.00000	0.00000	0.00000	0.24368	0.23402	-0.27901	0.24716
	7	0.00000	0.00000	0.00000	0.00000	0.22654	0.25592	-0.23021	0.25648
	8	0.00000	0.00000	0.00000	0.00000	0.20547	0.21451	-0.22241	0.21942
HUNGARY	0	0.03774	-0.00377	-0.01018	0.02961	16.26724	-1.65351	-9.25455	11.00743
	1	0.03427	0.00179	-0.01332	0.02874	15.64840	0.86893	-5.81659	8.35465
	2	0.03682	0.00085	-0.01446	0.02956	4.80052	0.21035	-2.90946	5.77344
	3	0.03654	-0.00190	-0.01551	0.02903	2.87264	-0.46117	-3.76456	6.73550
	4	0.04128	-0.00314	-0.01496	0.02952	2.39166	-0.40308	-2.49333	5.51776
	5	0.04243	-0.00246	-0.01393	0.03016	1.61454	-0.25492	-1.96197	5.39535
	6	0.04131	-0.00184	-0.01373	0.02991	1.05383	-0.14353	-1.86296	3.63426
	7	0.03916	-0.00131	-0.01372	0.02869	0.76365	-0.07830	-1.70435	2.66636
	8	0.03807	-0.00110	-0.01359	0.02761	0.57954	-0.05486	-1.54608	1.91736
INDIA	0	0.04231	-0.00339	-0.00285	0.06706	21.92228	-1.99412	-4.84999	20.07784
	1	0.04351	-0.00094	-0.00073	0.05120	10.87750	-0.26764	-0.17967	10.24000
	2	0.05506	0.00666	0.00257	0.04847	4.20305	0.84304	0.26855	5.87515
	3	0.05038	0.00028	-0.00068	0.05027	2.55606	0.02732	-0.06767	6.92424
	4	0.05179	0.00120	0.00113	0.04514	1.72864	0.08493	0.07166	5.41897

	5	0.05223	0.00222	0.00047	0.04554	1.22836	0.08006	0.03034	3.00991
	6	0.05180	0.00313	-0.00116	0.04673	0.74447	0.07394	-0.07047	1.36637
	7	0.04961	0.00571	-0.00086	0.04006	0.45514	0.11759	-0.04691	0.89062
	8	0.04908	0.00705	-0.00163	0.03948	0.28705	0.08720	-0.06797	0.55684
INDONESIA	0	0.04733	-0.00128	-0.01185	0.03631	19.08468	-0.52459	-6.92982	10.80655
	1	-0.00022	0.00341	-0.00227	0.00070	-3.50480	24.33976	-11.99789	1.78960
	2	0.00559	-0.00327	0.00181	0.00451	188.27888	-30.48098	9.64819	8.58100
	3	0.00479	-0.00225	-0.00434	0.00502	56.67298	-15.88759	-27.23394	10.07082
	4	0.00037	0.00059	-0.00125	0.00130	6.84212	7.64494	-16.48859	11.34479
	5	0.00148	-0.00389	0.00536	0.00142	26.72445	-27.22564	19.89016	2.69378
	6	-0.00051	0.00061	-0.00113	-0.00020	-23.35454	17.17436	-22.30997	-2.06807
	7	-0.00235	-0.00025	0.00147	0.00020	-33.89586	-2.52669	10.84791	1.21947
	8	0.00011	-0.00024	0.00015	0.00004	26.19259	-25.59728	11.41921	1.24735
IRELAND	0	0.02529	-0.00047	-0.01044	0.01275	11.70833	-0.16195	7.62044	5.42553
	1	0.00180	0.00070	0.00101	-0.00118	13.22946	3.63572	-5.13420	-5.29362
	2	-0.00052	0.00110	0.00083	0.00416	-1.66101	2.48201	-1.89736	10.27389
	3	-0.00125	-0.00270	0.00010	0.00131	-9.38016	-12.94405	-0.46808	2.95972
	4	0.00037	0.00007	-0.00098	-0.00097	4.34762	0.57635	7.98061	-6.63291
	5	0.00067	-0.00032	0.00019	-0.00032	15.40913	-5.18627	-2.99161	-3.91399
	6	0.00050	-0.00005	-0.00011	0.00042	41.94908	-2.85294	6.72264	8.33174
	7	-0.00210	0.00032	0.00005	-0.00047	-57.55001	6.06777	-0.81309	-2.57293
	8	-0.00017	-0.00008	-0.00002	0.00016	-9.94819	-3.51988	0.97774	7.10589
ISRAEL	0	0.02502	0.00040	-0.00465	0.02619	15.93631	0.21057	-6.16801	15.58929
	1	0.00221	0.00172	0.00033	-0.00432	10.82113	5.86770	1.04673	-17.53176
	2	0.00150	0.00214	0.00364	-0.00004	15.23926	13.73468	20.59756	-0.10573
	3	0.00224	-0.00263	0.00032	-0.00099	21.29682	-15.12363	1.60733	-3.66735
	4	-0.00065	-0.00085	0.00069	0.00045	-24.84530	-18.75204	9.62460	4.13537
	5	0.00163	0.00023	-0.00056	0.00050	50.44878	5.02758	-9.41208	4.80943
	6	0.00114	-0.00021	-0.00003	0.00033	41.74295	-5.39007	-0.62257	4.97419
	7	-0.00131	0.00042	0.00013	-0.00028	-39.74515	8.59499	2.34560	-3.40605
	8	-0.00023	-0.00018	0.00017	-0.00020	-996.04923	-31.48325	16.98106	-7.92072
ITALY	0	0.02090	-0.00025	-0.01213	0.01340	10.39801	-0.10553	-10.27966	7.12766
	1	0.00358	0.00065	0.00129	-0.00811	6.17913	0.79713	1.62986	-12.50675
	2	-0.00016	0.00117	-0.00081	0.00190	-1.46700	7.31159	-5.00752	9.27417
	3	-0.00174	-0.00076	-0.00088	-0.00103	-168.11594	-27.71968	-12.46155	-5.17900
	4	-0.00040	-0.00071	0.00025	-0.00074	-13.71655	-15.36132	4.80152	-6.73313
	5	0.00085	-0.00022	0.00044	0.00060	85.85685	-13.41455	12.86254	6.25987
	6	0.00138	-0.00007	0.00002	0.00039	61.14311	-2.22811	0.57625	3.72908
	7	-0.00047	0.00016	-0.00007	-0.00032	-131.73315	20.73440	-5.07791	-6.75805
	8	-0.00082	0.00010	-0.00003	-0.00006	-35.14643	3.19293	-0.81580	-0.99198
KOREA	0	0.03778	-0.00301	-0.00808	0.03257	14.04461	-1.44712	-8.62299	12.57529
	1	-0.00531	-0.00207	0.00108	-0.00178	-53.84849	-13.18471	5.55927	-4.56223
	2	0.00406	0.00003	0.00060	0.00044	32.10247	0.19371	3.43220	1.78613
	3	0.00127	-0.00126	-0.00254	0.00075	68.98425	-25.21513	-25.45345	3.12503
	4	0.00560	-0.00342	0.00316	0.00052	26.95807	-10.92861	10.04418	0.98070
	5	-0.00203	0.00040	0.00084	0.00064	-26.01897	3.60858	5.96861	4.52245
	6	0.00016	0.00006	0.00076	0.00003	11.32958	2.82176	29.05124	0.57446
	7	-0.00037	-0.00071	0.00068	0.00048	-18.78106	-20.22455	11.07715	5.31116

	8	-0.00098	0.00008	0.00018	-0.00125	-70.03515	4.12804	7.70187	-16.74930
MEXICO	0	0.03918	0.00064	-0.00478	0.01335	12.39873	0.17303	-2.86228	3.11916
	1	0.00161	-0.00086	-0.00050	-0.00331	4.57399	-1.72348	-0.90538	-10.24039
	2	0.00091	0.00037	-0.00065	0.00210	5.33166	1.54463	-2.56390	11.54163
	3	0.00104	-0.00346	0.00417	-0.00132	5.07490	-11.19306	13.23389	-1.50000
	4	0.00354	-0.00023	0.00103	-0.00071	18.16689	-0.82079	3.77801	-1.88840
	5	-0.00055	0.00040	0.00066	-0.00056	-13.14340	6.59980	11.21744	-3.93432
	6	-0.00005	0.00007	-0.00031	0.00071	-0.70401	0.71679	-3.02389	14.27583
	7	-0.00268	0.00021	0.00060	-0.00065	-128.59885	6.77860	14.67953	-2.14314
	8	0.00012	0.00013	0.00033	0.00015	18.74092	12.18094	15.28571	2.59226
NETHERLANDS	0	0.02590	-0.00119	-0.01157	0.01088	9.62825	-0.43431	-7.76510	3.88571
	1	0.00248	0.00175	-0.00025	-0.00669	3.65884	1.82043	-0.26929	-9.50703
	2	-0.00107	0.00035	0.00176	0.00440	-2.40077	0.55842	2.98184	9.34699
	3	-0.00157	-0.00026	0.00038	-0.00056	-300.76628	-19.27253	18.50870	-3.29904
	4	-0.00158	-0.00061	0.00026	0.00116	-10.05409	-2.74214	1.22841	5.11938
	5	0.00094	0.00003	0.00022	-0.00043	13.94560	0.29964	2.39080	-3.91347
	6	0.00137	-0.00003	-0.00066	-0.00041	15.58058	-0.20317	-5.65646	-2.51887
	7	-0.00016	0.00021	0.00003	0.00005	-15.40212	13.18147	2.04335	1.14378
	8	-0.00061	0.00005	0.00011	-0.00010	-48.85242	2.78800	6.20740	-1.61370
NEW ZEALAND	0	0.02278	-0.00066	-0.01422	0.02144	23.34279	-0.29662	13.41509	11.84530
	1	0.00212	0.00159	-0.00170	-0.00113	21.07356	10.52074	8.97287	-4.86943
	2	0.00379	-0.00244	0.00036	-0.00001	30.31757	-12.43692	-1.72034	-0.02924
	3	-0.00038	0.00091	0.00278	-0.00006	-367.83495	34.51626	-27.55749	-0.31621
	4	-0.00016	-0.00186	-0.00269	-0.00226	-2.90655	-18.69535	13.77439	-7.45579
	5	-0.00017	0.00054	-0.00007	0.00069	-6.04429	12.43479	1.44559	10.46332
	6	-0.00025	-0.00012	0.00012	-0.00026	-625.13811	-28.55366	-18.63226	-11.02717
	7	-0.00016	-0.00006	0.00003	0.00023	-12.52047	-3.23765	-1.56561	14.88066
	8	-0.00038	0.00024	0.00012	-0.00013	-48.99740	17.72660	-7.47532	-3.84079
NORWAY	0	0.02648	-0.00145	-0.01306	0.01739	13.86387	-0.57087	-10.61789	7.79821
	1	0.02956	-0.00053	-0.01162	0.01634	18.13497	-0.39099	-7.17284	5.77385
	2	0.03359	-0.00030	-0.00910	0.01482	5.70289	-0.09570	-2.69231	3.57108
	3	0.03091	-0.00180	-0.00928	0.01797	2.69721	-0.47120	-3.58301	4.97784
	4	0.03208	-0.00100	-0.00908	0.01774	1.89822	-0.12674	-2.25871	4.23389
	5	0.03277	-0.00155	-0.00907	0.01776	1.26427	-0.13362	-1.70810	4.03636
	6	0.03278	-0.00097	-0.00901	0.01738	0.81522	-0.06267	-1.78063	2.83524
	7	0.03174	-0.00089	-0.00908	0.01816	0.57355	-0.04173	-1.53120	2.34929
	8	0.03215	-0.00104	-0.00912	0.01803	0.44144	-0.03662	-1.34911	1.76074
PERU	0	0.03474	-0.00037	0.00002	0.04089	29.94828	-0.17740	0.02515	17.70130
	1	0.03612	0.00228	-0.00137	0.03636	14.80328	0.92683	-0.55020	10.75740
	2	0.03682	0.00148	-0.00076	0.03617	3.35643	2.40135	-0.76585	3.93152
	3	0.03675	0.00104	-0.00056	0.03551	6.31443	1.47127	-0.42840	1.60316
	4	0.03669	0.00051	-0.00028	0.03488	10.16343	0.23654	-0.06309	0.69069
	5	0.03661	0.00000	-0.00002	0.03427	3.20017	0.00117	-0.00326	0.37951
	6	0.03653	-0.00050	0.00023	0.03366	1.48980	-0.06218	0.01611	0.22136
	7	0.03646	-0.00099	0.00049	0.03306	0.73198	-0.07480	0.02152	0.13596
	8	0.03638	-0.00148	0.00074	0.03246	0.42258	-0.06795	0.01971	0.08668
PHILIPPINES	0	0.02277	0.00430	-0.00339	0.03905	15.28188	2.42938	-4.82823	22.31429
	1	0.00550	0.00206	0.00321	-0.00131	22.46181	5.89903	9.56268	-3.29369

	2	0.00292	0.00143	0.00113	0.00035	27.89720	9.40295	7.42200	1.74504
	3	0.00085	-0.00026	-0.00007	0.00371	20.57976	-4.16729	-1.04231	26.68297
	4	0.00149	-0.00300	-0.00294	0.00057	1565.49029	-31.72589	-15.71352	1.80225
	5	0.00107	0.00024	0.00070	0.00061	33.02469	5.15022	16.28949	7.31301
	6	0.00060	0.00038	-0.00018	-0.00002	32.25134	13.18261	-5.03158	-0.53619
	7	-0.00010	-0.00013	-0.00013	-0.00007	-27.15065	-20.37307	-16.31068	-4.62932
	8	-0.00053	-0.00010	-0.00023	-0.00013	-29.64338	-3.80071	-9.82973	-3.81904
PORTUGAL	0	0.02196	-0.00178	-0.01233	0.01623	15.25000	-0.70916	-10.62931	8.86885
	1	0.00367	0.00080	-0.00026	-0.00176	18.16832	2.78158	-0.91641	-6.13497
	2	-0.00049	-0.00192	-0.00109	0.00251	-3.88083	-9.95334	-5.47381	9.44426
	3	-0.00044	-0.00159	-0.00176	-0.00160	-6.67016	-15.37718	-11.63098	-6.03546
	4	0.00087	-0.00095	0.00096	-0.00101	11.63677	-8.63467	8.27570	-6.40132
	5	0.00098	-0.00001	0.00003	0.00016	39.75081	-0.17349	0.78538	2.48193
	6	-0.00086	0.00042	-0.00002	0.00008	-26.11887	8.83243	-0.36313	1.12342
	7	-0.00070	0.00005	-0.00026	-0.00018	-49.12685	2.39022	-10.41847	-3.21974
	8	-0.00053	0.00002	-0.00005	-0.00046	-127.05556	2.98296	-3.85522	-10.03122
RUSSIA	0	0.05895	0.00153	-0.00677	0.05053	18.42188	0.68000	-2.93074	12.76010
	1	0.06851	0.00499	-0.00959	0.05756	18.87328	1.50301	-2.64917	9.89003
	2	0.07443	0.00548	-0.02289	0.06534	8.81872	0.69987	-2.73150	4.14857
	3	0.07801	0.00234	-0.01946	0.05984	6.88526	0.34012	-1.84455	1.60171
	4	0.07390	0.00551	-0.03180	0.06458	3.32284	0.75171	-0.78519	1.32608
	5	0.07367	0.00394	-0.02987	0.06647	2.67308	0.36114	-0.40595	1.43688
	6	0.07513	0.00500	-0.03164	0.06868	0.78350	0.41946	-0.54336	1.33853
	7	0.07449	0.00377	-0.03036	0.06922	0.53310	0.31443	-0.22970	1.27360
	8	0.07622	0.00272	-0.03114	0.07093	0.69728	0.14338	-0.12624	0.99425
SINGAPORE	0	0.04144	-0.00314	-0.01177	0.06508	31.63359	-1.89157	-19.44426	18.64756
	1	0.00218	0.00026	0.00577	0.00181	27.03038	2.25843	24.64548	2.77701
	2	0.00429	0.00520	0.00370	-0.00086	21.21662	14.80174	9.25833	-1.31890
	3	-0.00492	-0.00152	-0.00409	0.00239	-18.61662	-4.00464	-10.89446	4.57478
	4	-0.00273	-0.00148	0.00153	0.00236	-19.05227	-7.08337	6.18482	8.25377
	5	0.00220	-0.00159	0.00089	0.00037	27.34958	-12.60105	6.39104	1.75117
	6	0.00278	-0.00040	0.00042	0.00193	43.93868	-4.45425	4.77706	9.97107
	7	-0.00115	0.00072	0.00040	-0.00033	-34.85905	13.53525	6.28563	-3.32957
	8	-0.00125	0.00015	-0.00029	-0.00050	-33.44929	2.76469	-5.53897	-5.87647
SPAIN	0	0.02950	-0.00605	-0.01392	0.09719	23.60000	-4.26056	-19.70583	24.05693
	1	0.00220	0.00136	-0.00441	-0.00164	17.65650	7.40056	-18.84213	-5.64447
	2	-0.00084	0.00062	-0.00205	-0.00152	-328.75097	27.08341	-22.45345	-11.20118
	3	-0.00629	-0.00015	-0.00392	0.00263	-25.60658	-0.44416	-9.86238	6.57106
	4	0.00031	-0.01572	0.00767	0.00103	7.38199	-26.38824	8.70266	0.78626
	5	0.00268	0.00069	-0.00002	0.00001	26.86717	4.83471	-0.16793	0.03360
	6	-0.00127	0.00152	0.00070	0.00139	-18.84553	13.55449	5.44779	9.04241
	7	0.00043	-0.00058	-0.00029	-0.00100	14.63492	-12.00230	-5.32853	-15.07841
	8	-0.01396	0.00150	0.00194	-0.00205	-27.65068	2.09544	2.72491	-2.64335
SWEDEN	0	0.04652	-0.00172	-0.01399	0.02898	20.49339	-0.79263	-12.27193	7.96154
	1	0.00437	0.00273	0.00094	-0.00205	17.66799	7.42393	2.48038	-4.33945
	2	0.00113	0.00243	0.00099	-0.00186	8.61018	11.74424	4.49183	-5.66193
	3	0.00169	-0.00563	0.00055	0.00005	26.10442	-28.03226	2.01478	0.07112
	4	-0.00024	-0.00242	0.00035	0.00320	-1.37977	-9.33354	1.27460	9.57024

	5	0.00289	-0.00004	0.00041	-0.00018	27.60531	-0.24615	2.77260	-0.85086
	6	0.00220	-0.00013	-0.00048	0.00091	90.38620	-3.66851	-14.04265	5.57956
	7	-0.00542	0.00084	0.00067	-0.00041	-34.28861	3.76017	2.97581	-1.02996
	8	-0.00225	-0.00048	0.00043	-0.00134	-1119.40299	-25.69441	15.93324	-7.28340
SWITZERLAND	0	0.01839	-0.00139	-0.01187	0.02416	13.32609	-0.86335	-14.34510	16.66207
	1	0.00240	0.00264	-0.00134	-0.00243	14.53312	10.31734	-5.28808	-7.80999
	2	-0.00078	0.00097	0.00146	0.00009	-16.42069	13.67410	18.17050	0.68738
	3	-0.00082	0.00031	0.00047	-0.00406	-8.80434	2.33214	3.89921	-25.26447
	4	0.00277	-0.00102	0.00101	-0.00144	22.02083	-5.70055	5.21506	-7.23109
	5	0.00229	-0.00034	-0.00048	0.00016	29.81383	-3.13905	-4.56500	1.19062
	6	0.00095	-0.00013	0.00016	0.00111	206.39394	-16.99868	6.73973	16.31154
	7	-0.00027	-0.00007	-0.00003	0.00042	-12.69958	-2.15291	-1.16123	17.68423
	8	-0.00114	0.00013	0.00013	-0.00041	-42.85714	3.52278	3.25704	-6.26337
TAIWAN	0	0.04762	-0.00246	-0.00452	0.05537	23.11650	-1.41379	-6.97875	17.35737
	1	-0.00331	-0.00432	-0.00351	-0.00609	-229.86111	-30.73421	-12.60323	-9.42797
	2	-0.00222	0.00433	0.00375	0.00129	-35.54275	26.82776	12.58305	2.17399
	3	0.00268	-0.00280	-0.00080	-0.00504	12.47963	-8.70999	-2.16440	-14.31127
	4	0.00281	-0.00325	-0.00347	-0.00259	23.14662	-16.16353	-10.92810	-4.82840
	5	-0.00099	0.00052	-0.00023	-0.00042	-42.19821	13.63878	-5.78157	-5.31149
	6	0.00122	-0.00060	-0.00004	0.00318	25.59262	-8.72447	-0.49633	23.61678
	7	-0.00142	0.00006	-0.00042	-0.00072	-44.58399	1.32522	-9.98438	-7.33534
	8	-0.00094	0.00053	0.00004	-0.00134	-140.63079	29.30466	1.65277	-16.55343
TURKEY	0	0.06107	-0.00264	-0.02222	0.06079	18.90712	-1.20000	-10.48113	11.71291
	1	0.06255	-0.00334	-0.00277	0.05136	13.77753	-0.68724	-0.55734	7.38993
	2	0.06875	-0.00871	0.00783	0.05600	6.68774	-0.91492	0.76241	2.33431
	3	0.06871	-0.01329	0.00576	0.06240	3.40486	-1.89586	0.32690	1.02665
	4	0.06973	-0.01148	0.01295	0.05326	3.03438	-1.02592	0.13285	0.63968
	5	0.06836	-0.01607	0.01111	0.05463	1.78672	-0.73885	0.08620	0.55893
	6	0.06644	-0.01659	0.01033	0.05303	0.35740	-0.63008	0.09925	0.44804
	7	0.06729	-0.01783	0.01091	0.04902	0.42724	-0.26178	0.02337	0.18456
	8	0.06772	-0.01964	0.00871	0.04908	0.29227	-0.30601	0.01491	0.08066
UK	0	0.01895	-0.00018	-0.00900	0.00851	9.57071	-0.07142	-7.14286	4.27638
	1	-0.00001	0.00138	-0.00028	-0.00291	-0.01027	1.22124	-0.25087	-2.53043
	2	-0.00090	-0.00013	0.00040	0.00089	-0.83016	-0.12591	0.37032	0.80469
	3	-0.00054	-0.00178	-0.00006	-0.00102	-0.49572	-2.37412	-0.05765	-0.90265
	4	-0.00036	0.00056	0.00007	0.00125	-0.33445	0.79213	0.06785	1.14679
	5	0.00081	0.00007	0.00157	0.00006	0.74564	0.10122	1.44037	0.05749
	6	0.00148	0.00073	0.00100	-0.00173	1.34545	1.00545	0.89258	-1.61682
	7	-0.00202	-0.00001	0.00024	-0.00020	-2.39461	-0.01967	0.67322	-0.33929
	8	0.00003	-0.00002	-0.00016	0.00009	0.03155	-0.06564	-0.50909	0.20971

Table 3b: Orthogonalized Impulse Response by variable and their respective ratios by country (daily returns)

Impulse Response							T-ratio			
		Home	US	EX	ADR		Home	US	EX	ADR
ARGENTINA	**0**	**0.01444**	**0.00004**	**-0.00472**	**0.02099**		**37.50747**	**0.08727**	**-19.50091**	**44.71856**
	1	0.01612	-0.00149	-0.00604	0.01454		29.71100	-2.69269	-10.90017	20.72820
	2	0.01677	-0.00028	-0.00651	0.01369		9.47458	-0.24555	-5.38017	12.00877
	3	0.01697	-0.00028	-0.00626	0.01372		5.95439	-0.29637	-6.75464	13.98658
	4	0.01760	0.00084	-0.00562	0.01458		4.15094	0.46959	-3.84932	12.46154
	5	0.01762	0.00057	-0.00530	0.01495		2.76609	0.24030	-2.44240	12.66949
	6	0.01768	0.00043	-0.00535	0.01470		1.81520	0.13839	-2.18367	8.35227
	7	0.01773	0.00036	-0.00542	0.01464		1.29985	0.08520	-1.77124	5.85600
	8	0.01782	0.00035	-0.00546	0.01464		0.96376	0.05980	-1.36160	3.83246
AUSTRALIA	**0**	**0.00599**	**-0.00011**	**-0.00528**	**0.00825**		**38.24055**	**-0.24212**	**27.38021**	**35.18574**
	1	0.00002	-0.00077	-0.00068	0.00024		0.08913	-3.22219	2.85489	1.00124
	2	0.00020	0.00030	0.00003	-0.00019		0.84789	1.25737	-0.13729	-0.80771
	3	0.00052	-0.00014	0.00047	0.00002		2.20643	-0.59997	-1.96343	0.07800
	4	-0.00014	0.00042	0.00021	0.00030		-0.62349	1.76109	-0.87877	1.32865
	5	-0.00001	0.00001	-0.00001	-0.00012		-0.29066	0.31516	0.19105	-0.84755
	6	0.00004	-0.00003	-0.00000	-0.00002		1.38968	-1.04602	0.03615	-0.62309
	7	-0.00002	-0.00002	0.00003	-0.00001		-0.90744	-0.95738	-1.24297	-0.45482
	8	-0.00001	0.00002	-0.00001	0.00000		-0.51105	0.85283	0.38453	-0.09299
AUSTRIA	**0**	**0.00620**	**-0.00050**	**-0.00445**	**0.02030**		**32.88601**	**-1.23182**	**-25.99755**	**49.00896**
	1	0.00053	0.00128	-0.00160	-0.00442		14.88329	23.63368	-22.11472	-39.75178
	2	0.00007	-0.00026	0.00029	0.00092		.	-36.76709	24.23633	41.21384
	3	0.00000	0.00005	-0.00007	-0.00020		.	.	.	.
	4	0.00000	-0.00001	0.00001	0.00004		.	-6.22340	.	.
	5	0.00000	0.00000	0.00000	-0.00001		.	.	.	.
	6	0.00000	0.00000	0.00000	0.00000		.	.	.	.
	7	0.00000	0.00000	0.00000	0.00000		.	.	.	.
	8	0.00000	0.00000	0.00000	0.00000		.	.	.	.
BELGIUM	**0**	**0.00670**	**0.00251**	**-0.00085**	**0.04289**		**31.75355**	**7.39170**	**-6.04388**	**66.32543**
	1	0.00208	-0.00189	-0.00015	-0.01485		0.40784	-3.05489	.	-65.30056
	2	0.00079	0.00198	0.00205	-0.00081		.	.	8.61562	.
	3	-0.00039	-0.00030	-0.00051	0.00259		-0.06492	-0.28151	-0.24066	0.42669
	4	0.00010	-0.00023	-0.00001	-0.00081		0.08941	-0.12307	-0.01436	-0.19406
	5	0.00003	0.00013	0.00009	-0.00011		.	0.18957	0.16207	.
	6	-0.00002	-0.00001	-0.00003	0.00016		-0.09102	.	-0.15261	.
	7	0.00000	-0.00002	0.00000	-0.00004		0.04800	.	.	-0.14553
	8	0.00000	0.00001	0.00001	-0.00001		.	0.10464	.	.
BRAZIL	**0**	**0.01938**	**0.00038**	**-0.00635**	**0.01289**		**44.74407**	**0.62452**	**-19.49527**	**19.44985**
	1	0.02143	0.00010	-0.00616	0.01057		41.04420	0.19560	-12.04254	12.29728
	2	0.02116	0.00045	-0.00511	0.00992		11.25532	0.40041	-4.40517	8.13115
	3	0.02034	0.00057	-0.00594	0.01087		5.89565	0.50839	-7.34730	10.15888
	4	0.01954	0.00151	-0.00669	0.01108		4.08787	0.60643	-4.91912	9.00813
	5	0.01967	0.00148	-0.00650	0.01157		2.77042	0.42529	-2.85088	9.64167
	6	0.01969	0.00144	-0.00634	0.01152		1.69595	0.31169	-2.74459	6.54545
	7	0.01969	0.00141	-0.00648	0.01139		1.20355	0.22488	-2.33094	4.43191

	8	0.01973	0.00137	-0.00650	0.01157		0.91725	0.16061	-1.80055	3.14402
CHILE	**0**	**0.00809**	**0.00031**	**-0.00313**	**0.00692**		**42.10252**	**0.58934**	**-15.02713**	**26.49412**
	1	0.01084	-0.00009	-0.00397	0.00741		46.54158	-0.39570	-16.88069	18.30760
	2	0.01174	-0.00009	-0.00409	0.00759		12.78060	-0.15411	-7.28627	12.18220
	3	0.01181	0.00005	-0.00425	0.00800		6.34946	0.06718	-8.50153	14.03312
	4	0.01235	0.00070	-0.00495	0.00805		4.21502	0.36984	-6.81959	12.08146
	5	0.01257	0.00083	-0.00511	0.00828		2.75658	0.26221	-4.77570	11.62171
	6	0.01263	0.00082	-0.00512	0.00829		1.72541	0.17301	-4.30252	6.85124
	7	0.01264	0.00083	-0.00517	0.00828		1.19133	0.12148	-3.42384	4.26804
	8	0.01265	0.00086	-0.00521	0.00834		0.86703	0.08772	-2.68557	2.83673
CHINA	**0**	**0.00174**	**0.00055**	**-0.00051**	**0.02479**		**6.21584**	**1.63343**	**-4.53754**	**67.80078**
	1	0.00148	-0.00074	-0.00072	0.02237		2.87078	-1.42789	-1.39911	36.54094
	2	0.00144	-0.00061	-0.00069	0.02262		0.09704	-5.28576	-1.76269	16.39130
	3	0.00142	-0.00062	-0.00069	0.02262		0.23786	-4.15185	-0.83681	1.22403
	4	0.00140	-0.00062	-0.00069	0.02264		0.13632	-0.81752	-0.43728	3.00265
	5	0.00137	-0.00062	-0.00069	0.02266		0.03732	-3.86927	-0.40801	1.73906
	6	0.00135	-0.00062	-0.00068	0.02268		0.04787	-0.78270	-0.22292	0.49541
	7	0.00133	-0.00062	-0.00068	0.02270		0.02635	-0.32962	-0.13477	0.63372
	8	0.00131	-0.00061	-0.00068	0.02272		0.01234	-0.47297	-0.10227	0.35701
COLOMBIA	**0**	**0.00700**	**0.00008**	**-0.00156**	**0.02745**		**32.17355**	**0.23252**	**-11.26272**	**63.82830**
	1	0.00297	-0.00057	-0.00151	-0.00080		0.00000	0.00000	-0.00002	0.00000
	2	0.00044	0.00026	-0.00019	-0.00002		0.00000	0.00000	0.00000	0.00000
	3	0.00012	0.00003	0.00011	0.00017		0.00000	0.00000	0.00000	0.00000
	4	0.00004	-0.00001	0.00000	0.00000		0.00000	0.00000	0.00000	0.00000
	5	0.00001	0.00000	-0.00001	0.00000		0.00000	0.00000	0.00000	0.00000
	6	0.00000	0.00000	0.00000	0.00000		0.00000	0.00000	0.00000	0.00000
	7	0.00000	0.00000	0.00000	0.00000		0.00000	0.00000	0.00000	0.00000
	8	0.00000	0.00000	0.00000	0.00000		0.00000	0.00000	0.00000	0.00000
DENMARK	**0**	**0.00720**	**-0.00021**	**-0.00418**	**0.01505**		**33.52736**	**-0.54689**	**-26.46910**	**52.21162**
	1	0.00034	0.00011	-0.00001	-0.00003		64.64662	13.82078	-1.89668	-4.00474
	2	0.00003	0.00001	0.00002	0.00010		.	18.21670	19.10886	53.94271
	3	0.00000	0.00000	0.00000	-0.00001		-0.04925	.	-0.06283	-0.08981
	4	0.00000	0.00000	0.00000	0.00000		0.10643	0.01003	0.05217	0.05570
	5	0.00000	0.00000	0.00000	0.00000		-0.13106	-0.02447	-0.04711	-0.04803
	6	0.00000	0.00000	0.00000	0.00000		0.07155	0.00739	0.03277	0.03775
	7	0.00000	0.00000	0.00000	0.00000		-0.05118	-0.01205	-0.03009	-0.03161
	8	0.00000	0.00000	0.00000	0.00000		0.04209	0.01110	0.02596	0.02746
FINLAND	**0**	**0.02198**	**0.00046**	**-0.00443**	**0.02223**		**41.74897**	**0.95860**	**-22.39410**	**33.77496**
	1	0.02194	-0.00136	-0.00579	0.01730		33.10749	-2.04437	-8.71083	18.97346
	2	0.02164	-0.00062	-0.00525	0.01745		9.61778	-0.44559	-4.03846	14.42149
	3	0.02136	-0.00047	-0.00683	0.01682		7.16779	-0.39306	-7.91636	12.64662
	4	0.02093	0.00026	-0.00563	0.01606		5.59626	0.12875	-4.46825	11.89630
	5	0.02097	0.00016	-0.00560	0.01703		3.90503	0.06816	-4.55285	10.25904
	6	0.02089	0.00005	-0.00554	0.01652		2.77056	0.01821	-5.12963	6.28137
	7	0.02082	0.00004	-0.00548	0.01652		2.23871	0.01467	-5.37255	5.09877
	8	0.02081	0.00003	-0.00549	0.01648		1.87647	0.00943	-5.77481	4.09950
FRANCE	**0**	**0.01175**	**0.00035**	**-0.00442**	**0.01226**		**36.02195**	**0.72627**	**-22.07572**	**33.25918**
	1	0.00007	-0.00128	-0.00075	-0.00532		0.17678	-3.31538	-1.94841	-13.86175

	2	-0.00023	0.00081	0.00078	-0.00013		-0.59726	2.12616	2.02101	-0.35161
	3	-0.00072	0.00011	-0.00108	-0.00030		-1.88516	0.28388	-2.81147	-0.80081
	4	0.00006	0.00103	0.00037	-0.00074		0.14544	2.68090	0.96985	-1.97384
	5	-0.00059	-0.00064	0.00048	0.00079		-1.53951	-1.66132	1.24470	2.26318
	6	0.00009	0.00002	0.00012	0.00016		0.69330	0.14665	0.94967	0.51643
	7	0.00003	-0.00011	-0.00005	-0.00029		0.45424	-1.33565	-0.79493	-2.66176
	8	0.00008	0.00001	-0.00004	0.00006		1.33740	0.12800	-0.66067	0.89018
GERMANY	**0**	**0.01413**	**0.00030**	**-0.00443**	**0.01559**		**45.47795**	**0.64475**	**-23.00821**	**35.82508**
	1	0.00006	-0.00137	-0.00120	-0.00422		0.14208	-2.99486	-2.62438	-9.21196
	2	-0.00068	0.00105	0.00072	-0.00017		-1.49210	2.29568	1.56686	-0.36833
	3	-0.00080	-0.00052	-0.00083	0.00013		-1.74739	-1.14063	-1.80212	0.28343
	4	0.00072	0.00154	0.00042	-0.00053		1.59762	3.35512	0.91717	-1.22889
	5	0.00014	-0.00025	0.00000	0.00058		1.25332	-1.99144	0.00802	2.11984
	6	-0.00003	-0.00011	0.00007	-0.00023		-0.38972	-1.37370	1.00171	-2.65556
	7	-0.00005	0.00002	-0.00002	0.00001		-0.83602	0.24822	-0.38416	0.14154
	8	0.00008	-0.00006	-0.00002	-0.00001		1.53116	-1.09923	-0.38248	-0.19598
GREECE	**0**	**0.00940**	**-0.00034**	**0.00041**	**0.06352**		**31.12789**	**-0.90213**	**2.61474**	**59.36449**
	1	0.01153	-0.00030	-0.00097	0.06259		7.73826	-0.19735	-0.64919	33.83243
	2	0.01168	-0.00006	-0.00102	0.06268		2.35484	-0.00266	-0.15156	16.80429
	3	0.01154	0.00014	-0.00105	0.06271		0.15771	0.00041	-0.04045	0.12580
	4	0.01136	0.00034	-0.00108	0.06274		0.04384	0.00006	-0.00400	0.02090
	5	0.01119	0.00053	-0.00111	0.06277		0.00824	0.00001	-0.00043	0.00202
	6	0.01101	0.00072	-0.00114	0.06280		0.00045	0.00000	-0.00005	0.00013
	7	0.01084	0.00091	-0.00117	0.06282		0.00004	0.00000	0.00000	0.00001
	8	0.01068	0.00109	-0.00119	0.06285		0.00000	0.00000	0.00000	0.00001
HUNGARY	**0**	**0.01341**	**-0.00031**	**-0.00308**	**0.01864**		**37.26553**	**-0.75240**	**-17.22402**	**44.14237**
	1	0.01382	-0.00062	-0.00557	0.01628		29.29269	-1.29109	-11.53376	26.03550
	2	0.01396	-0.00049	-0.00551	0.01707		10.18978	-0.10066	-3.77397	25.81474
	3	0.01385	-0.00041	-0.00560	0.01681		0.72211	-0.00863	-2.60465	0.62537
	4	0.01376	-0.00031	-0.00559	0.01679		0.31394	-0.00066	-0.11801	0.13008
	5	0.01367	-0.00022	-0.00560	0.01671		0.06175	-0.00005	-0.01883	0.01835
	6	0.01357	-0.00012	-0.00561	0.01665		0.00770	0.00000	-0.00389	0.00179
	7	0.01348	-0.00003	-0.00562	0.01659		0.00091	0.00000	-0.00039	0.00017
	8	0.01339	0.00006	-0.00563	0.01652		0.00011	0.00000	-0.00004	0.00002
INDIA	**0**	**0.01256**	**0.00045**	**-0.00025**	**0.03329**		**34.45060**	**1.19043**	**-1.93987**	**55.37167**
	1	0.01387	-0.00083	-0.00100	0.03336		17.91226	-1.04412	-1.25664	33.02970
	2	0.01399	-0.00060	-0.00107	0.03332		3.10889	-0.00492	-0.57838	7.24348
	3	0.01395	-0.00039	-0.00112	0.03303		0.00834	-0.00002	-0.03642	0.00743
	4	0.01390	-0.00018	-0.00117	0.03273		0.00074	0.00000	-0.00081	0.00058
	5	0.01384	0.00003	-0.00121	0.03243		0.00001	0.00000	-0.00001	0.00000
	6	0.01378	0.00025	-0.00125	0.03213		0.00000	0.00000	0.00000	0.00000
	7	0.01373	0.00045	-0.00129	0.03184		0.00000	0.00000	0.00000	0.00000
	8	0.01367	0.00066	-0.00133	0.03155		0.00000	0.00000	0.00000	0.00000
INDONESIA	**0**	**0.01519**	**-0.00006**	**-0.00531**	**0.02229**		**38.18118**	**-0.14264**	**-18.17871**	**44.79052**
	1	0.00246	-0.00027	-0.00117	-0.00139		52.74443	-4.05837	-15.65217	-22.16906
	2	-0.00010	0.00067	0.00042	-0.00059		-22.06105	55.64822	26.31285	-21.81713
	3	0.00037	0.00086	0.00021	0.00004		70.33523	57.78663	10.45237	1.21137
	4	-0.00053	0.00026	-0.00032	0.00005		-58.35746	19.73708	-23.37744	2.95833

	5	-0.00068	0.00029	0.00028	0.00104		-35.17785	10.68066	9.17814	42.93972
	6	0.00011	0.00000	-0.00017	-0.00059		16.73646	-0.33851	-14.63099	-61.96097
	7	0.00007	-0.00004	-0.00005	-0.00006		45.63946	-19.93023	-18.46008	-25.31837
	8	0.00004	-0.00004	0.00003	0.00007		684.24067	-67.42025	24.30357	33.38942
IRELAND	**0**	**0.00924**	**0.00000**	**-0.00360**	**0.00896**		**33.94064**	**-0.00650**	**17.46725**	**30.61992**
	1	0.01006	0.00029	-0.00427	0.00884		36.10653	1.04787	15.36579	21.07321
	2	0.01009	0.00039	-0.00399	0.00915		8.77391	0.60293	5.72897	3.92704
	3	0.01014	0.00051	-0.00419	0.00905		1.67051	0.81375	3.35200	1.06221
	4	0.01039	0.00098	-0.00391	0.00878		1.31853	0.38778	1.48106	0.54365
	5	0.01036	0.00100	-0.00386	0.00898		0.53183	0.09287	1.19876	0.45491
	6	0.01036	0.00099	-0.00382	0.00896		0.24602	0.01991	0.52044	0.16553
	7	0.01034	0.00099	-0.00381	0.00896		0.07262	0.00470	0.08948	0.02497
	8	0.01036	0.00097	-0.00382	0.00896		0.01117	0.00268	0.01908	0.00477
ISRAEL	**0**	**0.00788**	**0.00039**	**-0.00115**	**0.01523**		**30.80170**	**1.03491**	**-8.22780**	**53.49679**
	1	0.00191	-0.00063	-0.00046	-0.00077		60.53883	-13.91901	-8.89094	-15.09127
	2	0.00092	0.00026	-0.00017	-0.00050		56.22492	11.04324	-6.53000	-20.67657
	3	-0.00069	-0.00055	0.00053	-0.00068		-243.89716	-63.00346	34.61422	-22.15072
	4	-0.00027	0.00009	0.00002	0.00008		-60.55310	13.07846	2.21965	11.72957
	5	-0.00002	0.00003	0.00005	0.00004		-51.18266	45.69577	34.44526	18.77729
	6	0.00003	0.00002	-0.00005	0.00002		1214.11523	70.32176	-54.43385	8.39352
	7	0.00002	-0.00001	0.00000	-0.00001		58.76076	-13.70549	-3.94731	-15.35109
	8	0.00000	-0.00001	0.00000	0.00000		66.01620	-59.65858	-21.28034	-9.26624
ITALY	**0**	**0.00884**	**0.00029**	**-0.00416**	**0.01001**		**28.69478**	**0.62808**	**-21.62612**	**34.89994**
	1	0.00905	-0.00039	-0.00479	0.00719		30.74258	-1.31192	-16.11384	17.88246
	2	0.00921	0.00031	-0.00424	0.00729		16.75307	0.45676	-6.26728	3.83684
	3	0.00868	0.00037	-0.00477	0.00714		1.96380	0.24586	-9.18509	1.05621
	4	0.00941	0.00111	-0.00452	0.00672		0.68887	0.25170	-1.88333	0.39344
	5	0.00932	0.00103	-0.00448	0.00724		0.23776	0.07399	-0.73083	0.18164
	6	0.00932	0.00108	-0.00442	0.00700		0.11410	0.03208	-0.26216	0.07176
	7	0.00918	0.00114	-0.00442	0.00704		0.04869	0.01785	-0.13418	0.02283
	8	0.00919	0.00120	-0.00442	0.00699		0.01545	0.00485	-0.05927	0.00938
JAPAN	**0**	**0.01076**	**0.00014**	**-0.00427**	**0.01346**		**39.10594**	**0.31897**	**-22.29416**	**39.17802**
	1	0.01098	-0.00100	-0.00447	0.00898		29.70860	-2.65724	-11.83322	18.60947
	2	0.01084	0.00016	-0.00412	0.00942		15.24077	0.19804	-5.72326	5.26257
	3	0.01092	-0.00037	-0.00412	0.00987		3.72696	-0.53511	-6.69494	2.12258
	4	0.01079	-0.00021	-0.00390	0.00982		1.74032	-0.15477	-2.67123	1.29211
	5	0.01070	-0.00011	-0.00394	0.00952		0.83790	-0.01535	-1.87619	0.92338
	6	0.01062	0.00001	-0.00398	0.00949		0.90692	0.00106	-0.98030	0.33664
	7	0.01053	0.00012	-0.00402	0.00944		0.47114	0.00916	-0.83402	0.11756
	8	0.01046	0.00024	-0.00402	0.00936		0.13549	0.00581	-0.41701	0.08034
KOREA	**0**	**0.01424**	**-0.00007**	**-0.00299**	**0.01952**		**30.18612**	**-0.17540**	**-17.89455**	**43.80905**
	1	-0.00057	-0.00018	-0.00044	0.00020		-49.34402	-10.85801	-26.51814	9.87556
	2	-0.00046	0.00031	-0.00028	-0.00120		-96.83507	38.34487	-22.30926	-44.75942
	3	-0.00026	-0.00063	-0.00024	-0.00111		-36.62447	-46.40936	-12.84163	-35.89909
	4	-0.00069	0.00137	-0.00056	-0.00059		-122.264	63.95892	-18.08314	-10.41722
	5	0.00017	0.00004	-0.00003	0.00014		177.22314	27.08667	-15.96364	29.92100
	6	0.00007	-0.00007	0.00012	0.00016		253.77237	-65.60360	42.68864	28.18838

	7	0.00010	-0.00006	0.00009	0.00009		140.26123	-48.66667	43.44907	19.66597
	8	0.00001	-0.00006	-0.00001	-0.00004		12.71194	-56.43396	-9.42069	-15.62609
MEXICO	**0**	**0.01552**	**0.00009**	**-0.00192**	**0.00835**		**36.78422**	**0.12197**	**-6.77703**	**15.12873**
	1	0.00267	-0.00004	-0.00048	-0.00075		0.95018	-0.10924	-1.73612	-0.67547
	2	-0.00048	0.00002	0.00045	-0.00001		.	0.00000	0.00007	0.00000
	3	-0.00031	-0.00002	-0.00003	0.00009		.	0.00000	.	0.00004
	4	0.00000	-0.00002	-0.00001	-0.00006		0.00000	0.00000	0.00000	-0.00002
	5	0.00002	0.00001	0.00001	-0.00001		.	0.00000	0.00001	-0.00001
	6	0.00000	0.00000	0.00000	0.00001		0.00000	0.00000	-0.00001	0.00005
	7	0.00000	0.00000	0.00000	0.00000		0.00000	0.00000	-0.00001	0.00000
	8	0.00000	0.00000	0.00000	0.00000		.	0.00000	0.00002	-0.00002
NETHERLANDS	**0**	**0.01120**	**0.00023**	**-0.00428**	**0.01101**		**34.28431**	**0.47010**	**-20.71937**	**31.16773**
	1	0.01113	-0.00077	-0.00492	0.00759		32.55623	-2.21580	-14.19217	15.85511
	2	0.01108	-0.00006	-0.00400	0.00824		9.71930	-0.08582	-5.81666	13.63742
	3	0.01011	-0.00015	-0.00474	0.00819		6.24074	-0.19902	-10.41072	14.52875
	4	0.01025	-0.00019	-0.00460	0.00835		5.00000	-0.13257	-7.64679	14.71495
	5	0.01023	-0.00024	-0.00466	0.00803		3.65357	-0.14792	-7.40035	14.21667
	6	0.01027	-0.00019	-0.00461	0.00814		2.52334	-0.09937	-8.86061	8.60165
	7	0.01026	-0.00019	-0.00463	0.00817		1.97308	-0.08122	-9.05996	6.18939
	8	0.01027	-0.00019	-0.00462	0.00817		1.66721	-0.06320	-8.37639	4.77778
NEW ZEALAND	**0**	**0.00706**	**-0.00051**	**-0.00511**	**0.01251**		**45.12335**	**-1.29087**	**28.40309**	**45.83089**
	1	0.00054	-0.00011	-0.00079	-0.00037		1.70184	-0.33217	2.47762	-1.15509
	2	0.00054	-0.00004	-0.00021	-0.00076		1.68811	-0.12128	0.65078	-2.40035
	3	0.00028	0.00050	0.00015	-0.00027		0.89418	1.57982	-0.48195	-0.86364
	4	-0.00010	0.00046	0.00022	-0.00004		-0.32218	1.44141	-0.70036	-0.13907
	5	-0.00003	-0.00003	0.00004	0.00007		-0.54047	-0.58578	-0.73688	0.53314
	6	0.00002	-0.00007	-0.00001	0.00002		0.65697	-1.67407	0.24445	0.46495
	7	0.00004	-0.00004	-0.00000	0.00000		1.50017	-1.27873	0.18297	0.13996
	8	0.00001	0.00000	-0.00000	0.00000		0.96172	-0.05023	-0.29432	-0.23064
NORWAY	**0**	**0.00958**	**-0.00009**	**-0.00434**	**0.01164**		**32.31029**	**-0.20050**	**-22.88667**	**37.55566**
	1	0.01001	-0.00061	-0.00504	0.01137		31.45425	-1.86962	-15.57815	25.25152
	2	0.01012	-0.00061	-0.00510	0.01152		11.58956	-7.88850	-29.21632	7.48052
	3	0.01016	-0.00065	-0.00512	0.01143		5.58242	-3.37996	-7.66479	4.41313
	4	0.01020	-0.00067	-0.00512	0.01138		6.58065	-2.65298	-8.69683	5.95812
	5	0.01024	-0.00069	-0.00512	0.01133		5.88506	-2.67027	-5.16947	4.18081
	6	0.01027	-0.00071	-0.00513	0.01127		5.73743	-2.11330	-3.63830	2.76225
	7	0.01031	-0.00072	-0.00513	0.01122		3.60490	-1.39929	-3.44295	1.89848
	8	0.01034	-0.00074	-0.00513	0.01117		2.33937	-1.01619	-2.94828	1.48537
PERU	**0**	**0.01339**	**-0.00044**	**-0.00070**	**0.02442**		**67.57166**	**-1.14620**	**-5.23772**	**52.37197**
	1	0.01396	0.00094	0.00013	0.02127		24.20208	1.61953	0.22960	29.26970
	2	0.01288	0.00124	-0.00043	0.01936		1.65553	0.02719	-0.14462	6.16561
	3	0.01311	0.00041	0.00012	0.01885		0.02579	0.00012	0.00998	0.02076
	4	0.01324	0.00028	0.00008	0.01937		0.00149	0.00000	0.00006	0.00220
	5	0.01331	0.00033	0.00009	0.01937		0.00002	0.00000	0.00000	0.00003
	6	0.01327	0.00030	0.00007	0.01926		0.00000	0.00000	0.00000	0.00000
	7	0.01328	0.00023	0.00011	0.01917		0.00000	0.00000	0.00000	0.00000
	8	0.01329	0.00017	0.00014	0.01913		0.00000	0.00000	0.00000	0.00000
PHILIPPINES	**0**	**0.00882**	**0.00099**	**-0.00335**	**0.02335**		**33.94266**	**2.79279**	**-23.77404**	**58.50371**

	1	0.00970	-0.00016	-0.00256	0.01831		18.59270	-0.30741	-4.90798	29.26089
	2	0.00971	0.00087	-0.00305	0.01814		2.69722	0.08530	-2.96117	12.51034
	3	0.00944	0.00197	-0.00262	0.01817		0.26849	0.01108	-0.28142	0.20492
	4	0.01037	0.00315	-0.00300	0.01859		0.06699	0.00102	-0.02410	0.04266
	5	0.01050	0.00277	-0.00305	0.01866		0.00905	0.00005	-0.00451	0.00282
	6	0.01052	0.00268	-0.00299	0.01863		0.00052	0.00000	-0.00190	0.00016
	7	0.01058	0.00265	-0.00299	0.01862		0.00003	0.00000	-0.00010	0.00001
	8	0.01065	0.00265	-0.00300	0.01862		0.00000	0.00000	-0.00001	0.00000
PORTUGAL	**0**	**0.00839**	**0.00019**	**-0.00415**	**0.01060**		**38.18149**	**0.43005**	**-22.54700**	**38.28650**
	1	0.00158	-0.00023	-0.00138	-0.00274		5.25598	-0.73773	-4.49570	-8.91956
	2	0.00012	0.00089	0.00022	-0.00059		0.39906	2.93589	0.73697	-1.95263
	3	0.00002	0.00009	-0.00079	0.00012		0.06336	0.30609	-2.58754	0.39008
	4	0.00042	0.00074	0.00003	-0.00043		1.38545	2.44534	0.09928	-1.41765
	5	-0.00012	-0.00012	0.00013	0.00055		-0.41392	-0.40218	0.41426	1.92661
	6	-0.00005	0.00001	-0.00002	-0.00017		-0.61276	0.08201	-0.23210	-1.11715
	7	-0.00003	0.00001	0.00000	-0.00001		-0.57895	0.14784	-0.09684	-0.16408
	8	0.00008	-0.00002	-0.00003	0.00001		1.86584	-0.62394	-0.81804	0.28411
RUSSIA	**0**	**0.02124**	**-0.00116**	**-0.00164**	**0.02873**		**40.80378**	**-2.79673**	**-4.54936**	**43.93638**
	1	0.02343	0.00009	-0.00284	0.02823		31.45515	0.11613	-4.21979	27.95050
	2	0.02392	0.00025	-0.00597	0.02736		9.09506	0.10643	-2.37849	15.45763
	3	0.02482	0.00003	-0.00355	0.02803		2.75166	0.00873	-0.57724	8.75938
	4	0.02636	0.00059	-0.00434	0.02848		0.72818	0.13802	-0.17507	2.47222
	5	0.02673	0.00060	-0.00389	0.02895		0.45975	0.06524	-0.04186	1.27197
	6	0.02671	0.00050	-0.00250	0.02925		0.41650	0.01599	-0.02302	0.30523
	7	0.02688	0.00054	-0.00330	0.02919		0.18725	0.00687	-0.02030	0.08442
	8	0.02701	0.00049	-0.00287	0.02919		0.06916	0.00318	-0.00642	0.07665
SINGAPORE	**0**	**0.01212**	**-0.00054**	**-0.00270**	**0.02984**		**49.32243**	**-1.33728**	**-19.00338**	**51.47845**
	1	0.01173	-0.00180	-0.00269	0.03175		15.52409	-2.38269	-3.55844	32.92066
	2	0.01197	-0.00166	-0.00356	0.03125		3.66055	-0.96512	-2.04598	10.48658
	3	0.01213	-0.00157	-0.00360	0.03137		1.90125	-0.79695	-1.23288	4.79664
	4	0.01216	-0.00155	-0.00355	0.03141		1.48293	-0.75243	-0.72746	2.44817
	5	0.01215	-0.00156	-0.00355	0.03141		1.08385	-0.58427	-0.50426	1.55572
	6	0.01215	-0.00156	-0.00356	0.03140		0.84787	-0.43454	-0.36216	1.02147
	7	0.01215	-0.00156	-0.00355	0.03140		0.65782	-0.32298	-0.27079	0.69515
	8	0.01215	-0.00156	-0.00355	0.03140		0.54435	-0.24074	-0.20508	0.47296
SPAIN	**0**	**0.01102**	**-0.00060**	**-0.00224**	**0.04469**		**40.67922**	**-1.57207**	**-13.94596**	**56.81125**
	1	0.01096	-0.00053	-0.00226	0.04468		67.41297	-2.97021	-55.13540	56.80142
	2	0.01089	-0.00047	-0.00227	0.04466		160.52476	-2.65838	-50.52304	43.78431
	3	0.01084	-0.00040	-0.00229	0.04465		3857.651	-2.35017	-40.30271	42.52381
	4	0.01078	-0.00034	-0.00230	0.04464		458.91869	-1.96077	-43.20872	42.92308
	5	0.01072	-0.00028	-0.00232	0.04463		634.31953	-1.60497	-42.38991	42.91346
	6	0.01067	-0.00022	-0.00233	0.04462		556.01876	-1.25204	-42.58041	42.90385
	7	0.01061	-0.00016	-0.00234	0.04461		566.47090	-0.90983	-42.34528	42.89423
	8	0.01056	-0.00010	-0.00236	0.04460		551.14823	-0.57609	-42.37745	42.88462
SWEDEN	**0**	**0.01872**	**0.00071**	**-0.00503**	**0.02303**		**52.32119**	**1.63518**	**-27.21714**	**39.84843**
	1	0.00071	-0.00224	-0.00089	-0.00707		1.12696	-3.48806	-1.38052	-10.96515
	2	0.00020	0.00141	0.00110	0.00031		0.31018	2.18578	1.69850	0.47321
	3	-0.00067	-0.00009	-0.00154	0.00002		-1.04331	-0.13948	-2.37728	0.03314

	4	-0.00044	0.00160	-0.00017	-0.00062		-0.68384	2.47874	-0.26657	-0.95238
	5	0.00012	-0.00061	0.00074	0.00105		0.18268	-0.93749	1.14271	1.64618
	6	-0.00074	0.00075	-0.00017	0.00103		-1.16844	1.15271	-0.26126	1.74730
	7	-0.00014	-0.00006	0.00016	-0.00092		-0.76455	-0.31622	0.92369	-2.06486
	8	0.00014	0.00003	-0.00003	-0.00003		1.32776	0.28426	-0.33608	-0.18169
SWITZERLAND	**0**	**0.00753**	**-0.00017**	**-0.00465**	**0.01385**		**29.85844**	**-0.41753**	**-27.32883**	**48.42996**
	1	0.00814	-0.00035	-0.00513	0.01202		24.04727	-1.00659	-14.99080	27.44856
	2	0.00826	-0.00035	-0.00514	0.01224		11.21414	-4.31723	-63.93035	8.93431
	3	0.00834	-0.00042	-0.00517	0.01206		8.25743	-4.41848	-12.45453	6.12183
	4	0.00841	-0.00049	-0.00519	0.01194		5.76027	-7.52037	-11.38433	5.65877
	5	0.00848	-0.00056	-0.00521	0.01182		4.19802	-4.44222	-8.49364	3.22071
	6	0.00855	-0.00062	-0.00523	0.01169		3.50410	-3.87151	-5.46220	1.95485
	7	0.00862	-0.00069	-0.00524	0.01157		2.00000	-3.26807	-5.24246	1.41616
	8	0.00869	-0.00075	-0.00526	0.01146		1.29508	-2.56107	-2.81283	1.11805
TAIWAN	**0**	**0.01453**	**-0.00025**	**-0.00103**	**0.03029**		**42.33436**	**-0.66807**	**-7.98017**	**55.35251**
	1	0.01431	-0.00002	-0.00191	0.02948		20.60683	-0.02380	-2.74702	33.54384
	2	0.01544	-0.00068	-0.00147	0.02909		3.20332	-0.01337	-1.94710	10.85448
	3	0.01582	-0.00156	-0.00185	0.02790		0.02683	-0.00043	-0.04716	0.02314
	4	0.01358	-0.00041	-0.00164	0.02634		0.00143	0.00000	-0.00447	0.00275
	5	0.01349	-0.00032	-0.00166	0.02638		0.00002	0.00000	-0.00053	0.00004
	6	0.01324	-0.00009	-0.00171	0.02622		0.00000	0.00000	-0.00001	0.00000
	7	0.01310	0.00004	-0.00168	0.02622		0.00000	0.00000	0.00000	0.00000
	8	0.01316	0.00002	-0.00165	0.02621		0.00000	0.00000	0.00000	0.00000
TURKEY	**0**	**0.02000**	**-0.00052**	**-0.00700**	**0.04000**		**30.22746**	**-1.24215**	**-22.32001**	**37.03704**
	1	0.02605	-0.00492	-0.00626	0.03022		19.15441	-3.59124	-4.53623	18.65432
	2	0.02761	-0.00181	-0.00487	0.02954		6.97222	-0.69084	-1.79044	11.53906
	3	0.02800	0.00072	-0.00430	0.03100		5.28302	0.37656	-2.26316	13.59649
	4	0.02794	-0.00046	-0.00411	0.03222		4.14540	-0.16507	-1.48375	14.57919
	5	0.02791	-0.00086	-0.00418	0.03107		3.03370	-0.25958	-1.10875	11.05694
	6	0.02777	-0.00072	-0.00409	0.03114		2.02258	-0.17811	-1.12983	5.10492
	7	0.02784	-0.00077	-0.00385	0.03126		1.57644	-0.17608	-0.89120	3.99744
	8	0.02784	-0.00091	-0.00365	0.03129		1.25632	-0.16053	-0.70058	2.78877
UK	**0**	**0.00834**	**0.00031**	**-0.00345**	**0.00839**		**31.85030**	**0.63634**	**-18.25107**	**31.59837**
	1	0.00829	-0.00066	-0.00380	0.00542		31.83075	-2.49003	-14.37923	15.01468
	2	0.00784	-0.00003	-0.00338	0.00577		9.27317	-0.05261	-6.27087	12.75420
	3	0.00721	0.00012	-0.00377	0.00591		6.26957	0.21156	-9.98993	13.91210
	4	0.00737	0.00091	-0.00363	0.00560		5.01361	0.76226	-6.85190	11.56093
	5	0.00738	0.00075	-0.00363	0.00587		3.56522	0.52504	-6.14889	11.99256
	6	0.00738	0.00073	-0.00362	0.00562		2.53608	0.42900	-6.95205	8.27737
	7	0.00732	0.00073	-0.00362	0.00568		1.96774	0.34270	-6.84724	6.43757
	8	0.00733	0.00071	-0.00362	0.00569		1.61810	0.25569	-7.03090	4.82203

Table 4a: Proportions of Prediction Error Covariances by Variable (weekly data)

Variable	Home	US	ex	ADR
MEXICO	0.8605	0.00741	0.02286	0.10923
FINLAND	0.82785	0.00271	0.02926	0.14017
BRAZIL	0.74703	0.01517	0.10134	0.13646
NORWAY	0.69679	0.00108	0.0904	0.21172
IRELAND	0.68039	0.00972	0.11682	0.19307
UK	0.68036	0.00971	0.15351	0.15641
CHILE	0.67846	0.01845	0.10891	0.19418
NETHERLANDS	0.67699	0.00464	0.13652	0.18186
SWEDEN	0.66672	0.01462	0.06035	0.25831
JAPAN	0.66035	0.00235	0.13395	0.20334
FRANCE	0.65364	0.0056	0.13551	0.20525
GERMANY	0.62186	0.00442	0.08385	0.28987
ARGENTINA	0.60803	0.00128	0.0903	0.30039
INDONESIA	0.59503	0.00753	0.04352	0.35393
RUSSIA	0.57186	0.00181	0.03006	0.39626
KOREA	0.56115	0.00569	0.02785	0.4053
HUNGARY	0.559	0.0023	0.07722	0.36148
TURKEY	0.54566	0.00864	0.01903	0.42667
ITALY	0.52921	0.00284	0.17566	0.29228
PORTUGAL	0.52901	0.01067	0.1667	0.29362
AUSTRALIA	0.52216	0.00455	0.28277	0.19052
PERU	0.48346	0.000798	0.000254	0.51549
ISRAEL	0.45788	0.0105	0.02518	0.50644
NEW ZEALAND	0.44035	0.00799	0.17435	0.37731
INDIA	0.43397	0.00267	0.000737	0.56263
TAIWAN	0.41502	0.00931	0.00859	0.56709
DENMARK	0.35233	0.00416	0.08828	0.55523
SWITZERLAND	0.3121	0.00901	0.13109	0.54779
SINGAPORE	0.28229	0.00628	0.03237	0.67906
AUSTRIA	0.27064	0.000438	0.10834	0.62058
COLOMBIA	0.26572	0.02449	0.07191	0.63789
PHILIPPINES	0.26005	0.01158	0.01075	0.71762
BELGIUM	0.11509	0.00449	0.00588	0.87455
SPAIN	*0.08597*	*0.00365*	*0.02187*	*0.88851*
CHINA	*0.04083*	*0.00637*	*0.00876*	*0.94404*
GREECE	*0.03454*	*0.00273*	*0.00711*	*0.95561*
Average	0.492286	0.006824	0.077274	0.423616

Table 4b: Proportions of Prediction Error Covariances by Variable (daily data)

Variable	Home	US	ex	ADR
ARGENTINA	0.487660	0.001110	0.062280	0.448940
AUSTRALIA	0.270120	0.006690	0.213920	0.509270
AUSTRIA	*0.078150*	*0.003960*	*0.045240*	*0.872650*
BELGIUM	*0.023380*	*0.006520*	*0.002440*	*0.967660*
BRAZIL	0.720930	0.001030	0.063930	0.214120
CHILE	0.620490	0.000614	0.085970	0.292920
CHINA	*0.004210*	*0.000748*	*0.000824*	*0.994220*
COLOMBIA	*0.071040*	*0.000494*	*0.005830*	*0.922640*
DENMARK	0.175740	0.000185	0.058960	0.765120
FINLAND	0.563760	0.000663	0.038530	0.397050
FRANCE	0.403720	0.010130	0.064090	0.522060
GERMANY	0.410140	0.011670	0.045770	0.532410
GREECE	*0.030430*	*0.000017*	*0.000217*	*0.969340*
HUNGARY	0.371230	0.000386	0.052390	0.575990
INDIA	0.145110	0.000224	0.000754	0.853910
INDONESIA	0.309220	0.001730	0.038950	0.650090
IRELAND	0.508660	0.001480	0.081410	0.408440
ISRAEL	0.221470	0.003060	0.006090	0.769380
ITALY	0.502650	0.002090	0.124830	0.370430
JAPAN	0.482260	0.001010	0.071410	0.445330
KOREA	0.339780	0.004010	0.015950	0.640270
MEXICO	0.769390	0.000031	0.012820	0.217760
NETHERLANDS	0.543700	0.000665	0.095910	0.359720
NEW ZEALAND	0.214590	0.003130	0.114110	0.668170
NORWAY	0.390540	0.001260	0.095610	0.512590
PERU	0.291380	0.000939	0.000232	0.707450
PHILIPPINES	0.192370	0.006460	0.017830	0.783350
PORTUGAL	0.340470	0.006700	0.091980	0.560850
RUSSIA	0.416040	0.000256	0.011240	0.572470
SINGAPORE	0.128310	0.001980	0.009360	0.860350
SPAIN	0.056030	0.000108	0.002430	0.941430
SWEDEN	0.361860	0.010360	0.030600	0.597180
SWITZERLAND	0.268460	0.000556	0.103730	0.627260
TAIWAN	0.209020	0.000600	0.002490	0.787890
TURKEY	0.365610	0.002890	0.016400	0.615100
UK	0.534840	0.002420	0.113920	0.348820
Average	0.328410	0.002672	0.049957	0.618962

Table 5a: Proportions of Prediction Error Covariances by Variable for selected countries (weekly data)

Country	Variable explained	Home	US	EX	ADR
Australia	Home	0.96834	0.01402	0.00278	0.01486
	US	0.04134	0.94656	0.0015	0.0106
	EX	0.04208	0.00434	0.94511	0.00847
	ADR	0.52216	0.00455	0.28277	0.19052
Argentina	Home	0.97637	0.00253	0.01811	0.003
	US	0.00376	0.98301	0.01251	0.0007223
	EX	0.01823	0.00145	0.96069	0.01962
	ADR	0.60803	0.00128	0.0903	0.30039
China	Home	0.98463	0.00217	0.01041	0.0028
	US	0.00866	0.98543	0.00187	0.00405
	EX	0.0025	0.00040451	0.99698	0.00012269
	ADR	0.04083	0.00637	0.00876	0.94404
Germany	Home	0.9854	0.00602	0.00467	0.0039
	US	0.00744	0.95603	0.00827	0.02825
	EX	0.04257	0.00377	0.95129	0.00236
	ADR	0.62186	0.00442	0.08385	0.28987
Japan	Home	0.96377	0.0077	0.01129	0.01724
	US	0.02412	0.94374	0.01166	0.02047
	EX	0.01683	0.01458	0.96648	0.00211
	ADR	0.66035	0.00235	0.13395	0.20334

Table 5b: Proportions of Prediction Error Covariances by Variable (daily data)

Country		Home	US	EX	ADR
Australia	Home	0.815670	0.000502	0.003510	0.180320
	US	0.001510	0.996560	0.000835	0.001090
	EX	0.005220	0.001210	0.967280	0.026290
	ADR	0.270120	0.006690	0.213920	0.509270
Argentina	Home	0.985990	0.001540	0.009510	0.002950
	US	0.000578	0.997190	0.000650	0.001590
	EX	0.008250	0.000327	0.981640	0.009770
	ADR	0.487660	0.001110	0.062280	0.448940
China	Home	0.996810	0.000025	0.000416	0.002740
	US	0.000560	0.999380	0.000009	0.000052
	EX	0.000237	0.001120	0.998480	0.000160
	ADR	0.004210	0.000748	0.000824	0.994220
Germany	Home	0.961900	0.000071	0.003070	0.034960
	US	0.002020	0.992240	0.002030	0.003700
	EX	0.061010	0.000635	0.936320	0.002030
	ADR	0.410140	0.011670	0.045770	0.532410
Japan	Home	0.940860	0.000172	0.004390	0.054570
	US	0.000337	0.998270	0.000160	0.001230
	EX	0.008520	0.000546	0.988080	0.002850
	ADR	0.482260	0.001010	0.071410	0.445330

Table 6: SUR with contemporaneous returns (weekly returns)

Country	SIGMA	Intercept	US	Home	EX
ARGENTINA	0.034498	0.002095	-0.063551	0.743330***	-0.561425***
AUSTRALIA	0.011227	-0.000264	-0.036587	1.081492***	-0.900687***
AUSTRIA	0.031885	0.001088	0.030023	0.719658***	-0.956644***
BELGIUM	0.057771	-0.005319	0.053414	1.325644***	-0.932642***
BRAZIL	0.019468	-0.000466	0.005818	1.089642***	-0.770563***
CHILE	0.013016	-0.000677	-0.010818	1.106436***	-0.873026***
CHINA	0.035904	0.001771	0.048638	0.323349***	-1.823853
COLOMBIA	0.057079	0.003368	-0.078170	0.888067***	-1.198704***
DENMARK	0.026059	0.000324	-0.041101	1.041000***	-0.849740***
FINLAND	0.017661	-0.001329	-0.060409	1.206525***	-0.868981***
FRANCE	0.012770	-0.001202*	-0.034073	1.002255***	-0.930496***
GERMANY	0.013237	-0.000796	-0.043839	1.085204***	-0.974859***
GREECE	0.020572	0.000516	0.040941	0.951077***	-0.695317***
HUNGARY	0.030166	-0.002191	-0.092254	0.829188***	-0.699381***
INDIA	0.044006	-0.000610	-0.102426	0.847356***	-0.171186
INDONESIA	0.033381	0.002150	-0.098205	1.143970***	-0.473404***
IRELAND	0.011169	-0.001025	-0.058912***	1.129559***	-0.849700***
ISRAEL	0.026882	0.000328	-0.022437	0.776887***	-0.375720***
ITALY	0.013755	0.000235	0.002969	0.883807***	-0.953621***
JAPAN	0.014630	-0.000166	-0.015900	0.943873***	-0.556765***
KOREA	0.024030	-0.000779	0.011535	0.641697***	-0.825263***
MEXICO	0.011464	-0.001057	-0.006238	1.205893***	-0.614474***
NETHERLANDS	0.011977	-0.000324	-0.040600	1.055123***	-0.922381***
NEW ZEALAND	0.022424	-0.002546***	-0.066396	1.301287***	-0.916766***
NORWAY	0.013732	0.000486	0.018572	0.971224***	-0.940011***
PERU	0.044523	-0.001266	-0.024256	1.691685***	1.221583***
PHILIPINES	0.036701	0.001500	0.149679	0.973434***	-1.323500***
PORTUGAL	0.016119	-0.001081	-0.034587	1.206311***	-1.004556***
RUSSIA	0.034635	0.001316	-0.127916	0.743929***	-0.759784*
SINGAPORE	0.054858	-0.005795*	-0.250951*	1.401282***	-1.925131***
SPAIN	0.011957	-0.001243*	-0.044524	1.245504***	-0.842641***
SWEDEN	0.028141	-0.002502	0.003896	1.469350***	-0.929714***
SWITZERLAND	0.012258	-0.000141	0.012718	1.001261***	-0.995793***
TAIWAN	0.044995	-0.000497	-0.264228	1.038574***	-0.736225***
TURKEY	0.065801	-0.003179	-0.099982	1.032103***	-0.624343***
UK	0.008237	-0.000409	-0.026678	0.924040***	-0.853688***

Table 7: SUR with both contemporaneous and lagged values (weekly returns)

Country	INTERCEP	US	Home	EX	US1	Home1	EX1	US2	Home2	EX2
ARGENTINA	0.002158	-0.023743	0.768309***	-0.496183***	0.156327*	0.157351***	-0.269067***	-0.059731	-0.095125	0.080839
AUSTRALIA	-0.000293	-0.042157	1.083300***	-0.892999***	-0.014551	-0.004982	-0.051834	-0.002358	-0.013133	-0.011747
AUSTRIA	-0.000132	0.008579	0.714133***	-0.944190***	0.043837	0.213838	-0.048189	-0.026154	0.117116	0.121650
BELGIUM	-0.005911	0.026013	1.362971***	-0.923906***	-0.099322	-0.055236	-0.118478	0.106799	0.177519	-0.214343
BRAZIL	-0.000078	-0.010043	1.092253***	-0.763816***	-0.012940	-0.104541***	-0.085831***	0.030289	0.003242	0.025722
CHILE	-0.000769	-0.009961	1.088940***	-0.853220***	-0.004660	0.069247*	-0.214235***	0.044326	-0.033945	0.046618
CHINA	0.001517	0.039283	0.311354***	-1.968487	-0.042517	0.034745	-1.159126	0.155999*	0.025736	-0.085489
COLOMBIA	0.002491	-0.126396	0.839475***	-1.089914***	0.378296***	0.306469***	-0.524627*	0.037586	-0.125216	-0.285993
DENMARK	0.000592	-0.014999	1.036557***	-0.832733***	0.017529	-0.051286	0.200162***	-0.107124	-0.129549**	-0.211504**
FINLAND	-0.001333	-0.058390	1.203790***	-0.850799***	-0.027211	-0.006384	0.051108	-0.060330	-0.002912	-0.068688
FRANCE	-0.001249	-0.036158	0.997824***	-0.925917***	-0.020302	0.005564	-0.016161	0.034952	-0.013681	-0.031034
GERMANY	-0.000862	-0.045598	1.086190***	-0.971106***	-0.026900	0.001221	-0.024916	0.029667	-0.025091	-0.039045
GREECE	0.000250	0.032391	0.959943***	-0.691604***	-0.072716	-0.002351	-0.040585	0.012130	-0.005526	-0.199799**
HUNGARY	-0.002879	-0.114547	0.840841***	-0.704641***	0.006749	0.107947***	-0.185810***	0.132800*	-0.048024	-0.172191*
INDIA	-0.001225	-0.137632	0.835977***	-0.304930	-0.100024	-0.030801	0.074153	0.086487	0.241617***	1.010299***
INDONESIA	0.002391	-0.069918	1.142613***	-0.490814***	0.068420	-0.043468	-0.113450	0.082696	-0.026633	0.093387
IRELAND	-0.001014	-0.052518*	1.132534***	-0.853138***	0.021864	0.005175	-0.005810	-0.041741	-0.046794**	-0.027950
ISRAEL	0.000150	-0.013881	0.768307***	-0.472805***	-0.008182	0.184498***	0.145351	0.076042	-0.065051	0.217288
ITALY	0.000179	0.005233	0.880096***	-0.951412***	-0.028652	0.008330	0.005259	0.039491	-0.052527**	-0.061539
JAPAN	-0.000202	-0.016784	0.946593***	-0.562172***	-0.001468	0.046513*	-0.030163	0.056651	-0.025203	0.038058
KOREA	-0.001131	-0.005635	0.654436***	-0.817598***	0.020878	-0.002345	-0.289178***	-0.002698	-0.030327	-0.181912
MEXICO	-0.000965	-0.006834	1.203764***	-0.611374***	-0.053565*	0.020679	0.021802	0.011078	-0.042453	0.031833
NETHERLANDS	-0.000381	-0.035270	1.048591***	-0.908128***	-0.015175	0.052046***	-0.021606	0.008792	-0.031016**	-0.044698
NEW ZEALAND	-0.002947***	-0.082841	1.320234***	-0.914386***	0.005475	0.083094	-0.111260	0.044644	-0.037573	-0.069102
NORWAY	0.000316	0.014985	0.961984***	-0.924860***	-0.007200	0.044746*	-0.022373	-0.062775*	0.031037	-0.000508
PERU	0.000144	0.020806	1.686025***	1.149558***	0.101409	-0.210042	0.325305	-0.252109**	-0.148636	0.145027
PHILIPINES	0.001039	0.141428	0.991194***	-1.262948***	0.071588	0.214005***	0.664312***	0.162744*	-0.017270	0.437317
PORTUGAL	-0.001029	-0.024820	1.204594***	-0.992829***	-0.056360	0.052276	0.062750	-0.034294	-0.054675	-0.040629
RUSSIA	0.001645	-0.127020	0.740789***	-0.930174***	-0.075698	-0.046710	-0.315629	0.057022	0.021708	1.073066
SINGAPORE	-0.005987	-0.252005	1.365610***	-1.935492***	-0.198821	0.299724***	0.477466	0.235407*	0.078716	0.364289
SPAIN	-0.001347*	-0.046949	1.240368***	-0.837340***	-0.028451	0.011654	-0.045561	0.008246	-0.011386	-0.061566
SWEDEN	-0.002807*	-0.005725	1.468164***	-0.919767***	0.008487	0.054190	-0.096266	-0.121691*	0.043800	-0.149049
SWITZERLAND	0.000022	0.022629	1.001604***	-0.993412***	-0.012246	-0.058180***	0.073948	-0.014549	-0.071309**	0.023307
TAIWAN	-0.000401	-0.253708***	1.038595***	-0.918462***	-0.093887	-0.055370	0.279379	0.195946*	-0.016571	0.671038*
TURKEY	-0.003125	-0.116623	1.044515***	-0.613989***	0.126488	-0.010217	-0.069117	-0.015501	0.021549	-0.016460
UK	-0.000459	-0.029055	0.922074***	-0.853420***	-0.046242***	0.008736	-0.022440	0.014290	-0.042040**	-0.055850**

CHAPTER FOUR: REGIME SWITCHING ANALYSIS OF ADR HOME MARKET PASS-THROUGH

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 in particular, the following questions: What determines the price movements of exchange-listed 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. I 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. I 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 and non-overlapping trading hours across countries (Kim, Szakmary and Mathur 2000, Fang and Loo 2002). This "pricing-to-market" effect may also be time varying, depending on the performance of US economy and its covariance with the ADR returns.

Early research on ADRs has examined ADRs and their underlying assets in search for 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 this research, 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 the "pass-throughs" of home shares and are expected to be priced the same as their home-market shares, barring the effects of the appropriate exchange rates. Later studies focus on the portfolio diversification effects of ADRs and find 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 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 that perform differently from the underlying shares (Alaganar and Bhar 2001, Foerster and Karolyi 2000). It is generally now agreed that although ADRs are, to a certain extent, reflecting their underlying shares' value, they should be priced with consideration of their own risk characteristics. How does the US market affect ADR returns? What factors are causing ADR prices to deviate from home prices? Kadiyala and Subrahmanyam (2004) study one-year post-listing prices and returns for ADRs that listed in the US between January 1991 and October 2000. They find that the excess demand from US investors is an important determinant of the price difference in the short run (30-day), while over the one-year horizon, Nasdaq-listed ADRs earn a larger premium than their NYSE/AMEX listed counterparts. This premium may relate to a higher liquidity associated with the trading on NASDAQ. Two recent research essays touch upon the liquidity effects on the differences of ADRs and the underlying assets (Chan, Hong and Subrahmanyam 2008, Silva and Chavez 2008). These studies provide explanations on the deviations of ADRs prices from home market prices, including the effects of transaction costs and order flow competition for ADRs from various countries. Chan, Hong and Subrahmanyam (2008) directly study the liquidity-premium relationship of ADRs and their underlying shares. They find that a higher ADR premium is associated with higher ADR liquidity in the US market and lower liquidity in the ADRs' home markets. This liquidity effect remains strong even after they control the expected change in the foreign exchange rate, the stock market performance, as well as several variables measuring the openness and transparency of the home market. Instead of market liquidity, Silva and Chavez (2008) analyze liquidity costs for stocks and ADRs from the four main Latin American markets – Argentina, Brazil, Chile and Mexico. Their results indicate that in the local market, stocks that cross-list internationally do not always present a liquidity cost advantage relative to non-cross-listed stocks. Furthermore, Silva and Chavez (2008) categorize ADRs with the size of the firm and find that when the ADR and the local stock markets are compared, large firms present lower trading costs in the home market. The opposite occurs for small firms.

Among the few recent research essays that touch upon the pricing factors of ADRs, US market risks and exchange rate risk are found to have an impact on ADR prices (Kim, Szakmary and Mathur 2000, Fang and Loo 2002, Chan, Hong and Subrahmanyam 2008). The effect of US market on ADR returns may be due to a US market sentiment effect. Here the market sentiment is related to the literature on noise trading, which refers to "trading based on pseudo-signals"

(Schiller 1989), such as the mass psychology or speculative enthusiasm that might influence investors' expectation on the market. Bodoutha et al (1995) study closed-end country fund premium with their foreign asset values and find a U.S.-specific risk that affects country fund premium movement. Chan, Hong and Subrahmanyam (2008) also discuss the US market sentiment hypothesis and indicate that US market return as a proxy for market sentiment have a positive impact on the ADR premium in their sample. Here I use the term "pricing to market" to summarize the effects of US market on ADR pricing, including both macroeconomic development and the time varying market sentiment in the United States. Exchange rate risk is beyond the scope of this study as I focus on exploring the market systematic risks for ADR pricing.

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, I 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 (RS model) to characterize the uncertainty nature.

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 a reflection of their home-market underlying assets using domestic Capital Asset Pricing Model (CAPM). In the pricing to market regime, ADRs are treated as US domestic assets and priced using its covariance with the US market. The covariances in this research are estimated in a Generalized Autoregressive Conditional Hetetoreskedasticity framework (GARCH). 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.

Regime switching models allow the data to be drawn from two or more distributions. The transition from one regime to another is driven by a regime variable which follows a Markov chain process. The transition probabilities can be understood as a probability that the process will stay in the same regime or transfer to a different regime next period. The transition probabilities may be constant or they may depend on other variables (see the applications of state-dependent transition probabilities in Bekaert and Harvey 1995, Gray 1996, Ang and Bekaert 2002a, 2002b). However, econometricians do not observe the regime, and they have to infer from the data the regime at each point of time by constructing the regime probability. Regime probability is the probability of one particular regime to be the next period's regime given current and past information. The inference of regime probability can be done using a maximum likelihood technique (Hamilton 1994, Cai 1994, Gray 1996, Ang and Bekaert 2002a, 2002b), the EM algorithm of Hamilton (1990), or Bayesian techniques (Albert and Chib 1993, Kim, Nelson and Startz 1998).

Regime switching models have been previously employed in the interest rate models and the volatility of equity returns (Cai 1994, Hamilton and Susmel 1994, Gray 1996, Kim, Nelson and Startz 1998, Ang and Bekaert 2002a, 2002b). Cai (1994) presents the regime switching ARCH model to examine the monthly excess returns of the three-month treasury bill. In his model, the regime variable follows a Markov chain and affects only the intercept value of the conditional variance. He identified two periods during which there is a regime shift associated with oil shock and Fed policy changes, and the variances appear to be much higher during these two periods than the rest. Similarly, Hamilton and Susmel (1994) point out that GARCH models often impute a lot of persistence to stock volatility and yet give relatively poor forecasts which might be due to the different consequences of large shocks and small shocks on subsequent volatilities. They explore US weekly stock returns with another parameterization of regime switching ARCH model. In the model, it is the regime variable that is the scale variable for the ARCH process. Their estimates attribute most of the persistence in stock price volatility to the persistence of low-, moderate-, and high-volatility regimes, which typically last for several years. They also find that the high volatility regime is to some degree associated with economic recessions.

Gray (1996) presents a method to avoid the path-dependence problem of regime switching GARCH model by assuming that conditional variance depends only on the current regime, not on the entire past history of the process. His regime switching model of short rates shows that short rates exhibit a different form of conditional heteroskedasticity in each regime. In addition, the regime switching model outperforms the simple single-regime model in out-of-sample forecasting. Klaassen (2002) further expands Gray's regime switching GARCH model by allowing the conditional variance process to have different dynamics across regimes. That is, instead of specifying both regimes in conditional variance to be GARCH (1,1) as in Gray (1996), Klaassen (2002) allows one regime to be ARCH(2) process while another regime to be GARCH(1,1). Using about twenty years of daily data on three U.S. dollar exchange rates (British pound, German Mark and Japanese yen), the research shows that regime switching GARCH yields significantly better volatility forecasts than single regime GARCH.

To further the comparison of regime switching models with single regime models, Ang and Bekaert (2002a) apply two statistical criteria to compare and rank alternative single regime and regime switching models of short rates – the fit of unconditional moments and the forecasting power. They examine the econometric performance of regime switching models for interest rate data from the US, UK and Germany. They find that in matching sample moments, RS models do not systematically outperform one-regime models; however, RS models almost invariably do better in forecasting out of sample. Ang and Bekaert (2002b) apply the regime switching GARCH model to US, UK and German equity returns and find international equity returns appear to be characterized by two regimes: a normal regime and a bear market regime where the stock market returns are low on average and more volatile. They find that the correlations between market returns are higher in the bear market regime than in the normal regime. However, they find that the existence of a high-volatility bear market regime does not negate the benefits of international diversification, and the cost of ignoring the regimes are small for all-equity portfolios but increase when a conditionally risk-free asset can be held.

What are the advantages of regime switching models? First, and most importantly for this study, the regime probability gives a proxy of which distribution ADR returns are probably drawn from, either their home market pass-through regime or pricing-to-US-market regime. Under covariance risks framework, it provides a comparison in which regime ADRs are likely to be priced at each point in time, which in turn captures the time-varying market risks as indicated by selected macroeconomic variables as well as the covariance risks with the US and home market. This is the question that this research tries to answer – which market affects ADR returns more? A conditional CAPM with covariance risks without regime switching weighs the effects of the covariance risks equally in the model, but does not have the capability to estimate the mixed distribution probability.

Secondly, RS models bring non-linearity to "model data generated by different economic mechanisms, all within a single, unified model" (Gray 1996).[21] Urrutia and Vu (2006) find statistically significant evidence of non-linearity and low deterministic chaotic behavior in ADR returns and they suggest that pricing forecasting models for ADR returns should include non-linear terms. In this sense, RS model for ADR pricing is more advantageous than standard asset pricing models.

Thirdly, empirical research shows that the regime switching model outperforms the GARCH models in estimating volatilities forecast (Hamilton and Susmel 1994, Klaassen 2002). Klaassen (2002) discusses that GARCH forecasts are too high during volatile period because of the high persistence of individual shocks in those forecasts, while regime switching GARCH models have better forecasts than GARCH models in terms of mean squared error. The conditional mean of equity returns depends on its conditional covariances with the risk factors, which in turn are affected by the conditional volatilities. In terms of the conditional variance and covariance forecast, the RS conditional CAPM is better than one-regime conditional CAPM model. Ang and Bekaert (2002a) also note that, whereas regime switching models do not always outperform single regime models in the in-sample diagnostics, they forecast very well out of sample.

In our regime switching model, ADR returns comes from a mixture normal distribution and transition probabilities are constant. We apply this regime switching framework to Argentina, Japan, China and Germany. A proxy for home-market pass-through effect is developed for each country from 1998 to 2006. In pricing ADR index returns, Japan and China have a pricing-to-

[21] In modeling short rate changes, Gray (1996) notes that a regime switching model is flexible enough to incorporate a different speed of reversion to a different long run mean at different times throughout the same period and it is one way of relaxing the linearity inherent in most single-regime models. Ang and Bekaert (2002b) also illustrates that by state-dependent distribution function captures fat tails, stochastic persistent volatility and other properties of equity returns.

market regime dominance, while Germany and Argentina show home market pass-through regime dominance when home market is more volatile. The regime switching model is also compared with other conditional CAPM models, and out of sample forecasts are greatly improved for Germany, China and Japan, over the simple factor pricing model with US and home markets.

Section II of this essay discusses the regime switching framework in further details 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. Section VI compares the regime switching model with other single regime models and discusses the advantages of the set-up of our model. Section VII discusses an alternative regime switching framework (RS2) with "pricing-to-US-market" regime replaced by "pricing-to-world-market" regime. The final section summarizes the essay and points out further extensions of this research.

II. The Regime Switching Framework

Factor asset pricing models in current research is mostly based on the Sharpe (1964), Lintner (1965) and Black (1972) Capital Asset Pricing Models (CAPM), which are often called the beta-models, as they measure returns based on the exposure to risks. [22] Our base model starts

[22] There is another strand of model, often referred to as inter-temporal capital asset pricing models, in which prices are equal to future payoffs, multiplied by a simple discount factor. See Cochrane (2001) for details on consumption-based models.

with a conditional CAPM[23] in a completely integrated market with the absence of exchange rate risk:

$$E_{t-1}\left[R_{n,t}^{adr}\right]=\lambda_{t-1}\operatorname{cov}_{t-1}\left[R_{n,t}^{adr},R_{t}^{m}\right] \tag{36}$$

where n=1, 2, …N countries, λ_{t-1} is the price of the market risk at time *t-1*, $\operatorname{cov}_{t-1}\left[R_{n,t}^{adr},R_{t}^{m}\right]$ 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, it is unknown as to 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, I 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 multiplied by 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 (36) is then specified as:

$$E_{t-1}\left[R_{n,t}^{adr}\right]=\lambda_{t-1}^{us}\operatorname{cov}_{t-1}\left[R_{n,t}^{adr},R_{US,t}\right] \tag{37}$$

[23] 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 $n=1, 2, \ldots N$ 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 multiplied by the ADRs' exposure to the changes in the home market returns.[24] The expectation equation is

$$E_{t-1}\left[R_{n,t}^{adr}\right] = \lambda_{t-1}^{h} \text{cov}_{t-1}\left[R_{n,t}^{adr}, R_{n,t}^{\$}\right] \quad (38)$$

where λ_{t-1}^{h} is the home market price of risk at time *t-1*, $\text{cov}_{t-1}\left[R_{n,t}^{adr}, R_{n,t}^{\$}\right]$ 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:

$$E_{t-1}\left[R_{n,t}^{adr}\right] = \phi_{n,t-1}\lambda_{t-1}^{us} \text{cov}_{t-1}\left[R_{n,t}^{adr}, R_{US,t}\right] + (1-\phi_{n,t-1})\lambda_{t-1}^{h} \text{cov}_{t-1}\left[R_{n,t}^{adr}, R_{n,t}^{\$}\right] \quad (39)$$

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

$$\phi_{n,t-1} = prob[S_t = 1 | Z_{n,t-1}]. \quad (40)$$

Equation (40) can be viewed as an approximation of the 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). It is assumed that there is an "invisible hand" in the

[24] 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.

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.

To capture the time-varying characteristics of regime probability, I 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}.[25] Suppose the regime transition probabilities are the following (where the country subscript, n, has been suppressed):

$$\begin{aligned} \Pr(S_t = 1 \mid S_{t-1} = 1) = \mathrm{P} \\ \Pr(S_t = 2 \mid S_{t-1} = 2) = \mathrm{Q} \end{aligned} \tag{41}$$

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 the expected returns are incorporated in the model– the variation in the price of risk and the variation in the conditional risk measures (market betas).[26] Derivation of the likelihood function will be introduced in the methodology section. Following Bekaert and Harvey (1995), I calculate the local market volatility in US dollar terms in this model. That is, the home market return series in ADR home currency are converted to US dollar returns by adding the home currency returns. Therefore, the home market pass-through is the combination of the home market effect and the exchange rate fluctuations.

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

[26] 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.

III. Methodology - Regime Switching GARCH

As the mean equation (39) involves the conditional covariance in both regimes, I assume that conditional covariance in different regimes follow a General Autoregressive Conditional Heteroskedasticity (GARCH) process.[27] This approach differs from Bekaert and Harvey (1995) who adopt the ARCH method and provide parsimony. 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:

$$\begin{aligned} y_{n,t} &= [R_{n,t}^{adr}, R_{i,t}]' \\ R_{n,t}^{adr} &= \phi_{n,t-1}\lambda_{t-1}^{us}\operatorname{cov}_{t-1}\left[R_{n,t}^{adr}, R_{US,t}\right] + (1-\phi_{n,t-1})\lambda_{t-1}^{h}\operatorname{cov}_{t-1}\left[R_{n,t}^{adr}, R_{n,t}^{\$}\right] + e_{n,t} \\ R_{i,t} &= \lambda_{t-1}^{us}\operatorname{var}_{t-1}[R_{i,t}] + e_{i,t} \end{aligned} \tag{42}$$

Here i refers to the US market portfolio in regime one and 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. The conditional variance processes are defined under the two different regimes as

$$\begin{aligned} H_{1t} &= E[e^1 e^{1\,\prime} \mid Z_{n,t-1}] \\ H_{2t} &= E[e^2 e^{2\,\prime} \mid Z_{n,t-1}] \end{aligned} \tag{43}$$

$\operatorname{cov}_{t-1}\left[R_{n,t}^{adr}, R_{US,t}\right]$ is the off-diagonal element of H_{1t}, and $\operatorname{cov}_{t-1}\left[R_{n,t}^{adr}, R_{n,t}^{\$}\right]$ is the off-diagonal element of H_{2t}, and the conditional variance dynamics are modeled as a diagonal GARCH(1,1)

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[27] 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.

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, the system is assumed to be covariance-stationary for applying GARCH parameterization. This assumption is specified as follows:

$$\begin{aligned} H_{1t} &= C^1 C^1{}' + A^1 A^1{}' \otimes \mathrm{e}_{t-1}\mathrm{e}_{t-1}{}' + B^1 B^1{}' \otimes H_{t-1} \\ H_{2t} &= C^2 C^2{}' + A^2 A^2{}' \otimes \mathrm{e}_{t-1}\mathrm{e}_{t-1}{}' + B^2 B^2{}' \otimes H_{t-1} \end{aligned} \tag{44}$$

where $C_{s_t}, A_{s_t}, B_{s_t}$, 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,[28] the diagonal BEKK is less parameterized (Engle and Kroner 1995). Regime switching GARCH models are found to be subject to the path-dependence problem (Cai 1994, Hamilton and Susmel 1994, Gray 1996). That is, the conditional variance depends on the entire past history of the data in a GARCH model, which is embedded in the regime switching GARCH framework. Cai (1994) and Hamilton and Susmel (1994) only included ARCH terms to avoid this problem. Gray (1996) provides a non-path dependent approach for short rate changes by integrating out the unobserved regime path directly in the GARCH term. We follow Gray (1996) that conditional variance for ADR returns (the element (1, 1) for both matrices H_{1t} and H_{2t}) can be written as the following -

$$\begin{aligned} h_t = E(R_t^2 \mid Z_{t-1}) - [E(R_t \mid Z_{t-1})]^2 = p_{t,S_t=1}(u_{t,S_t=1}^2 + h_{t,S_t=1}) + (1-p_{t,S_t=1})(u_{t,S_t=2}^2 + h_{t,S_t=2}) \\ - [p_{t,S_t=1}u_{t,S_t=1} + (1-p_{t,S_t=1})u_{t,S_t=2}^2]^2 \end{aligned} \tag{45}$$

where $p_{t,S_t=1}$ is the regime 1 probability at time t ; $u_{t,S_t=1}$ is the mean at time t given regime 1; and $h_{t,S_t=1}$ is the conditional variance for ADR returns at time t given regime 1.

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

The price of risk is assumed to be time varying, and estimated with a latent variable approach using macroeconomic variables (Harvey 1991 and Bekaert and Harvey 1995).

$$\lambda_{t-1}^{us} = \exp(\delta' Z_{t-1}^{*}) \\ \lambda_{t-1}^{h} = \exp(\delta_n' Z_{n,t-1}^{*}) \tag{46}$$

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. According to Bekaert and Harvey (1995), the exponentiation ensures that the price of risk is positive.

For a particular country's information set, $Z_{n,t-1}^{*}$, the following variables are chosen 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), I 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 I use weekly data, there is no available data for GDP in this frequency, and changes of the local stock market value will help capture the effect of the change of market size, which directly reflects the state of the economy and affects the degree of home market pass-through.

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

$$f(y_t \mid S_t = i, Z_{t-1}) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left\{ \frac{-(y_t - \mu_i)^2}{2\sigma_i^2} \right\} \quad \text{i=1,2} \tag{47}$$

So the conditional probability density function is

$$f(y_t \mid Z_{t-1}) = \sum_{i=1}^{2} f(y_t, S_t = i \mid Z_{t-1}) = \sum_{i=1}^{2} f(y_t \mid S_t = i, Z_{t-1}) \Pr(S_t = i \mid Z_{t-1}) \tag{48}$$

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

$$f(y_t;\theta) = \frac{\phi}{\sqrt{2\pi}\sigma_1} \exp\left\{ \frac{-(y_t - \mu_1)^2}{2\sigma_1^2} \right\} + \frac{(1-\phi)}{\sqrt{2\pi}\sigma_2} \exp\left\{ \frac{-(y_t - \mu_2)^2}{2\sigma_2^2} \right\} \tag{49}$$

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

$$\log L(\theta) = \sum_{t=1}^{T} \log f(y_t;\theta) \tag{50}$$

After the conditional variance and covariance is parameterized, the log-likelihood function in above equation is expressed in the following multivariate form that nests the regime switching model and GARCH process, which I call a hybrid ML function:

$$\log L = \sum_{t=1}^{T} (\log[\frac{\phi_{n,t-1}}{\sqrt{2\pi}} \mid H_{1t} \mid^{-0.5} \exp\left\{ \frac{-(e^{1}{}'(H_{1t})^{-1} e^{1})}{2} \right\} + \frac{(1-\phi_{n,t-1})}{\sqrt{2\pi}} \mid H_{2t} \mid^{-0.5} \exp\left\{ \frac{-(e^{2}{}'(H_{2t})^{-1} e^{2})}{2} \right\}]) \tag{51}$$

Therefore the parameters that need to be estimated, 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.[29] This form is also called Quasi-Maximum Likelihood (QML) approximation, which is applied to calculate ML standard errors. The

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

appendix at the end of the essay provides details about the inference of unobserved regime probabilities.

To estimate this model, I adopt the two-step procedure by Bekaert and Harvey (1995). First, I use the univariate non-linear GARCH (1,1) model to estimate the parameters related to country market returns alone. Particularly $C^1(2,1)$, $A^1(2,1)$, $B^1(2,1)$ and δ' are estimated firstly using the US market returns and US information variables Z^*_{t-1}, and $C^2(2,1)$, $A^2(2,1)$, $B^2(2,1)$ and δ_n' are estimated using the home market returns and predictable information variables $Z^*_{n,t-1}$. In step two, these estimates from the first step are plugged back to the whole model and the rest of the parameters will be estimated in the multivariate form, as represented by equation (42).

IV. Data

In this study, I use ADR price indices data developed by Bank of New York (BNY) for Japan, Germany, Argentina, and China.[30] Market indices are obtained from DataStream 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 I 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, I 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

[30] There are 39 country-specific ADR indices in the BNY ADR database (www.bnyadr.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 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.

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 inter-bank 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.[31] Table 1 provides summary statistics for the ADR returns and predictable variables for US, and Japan, Germany, Argentina, and China.

V. Empirical Results

V.1. Step one: Estimating market price of risks

In step one, I 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

$$\begin{aligned} R_{US,t} &= \lambda_{t-1}^{us} \operatorname{var}_{t-1}[R_{US,t}] + e_{us,t} \\ \lambda_{t-1}^{us} &= \exp(\delta' Z_{t-1}) \end{aligned} \tag{52}$$

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

$$h_t = c + \alpha_1 e_{us,t-1}^2 + \alpha_2 h_{t-1} \tag{53}$$

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

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

$$\log L = \sum_{t=1}^{T} \log\left[\frac{1}{\sqrt{2\pi h_t}} \exp\left\{ \frac{-(R_{US,t} - \lambda_{t-1}^{us} \operatorname{var}_{t-1}[R_{US,t}])^2}{2h_t} \right\} \right] \tag{54}$$

I 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. Given the restricted and unrestricted estimates, log-likelihood ratio tests would be performed.

During the estimation process, I obtain the maximized log likelihood value with every set of random starting values for model parameters. I 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, the covariance matrix would be calculated following Kim and Nelson (1999, page 16), i.e., with constrained maximization, the model covariance would be adjusted by the gradient of constrained function. The estimated time series for the US price of risk and residuals would be saved 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: $\alpha_1 = \alpha_2 = 0$. 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, equation (52) is estimated 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 correspond to home predictable variables in the order of: a constant, changes of short rate,[32] 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.

V.2. Step two: Estimating MLE country by country.

In this step, a country-specific analysis is performed using our regime switching multivariate GARCH model (Equation 42). As discussed before, the local macroeconomic variables $Z^*_{n,t-1}$ monitor the price of risk in the ADR home markets. I adopt the flow chart from Kim and Nelson (1999) for estimating regime switching models and add in the GARCH-in-

[32] We use the log differences to measure the percentage 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.

mean steps in our model (see the appendix).[33] 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), I 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 I use the form of { $H_{1,0}$= ee1 .*(i*i'-A1*A1'-B1*B1') and $H_{2,0}$= 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, special attention needs to be paid to the numerical optimization of the hybrid maximum likelihood function – I try at least 50 sets of starting values, choose the highest log-likelihood value and then use the corresponding estimates as model starting values to repeat the estimation process, so that the convergence of results is ensured.

Table 4 summarizes the estimation results from step 2. Estimates of regime transition probabilities (P and Q) are presented in the first two rows for each country, with the Quasi-Maximum Likelihood errors in the parenthesis. They are all statistically significant except Q for China and Japan. The GARCH estimates under two regimes are presented in the next six rows. For the estimates of constant transition probabilities, P and Q are both high (>90%) for Argentina and Germany, which means that probability of staying in regime one (two) in one period to 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.[34] It is called "inertia to change." However, for China and Japan, both of them have a greater P than Q, which indicates that the regime one (pricing-to-US market) is more persistent than regime two (home-market pass-through). In particular, China has a P value of over 99%, while Q is less than 1%. It implies that

[33] Authors acknowledge the insights from the programs provided by Kim and Nelson (1999).
[34] 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.

for Chinese ADRs, once regime one sets in, there is a 99% probability of staying in regime one but when regime two sets in, the probability of staying in regime two is less than 1% while the probability of switching to regime one is over 99%. Therefore, it shows a strong dominance of the pricing-to-market regime, Regime one, for Chinese ADRs.

Figures 1-4 compares the time-varying pass-through for the four countries. Figure 1 depicts the time path of home market pass-through for Argentina. I observe that probabilities of home-market pass-through regime are over 80% at the end of 1998 and then decrease to less than 40% during 1999. Home-market pass-through regime clearly dominates from the end of 1999 till early 2003, while pricing-market regime takes over from then (with an average of home market pass-through probability less than 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 pass-through probability, the home market regime has much higher probabilities in influencing the ADR returns. 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, as the systematic risks in the US market are weighted higher in ADR pricing in terms of higher probabilities of the pricing-to-market regime. A smoothed time-path of home market pass-through regime probability is presented with the dashed line. 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 pass-through probabilities before and after 2003.

Germany has a clear regime dominance division around the end of 2003. The regime probabilities for home market pass-through dominate mostly from 1998 to the first half of 2003, while afterwards pricing-to-market regime sets in. German firms traditionally were reluctant to list in the United States given the strict disclosure requirement with SEC, such as the case of

Daimler's NYSE Listing in 1994. However starting from 1998, I observe more German firms listing in the US. From 2000 to 2002, Germany also experienced the beating in the economy from the tech bubble. In terms of market returns in Germany, I observe large fluctuations in the pre-2003 time period. It appears that Germany ADRs tends to be influenced greatly by their home markets when home markets exhibits higher volatility. It is also plausible that the Germany ADR listings during this period were relative new so that the demand in the US market was small and has relative weak effects on ADR returns. From 2003 German government also started a series deregulatory reform in the economy and economy was moving out the recession, which might contribute to the lesser weight of home market in ADR returns in the last few years in our data.

The time paths of regime two probabilities (home market pass-through) for Japan and China appear very similar. As shown from Figures 3 and 4, the regime probabilities of staying in regime two are kept very low for both countries. It indicates that the pricing-to-market regime dominates most of the time. There are two immediate jumps of the home market pass-through regime probabilities in April 2000 and September 2001, which coincide with two large drops of US market returns -14% and -12% respectively. During the short-lived high regime probabilities of home market pass-through, the ADR index returns for both countries are priced to the home markets.

V.3. Model specification and diagnostics

V.3.1. Model Diagnostics Tests

Besides the usual residual properties, I use a summary point statistic to capture the quality of regime classification as in Ang and Bekaert (2002). An ideal RS model should classify regimes distinctively so that I can see regime probabilities close to 1 or 0 (Ang and Bekaert 2002). That is, if the regime probabilities over time are close to a half, I cannot clearly classify a dominant regime, and as such the model is inferior and has weak regime inference. Weak regime may indicate misspecification. Following Ang and Bekaert (2002a), I define the regime classification measure (RCM) as the following:

$$RCM = 100K^2 \times \frac{1}{T}\sum_{t=1}^{T}(\prod_{i=1}^{K} p_{i,t}) \tag{55}$$

where K is the number of states and the constant serves to normalize the statistics to be between 0 and 100. The RCM is reported in Panel B of Table 4. The smaller the RCM is, the better the regime classification. All four countries have relatively small RCM statistics (less than 21). Japan and China have RCMs around 1, which further strengthens my discussion earlier on the dominance of pricing-market regime. I also report a few residual diagnostic tests in Panel B of Table 4 for my sample. Ljung-Box Q statistics (lag 8) for residuals are insignificant for all four countries except Argentina, while the Q statistics for the squared residuals are significant for all four countries. It indicates that there might be further GARCH effects in the residuals. However, in this essay, as I am mainly interested in weighing the time varying effects of the US and home markets on ADR returns, I do not go to the details on the GARCH specification. When I compare RS model with other conditional CAPMs, I apply GARCH(1,1) as well and focus on whether or not adding regime switching improves the model forecast.

V.3.2. Model Specification Test

To make sure the model is specified correctly, I also perform a model specification test. The residuals $e_{n,t}$ from step 2 are saved for each country, then regressed over ADR home market macroeconomic variables and the US macroeconomic variables. 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 parenthesis for each country. Among the four countries, China has the lowest R-squared value and I did not find any joint explanatory power for China's residuals at 5% confidence level (insignificant Global F). I find that the coefficients corresponding to the US predictable variables are all non-significant for all four countries. Two of the local predictable variables - local market dividend yields and short rates, are insignificant for all four countries.

However, there is still significant explanatory power for two home market predictable variables – the market value changes for Argentina, Germany and Japan, and exchange rate changes for Argentina and Japan. This indicates that market value changes and exchange rate changes capture some risks contained in the model residuals. As market value and exchange rate changes enter the model indirectly as home country predictable variables when I estimate time-varying price of risks in step one, it is possible that they may still explain, to some extent, the residuals from step two. It is also plausible, as I assume only home market pass-through regime or pricing-to-US-market regime in ADR returns at any particular point of time.

VI. Regime switching model with single regime GARCH models

The foremost advantage of our regime switching model is that the regime probabilities give a proxy of how "pricing to US market" and "home market pass-through" regimes change over time. Furthermore, the single regime GARCH models usually suffer from high persistence in the conditional variance, while regime switching models provide better out of sample forecast (Klaassen 2002, Ang and Bekaert 2002a and 200b).

Therefore, I compare our model with three other benchmark models – the conditional CAPM with world factor (CCAPM1), the conditional CAPM with world and home factors (CCAPM2), and the conditional CAPM with US and home factors (CCAPM3). CCAPM1 assumes full integration of the world market. CCAPM2 assumes partial integration of the world market with significant idiosyncratic risks from individual markets. CCAPM3 assumes market segmentation as US and home market factors are treated as two most important market risk factors for ADR returns. In this sense, my regime switching CAPM (RS1) with US and home market factors also assumes segmentation of world markets.

CCAPM1 – Conditional CAPM with world market

The conditional CAPM with world factor is the simplest version. It is a conditional capital asset pricing model that measures ADR returns based on its exposure to world market risks. I assume world market integration with the absence of exchange rate risk.

$$E_{t-1}\left[R_{n,t}^{adr}\right]=\lambda_{t-1}^{w}\operatorname{cov}_{t-1}\left[R_{n,t}^{adr},R_{w,t}\right] \tag{56}$$

where $R_{w,t}$ is the return to world market portfolio at time t while λ_{t-1}^{w} gives the price of risks in the world market at time *t-1*. To estimate this model, I add in the world market portfolio equation and estimate with a multivariate GARCH-in-mean Model.

$$E_{t-1}\left[R_{w,t}\right]=\lambda_{t-1}^{w}\operatorname{var}_{t-1}\left[R_{w,t}\right] \tag{57}$$

The conditional variance setup also follows BEKK framework. I only consider GARCH(1,1) format because I am mainly interested in seeing whether it improves our model estimation by adding regime switching framework combining US and home market. The model set up is as the following.

$$\begin{aligned} y_{n,t} &= [R_{n,t}^{adr}, R_{w,t}]' \\ R_{n,t}^{adr} &= \lambda_{t-1}^{w} \operatorname{cov}_{t-1}\left[R_{n,t}^{adr}, R_{w,t}\right] + e_{n,t} \\ R_{w,t} &= \lambda_{t-1}^{w} \operatorname{var}_{t-1}[R_{w,t}] + e_{w,t} \\ e_t &= [e_{n,t} \quad e_{w,t}]' \end{aligned} \tag{58}$$

And the price of risk is estimated the same way as before

$$\lambda_{t-1}^{w} = \exp(\delta Z_{t-1}^{*}) \tag{59}$$

To estimate the model, I use GARCH(1,1) setup. The conditional variance follows

$$H_t = CC' + AA' \otimes \mathrm{e}_{t-1}\mathrm{e}_{t-1}' + BB' \otimes H_{t-1} \tag{60}$$

Here *C, A, B* are 2×1 vectors of unknown parameters, and $\otimes$ represents element by element matrix multiplication (Hadamard product). To ensure the model parameters for the world market will not be greatly affected by individual market, I also use two-step procedure, i.e., I estimate the model parameters for the world market equation then plug it back to estimate the rest of parameters. The estimation is done country by country for the same period (1998-2006). I use the DataStream world market index data as a proxy to the world market portfolio to calculate world market weekly returns.

The results are shown in Table 6. As all countries share common world price of risks, I only report the first element in *C, A, B* as in equation(60). GARCH parameters are statistically significant. For ADRs from all four countries, the conditional variances are characterized by high persistence (higher b_1), and low sensitivity to individual shocks (lower a_1). That is, the effect of individual shocks dies out quickly, and the conditional variance appears to be path-dependent.

CCAPM2– Conditional CAPM with world market and home market

The second conditional CAPM model considers both the world market risk and local market risk. Recent studies show that emerging market risks are also priced in global equity prices

(Carrieri, Errunza and Majerbi 2006). Patro (2000) also find that the returns on ADRs have significant risk exposures to the returns on the world market portfolio and their respective home market portfolios. Therefore, the second conditional capital asset pricing model contains two covariance risks – the world market risk and local market risk. I assume that in addition to world market risk, country specific risk is another specific source of risk for ADR returns as measured by covariance of ADR returns with the local market portfolio. Again, I assume the absence of exchange rate risk.

$$E_{t-1}\left[R_{n,t}^{adr}\right]=\lambda_{t-1}^{w}\operatorname{cov}_{t-1}\left[R_{n,t}^{adr},R_{w,t}\right]+\lambda_{t-1}^{h}\operatorname{cov}_{t-1}\left[R_{n,t}^{adr},R_{n,t}^{\$}\right] \tag{61}$$

To estimate this model, I add two auxiliary equations - the local market portfolio and world market portfolio and estimate the system with a multivariate GARCH-in-mean Model.

$$\begin{aligned} E_{t-1}\left[R_{n,t}^{\$}\right]&=\lambda_{t-1}^{w}\operatorname{cov}_{t-1}\left[R_{n,t}^{adr},R_{w,t}\right]+\lambda_{t-1}^{h}\operatorname{var}_{t-1}\left[R_{n,t}^{\$}\right]\\ E_{t-1}\left[R_{w,t}\right]&=\lambda_{t-1}^{w}\operatorname{var}_{t-1}\left[R_{w,t}\right] \end{aligned} \tag{62}$$

The model set up is similar to CCAPM1. However, I am estimating a triviate GARCH(1,1) model as the following.

$$\begin{aligned} y_{n,t}&=[R_{n,t}^{adr},R_{n,t}^{\$},R_{w,t}]'\\ R_{n,t}^{adr}&=\alpha_{n,1}+\lambda_{t-1}^{w}\operatorname{cov}_{t-1}\left[R_{n,t}^{adr},R_{w,t}\right]+\lambda_{t-1}^{h}\operatorname{cov}_{t-1}\left[R_{n,t}^{adr},R_{n,t}^{\$}\right]+e_{n,t}^{adr}\\ R_{n,t}^{\$}&=\alpha_{n,2}+\lambda_{t-1}^{w}\operatorname{cov}_{t-1}\left[R_{n,t}^{adr},R_{w,t}\right]+\lambda_{t-1}^{h}\operatorname{var}_{t-1}\left[R_{n,t}^{\$}\right]+e_{n,t}\\ R_{w,t}&=\lambda_{t-1}^{w}\operatorname{var}_{t-1}[R_{w,t}]+e_{w,t}\\ e_{t}&=[e_{n,t}^{adr}\quad e_{n,t}\quad e_{w,t}]'\\ H_{t}&=CC'+AA'\otimes \mathrm{e}_{t-1}\mathrm{e}_{t-1}'+BB'\otimes H_{t-1} \end{aligned} \tag{63}$$

where *C, A, B* are 3×1 vectors of unknown parameters, and $\otimes$ represents element by element matrix multiplication (Hadamard product).

The results are shown in Table 7. All GARCH parameters for the four countries are statistically significant (numbers in parenthesis give the QML errors). In CCAPM2, I find stronger evidence of GARCH persistence, as elements in *B* are over 94% for ADRs for all four countries. Compared with CCAPM1, CCAPM2 implies that after adding the covariance factor with the home market, conditional variances for ADRs have much higher persistence.

CCAPM3– Conditional CAPM with US market and home market

If I replace world factor with US factor in the conditional CAPM model 2, I implicitly assume that the international market is still segmented. ADR prices are only affected by the home markets and the US market. This model is a single regime version of our base model (RS model) introduced in section II. In CCAPM3, I estimate the similar triviate model as (63). The results are similar to CCAPM2 (Table 8), in that I find strong evidence of high persistence of conditional variances for ADRs. CCAPM2 appears to perform better than CCAPM3 in terms of likelihood value for all four countries.

Forecast Comparison

To compare the out of sample performance of the regime switching model with single regime conditional CAPMs, I add one year data for 2007. The forecast method is to estimate the parameters using the in-sample period (1998-2006) and then use the estimated parameters to estimate on the data from 2007. I use two point statistics to calculate unconditional forecast errors as in Ang and Bekaert (2002) – the root mean square error and mean absolute deviation, as defined by the following –

$$\begin{aligned} RMSE &= \sqrt{\frac{1}{T}\sum(R_{n,t}^{adr} - \hat{R}_{n,t}^{adr})^2} \\ MAD &= \frac{1}{T}\sum| R_{n,t}^{adr} - \hat{R}_{n,t}^{adr} | \end{aligned} \qquad (64)$$

Both RMSE and MAD statistics for both residuals and squared residuals are presented in Table 9. My regime switching model with US market and home market is reported under the RS1. I observe the smallest RMSE for residuals from CCAPM2 for Argentina, Japan and Germany, but from CCAPM1, only China. Ang and Bekaert (2002a) also find that one-regime GARCH models produce the best results, as with my CCAPM1 and CCAPM2 models. However, if I compare RS1 with single regime counterpart (CCAPM3), RS1 provides better forecasts for Japan, China and Germany in terms of both of point statistics in residuals and squared residuals.

VII. Pricing-to-US market or Pricing-to-World market?

An alternative setup to this regime switching framework is to adopt the International CAPM, using the world market beta. 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. Instead, using the covariance risk with the US market factor to denote the "pricing-to-market" regime (RS1), I use the covariance risk with the world market to define the "pricing-to-market" regime, i.e. the regime switching CAPM with world and home factors (RS2). Since US market and world market is highly correlated with over 90% contemporaneous correlations (see Figure 5), I would expect similar results when substituting US market price index with world price index. The results of the second regime switching model (RS2) are shown in Table 9.

The estimated time paths of home-market pass-through regime show similar pattern for all four countries.[35] It is plausible as US market is weighted heavily in the world market portfolio and world market index is highly correlated with US market index. From the likelihood value, it

[35] Figures are not reported here but available upon request.

appears that regime switching model using "pricing to US market" regime performs better than "pricing to world market" regime for Germany and Japan (higher likelihood value), but not for Argentina and China (lower likelihood value). In terms of out-of-sample forecast as in Table 10, RS1 produces better results for Germany than RS2 but not for Argentina, Japan and China. Given the mixed results, I prefer "pricing-to-US market" over "pricing to world market" as ADRs are directly affected by the US market sentiment and the model does not need a stronger assumption of "a world market portfolio".

VIII. Summary

In this essay, I 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). A regime switching model is employed to nest these two regimes. Different degrees of pass-through of ADRs are found in the four countries studied. In pricing ADR index returns, Japan and China have a pricing-to-market dominance (low home market pass-through regime probability). Germany and Argentina have a "home-market pass-through" regime dominance till 2003 when their home markets are experiencing high volatility from economy downturns or even financial crisis, then "pricing-to-US-market" regime dominates from 2003 to 2006.

I compare the regime switching models with different versions of single-regime conditional capital asset pricing models in terms of out-of-sample forecast, and find that the regime switching model with US and home market factor performs better than the single regime counterpart for Japan, China and Germany. I also check whether it will improve the model forecast by replacing the US market factor with world market factor. The alternative regime switching model (RS2) produces very similar estimates and the time path of home market pass-through regime probabilities show similar pattern for all four countries.

There are a number of possible extensions of the essay. Firstly, as this essay only addresses four countries, it is a satellite test of how these two regimes affect ADR returns. To have a complete view of this home market pass-through of ADRs, it needs 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 research is to separate exchange rate returns from home market returns in assessing home market pass-through (regime two). As this research 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 exchange rate risk is estimated specifically. Thirdly, in this model, the transition probabilities (P and Q) between the two regimes are assumed to be 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). This 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

$\Pr(S_0)=\pi_j(i.e., \pi_{1,0}, \pi_{2,0}$ for state 1 and state 2 at time 0) (steady-state probability)

And at time 0, the initial values of $\mathrm{h}_{1,0}, \mathrm{h}_{2,0}, \mathrm{e}_{1,0}, \mathrm{e}_{2,0}$

$\Downarrow$

$\Downarrow$

$\mu_0=\pi_{1,0}\mu_{1,0}+\pi_{2,0}\mu_{2,0}$ and

$\mathrm{h}_0=\pi_{1,0}(\mu_{1,0}^2+h_{1,0})+\pi_{2,0}(\mu_{2,0}^2+h_{2,0})\rightarrow \mathrm{h}_{1,1}, \mathrm{h}_{2,1}; \mathrm{e}_1$ at time 1

$\Downarrow$

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

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

$\Downarrow$

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

$\Downarrow$

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

$\Downarrow$

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

$\Downarrow$

h_1, and $\mathrm{h}_{1,2}, \mathrm{h}_{2,2}; \mathrm{e}_2$ at time 2

$\Downarrow$

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

Note: Based on the flowchart for regime switching by Kim and Nelson (1999), I add in the GARCH-in-mean effects. While I are updating information on the regime probability from Z_{t-1} to Z_t, I also update conditional variance and forecast error and iterate the process.

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 US 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,

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

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

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

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

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

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

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 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 for regime switching ADR

	Panel A: Parameter estimates							
	Argentina		China		Germany		Japan	
P	0.99344818*	(0.005427)	0.99319995*	(0.004769)	0.99761268*	(0.001501)	0.944289*	(0.00496568)
Q	0.99148588*	(0.006672)	*0.000358*	(0.000855)	0.99779928*	(0.001593)	0.717864	(0.85604457)
C1(1,1)	-0.000019	(0.000591)	-0.000009*	(0.0000046)	0.000042*	(0.0000198)	-0.000232*	(0.00010286)
C2(1,1)	0.000055	(0.000105)	0.026607*	(0.014397)	0.002174*	(0.000444)	0.271321	(0.93615907)
A1(1,1)	0.9357407*	(0.0413)	0.91302718*	(0.006162)	0.92643476*	(0.009646)	0.853818*	(0.02462627)
A2(1,1)	0.93000717*	(0.041136)	0.50965788*	(0.077138)	0.97678234*	(0.003605)	0.628681	(2.19232864)
B1(1,1)	-0.003833	(0.008563)	-0.002650*	(0.001075)	0.005223*	(0.005155)	-0.08338*	(0.03846733)
B2 (1,1)	-0.000003	(0.002035)	0.560164*	(0.214818)	0.005307	(0.001002)	0.208102	(1.34792843)
Likelihood value	2797.0842		2728.965858		2941.4748		2807.346	
	Panel B: Residual Diagnostics							
Ljung-Box $Q(e)_8$	19.767	*p=0.011*	11.286	*p=0.186*	6.777	*p=0.561*	6.85	p=0.553
Ljung-Box $Q(e^2)_8$	22.435	*p=0.004*	122.488	*p=0*	34.488	*p=0*	39.556	p=0
RCM	20.9533133		1.123515129		12.44163674		0.26988	

Note: In Panel A, for each country, the first columns give the parameter estimates, while the second column presents the Quasi-Maximum Likelihood errors inside the parenthesis. Panel B gives Ljung-Box Q statistics for residuals and squared residuals and regime classification measure (RCM) as Ang and Bekaert (2002).

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

		Home market				US 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	0.000796	-0.196681	0.970926*	1.232971	1.285884*	1.3863	0.191078	-1.10296	0.403881	0.69334
	(-0.00619)	(-0.354232)	(-0.034375)	(-0.887105)	(-0.891448)	(-1.955098)	(-1.360005)	(-0.595521)	(-0.408392)	
e_germany	-0.0034	-0.2006	0.9929*	-0.0073	-0.1199	-0.0569	0.0020	0.0134	0.4069	0.547432
	(-0.0177)	(-0.2132)	(-0.0809)	(-0.0051)	(-0.1036)	(-0.0783)	(-0.0045)	(-0.0104)	(-0.7309)	
e_argentina	-0.0041	-0.0177	0.5435*	-0.0013	-0.4682*	0.1060	0.0043	-0.0010	1.5269	0.413351
	(-0.019)	(-0.0127)	(-0.0931)	(-0.0016)	(-0.1135)	(-0.0757)	(-0.005)	(-0.0096)	(-1.3462)	
e_china	-0.0031	-0.0200	0.0728	0.0063	-2.5992*	0.0264	0.0116	0.0006	-0.4889	0.003296
	(-0.0235)	(-0.1847)	(-0.0419)	(-0.0046)	(-0.842)	(-0.0742)	(-0.0096)	(-0.0114)	(-1.1937)	

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.

Table 6. CCAPM1 – Conditional CAPM with world market

GARCH-in-mean (1,1)				
	Argentina	China	Germany	Japan
C(1,1)	0.0156	0.0216	0.0047	0.0144
	(0.002)	*(0.0034)*	*0.0048*	*(0.0014)*
A(1,1)	0.0537	0.1152	0.1856	0.1002
	(0.0133)	*(0.0406)*	*0.0261*	*(0.0201)*
B(1,1)	0.9463	0.8848	0.9801	0.8998
	(0.0133)	*(0.0406)*	*0.0073*	*(0.0201)*
Likelihood value	2216.867	2260.904	2469.103	2502.213
Ljung-Box $Q(e)_8$	23.072	4.761	7.279	8.296
	p=0.003	*p=0.064*	*p=0.507*	*p=0.405*
Ljung-Box $Q(e^2)_8$	32.348	9.846	37.447	6.67
	p=0	*p=0*	*p=0*	*p=0.573*

Note: The first elements of multivariate conditional variances in equation (25) are reported here. For each parameter estimated, the maximum likelihood errors are reported inside parenthesis.

Table 7. CCAPM2– Conditional CAPM with world and home market

Panel A: Parameter estimates from CCAPM2								
	Argentina		China		Germany		Japan	
C1	0.0023	(0.001)	0.0036	(0.0008)	0.0035	(0.0025)	0.0042	(0.0007)
C2	0.0017	(0.001)	0.0012	(0.0005)	0.0023	(0.0014)	0.0023	(0.0004)
A1	0.3356	(0.0373)	0.2196	(0.0434)	0.165	(0.3316)	0.1375	(0.0202)
A2	0.3694	(0.0356)	0.0574	(0.0358)	0.0603	(0.3635)	0.1695	(0.0269)
B1	0.9535	(0.0077)	0.9722	(0.0072)	0.9763	(0.0459)	0.9811	(0.0022)
B2	0.9419	(0.0088)	0.9975	(0.0018)	0.992	(0.0208)	0.982	(0.0041)
$\delta 1$	-27.9038	(36.5224)	0.0767	(0.033)	0.2601	(50.4143)	-0.5618	(3.0335)
$\delta 2$	12.1839	(9.3049)	-5.1961	(0.5458)	-1.9581	(138.616)	6.8948	(16.9601)
$\delta 3$	14.8911	(25.7557)	6.9667	(0.9918)	47.1129	(622.0315)	-36.0197	(47.1842)
$\delta 4$	732.0465	(2055.306)	-528.229	(111.9291)	-131.134	(159.9469)	-18.4509	(32.6056)
$\delta 5$	12.333	(45.114)	-308.772	(31.8717)	29.6355	(76.7265)	70.9004	(41.5628)
Likelihood value	3953.4249		3885.539		4100.075		4369.004	
Panel B: Residual Diagnostics								
Ljung-Box $Q(e)_8$	28.895	*p=0*	13.675	*p=0.091*	7.316	*p=0.503*	4.846	*p=0.774*
Ljung-Box $Q(e^2)_8$	38.512	*p=0*	147.442	*p=0*	38.523	*p=0*	5.865	*p=0.662*

Note: The first two elements of trivariate conditional variances in equation (28) are reported here. For each parameter estimated, the maximum likelihood errors are reported inside parenthesis. 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.

Table 8. CCAPM3 – Conditional CAPM with US market and home market

Panel A: Parameter estimates from Model 2 (US,home)								
	Argentina		China		Germany		Japan	
C1	0.0057	0.0019	0.0037	0.0013	0.0053	0.0014	0.0261	0.0032
C2	0.0077	0.0016	0.0195	0.0043	0.0053	0.0017	0.0294	0.0013
A1	0.3414	0.0441	0.2819	0.0424	0.3503	0.0669	0.2843	0.0557
A2	0.3584	0.0364	0.3838	0.0922	0.5379	0.0685	0.3089	0.0698
B1	-0.9445	0.0105	0.9585	0.0105	0.9355	0.0121	0.5351	0.1185
B2	-0.9271	0.0123	0.6664	0.1507	0.8881	0.0176	0.0821	0.1693
δ1	-182.04	88.226	-0.1437	0.2178	-52.3568	187.5327	0.361	0.58
δ2	34.3541	19.5136	-5.7654	1.5348	-420.262	1422.524	3.0127	3.3274
δ3	107.1389	60.9343	7.7194	1.1396	-520.225	1793.421	-19.8877	9.6918
δ4	5753.493	2725.88	-604.59	100.9889	-1894.01	6531.863	-3.4788	6.0042
δ5	-37.9892	25.6348	-332.053	29.6	-16.7289	243.1933	62.4412	9.1185
Likelihood value	3846.499		3747.338		4051.593		4171.127	

Panel B: Residual Diagnostics								
Ljung-Box $Q(e)_8$	19.232	*P=0.014*	13.606	*P=0.093*	4.177	*P=0.841*	3.247	*P=0.918*
Ljung-Box $Q(e^2)_8$	23.583	*P=0.003*	147.906	*P=0*	102.699	*P=0*	11.588	*P=0.171*

Note: The first two elements of trivariate conditional variances in equation (28) are reported here. For each parameter estimated, the maximum likelihood errors are reported inside parenthesis. 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.

Table 9. Regime switching framework with the world and home market under market segmentation hypothesis

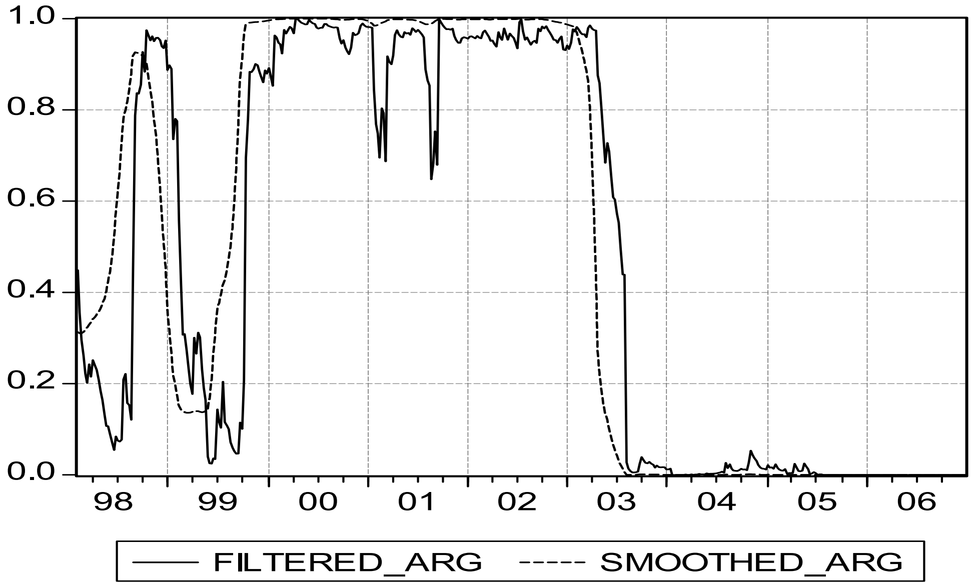
Panel A: Parameter estimates from RS2								
	Argentina		China		Germany		Japan	
p	0.985374	(0.00013295)	0.979707	(-0.00000531)	0.999317	(-0.000246)	0.624445	(-0.017849)
q	0.995116	(0.00031237)	0.739360	0.0000000	0.995211	(-0.00133)	0.512773	(-0.003198)
C1(1,1)	0.000050	(0.00000416)	0.000000	(-0.00000016)	0.000066	(-0.0000919)	-0.000012	(-0.0000853)
C2(1,1)	0.000000	(0.00000027)	-0.044970	(-0.000134)	0.000033	(-0.000663)	-0.014982	(-0.013266)
A1(1,1)	0.943808	(0.01006435)	0.861981	(-0.0000736)	0.905974	(-0.033876)	0.699660	(-0.008549)
A2(1,1)	0.945115	(0.00074662)	0.940815	(-0.001806)	0.992789	(-0.001389)	0.448857	(-0.298608)
B1(1,1)	0.000000	(0.00036159)	-0.000001	(-0.00000187)	0.001566	(-0.009448)	0.221197	(-0.012406)
B2 (1,1)	0.000000	(0.00000032)	0.503988	(-0.001093)	0.000146	(-0.004711)	0.296936	(-0.150731)
Likelihood value	2814.3259		2784.989968		2938.617		2635.8275	
Panel B: Residual Diagnostics								
Ljung-Box $Q(e)_8$	18.3	*p=0.019*	12.864	*p=0.117*	5.746	*p=0.676*	9.018	*p=0.341*
Ljung-Box $Q(e^2)_8$	25.115	*p=0.001*	150.946	*p=0*	4.463	*p=0*	9.52	*p=0.3*

Note: In Panel A, for each country, the first columns give the parameter estimates, while the second column presents the Quasi-Maximum Likelihood errors inside the parenthesis. Panel B gives Ljung-Box Q statistics for residuals and squared residuals and regime classification measure (RCM) as Ang and Bekaert (2002a).

Table 10. Forecast comparison of RS models with single regime models

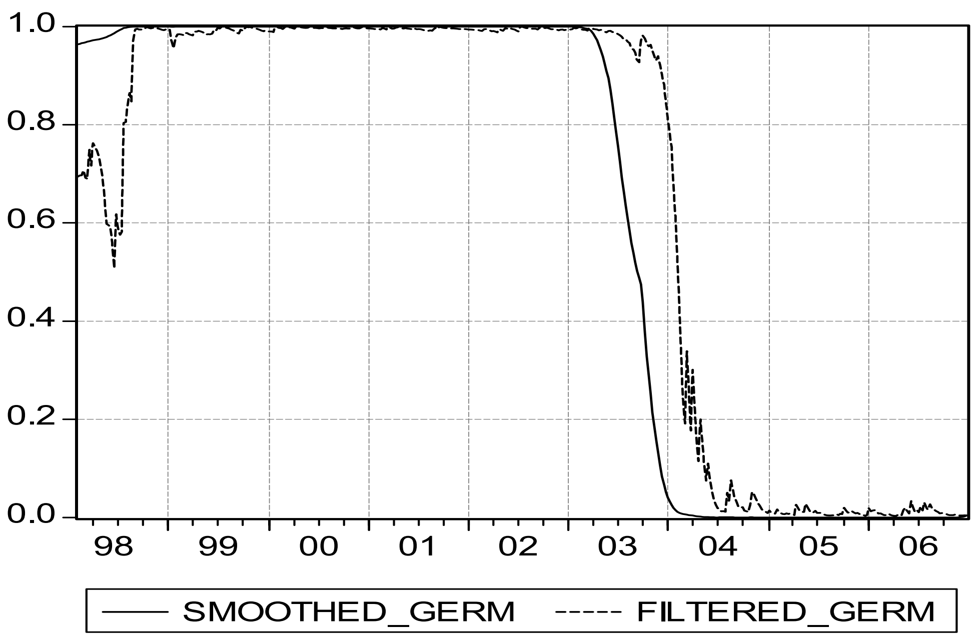
	Statistic	CCAPM1	CCAPM2	CCAPM3	RS1	RS2
		world	world+home	US+home	RS US+home	RS world+home
		Argentina				
e	RMSE	0.0347537	0.03444683	0.03606447	0.03662867	0.03456432
	MAD	0.0264241	0.02646633	0.02865134	0.02890904	0.02736459
squared e	RMSE	0.0021106	0.00203781	0.0022041	0.00230912	0.00200019
	MAD	0.0012078	0.00118658	0.00130065	0.00134166	0.00119469
		Japan				
e	RMSE	0.0281079	0.0275874	0.03251435	0.03103743	0.0270177
	MAD	0.0210862	0.02055785	0.02255336	0.02351854	0.02033851
squared e	RMSE	0.0015015	0.0014618	0.00275724	0.00170682	0.00135975
	MAD	0.0007901	0.00076106	0.00105718	0.00096332	0.00072996
		China				
e	RMSE	0.0429862	0.043249	0.05490281	0.05429863	0.05207142
	MAD	0.0305804	0.03107605	0.03916213	0.0376844	0.03595433
squared e	RMSE	0.0044372	0.00430614	0.0060867	0.00772278	0.00617211
	MAD	0.0018478	0.00187048	0.00301432	0.00294834	0.00271143
		Germany				
e	RMSE	0.0305655	0.02726209	0.17308317	0.02699866	0.02781796
	MAD	0.021912	0.02022538	0.07919304	0.02013394	0.02096474
squared e	RMSE	0.0018882	0.00148757	0.1127255	0.0014515	0.00148747
	MAD	0.0009343	0.00074322	0.02995778	0.00072893	0.00077384

Figure 1



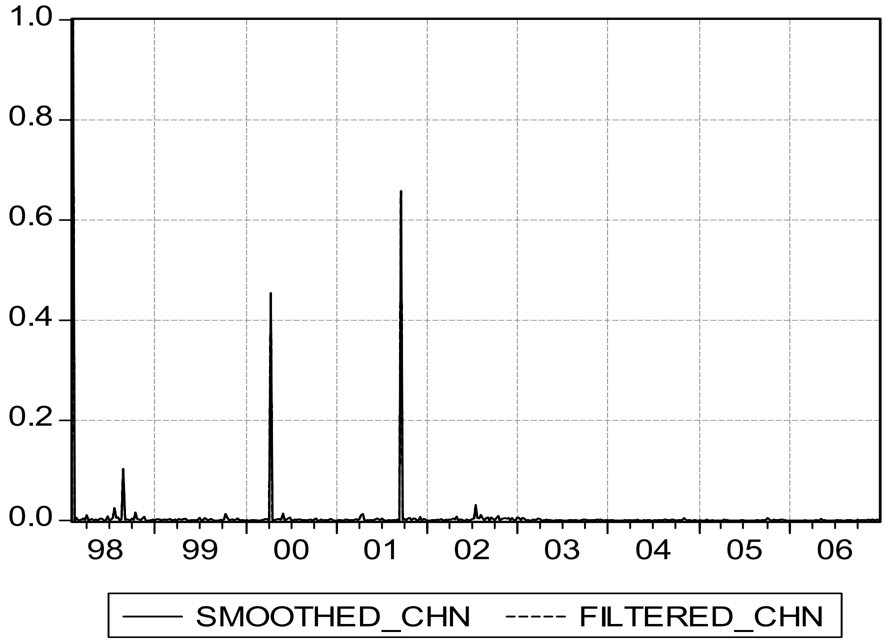
Note: Filtered_arg gives the time varying regime two (home market pass-through) probability estimated in our model, (1-phi), for Argentina. Smoothed_arg is the smoothed series of the regime two probabilities and is estimated based on the algorithm from Kim and Nelson (1999).

Figure 2



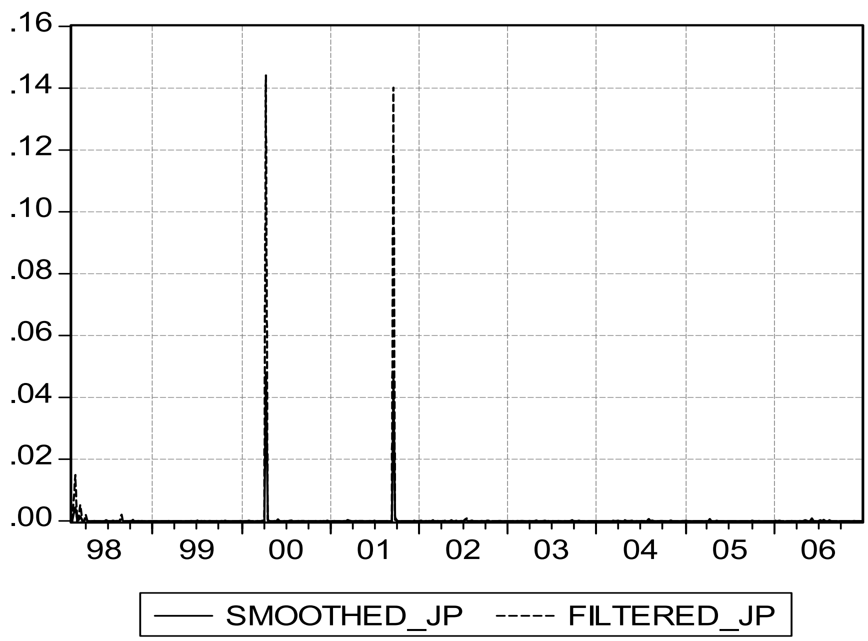
Note: Filtered_germ gives the time varying regime two (home market pass-through) probability, (1-phi), for China. Smoothed_ germ is the smoothed series of the regime two probabilities and is estimated based on the algorithm from Kim and Nelson (1999).

Figure 3



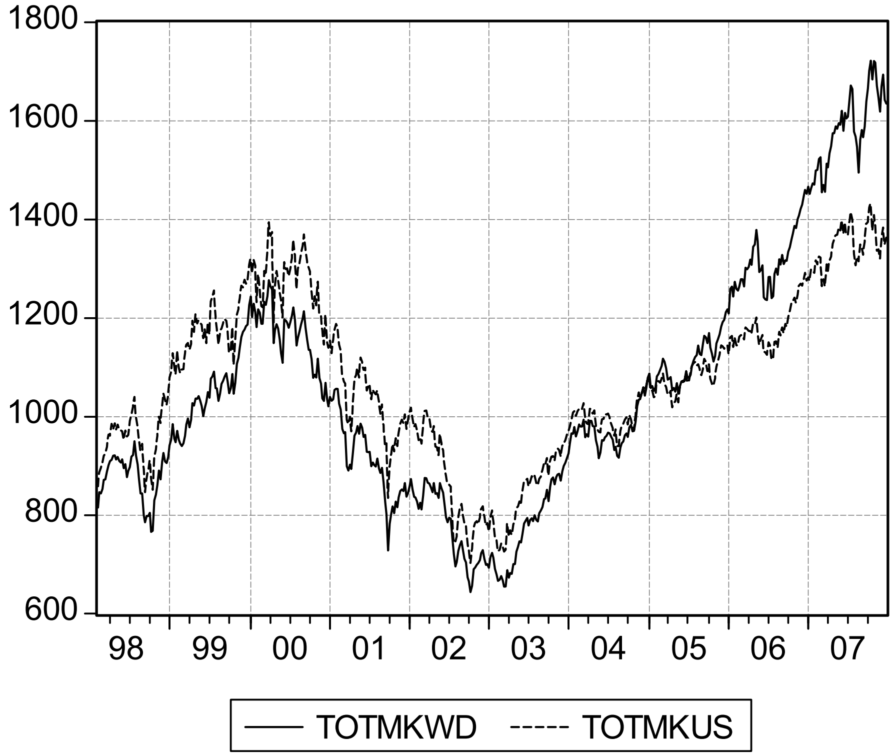
Note: Filtered_chn gives the time varying regime two probability (home market pass-through), (1-phi), for China. Smoothed_ chn is the smoothed series of the regime two probabilities and is estimated based on the algorithm from Kim and Nelson (1999).

Figure 4



Note: Filtered_jp gives the time varying regime two probability (home market pass-through), (1-phi), for Japan. Smoothed_jp is the smoothed series of the regime two probability and is estimated based on the algorithm from Kim and Nelson (1999).

Figure 5



Note: TOTMKWD denotes the Datastream world price index; TOTMKUS denotes the total market index for US. Both series are retrieved from Datastream.

CHAPTER FIVE: EXCHANGE RATE PASS-THROUGH IN ADRs

I. Research Question

ADR investments, although denominated in US dollars, are investments on foreign assets. Therefore, an investment on ADRs is both an investment in the performance of the foreign assets and an investment in the performance of the foreign currency in terms of domestic currency. In the international asset pricing models, exchange rate risk is priced (e.g. Solnik 1974, Stulz 1981 and Adler and Dumas 1983, see survey Stulz 1994). Purchasing power parity (PPP) does not hold if relative prices of goods differ across countries or if investors have different preferences over goods across countries (Stulz 1994). If PPP does not hold, there are two important implications for portfolio choice and asset pricing in equilibrium: (1) optimal portfolio differs across countries and (2) the expected return of any asset must include a market premium as well as a currency premium (Dumas and Solnik 1995, DeSantis and Gerard 1998). The Conditional International Asset Pricing Models contains risk premia that are based on the covariances of assets with the exchange rates, in addition to the traditional risk premium based on the covariance with the market portfolio given deviation from PPP (Dumas and Solnik 1995).

Econometrically, to estimate the conditional asset pricing models with exchange rate premia, Dumas and Solnik (1995) use a latent-variable approach and constrain market price of risks to be time varying, then use a Generalized Method of Moment (GMM). DeSantis and Gerard (1998) specify the dynamics of the second moment and test the currency risk premium with a diagonal multivariate GARCH process. Carrieri Errunza and Majerbi (2006) use a similar multivariate GARCH technique and find that emerging market currency risk is priced separately from other local risk factors and that it represents a significant component of equity returns in both developed and emerging markets.

The ADR literature on the diversification benefits of ADRs for portfolio investment focus on the low return correlations, but relatively little has been done on the role of exchange rate risk. Patro (2000) considers the exchange rate risk in addition to the world market and home market factors in the unconditional factor pricing models, but finds that country specific exchange rates are insignificant risk measures for ADR portfolio returns. Contrary to Patro (2000), Kim, Szakmary and Mathur (2000) incorporate exchange rate risk with two other factors (underlying shares in the local currency and US market index) and find that exchange rate risk has an impact on ADR prices. Fang and Loo (2002) find that the sensitivity of ADR returns to the unanticipated exchange rate movement (i.e., the beta to exchange rate) is significant and negative for most cases, i.e., ADR returns are substantially harmed by an unanticipated appreciation of the home currency, and vice versa when the home currency depreciated. They also find that although US investors are exposed to incremental risk from foreign market when investing in ADRs, they do not command a risk premium as the risk can be diversified or effectively hedged by ADR investors. It is still an unsettled question whether the exchange rate risk is a significant risk factor for ADRs, and whether or not this risk factor is priced in ADR returns.

Different from previous factor pricing literature, this essay uses the regime switching framework to model the effects of exchange rate risks. The exchange rate risk in this model is derived from the uncertainties of investments on foreign currency. When US investors view ADR investment no different from other domestic investments which are denominated in US dollars, the intra-market trading of ADRs is largely based on the dollar demand and dollar supply. In the pricing-to-US regime, the uncertainties of foreign currency returns are assumed to unrelated and absent in the model. However, in the home market pass-through regime, the uncertainties in investing the foreign assets and foreign currency will both be considered. Exchange rate risks will be incorporated into the home market pass-through regime when ADRs are treated as perfect substitute of underlying shares. As to how much of this exchange rate risk is passed to investors' expectation on future ADR returns will depend on home market pass-through regime probability. This is the contribution of this essay to the literature.

This chapter extends the previous chapter by separating exchange rate risk out of home market risk in the regime switching framework for exchange-listed ADRs. Instead of using US dollar as a numeraire, the home market portfolio will be measured in terms of local currency. The research question that will be explored in this chapter is, "in the regime switching CAPM framework, will it change the time path of home market pass-through if the exchange rate premium is added in?" With the regime switching framework, I expect to identify a new home market pass-through proxy and see whether there are cross-country differences. This is also an extension of the regime switching model in Bekaert and Harvey (1995).

II. Regime Switching Model with Currency Risk

In regime one – pricing to market, ADRs are treated as US assets, and there is no need to consider currency risks in this regime. ADR returns are determined by the price of US market risk multiplied by the exposure of ADR returns to the changes of US market returns. It is specified as:

$$E_{t-1}\left[R_{n,t}^{adr}\right] = \lambda_{t-1}^{us} \operatorname{cov}_{t-1}\left[R_{n,t}^{adr}, R_{US,t}\right] \tag{65}$$

In regime two – home market pass-through, ADR investments are treated as a foreign investment, which combines the investments to the performance of the foreign assets and the performance of the foreign currency. ADR returns is equivalent to the sum of two components – the expected returns of ADRs measured in local currency priced in home CAPM and the expected returns of the local currency itself for time *t* at time *t-1*, i.e.,

$$E_{t-1}[R_{n,t}^{adr}] = E_{t-1}[R_{n,t}^{adr}]_{LC} + E_{t-1}[R_{\$/LC,t}] \tag{66}$$

$E_{t-1}[R_{\$/LC,t}]$ is the expected return of holding the local currency instead of US dollars for time *t* at time *t-1*. With $R_{\$/LC,t}^{e} = E_{t-1}[R_{\$/LC,t}]$, it is equivalent to

$$E_{t-1}[R_{n,t}^{adr}] = \lambda_{t-1}^{h} \operatorname{cov}_{t-1}[R_{n,t}^{adr}, R_{n,t}^{m}] + R_{\$/LC,t}^{e} \tag{67}$$

Here $R_{n,t}^{adr}$ is the return of an ADR from country *n* at time *t*. $R_{n,t}^{m}$ is the home market portfolio denominated in local currency. 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:

$$E_{t-1}\left[R_{n,t}^{adr}\right] = \phi_{n,t-1}\lambda_{t-1}^{us} \operatorname{cov}_{t-1}\left[R_{n,t}^{adr}, R_{US,t}\right] + (1-\phi_{n,t-1})\{\lambda_{t-1}^{h} \operatorname{cov}_{t-1}[R_{n,t,lc}^{adr}, R_{n,t}^{m}] + R_{\$/LC,t}^{e}\} \tag{68}$$

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

$$\phi_{n,t-1} = prob[S_t = 1 | Z_{n,t-1}]. \tag{69}$$

Equation (69) can be viewed as an approximation of probability of regime one being responsible for the ADR return at a particular time *t*. Hence the results of $(1-\phi_{n,t})$ will give us the proxy of ADRs home market pass-through when exchange rate premium is explicitly specified. The rest of the specification is the same as Chapter four.

To capture the time-varying characteristics of regime probability, the standard Hamilton (1988, 1989) method is applied, 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}.[36] Suppose the regime transition probabilities are the following (where the country subscript, n, has been suppressed):

$$\begin{aligned} \Pr(S_t = 1 \mid S_{t-1} = 1) = \mathrm{P} \\ \Pr(S_t = 2 \mid S_{t-1} = 2) = \mathrm{Q} \end{aligned} \tag{70}$$

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).[37] It is also assumed that the price of risk is time varying, and adopts 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.

$$\begin{aligned} \lambda_{t-1}^{us} = \exp(\delta' Z_{t-1}^{*}) \\ \lambda_{t-1}^{h} = \exp(\delta_n' Z_{n,t-1}^{*}) \end{aligned} \tag{71}$$

[36] See detailed discussions in Hamilton (1994), Chapter 22.
[37] 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.

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, $Z^*_{n,t-1}$, the following variables are chosen to proxy the state of the economy – a constant, short rate changes, local market dividend yields, exchange rate changes and changes of local stock market value.

III. Methodology

The methodology is similar to chapter four. As the mean equation (68) involves the conditional covariance in both regimes, the conditional covariances in different regimes are assumed to follow a General Autoregressive Conditional Heteroskedasticity (GARCH) process.[38] 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:

[38] 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.

$$
\begin{aligned}
&y_{n,t} = [R_{n,t}^{adr}, R_{i,t}]' \\
&R_{n,t}^{adr} = \phi_{n,t-1}\lambda_{t-1}^{us} \operatorname{cov}_{t-1}\left[R_{n,t}^{adr}, R_{US,t}\right] + (1-\phi_{n,t-1})\{\lambda_{t-1}^{h} \operatorname{cov}_{t-1}[R_{n,t}^{adr}, R_{n,t}^{m}] + R_{\$/LC,t}^{e}\} + e_{n,t} \\
&R_{i,t} = \lambda_{t-1}^{i} \operatorname{var}_{t-1}[R_{i,t}] + e_{i,t}
\end{aligned}
\quad (72)
$$

Here i refers to the US market portfolio in regime one and 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 the conditional variance processes are defined under the two different regimes as

$$
\begin{aligned}
H_{1t} &= E[e^1 e^{1\prime} \mid Z_{n,t-1}] \\
H_{2t} &= E[e^2 e^{2\prime} \mid Z_{n,t-1}]
\end{aligned}
\quad (73)
$$

$\operatorname{cov}_{t-1}\left[R_{n,t}^{adr}, R_{US,t}\right]$ is the off-diagonal element of H_{1t}, and $\operatorname{cov}_{t-1}[R_{n,t}^{adr}, R_{n,t}^{m}]$ 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, the system is assumed to be covariance-stationary for applying GARCH parameterization. This assumption is specified as follows:

$$
\begin{aligned}
H_{1t} &= C^1 C^{1\prime} + A^1 A^{1\prime} \otimes e_{t-1} e_{t-1}' + B^1 B^{1\prime} \otimes H_{1,t-1} \\
H_{2t} &= C^2 C^{2\prime} + A^2 A^{2\prime} \otimes e_{t-1} e_{t-1}' + B^2 B^{2\prime} \otimes H_{1,t-1}
\end{aligned}
\quad (74)
$$

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,[39] the diagonal BEKK is less parameterized (Engle and Kroner 1995). I follow Gray (1996), in that conditional variance

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

for ADR returns (the element (1, 1) for both matrices H_{1t} and H_{2t}) can be written as the following -

$$h_t = E(R_t^2 \mid Z_{t-1}) - [E(R_t \mid Z_{t-1})]^2 = p_{t,S_t=1}(u_{t,S_t=1}^2 + h_{t,S_t=1}) + (1 - p_{t,S_t=1})(u_{t,S_t=2}^2 + h_{t,S_t=2}) \\ - [p_{t,S_t=1}u_{t,S_t=1} + (1 - p_{t,S_t=1})u_{t,S_t=2}^2]^2 \qquad (75)$$

where $p_{t,S_t=1}$ is the regime 1 probability at time t ; $u_{t,S_t=1}$ is the mean at time t given regime 1; and $h_{t,S_t=1}$ is the conditional variance for ADR returns at time t given regime 1.

Assuming Uncovered Interest Rate Parity (or International Fisher Effects) holds, forward rate is the best unbiased predictor of future spot rate (Bekaert and Hodrick (1992)). Thus forward premium reflects the expectation of the future currency returns.

$$FP_{\$/LC,t} \approx R^e_{\$/LC,t} \qquad (76)$$

Forward premium of the related foreign currency ($FP_{\$/LC,t}$) will be calculated as the log difference of forward rate and spot exchange rate.

To estimate this model, a two-step procedure from chapter four will be used. Specifically, the univariate non-linear GARCH (1, 1) model will be used to estimate the parameters related to country market returns alone. Particularly, I 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, the rest of the parameters will be estimated in the multivariate form given results from step one, as represented by equation (72) .

IV. Data

In addition to the data on chapter four, the forward rate collected is the 1 week WM/REUTERS closing forward rates, retrieved from DataStream. The log ratio of 1 week forward rates (in US dollars) and spot rates (in US dollars) gives the 1 week expected return of the Yen, Chinese RMB, Argentina Peso and Euro (German mark for pre-1999). The series for Japan and Germany covers the entire period 1998-2006, but the Argentina peso 1 week forward rates starts from March 29, 2004 and the one for Chinese Yuan starts from February 11, 2002. Therefore, Japan and Germany have 470 data points each, while China has 255 weekly data and Argentina has 144 weekly data. I estimate the regime probabilities country by country. Forward premium is calculated using the log ratio of one week forward rate over weekly spot rate (Friday).

Table 1 reports the summary statistics of weekly forward premiums using each country's available data. China, Japan and Germany all have a positive average premium which implies a positive return over investments on these countries currencies. Figure one graphs individually the weekly forward premium for Argentina Peso, Chinese Renminbi, Euro (German Mark pre-1999) and Japanese Yen. Among them, Japan has the highest average weekly forward premium. The weekly forward premium has bee mostly negative for Argentina Peso.

V. Empirical results

V.1. Home market pass-through regime probabilities

The estimation is done country by country. Germany and Japan have data available for the whole sample period; therefore their results can be used directly in comparison with results from previous chapter. Table 2 gives the main results of the model. Regime transition probabilities P and Q are reported first two rows. Germany and Japan have similar values of P and Q in the regime switching (exchange rate) model compared to those in the previous regime switching (no exchange rate) model. Both P and Q for Germany are very high (over 99%), which implied great regime persistence. That is, once one regime sets in, it tends to stay in the same regime. Japan has a P of over 94% and Q of 70%. Time paths of home market pass-through regime for Germany and Japan are shown in the lower two graphs of Figure 2. Similar to the time path in chapter four, Germany has a home market pass-through regime dominance from 1998-2003 and the pricing-to-US- market regime dominates the latter period 2004-2006. For Japan, the home market pass-through regime probability is very low, less than 1% over the whole sample period. The pricing-to-US- market regime dominance in Japan is also consistent to the results in the previous chapter. When we specifically add local currency returns to ADR premiums with the home market, there is not much change in the home market pass-through regime for Germany and Japan.

For China and Argentina, the estimates cannot be directly compared with results in chapter 4 given the different samples used. Due to the data constraints, only a smaller sample is used in the current model for China and Argentina. Researchers have discussed the effects on small sample size on the performance of regime switching models such as the model specification and out of sample forecast (Ang and Bekaert 2002a). Nevertheless, the given period estimates of home market pass-through regime probability for both China and Argentina show similarities with results in chapter four. The time path of Argentina is shown in the first graph of Figure 2. Pricing-to-US- market regime dominates for the whole sample period 2004-2006, i.e., home market pass-through probabilities lower than 1%. China also has a pricing-to-US- market regime dominance from 2002-2006 except few probabilities at the beginning of 2002.

The models for all four countries are converged with pricing-to-US- market regime dominance from 2004-2006. It indicates that during this period, the returns of ADRs from these four countries are most probably priced with US market risks than home market risks, even after we specifically include the local currency returns in the home market exposure. The exchange rate pass-through in this model is the same as the home market pass-through. The low exchange rate pass-through might come from the low expected local currency returns proxied by forward premium, which made the effects of local currency returns relatively small portion in the total ADR risk premiums. It might also be due to the fact that investors commonly hedge their exchange rate exposures when doing foreign portfolio investments.

V.2. Model Diagnostics and Specification Tests

In this section, I will check the regime classification and do the residual diagnostic check. To capture the quality of regime classification, the regime classification measure (RCM) is applied as in Ang and Bekaert (2002). The reason why it is important to have a good regime classification is that if the regime probabilities over time are close to a half, we cannot clearly classify a dominant regime, and the model would be inferior and have a weak regime inference. Weak regime may indicate misspecification. The regime classification measure (RCM) is reported in Panel B of Table 2. The smaller the RCM is, the better the regime classification. All four countries have relatively small RCM statistics (less than 12). Japan and Argentina have the lowest RCMs (lower that 0.1) which provide further support on earlier discussion of regime dominance.

In Panel B of Table 2, Ljung-Box Q statistics (lag 8) for residuals are insignificant for all four countries, while the Q statistics for the squared residuals are significant for all four countries except Argentina. It indicates that although residuals seem to be random, there might be further GARCH effects in the residuals. However, the main interest here is to check whether or not adding local currency returns explicitly will affect the home market pass-through regime. I use GARCH order (1, 1) to be consistent with chapter four.

VI. Summary

This chapter extended chapter four by explicitly adding local currency returns to the ADR premium with home market in the regime switching framework. Under the regime switching framework, the ADRs are assumed to have no exchange rate risk in regime one (pricing-to-US-market) given that they are treated the same as any other US financial assets. The exchange rate pass-through to the returns of ADRs in the model equals the home market pass-through, since in this model the effects of exchange rate risk to ADR returns only play a role under home market pass-through regime. The local currency expected returns are estimated using the forward premium of the local currency.

The estimated results for Argentina, China, Japan and Germany show a common feature of pricing-to-US-market regime dominance during the 2004-2006 period. The time path of home-market passthrough regime for Germany is almost identical to that estimated in chapter four. It shows a regime dominance switching in 2003 changing form home market pass-through regime to the pricing-to-US-market regime. Japan continues to be mainly pricing-to-US-market regime dominant over the whole period. Given data constraints, China and Argentina models are only estimated using smaller sample, but the regime classification measure shows that their regimes are strongly classified with very small RCMs.

Comparing results in this chapter with the regime switching (no exchange rate risk) in chapter four, we observe very similar estimates and the basic pattern of home market pass-through regime does not change either. In another words, explicitly adding currency return factor does not change our results greatly. The low exchange rate pass-through might be due to the smaller size of currency return itself, relative to the total asset risk premium. It is also plausible that investors commonly hedge their exchange rate exposures when doing foreign portfolio investments and hence the pass-through of local currency return is weak.

The limitation of this research firstly comes from the data constraints. When we find regime dominance as in the case of the pricing-to-market regime dominance for all four countries during 2004-2006, it does not indicate that this particular regime will always dominate for one particular country's ADR index. When we are able to obtain a longer series, it will provide a longer horizon to study possible regime switching at a different time period or state of the economy. Another limitation of the research, and one that may be a future research topic, is to test whether it is necessary to have another regime specifically for exchange rate risk.

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Table 1. Summary statistics of forward premiums

	FP_Argentina	FP_China	FP_Germany	FP_Japan
Mean	-0.000788	0.000447	0.00013	0.000706
Median	-0.000536	0.000322	0.00023	0.000787
Maximum	0.001722	0.003692	0.00083	0.001511
Minimum	-0.004126	-0.00022	-0.000399	0.000183
Std. Dev.	0.000903	0.000515	0.000311	0.00035

Note: Forward premium (weekly) of the local currency is calculated using the log ratio of one week forward rate over spot rate (Friday) using data from 01/02/1998 to 12/29/2006. Forward rate data is the 1 week WM/REUTERS closing forward rates, retrieved from DataStream. Spot exchange rate is the weekly data of closing spot rate (WMR) from DataStream. Exchange rates are expressed as US dollar per local currency. Due to the missing data, Japan and Germany have 470 data points each, while China has 255 weekly data and Argentina has 144 weekly data.

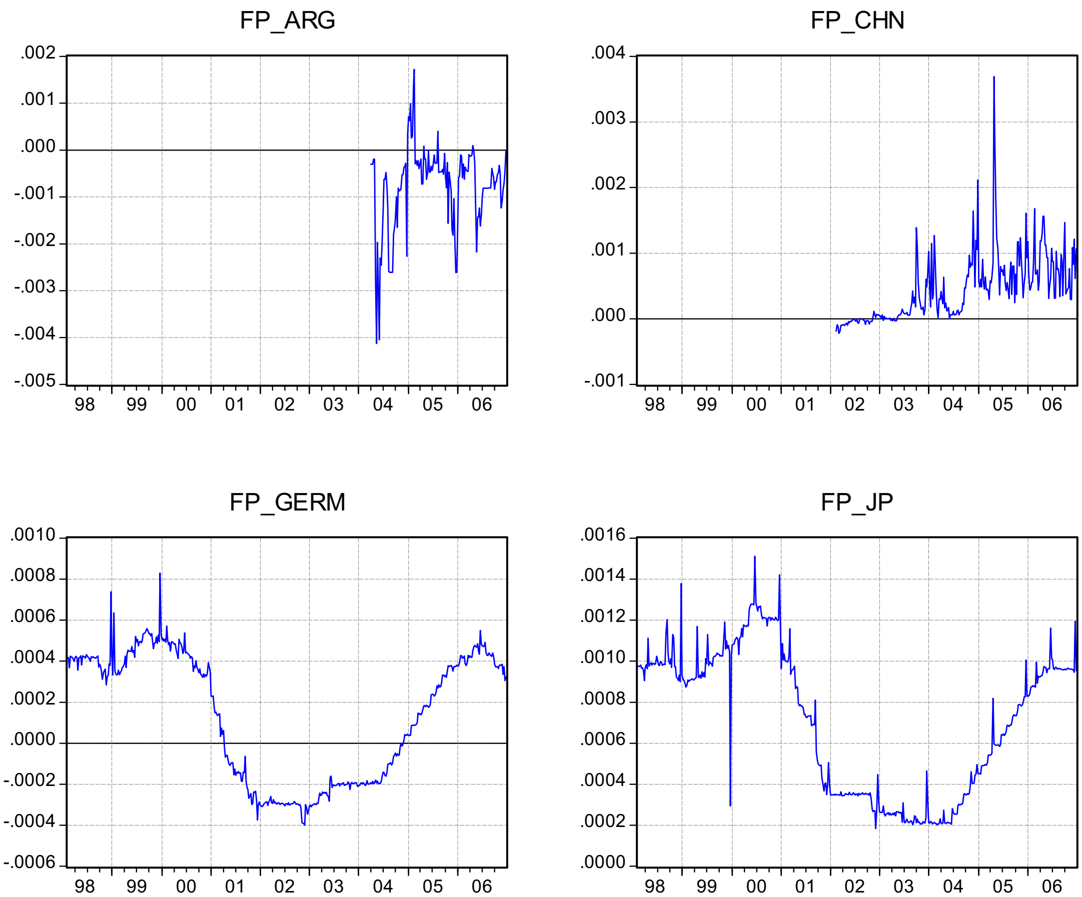
Table 2. Model Estimates

	Argentina		China		Germany		Japan	
Panel A: Parameter estimates								
P	0.98370153*	(0.00135874)	0.99618455*	(0.00259856)	0.996997*	(0.0011776)	0.98315756*	(0.0009405)
Q	0.0001309	(0.00030411)	0.95817761*	(0.26629962)	0.998015*	(0.0012988)	0.71733185*	(0.1554731)
C1(1,1)	-0.00001325	(0.00001278)	-0.00000244	(0.00000193)	0.000041*	(0.0000203)	0.00811234	(0.0037817)
C2(1,1)	0.44954004*	(0.03062272)	0.00690918*	(0.00181637)	0.002351	(0.003863)	0.79855241*	(0.2945853)
A1(1,1)	0.93281706*	(0.00757511)	0.91032875*	(0.00978454)	0.926555*	(0.0093763)	0.51240405*	(0.0621621)
A2(1,1)	7.68119576*	(0.26444898)	0.44180274*	(0.00510854)	0.976393*	(0.0086348)	0.43945494	(0.1855725)
B1(1,1)	-0.00644395*	(0.00126449)	-0.00439451	(0.00260523)	0.005033*	(0.0015659)	0.2829573*	(0.0396799)
B2 (1,1)	0.54159515*	(0.01496821)	0.04257574	(0.04285689)	0.004861	(0.0058123)	0.36330704	(0.1829325)
Likelihood value	907.726843		1601.82723		2939.0285		2688.933589	
Panel B: Residual Diagnostics								
Ljung-Box $Q(e)_8$	10.904	*p=0.207*	4.757	*p=0.783*	6.626	*p=0.577*	7.6	*p=0.473*
Ljung-Box $Q(e^2)_8$	15.021	*p=0.059*	20.437	*p=0.009*	34.845	*p=0*	27.179	*p=0.001*
RCM	0.05344644		1.56081194		12.496747		0.011411462	

Note: In Panel A, for each country, the first columns give the parameter estimates, while the second column presents the Quasi-Maximum Likelihood errors inside the parenthesis. Panel B gives Ljung-Box Q statistics for residuals and squared residuals and regime classification measure (RCM) as Ang and Bekaert (2002). Following Ang and Bekaert (2002a), the regime classification measure (RCM) is defined as

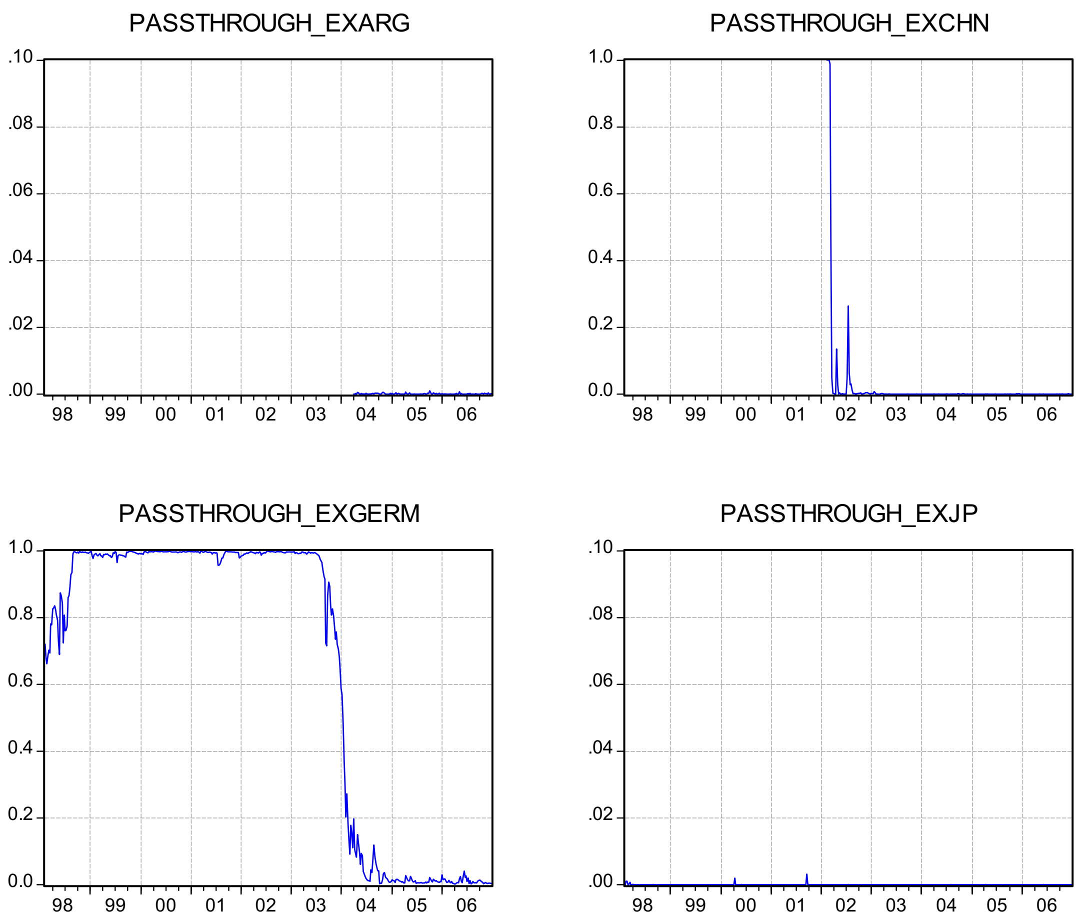
$$RCM = 100K^2 \times \frac{1}{T}\sum_{t=1}^{T}\left(\prod_{i=1}^{K} p_{i,t}\right).$$

Figure 1. One week forward premiums for four currencies



Note: Forward premium (weekly) of the local currency is calculated using the log ratio of one week forward rate over spot rate (Friday) using data from 01/02/1998 to 12/29/2006. Forward rate data is the 1 week WM/REUTERS closing forward rates, retrieved from DataStream. Spot exchange rate is the weekly data of closing spot rate (WMR) from DataStream. Exchange rates are expressed as US dollar per local currency. Due to the missing data, Japan and Germany have 470 observations each, while China has 255 weekly observations and Argentina has 144 weekly observations. FP_ARG plots the series for Argentina, and FP_CHN for Argentina, FP_GERM for Germany and FP_JP for Japan.

Figure 2. Home market pass-through regime probabilities



Note: PASSTHROUGH_EXARG gives the time varying regime two probability (home market pass-through), (1-phi), for Argentina. PASSTHROUGH_EXCHN gives the time varying regime two probabilities (home market pass-through) for China. PASSTHROUGH_EXGERM gives the time varying regime two probabilities (home market pass-through) for Germany. PASSTHROUGH_EXJP gives the time varying regime two probabilities (home market pass-through) for Japan.

CHAPTER SIX: SUMMARY AND FUTURE RESEARCH

I. Summary of Findings

This dissertation addresses the question of exchange-listed ADRs' pricing with market risk factors (US market and home market) and exchange rate risk factors. Chapter three starts with the traditional factor pricing models in the literature and provides evidence of ADR country portfolios from 36 countries during the period from 1998 to 2006.

Time series analysis shows the significant responses of the ADR returns to the innovations of the home market returns and the exchange rate changes. The magnitude of the impulse responses to exchange rate changes is smaller compared to that of the home market returns. The results also show that responses of ADR returns to the innovation of the home market and exchange rate risk factors stay over the same calendar day for about two third of the countries studied and stay significant over to the future days, but mostly diminish after a week. The responses of the daily ADR returns to the innovations of US market returns are small relative to impulse responses to the home market returns and exchange rate changes in general. However, there is no significant response to contemporaneous US market shocks, but there is significant response to US market shocks at lag 1 or higher for more than half of the countries studied. It is interesting to see that although ADRs are traded in the United States, they are mostly affected by the information from US markets from the previous calendar day. It might come from the fact that US stock exchanges open later than most of the countries studied; the information from the US market will affect the next day trading of the ADR home markets and then to the ADR returns with the time lag.

The prediction error variance analysis shows that home market innovations contribute the most to the prediction error variance of ADR returns with an average of 32% for daily series. While innovations of exchange rate changes contribute about 5% on average, the innovations of the US market returns contribute less than .5%. The weekly innovations from the home market, exchange rate and US market shocks to ADRs contribute about 50%, 7.7% and .68% respectively, after taking the average of the 36 countries.

The Seemingly Unrelated Regression of weekly returns confirms the VAR results and shows that ADR portfolios are more sensitive to home market risks than US market risks, and that the exchange rate change is also a significant risk factor. Compared with previous studies, the exchange rate risk sensitivities are found to be higher in this research than the daily data in Kim, Szakmary and Mathur (2000), and US market risk sensitivities are found to be lower than Kim, Szakmary and Mathur (2000) and Alaganar and Bhar (2001) for Australia.

The second essay (Chapter four) explores the regime switching model for Argentina, China, Japan and Germany. The probabilities of home market pass-through regime are used as a proxy of the home market effects on ADR returns relative to the US market effects. Exchange rate risk is suppressed, as all returns are converted to US dollar. I find different degrees of pass-through of ADRs in the four countries studied – this is consistent with ADR arbitrage literature that the relationships between ADRs with home market vary across time and countries. In pricing ADR index returns, Japan and China have a pricing-to-market regime dominance, while Germany and Argentina show home market pass-through regime dominance when the home market is more volatile. The regime switching model is also compared with other conditional CAPM models, and out of sample forecasts are greatly improved for Germany, China and Japan with a regime switching framework than a single regime factor pricing model with US and home markets.

Compared to results in essay one, essay two gives a time varying probability of ADR returns being priced within the home market of the US market. There is a need to clarify that the probabilities in essay two cannot be directly compared with the SUR regression coefficients with home market returns and US market returns. It is for two reasons: (1) exchange rate risk is assumed to be absent in essay two, while essay one considers both market risks and exchange rate risks; (2) the pricing model in essay two considers the effects of the second moments – i.e., variances and the covariance, while SUR in essay 1 is estimated based on the first moments, though adjusted for any heteroskedasticity.

In the third essay (chapter five), I add local currency returns to the ADR premium with home market in the regime switching framework from chapter four. Under the regime switching framework, the ADRs are assumed to have no exchange rate risk in regime one (pricing-to-US-market) given that they are treated the same as any other US financial assets. The exchange rate pass-through of the returns of ADRs in the model equals the home market pass-through. The estimated results for Argentina, China, Japan and Germany show a common feature of pricing-to-US-market regime dominance during the 2004-2006 period. The time path of home-market pass-through regime for Germany is almost identical to that estimated in chapter four. Given data constraints, China and Argentina models are only estimated using smaller sample, but the regime classification measure shows that their regimes are strongly classified with very small RCMs.

Comparing results in this chapter with the regime switching (no exchange rate risk) in chapter four, we observe very similar estimates, and the basic pattern of home market pass-through regime does not change either. In another words, explicitly adding currency return factor does not change our results greatly. The low exchange rate pass-through might be due to the smaller size of currency return itself, relative to the total asset risk premium. It is also plausible that investors commonly hedge their exchange rate exposures when doing foreign portfolio investments and hence the pass-through of local currency return is weak.

II. Contributions

II.1. Contribution to the development of ADR pricing models

The major contribution of this dissertation is the attempt to compare the home market effect and US market effect on the returns of exchange-listed ADRs. A regime switching framework is developed based on conditional asset pricing models. It treats the market effects as time varying, which is determined by a random variable (Markov Chain process here). The probability of ADRs being priced in the home market or US market is estimated by time-varying regime probabilities conditioning over the information available. The home market pass-through regime probabilities are estimated Argentina, China, Germany and Japan from 1998 to 2006. Those probabilities serve as a proxy for home market pass-through effects. This regime switching framework is adopted from Bekaert and Harvey (1995), who use it for international integration analysis, and in this study is applied to fit the characteristics of exchange-listed ADRs.

As an extension to Bekaert and Harvey (1995), the exchange rate risk is added to the home market effect. Given regime definition, the local currency return is only included to home-market pass-through regime. The pass-through of exchange rate risk to ADR returns will thus depend on the home-market pass-through regime probability as well. After adding the local currency returns, it will be revaluated for the question of whether or not ADRs are more affected by home market or US market. The set-up of exchange rate risk here is different from previous research which treats exchange rate risk as a risk factor independent of home market risk.

II.2. Contributions on data and methodology

Firstly, previous related works mainly created their own equally-weighted ADR portfolios using selected ADRs from that country. It might be one of the reasons why there are mixed results among these studies. In contrast, this research uses ADR indices created by the Bank of New York, which covers all exchange-listed ADRs from a particular country.

Secondly, in terms of scope of the data, this research includes 36 countries which is the largest sample so far. In terms of time period, this research covers data from 1998 to 2006 which is relatively recent data period compared with previous research.

Thirdly, as for methodology, this study not only applies the time series and regression analysis from previous studies, it also develops a regime-switching-GARCH (1,1) that provides estimation for the conditional regime-switching-2-state asset pricing model.

II.3. Significance

This study provides further understanding of relationships of ADR returns with home market portfolios and US portfolios. Knowing how returns of exchange listed ADRs are affected by home market portfolio, US market portfolio and exchange rate risk will give significant implications to ADR holders, such as investors who buy ADR to diversify their portfolios. It is also useful for asset managers hedging market risks to know how the market effects change over time, so that they develop pertinent hedging strategies and maximize their investment returns.

III. Limitations and Future Research

The first limitation comes from the regime switching framework used in the second and third essays. It is assumed that 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 (see the applications of state-dependent transition probabilities in Bekaert and Harvey 1995, Gray 1996, Ang and Bekaert 2002a, 2002b[40]). This model could be modified to allow time-varying transition probabilities, which may provide a better fit for the data. Another extension in the regime switching framework is to use Bayesian methods instead of the maximum likelihood in the estimation. Gibbs-sampling methods present a feasible estimation of the state-space models with Markov switching in the Bayesian Framework (Albert and Chib 1993, Kim and Nelson 1998).[41] Future research could explore further regime switching effects in ADR returns beyond home market and US market regimes, i.e., random number of regimes with high operational Bayesian methods.

Furthermore, this dissertation uses a portfolio approach. Firm-specific characteristics are suppressed by using country indices. Therefore, a future study that uses firm-specific ADR returns instead of ADR indices will help to reveal firm-specific pass-through effects. Furthermore, ADR index portfolios contain both Level II and Level III ADRs. Level III

[40] Reference details have been included in Chapter four.
[41] See Chapter four.

ADRs raise capital in the US market and it might be further influenced by the demand in the US market or the US investors' sentiment. Therefore it worth a closer look on whether or not capital-raising ADRs are more influenced by the US market relative to the home market than non-capital-raising shares.

Thirdly, the regime switching framework is based on the conditional capital asset pricing model and it only considers the market systematic risks. To further our understanding of why ADR returns are correlated with these two market portfolio returns, it would be useful to look at the economic fundamentals and industry factors and see how macroeconomic development affect the time varying characteristics of the relationship of ADRs with the US market and home market.