Volatility Spillover: Analysis of Mainland China-US Real Estate

Garth Mortensen

EDHEC Business School

Contents

mortensengarth@outlook.com
www.linkedin.com/in/mortensengarth
December, 2012

On the Web

An **online tutorial** on how to conduct a GARCH spillover analysis can be found online. Happy GARCHING!

https://sites.google.com/site/garthmortensenthesis/

Abstract

This study examines volatility spillover between the Mainland China and US real estate markets. The daily closing prices of exchange traded real estate funds with exposure to both commercial and residential real estate serve as local market proxies from 2001 and 2011.

The study uses a multivariate GARCH methodology allowing for constant and dynamic conditional correlations. Empirical results show that spillovers were historically tranquil until the 2008 Subprime Crisis, when cross-market risks suddenly increased. From then onwards, spillovers have been periodically surging across the Pacific, carrying with them implications for investors, companies and governments.

Introduction

When in 2008 the US Subprime Crisis rattled exchanges worldwide, it became clear how small our global marketplace had become. Previous risk controls were proven inadequate at handling ever tightening marketplace relationships. This paper seeks to contribute to their upgrading by measuring the cross border risks tied to commercial and residential real estate, with respect to Mainland China and the US.

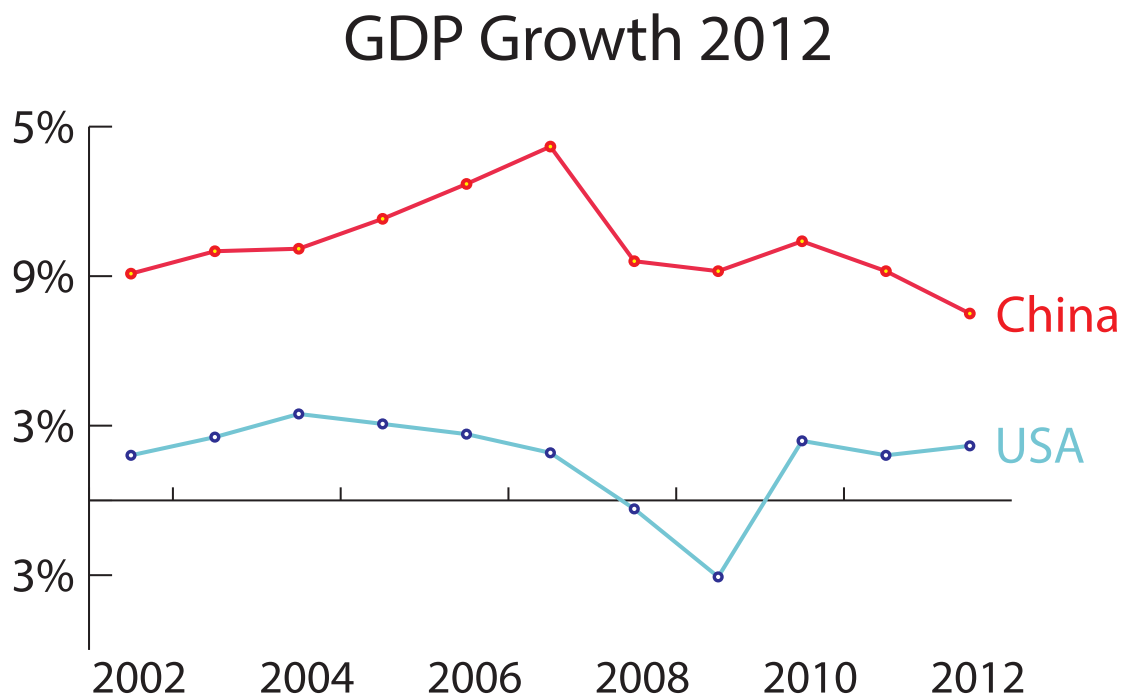
Financial markets are highly complex and tightly interwoven, making research on how they interact a formidable challenge. One form of cross-border links can be seen in how markets move together. An example of this is the Subprime Crisis sending repercussions to foreign markets.

The most readily available information on market movements are daily price quotes. However, underlying such price movements is a returns process, which after being squared renders a measurement of implied market volatility. Though obscure, this lattermost measure can provide powerful evidence that two markets move in tangent.

Understanding international market linkages is imperative to investors, companies and governments. Investors seeking to diversify their assets by investing in a global portfolio should avoid strong country linkages. Shedding light on them can help improve trading and hedging strategies. The capital asset pricing model which lies in the very core of financial theory depends on systemic risk, which is influenced by cross-border risk. Further, knowing the relationship of returns is the first step to designing an optimal portfolio or hedging strategies. After measurement, Hammoudeh et. al (2009) and Chang et al. (2010, 2011) go on to design optimal hedge ratios and portfolio weights for risk management.

Multinationals may examine the risks associated with market linkages before undertaking in overseas operations. Furthermore, strong linkages weaken the effectiveness of independent monetary policy, thereby eroding a nation's insulation to external shocks.

The prevalence and magnitude of spillovers grow in lockstep with continued globalization and market integration brought about by financial liberation. Information on the risk and return relationship between different markets is necessary because it directly influences portfolio performance and risk management.



Source: CEIC (FOREX), Oxford Economics (GDP)

When spillover studies first became prevalent, attention was given to developed market equities and bonds. From there, emerging market equity began to capture the eyes of academia. The novelty of this paper lays in its focus on Chinese real estate. Studies focused on this branch can be counted on one hand, though seemingly none have been motivated by today's potentially unstable market conditions.

This absence is made less startling by the Mainland market's lack of transparency. Despite this, one would still expect China's strong economic performance to justify greater scrutiny. Several years of strong, persistent RMB appreciation coupled with long term economic growth elevated China in Q4 2011 to being the world's second largest economy. As shown in Figure 1, that lead is forecast to grow larger.

Its place in the financial marketplace is of near equal importance, representing 5.58% of the world market capitalization, standing as fifth largest being the Hong Kong (5.92%), the UK (6.46%), Japan (7.18%) and the US (33.78%). As shown in Figure 2, both markets lost ground in 2008, but are now on the mend.

As the second largest economy, China's trade ties are closely intertwined with both local and global markets. Even amid a global downturn, its gross domestic product has been moving at a fast stride. Financial market development has kept pace. In its 2011 annual report, the China Securities Regulatory Commission counted 2,342 firms listed on the Shenzhen and Shanghai stock exchanges. Many of these firms are in a long term process of opening up.

Source: Bloomberg Exchange Market Inflation indices

Economic Indicators 2001 - 2012	Min	Max	Avg
GDP groth (YoY)	7.51%	14.20%	10.31%
Unemployment	3.60%	4.26%	4.09%
Inflation (CPI growth)	-0.77%	5.86%	2.47%
USD/RMB	0.12	0.16	0.13
SZSE Composite index	254.47	1532.67	655.54
SZ RE Price	265.43	3221.64	986.90
SZ RE Return	-0.10	0.10	0.00

Source: National Bureau of Statistics, CEIC, State Administration of Foreign Exchange

Economic Indicators 2001 - 2012	Min	Max	Avg
GDP groth (YoY)	-3.07%	3.47%	1.68%
Unemployment	4.61%	9.63%	6.52%
Inflation (CPI growth)	3.20%	3.82%	2.43%
USD/RMB	6.34	8.28	7.52
DJIA index	7062.93	13930.01	10509.91
IYR Price	22.21	94.57	54.75
IYR Return	-0.23	0.15	0.00

Source: NIPA/Haver Analytics, IMF

Source: NIPA/Haver Analytics, IMF

Meanwhile, Chinese originated American Depository Rights and a post crisis wave of dual listings are reaching the American market.[1] Karolyi (2004), and Bennett and Keller (1988) claim such trends are accelerating the integration between emerging and developed markets.

An overview of economic indicators for the US and China can be found in Tables 1 and 2. Neither market appears correlated in terms of GDP growth, unemployment, inflation and interest rates, or their main market indices. But within each country, there appears to be some correlation between their main market index and their real estate index. This suggests the real estate indices may be more tightly linked to their financial markets as opposed to their greater economies.

Real estate as an asset class is also of growing importance. Amid high volatility in the equity space and a low interest rate environment, real estate's ability to provide superior overall returns as an asset class is ordaining it with evermore importance. According to Bruce Flatt, CEO of Brookfield Asset Management, institutional investor allocation to real estate may reach 25% to 40% in the coming decade (Lee, 2012).

According to Knight Frank (2012), Shanghai is set to become the most expensive property market by 2050, while Beijing topped global office performance charts in August 2012 (Cushman & Wakefield, 2012). But according to some economists monitoring China's real estate market, current prices are far too high and the consequences of a bubble could be catastrophic. The past few years' macroeconomic environment has urged these proponents to become more vocal.

In the wake of the Subprime Crisis, China, like many other countries, orchestrated twin monetary and fiscal policies to reinforce economic growth. Consumer spending was incentivized through the sale

1 Chinese enterprises aren't just waiting for investors to come to them anymore either. A wave of Chinese companies listed on the NYSE in 2010, though the fundraising sharply curtailed in 2011 (Caixin, 2011).

of automobiles and white goods, while government money was channeled into heavy infrastructure spending on roads and railways. Strong growth enriched spending habits and turned property into gold. All the while, speculative property investment was growing hotter.

Regulators came to the rescue, towing behind them a series of measures aimed to cool the market. They sequentially barred lending for third, then second home purchases in various cities, and reigned back on bank lending.[2] Success was by no means universal.[3] Leading developers were forced into bankruptcy, others were rumored as unable to meet payroll and some conglomerates stepped out of the market.

Those are all clearly visible events. So is the property on the edge of collapse? With so many polar viewpoints and a plentitude of confounding statistics, it looks like an unstable house of cards at the very least.

This study bypasses the question, and rather skips forward to the implications of a collapse. The plain-vanilla Generalized Autoregressive Conditional Hetereoskedasticity (GARCH) methodology outlined by Focardi et. al (2007) and Alexander (2008) is used to understand how volatility transmits between China's real estate market and that of the US. Markets more often move together in terms of volatility than prices.

Though GARCH models are used to analyze and model volatility, it is still important to first model a conditional mean. To do so, Autoregressive Moving Average (ARMA) models are estimated to capture a conditional mean, resulting in residuals which satisfy the white noise assumption. These residuals, used to represent market shock, are then fed into GARCH models.

Univariate and bivariate GARCH equations are estimated with the maximum likelihood estimator, producing conditional volatility equations. For comparison, two methods are used to compute conditional correlations; one constant and the other dynamic.

Results did not meet all expectations. Market correlation turned out to be surprisingly weak, but cross market volatility was lifted by strong local volatility. Empirical results show that volatility in the two real estate markets became substantially more influential over each other around the time of the Subprime Crisis.

The remainder of this paper is organized as follows. The next literature review section provides a discussion on the existing body of spillover research. The next section discusses the methodology, explaining the ARMA and GARCH models. The indices which feed the models are explained in the data and descriptive statistics section, followed by the empirical results. Lastly, the study closes with a conclusion containing a final review and recommendations for future research.

2 Foreign investors began pouring liquidity into the dry market through programs such as QFII and real estate investment vehicles (REITs).

3 Critics say the 'market froth' could have been prevented early on by the introduction of a single measure strong enough to discourage speculation. The Ten Measures (国十条) so far serve as the landmark of strong policy.

Literature Review

It's no surprise that since globalization began its reign in the 1980s, many economists have come to specialize in dissecting market linkages. An appropriately large volume of academic publications has been written dedicated to the subject. The research is primarily focused on finding if, and to what extent markets interact. One way in which interactions occur is through the transmission of volatility.

It's widely tested for instance if the echo of a stock market crash can be heard overseas. The October 1987 stock market crash prompted Hamao et al. (1990) and others to examine spillovers both before and after the event. Econometricians most often turn to co-integration testing, but other popular methods include copulas, stochastic models and GARCH. When it comes to volatility spillover studies, preferences lie with the lattermost.

The majority of volatility spillover studies can be categorized as focusing on high-frequency data (Susmel and Engle, 1990), fat-tails (Hung et. al, 2008), as well as global and regional effects (Beirne et al., 2010).

The branch which delves into unexplored markets has also grown fastest. According to Beirne et al. (2010) and Zhou and Zhang (2012), early spillover studies mainly scrutinized developed economies. However, studies on emerging markets such as Central and Eastern Europe (Saleem, 2009, Li and Majerowska, 2008), Asia (Mukherjee and Mishra, 2010), and the Mideast (Hammoudeh et al., 2009) now proliferate.

Their prevalence in academia mirrors their performance in the markets. Capital continues to gravitate towards diversification benefits and relatively stronger economic growth, powered by globalization and financial liberalization. But these two seemingly irreversible twin forces also come with a darker side; decreasing average returns, increasingly correlated price movements across markets, along with rising betas of domestic and foreign markets. Longin and Solnik (1995) found that international equity returns increased in correlation from 1960 to 1990. According to Bekaert and Harvey (2000, 2003), international diversification is resultantly becoming ever more elusive.

Integration has thus left our markets highly contagious to crises. Studies show this doesn't only encompass mature financial centers like New York, London and Tokyo, but even those still in their infancy.

Differing spillovers have been explained with several reasons, such as trade relationship, market openness and geographical proximity. Intuition suggests that larger markets pose more absolute trade importance, and spillover potential, to their smaller partners than vice versa. But since spillover is determined by many factors, determining whether the US or Tokyo bears greater influence on Taiwan requires examination.

Wei et al. (1995) showed that New York had strong influence over the Taiwanese and Hong Kong markets; more than Tokyo in fact. Later on, Chan-Lau and Ivanschenko (2003) found spillovers also transmit to and fro between Hong Kong, Japan and Singapore, and the US. That is, perhaps when *Shenzhen* sneezes, *New York* catches a cold.

Beirne et al. (2010) determined that the vast majority of emerging market economies exhibited regional and global spillovers of varying strength. However, because studies experiment with unique specifications such as methodology, time period, observation time frequency and geographical coverage, results remain mixed (Saleem, 2009).

*“since **real estate** became **globalized** over the past few decades,*

Mainland China's economic significance is newfound. Of those early pioneers who delved into the market, Bailey (1994) was one of the first. His work found that Shanghai and Shenzhen were not globally integrated, though his results were exclusively based on only 52 weekly observations distributed across one year. One of his later studies (2004) reconfirmed the results for the early 1990s.

When Wang and Firth (2004) examined the period of 1994-2001, they concluded that developed market volatility was impacting China but not vice versa. However, the split-sample analysis went on to show that the 1997 Asian Financial Crisis transformed volatility spillovers to become bi-directional. Jang and Sul (2002) found the crisis also increased Asian co-market movements. Wang and Di Iorio (2007) contrarily found that between 1994 and 2004, China's market was isolated. Zhou et. al (2012) found that China's downward market correction in 2007 significantly contributed to volatility spillovers.

The case is nowhere near being closed. The plot thickens when different asset classes, markets and share types are considered, which opens the door to many as of yet unexplored avenues.[1]

Enter real estate. One needs only to glance at the cranes lining the skyline of any Chinese city to see how pivotal a role the sector plays to the greater economy. But few studies are dedicated to the

1 The Chinese market is composed of an alphabet soup of share types. See Howie and Walter (2006) for more.

*the market may be **highly susceptible** to contagion.”*

market. Given past and present market conditions, the time is ripe for more.

A flurry of real estate volatility spillover studies followed in the wake of the US Subprime Crisis. Real estate contagion studies such as that by Hatemi and Roco (2011) conveniently serve as a backdrop for this study. Zhou et al. (2012) found the US market had a dominant volatility impact on other markets during the Subprime Crisis. In particular, bad news in the US triggered market losses, which then emanated abroad to other markets. Driven by their own bad news, these markets in turn transmitted massive volatilities back to the US.

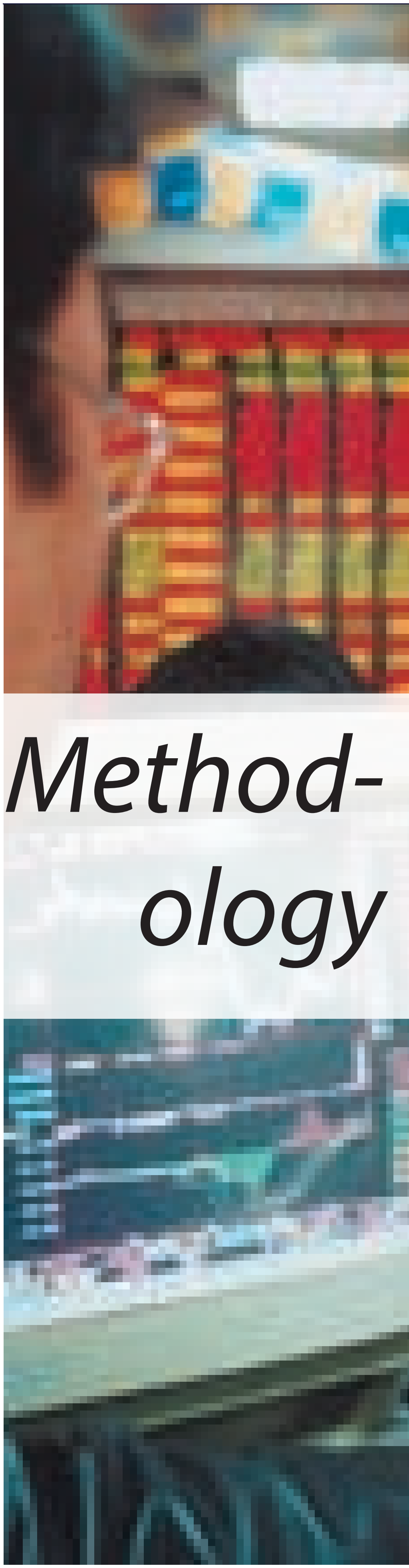
It's well documented that market correlations strengthen during crises. Zhou et. al (2012) showed that Chinese volatility has strongly impacted other markets since 2005. The Chinese market's downward correction between February and July 2007 significantly contributed to foreign market volatility. The authors speculate that due to restrictions on foreign investment, the Chinese stock market wasn't greatly affected in terms of volatility during the subprime crisis.

(Eicholtz et al., 2009) explains that real estate service providers have gone multinational and new financial instruments give foreign investors nearly the same footing as local investors. Bardhan and Kroll (2007) claimed that since real estate became globalized over the past few decades, the market may be highly susceptible to contagion. According to Eichholtz and Kok (2007), real estate investment vehicles have urged such internationalization.

Hatemi and Roco's work (2011) points out that when hit by a crisis, investors and banks may be struck by liquidity problems and thus sell off their holdings. Moreover, changing asset prices may prompt investors to rebalance their portfolios, changing market conditions elsewhere. Further explanations of cross-border ties recorded during an interview with the editor and real estate analyst of China's leading financial publications are included in the appendix.

Eichholtz et al. (2009) point to the internationalization of real estate providers, greater market transparency, dismantled political barriers, and financial liberation to contribute to foreign direct investment. This lends support to the argument that markets should display co-movements.

But working in opposition is the fact that real estate is not directly market traded. The closest exposure to be found is through investing in indices, funds or the securities of related industries such as property developers. Furthermore, Bardhan et al. (2007) showed that real estate markets don't respond quickly to international shocks. Thus, such investigations must be made on a case-by-case basis, warranting this study.



Methodology

GARCH models have been fashioned in more than 330 variations to apply to all the main asset classes, including real estate (Bollerslev, 2008). This study employs the multivariate GARCH methodology outlined by Focardi et. al (2007) and Alexander (2008). By using this plain vanilla approach, more focus can be put towards estimating meaningful, interpretable parameters than solving the computational difficulties associated with more complex GARCH variations.

Scheicher (2001) uses the MV-GARCH approach with a Constant Conditional Correlation (CCC) to examine the national stock indices of Eastern Europe from 1995 to 1997, laying a foundation for this study's usage of CCC. However, numerous studies have revealed that correlation varies with time.

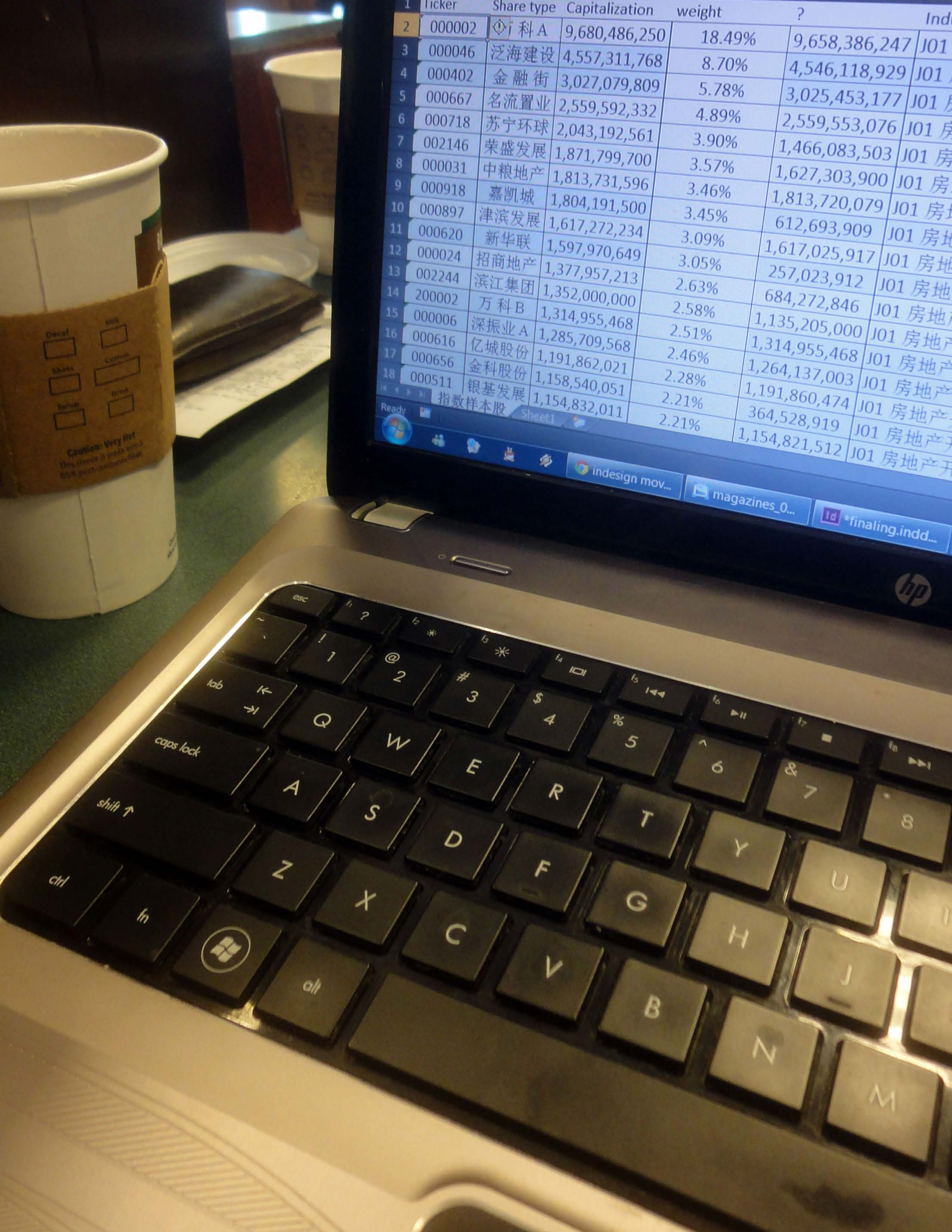
Kaplanis (1988) showed that several national equity indices' correlation and covariance shifted on a monthly basis over a 15-year period. In a study by Bekaert and Harvey (1995), correlation was seen to vary over shorter periods as well.

Despite the counterevidence, CCC still proves a reasonable method to model equities. Estimating multivariate probability density functions for more than two variables grows exponentially difficult. Alexander (2008) defends the method as being preferred for covariance matrices of foreign exchange rates or equity indices.

This study uses a two-step procedure of first estimating an ARMA equation to extract the conditional mean. The residuals are then used to estimate a GARCH equation to extract the conditional variance. Initially, two sets of univariate GARCH parameters are estimated, which are later compared with MV-GARCH parameters.

Once a returns process is shown to be stationary, an ARMA(p,q) model can be used.[1] An autoregressive term is included to recognize the possibility that returns from one day to the next could be autocorrelated. The autoregressive term creates a mean reverting process. A moving average term is included to represent the process as the sum of its different lags.

1 The model is stationary if and only if the moving average coefficients are finite and, under its characteristic equation representation, all lie within the unit circle. See Alexander (2007) II.5.5. for more.


Ticker Share type Capitalization weight ?
000002 科A 9,680,486,250 18.49% 9,658,386,247 J01
000046 泛海建设 4,557,311,768 8.70% 4,546,118,929 J01
000402 金融街 3,027,079,809 5.78% 3,025,453,177 J01
000667 名流置业 2,559,592,332 4.89% 2,559,553,076 J01
000718 苏宁环球 2,043,192,561 3.90% 1,466,083,503 J01
002146 荣盛发展 1,871,799,700 3.57% 1,627,303,900 J01
000031 中粮地产 1,813,731,596 3.46% 1,813,720,079 J01
000918 嘉凯城 1,804,191,500 3.45% 612,693,909 J01
000897 津滨发展 1,617,272,234 3.09% 1,617,025,917 J01
000620 新华联 1,597,970,649 3.05% 257,023,912 J01 房地
000024 招商地产 1,377,957,213 2.63% 684,272,846 J01 房地
002244 滨江集团 1,352,000,000 2.58% 1,135,205,000 J01 房地
200002 万科B 1,314,955,468 2.51% 1,314,955,468 J01 房地产
000006 深振业A 1,285,709,568 2.46% 1,264,137,003 J01 房地产
000616 亿城股份 1,191,862,021 2.28% 1,191,860,474 J01 房地产
000656 金科股份 1,158,540,051 2.21% 364,528,919 J01 房地产
000511 银基发展 1,154,832,011 2.21% 1,154,821,512 J01 房地产
Ready
指数样本股
Sheet1
indesign mov...
magazines_0...
*finaling.indd...

The first order equation is fitted with an autoregressive and moving average term;

$$X_t = c+\varepsilon_t+\sum_{i=1}^{p}\varphi_i X_{t-i}+\sum_{i=1}^{q}\theta_i\varepsilon_{t-i},$$

where c is a constant, p is the autoregressive term and q is the moving average term. The combination of a zero mean and a time varying conditional variance is assumed to result in a conditional normal process, essentially leaving behind the same error term as from an ordinary least squares regression.

After extracting the conditional mean, the error process is white noise.

$$r_t|I_t - 1\ N(0,\sigma_t^2)$$

Since the information set is entirely composed of observed values, error is assumed to be determinate. The error term can thus be interpreted as the unexpected return or market shock.

The ARMA residuals are then used to estimate the conditional variance of the error term, given by:

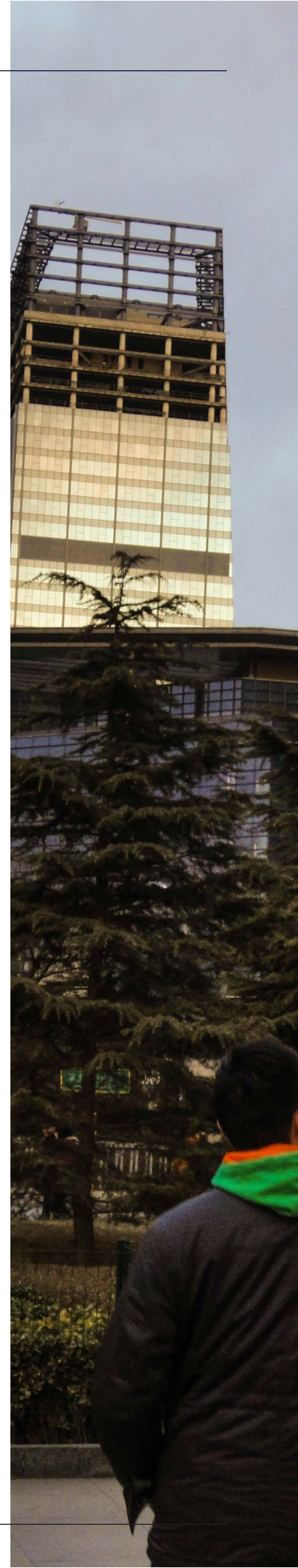
$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2,$$

where σ^2_t is the conditional variance at time t, conditional on the information set.

Conditional variance is transformed into conditional volatility using the square root of time rule. Multiplying this conditional variance series by its annualized square root renders the GARCH conditional volatility.

Thanks to the simplicity of this model, its omega (ω, w), alpha (α, a) and beta (β, b) parameters are easy to interpret. Alpha measures how sensitive conditional volatility is to market shocks. The larger its value, the more sensitive conditional volatility is. Beta tells the persistence of conditional volatility when the market is devoid of shocks. The larger its value, the longer it takes for volatility to fade out. Combining the two parameters gives conditional volatility's rate of convergence to the long term average level. The constant omega parameter determines this long term unconditional volatility level, given by ω / (1 - α + β). A high omega translates into a high level of long term volatility. Furthermore, mean lag variance can be calculated as 1 / (1 – β).

Parameters were estimated in Matlab with the Levenberg-Marquardt algorithm to solve the maximum likelihood density function:[2]



2 Estimations were also run through Microsoft Excel 2010. However, its Solver tool rendered considerably different estimation results from Matlab. The Leven-

$$lnL(\Theta) = -\frac{1}{2}\sum_{t=1}^{T}(ln(\sigma^2) + (\frac{\varepsilon_t}{\sigma_t})^2$$

Using Bollerslev's (1990) constant correlation estimator, the conditional covariance can be estimated using equation:

$$V = DCD,$$

where C is correlation and D are the time varying conditional volatilities. The correlation matrix can contain any correlations, so long as the matrix is positive definite. According to Longin and Solnik (1995), time varying correlations can be explained with conditional covariance. This study models correlation with both CCC and, following Engle's (2002) lead, extends it to the Dynamic Conditional Correlation model (DCC), where correlation is time varying.

Correlation is estimated using Exponentially Weighted Moving Averages (EWMA) of the cross product of the standardized returns. This EWMA variation of the DCC model is symmetric and has no mean-reversion.

The conditional covariance is obtained from equation:

$$\sigma_t^2 = \lambda(\sigma_{t-1}) + (1-\lambda)u_{t-1}^2,$$

where

$$\sigma = (r - \overline{r})^2$$

From there, the covariance can be calculated as:

$$Cov_t = \lambda(cov_t{-}1){+}(1{-}\lambda)(\sigma_{r(IYR)})(\sigma_{r(SZRE)}),$$

where λ is a weighting constant which is determined by the period of observations[3]. Using this, both correlations can be estimated from the data available up to time t. This time varying conditional covariance (C) is then used to stitch together the two time varying conditional volatilities (D), resulting in a dynamic conditional correlation.

---

berg-Marquardt is argued to be the best optimized for GARCH models (Majerowska, 2008 and Alexander II.4.2.2, 2008). The BHHH algorithm is also often preferred (Saleem 2009).

3 RiskMetrics established the convention of using a weighting constant of 0.97 for weekly returns, 0.95 for monthly and continually larger values for wider intervals.

Data & Descriptives

统计

This study uses two exchange-traded real estate funds to proxy the commercial and residential real estate sectors. Both indices are capitalization weighted and neither are leveraged or actively managed.

The iShares Dow Jones US Real Estate Index Fund (NYSEA: IYR) is used to proxy the US market. Of its 84 members, the index' largest by weight are shown in Table 3. The IYR tracks the Down Jones US Real Estate Industry Group Index with investments and weights fashioned after the Dow Jones index.[1] This latter index is composed of Real Estate Investment Trusts and other companies directly or indirectly invested in real estate through development, management or ownership, including property agencies worth USD 508 billion as of August 16, 2012. Its base price was set at 100 on December 31, 1991 and is traded in USD.

Regarding China, there exists two leading real estate indices listed which bear similar characteristics. They are the Shenzhen Stock Exchange Real Estate Index (深圳地产指数, SZSE:399200) and the Shanghai Stock Exchange Real Estate Index (上海地产指数, SSE:000006). The Shenzhen Stock Exchange Real Estate Index, referred to hereafter as SZ RE, was selected for being about 40% larger in terms of turnover and total volume transaction than Shanghai's equivalent. The SZ RE is directly or indirectly invested in commercial and residential real estate through development, management or ownership, and is traded in the local RMB currency. Of its total 62 members, the index' largest by weight are shown in Table 4.

As mentioned, neither index is exposed purely to commercial real estate. Both are invested in companies with operations tied to the residential sector,

Top 10 IYR members by weight

Ticker	Company		Weight
SPG	Simon Property		9.20%
AMT	American Tower		5.51%
PSA	Public Storage		4.02%
HCP	HCP		3.71%
VTR	Ventas		3.61%
EQR	Equity Residential		3.56%
BXP	Boston Properties		3.27%
NLY	Analy Capital Management		3.24%
PLD	Prologis		3.04%
VNO	Vornado Realty		2.98%
		Total	**42.14%**

Source: Bloomberg

Top 10 SZ RE members by weight

Ticker	English name	Chinese name	Weight
000002	Vanke	万 科 A	18.49%
000046	Oceanwide Real Estate	泛海建设	8.70%
000402	Financial Street Holdings	金 融 街	5.78%
000667	Celebretities Real Estate Development	名流置业	4.89%
000718	Suning Universal	苏宁环球	3.90%
002146	RiseSun Real Estate Development	荣盛发展	3.57%
000031	COFCO Property	中粮地产	3.46%
000918	China Calxon	嘉凯城	3.45%
000897	Jinbin Development	津滨发展	3.09%
000620	Macrolink	新华联	3.05%
		Total	**58.38%**

Source: Shenzhen Stock Exchange

1 More information on these exchanges is available at www.szse.cn/main/en and www.nyse.com.

making them an inherently imperfect at reflecting the commercial sector. Nevertheless, commercial still dominates their weightings. The SZ RE is invested in 22 fewer companies and puts 16.24% more weight to its ten largest members. Being less diversified and more top heavy, the index should exhibit greater volz

Coinciding with the Shenzhen index' debut, the sample period begins July 2, 2001 and ends March 19, 2009. It was chosen to use the longest possible period in order to include the effects of several financial crises, as well as the evolution of their integration. The indices are locally denominated, thus disentangling them from foreign exchange values and restricting movements solely to security prices.

The original SZSE price series contains 2,795 daily observations and the NYSEA, 3,066. The difference results from separate holidays. Void of any holiday, both markets trade Monday to Friday. Any dates for which both markets weren't open were subsequently pulled from the price series, as were any dates with missing prices due to no trading, as illustrated in Figure 4. As an example, because Greater China's stock markets usually close for a week or more usually in late January or early February for the Lunar New Year holidays, these dates were removed from both indices. After filtering, 2,795 observations remain.

Figure 5 displays the price development of the index values.[2] Table 5 presents their price descriptive statistics. This first impression suggests that the two indices follow similar paths. Of worthwhile note is the turbulence both experience from 2008 onwards. Knowing that market correlations increase in down periods, we should expect to see some of that volatility appearing in their conditional volatility at this time.

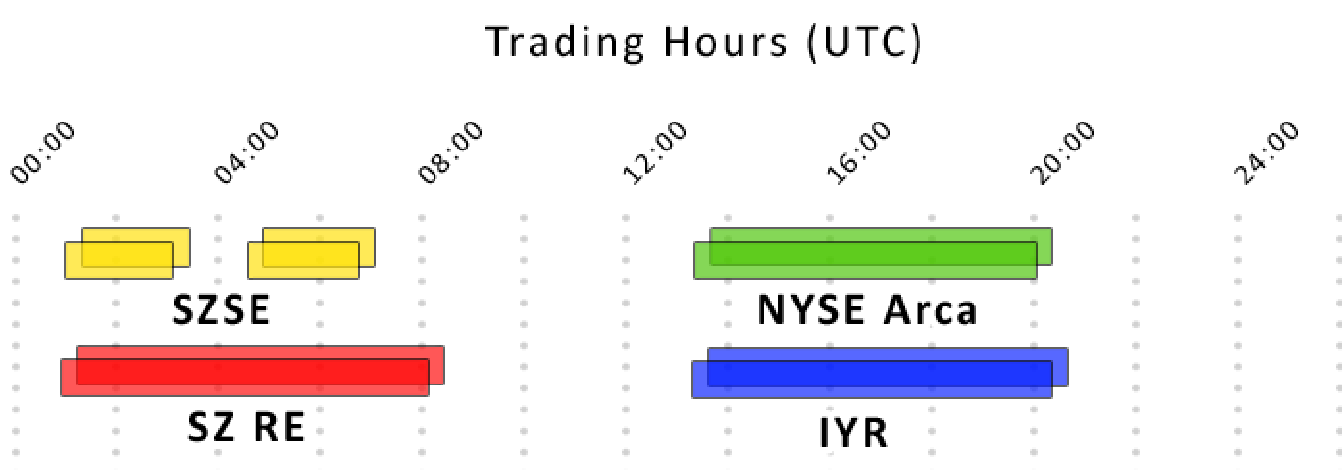
Returns were calculated as continuously compounded changes in log prices:

$$r_t = ln(P_t) - ln(P_{t-1}),$$

where r_t denotes the closing value of the index. Chan-Lau and Ivaschenko (2003) pointed out that close-to-close returns may strengthen cross-autocorrelation between markets, but that Hamao et al. (1990) found no significant improvement by using open-to-close returns.

Figure 6 reveals the returns process of each series,

2 The unfiltered and filtered US index series, price and all hereafter, were characterized by minor nuances. No change occurred in the Shenzhen index since no observations were deleted by the filter. Tests and figures are available upon request.



UNFILTERED TRADING DAYS			
Date	SZSE	Date	NYSE
1/3/2001	54	1/3/2001	43
1/5/2001	13	2/1/2001	56
1/3/2002	65	5/4/2001	1
1/4/2002	99	8/2/2001	64
4/2/2003	44	9/2/2001	23
		1/4/2002	65
		3/6/2002	22
		4/2/2003	9

FILTERED TRADING DAYS		
Date	SZSE	NYSE
1/3/2001	54	43
1/4/2002	99	65
4/2/2003	44	9

while Table 6 presents their descriptive statistics. The means range from 0.00019% to 0.00022%, led by China. These very small means suggest the ARMA zero mean residuals should closely resemble this returns process.

The minimums and maximums, in conjunction with the variance levels (standard deviations) reveal some of these markets' nature. The US market took the deepest daily dive of -23% on December 1, 2008**.** This doubled Shenzhen's -10%, occurring June 10th, 2008. The US also recorded the largest gain of 15% on October 28, 2008, beyond Shenzhen's 9.5% on September 19th, 2008. Noteworthy is both markets having marked their record gains and losses very close to the Subprime Crisis' outset. This should be expected, as vast amounts of new information, both positive and negative, was being brought to the market during this period.

Finally, overall volatility is higher in Mainland China, with a standard deviation of 0.02285 compared to the US' 0.02017.

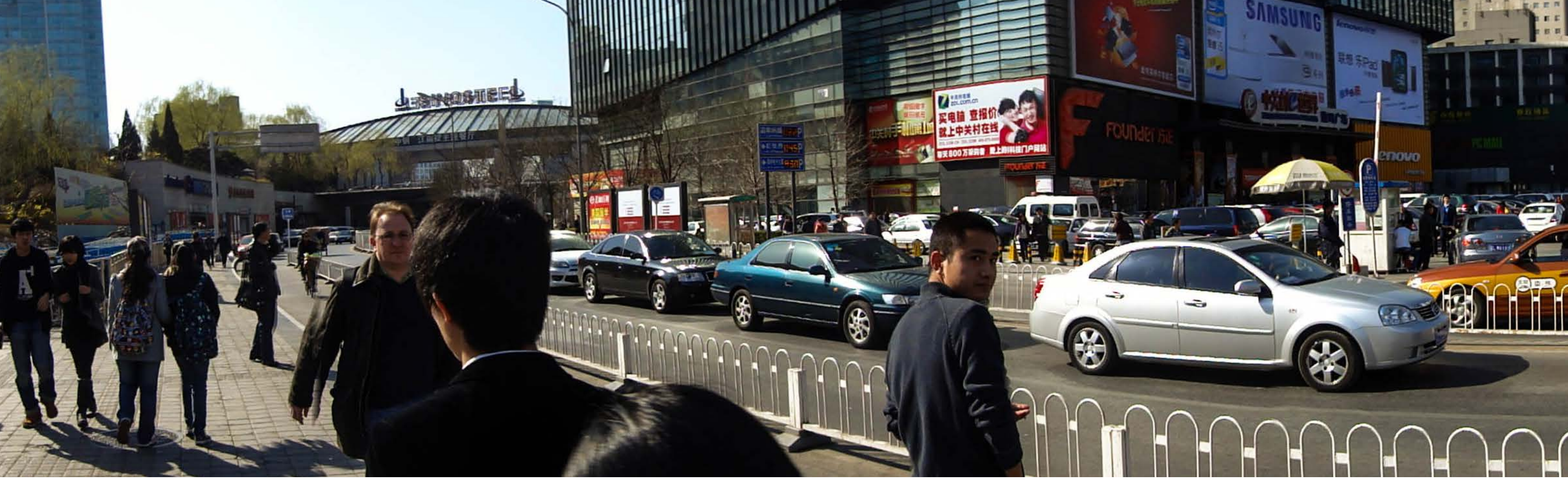
Altogether, the risk-reward relationship mirrors the findings by Harvey (1995) that emerging markets exhibit high expected returns and high volatility. It also consistent with China-focused studies (Zhou et. al, 2012).

As reflected by the high and very high leptokurtoses in China and the US, respectively, both series have significant fat tails and high peaks. Coupled with that, both markets are negatively skewed, indicating the risk of significant negative losses. These characteristics can also be found in Figure 7.

The distributions come as little surprise. The Chinese market has been recognized for a high churn rate, frequent ups and downs, as well as a high prevalence of day trading.

The indices also exhibit volatility clustering, where large (small) volatilities are followed by large (small) volatilities. According to Gebka and Serwa (2007), national capital markets are often affected by common global or regional shocks. This may be visible in these two indices, as volatilities tend to jump during the same time periods. For this reason, volatility should be modeled simultaneously.

The most prevalent unit-root test for checking if price and return series are stationary is the augmented Dickey Fuller (ADF) test. The null hypothesis indicates a times series is non-stationary I(0). If the test statistic is greater than the critical value, then the null hypothesis cannot be rejected. A lower p-value adds to the likelihood the test came to the correct conclusion. The results of testing at a 5% sig-



nificant level for all series are summarized in Table 7.

Table 7: Unit-root tests

	ADF test	
	US IYR	SZSE RE
Price	Null (non-stationary)	Null (non-stationary)
Return	Alternative (stationary)	Alternative (stationary)

The unconditional correlation between the indices' returns is 0.0127, a fairly weak level of correlation.

The Box, Jenkins and Reinsel test is used to do a visual check for autocorrelation, i.e. serial correlation, in prices and squared returns using a range of lags, with the results respectively plotted in Figures 8 and 9.

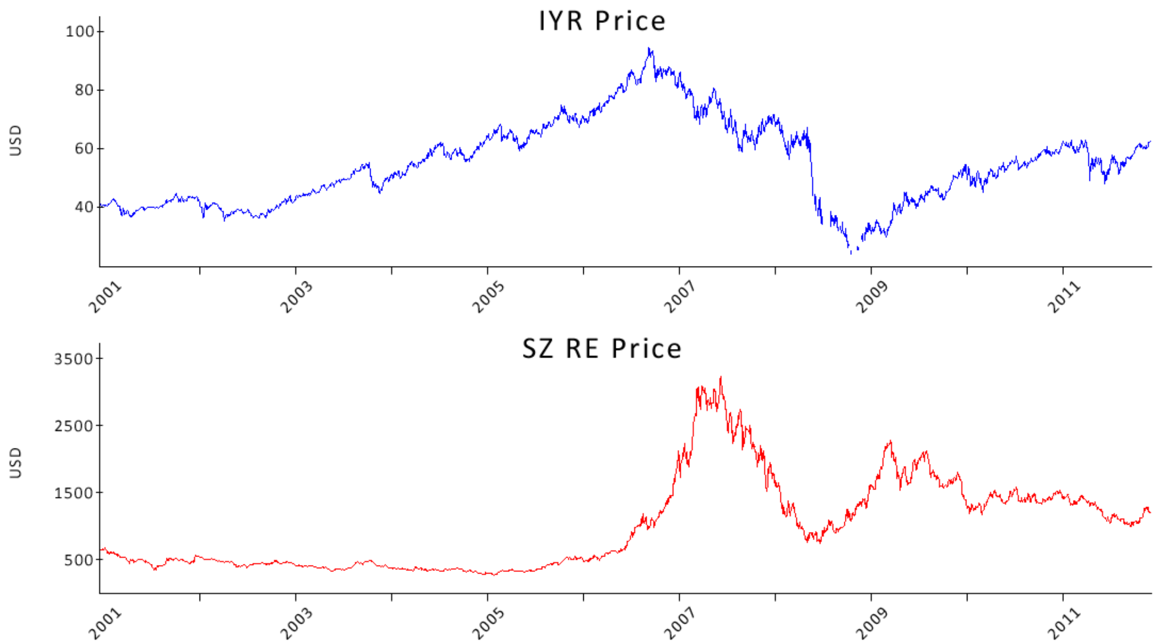
As evident, there is considerable autocorrelation in the data. This necessitates a conditional variance

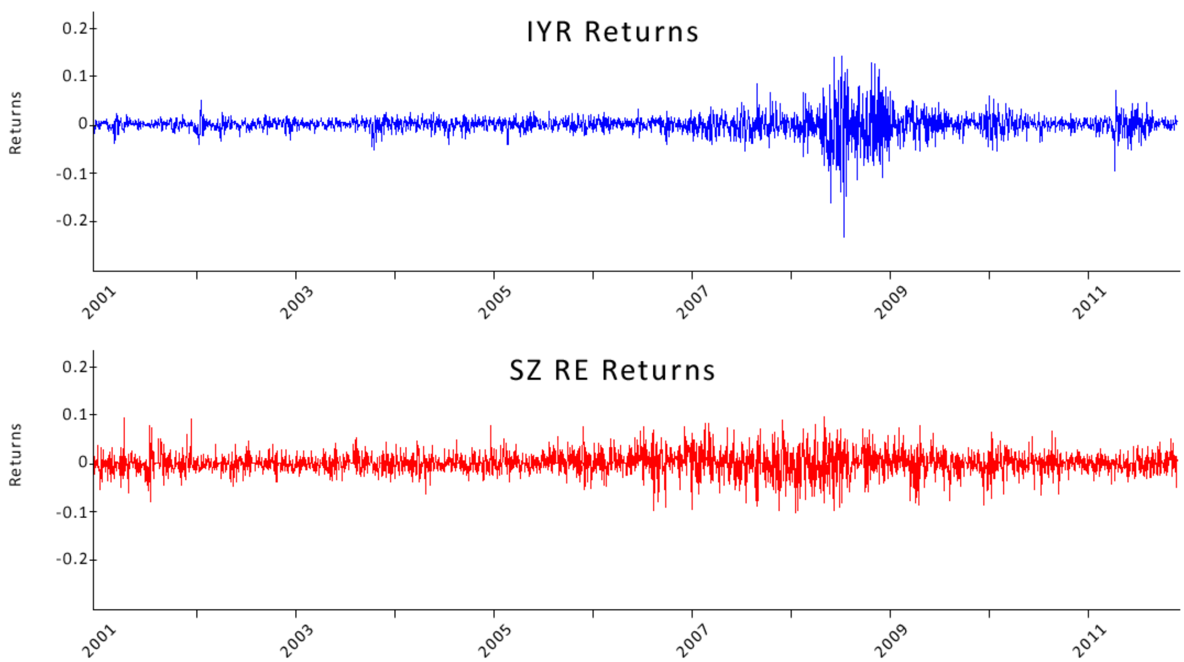
Filtered price observations

	US IYR	SZSE RE
# observations	2,796	2,796
Mean	54.75	986.90
Median	54.31	671.81
Min	22.21	265.43
Max	94.57	3,221.64
Std. deviation	14.48	677.14
Skewness	0.37	1.00
Kurtosis	2.53	3.29

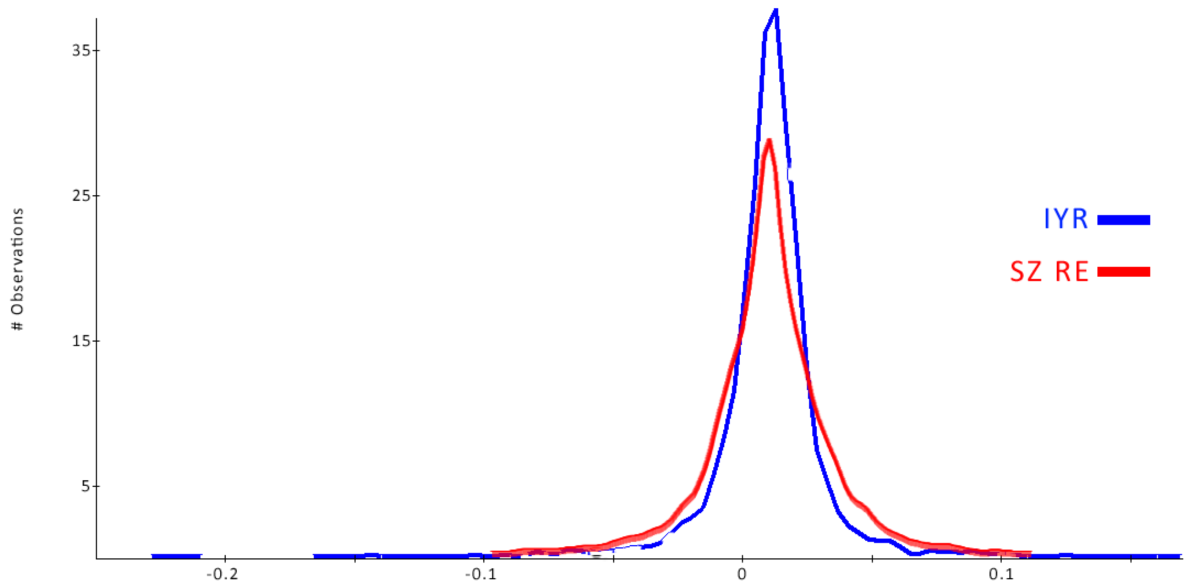
Filtered return observations

	US IYR	SZSE RE
# observations	2,795	2,795
Mean	0.00015	0.00022
Median	0.00037	-
Min	(0.23081)	(0.10109)
Max	0.15122	0.09506
Std. deviation	0.02102	0.02285
Skewness	(0.46984)	(0.17073)
Kurtosis	18.13215	5.45475

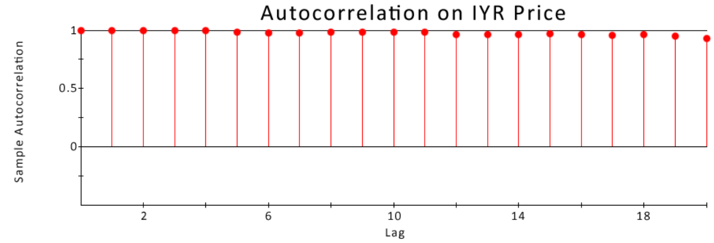

IYR Price
USD
100
80
60
40
2001
2003
2005
2007
2009
2011
SZ RE Price
USD
3500
2500
1500
500
2001
2003
2005
2007
2009
2011


IYR Returns
Returns
0.2
0.1
0
-0.1
-0.2
2001
2003
2005
2007
2009
2011
SZ RE Returns
Returns
0.2
0.1
0
-0.1
-0.2
2001
2003
2005
2007
2009
2011

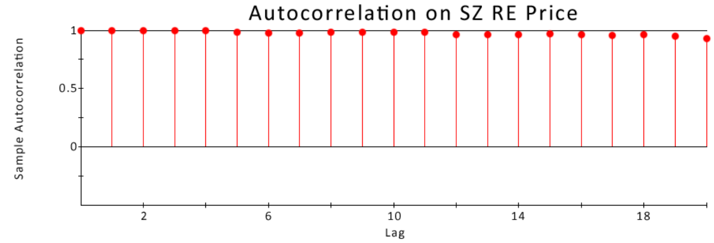
Smoothed Return Distributions



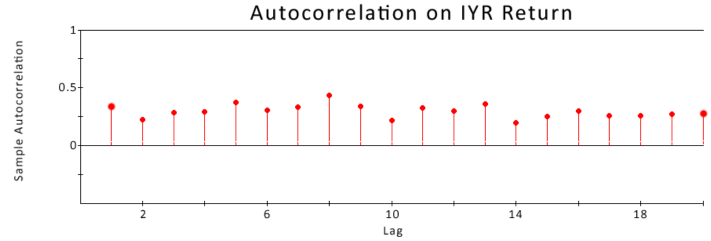
Autocorrelation on IYR Price



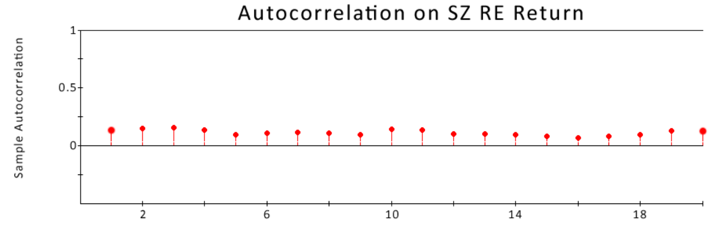
Autocorrelation on SZ RE Price

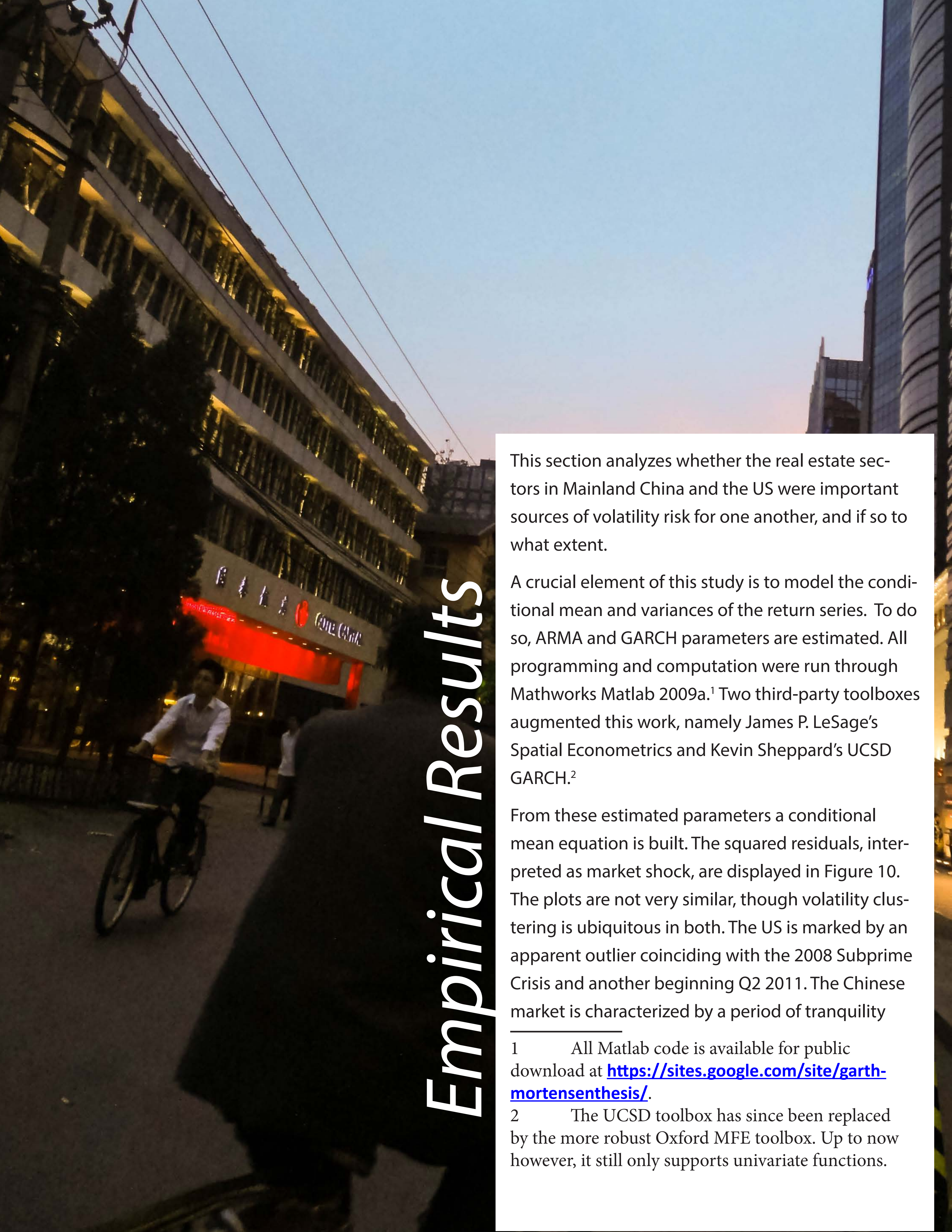


Autocorrelation on IYR Return



Autocorrelation on SZ RE Return





Empirical Results

This section analyzes whether the real estate sectors in Mainland China and the US were important sources of volatility risk for one another, and if so to what extent.

A crucial element of this study is to model the conditional mean and variances of the return series. To do so, ARMA and GARCH parameters are estimated. All programming and computation were run through Mathworks Matlab 2009a.[1] Two third-party toolboxes augmented this work, namely James P. LeSage's Spatial Econometrics and Kevin Sheppard's UCSD GARCH.[2]

From these estimated parameters a conditional mean equation is built. The squared residuals, interpreted as market shock, are displayed in Figure 10. The plots are not very similar, though volatility clustering is ubiquitous in both. The US is marked by an apparent outlier coinciding with the 2008 Subprime Crisis and another beginning Q2 2011. The Chinese market is characterized by a period of tranquility

---

1 All Matlab code is available for public download at https://sites.google.com/site/garthmortensenthesis/.

2 The UCSD toolbox has since been replaced by the more robust Oxford MFE toolbox. Up to now however, it still only supports univariate functions.

dating from 2002 until H1 2006, when it then shifts to a prolonged state of turbulence.

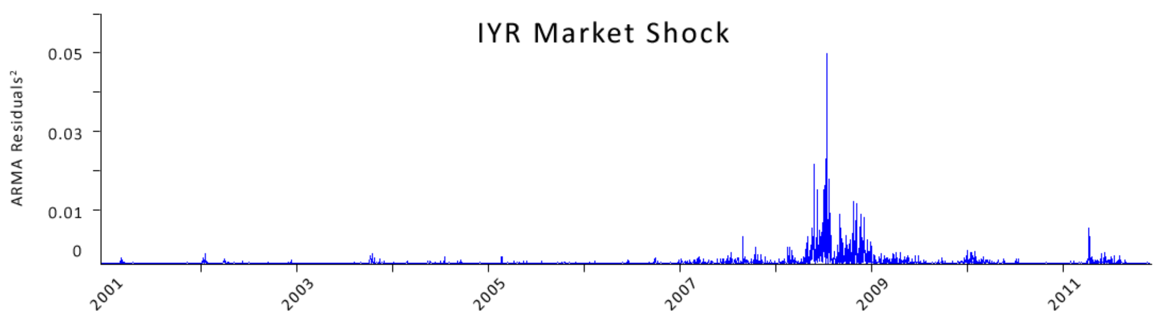
Bardhan et. al (2007) found that real estate does not rapidly respond to international shocks. Therefore, if links are found, they possibly rose through alternative market channels such as investor liquidity or portfolio rebalancing (Hatemi-J, Roco, 2007).

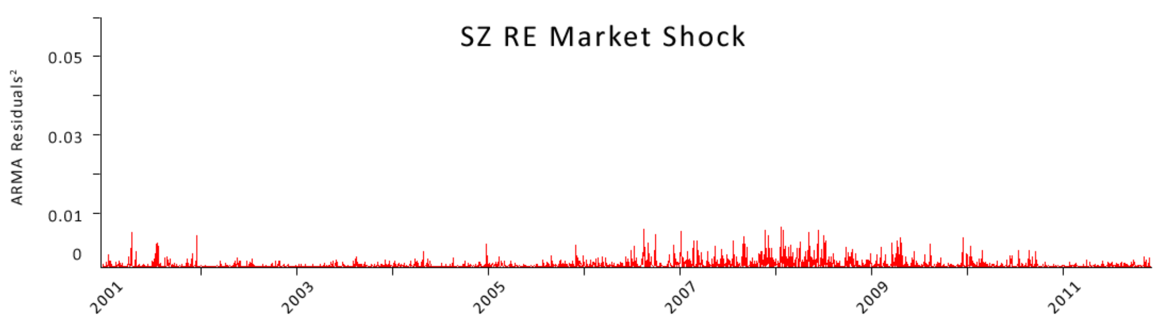
On a daily basis, the largest market shock in the US took place on November 12, 2008, while a number of others also fell within a month time from then. Shenzhen experienced its largest shock on September 30, 2009. Within the top fifty largest daily shocks, only one fell within the US' chaotic period. This suggests that the 2008 Subprime crisis was not the leading contributor to Shenzhen market shocks. Rather, Figure 10 reveals that conditions remained more or less constant throughout the US age of turbulence.

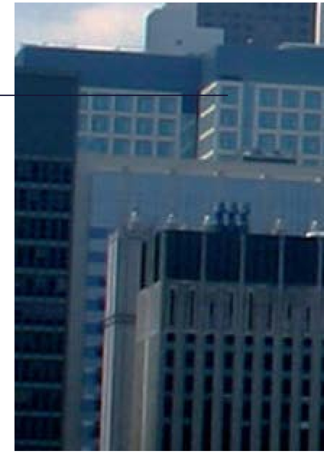
The alpha estimates are small, though Shenzhen's is less than half that of the US, indicating the latter is much more sensitive to conditional volatility. The beta parameters are both close to one, although Shenzhen's larger value shows it takes more time for a volatility impact to fade from the market. Adding each market's respective alpha and beta together result in two similar measures very close to one, indicating their rate of convergence to their conditional long term volatilities are rather slow. However, Shenzhen's higher value indicates that following a shock, convergence to the long run equilibrium takes more time. Furthermore, Shenzhen's conditional long term volatility estimate stands above the US', while its mean lag variance is well over double. All these measurements suggest the US market is more

Univariate ARMA(1,1) mean equation

	US IYR	*t-ratio*	SZSE RE	*t-ratio*
Constant	0.00012517	*0.01*	0.00028737	*0.01*
AR(1)	0.145	*6.99*	-0.333	*(14.58)*
MA(1)	-0.318	*(15.34)*	0.377	*16.52*







capable at quickly digesting volatility and returning to normalcy.

Assembling the univariate GARCH parameters into the form of conditional variances equations produced what is seen in Figure 11. A prevalent relationship is not evident throughout the volatility series. There are however short moments when they seem to move in tangent, such as briefly at the turn of the century when tech-bubble burst, and both volatilities stand tall from 2007 to mid-2010.

Figure 11: GARCH conditional volatilities

As seen in Table 10, bivariate CCC estimation renders similar variance processes. Figure 12 displays their estimated bivariate conditional volatilities.

The most pronounced difference between univariate and bivariate estimation results is found in the convergence of the markets' mean lag variances, resulting from changed betas. The US market's mean lag variance lengthened from 7.75 days to 8.28, meaning the time required to dissipate volatility increased. Meanwhile, the Chinese market shortened from 16.88 days to 13.43, indicating volatility takes less time to die out.

Since correlation has been widely shown to vary with time, the previously used constant correlation figures are most likely a poor representation. Specifically, the constant correlation can be remade into a dynamic conditional correlation via an exponentially weighted moving average correlation.

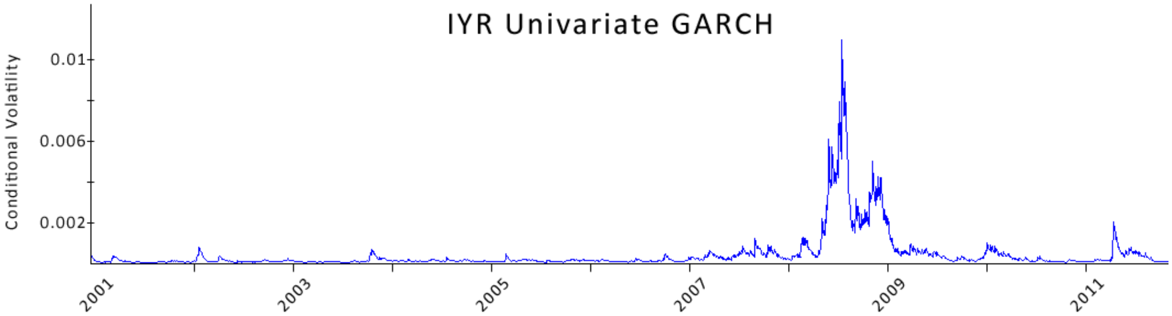
The covariance series is displayed in Figure 13, using a lambda (smoothing constant) of 0.97. It is clear that covariance between the two varies with time. However, the only conclusion that can be made is that covariance appears to have some cyclical nature, staying mostly within the bounds of -0.4 and 0.4.

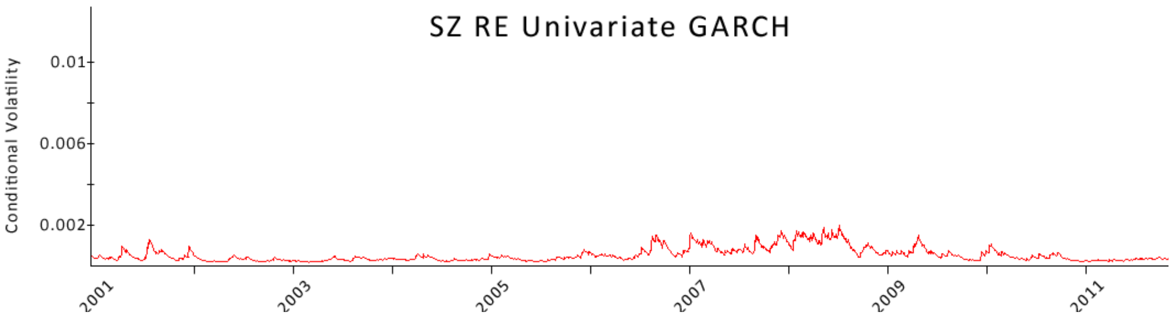
Lastly, combining the two conditional variance series together with this conditional correlation series renders a final GARCH dynamic conditional correlation series, shown in Figure 14.

When conjoining the previous undulating covariance series with both conditional volatility series, the picture of an interrelationship appears. From the beginning of the sample period in 2001 and lasting until around 2006, the two indices are fairly independent. In 2007, it becomes apparent the relationship has changed to one of interdependence, becoming most pronounced in 2008, coinciding with the Subprime Crisis. Interestingly, the US tech bubble's bursting at the turn of the century had no such effect. Thereafter, the two oscillate between periods of relative independence and sudden positive correlations (0.1).

Overlap Univariate GARCH(1,1) variance equation

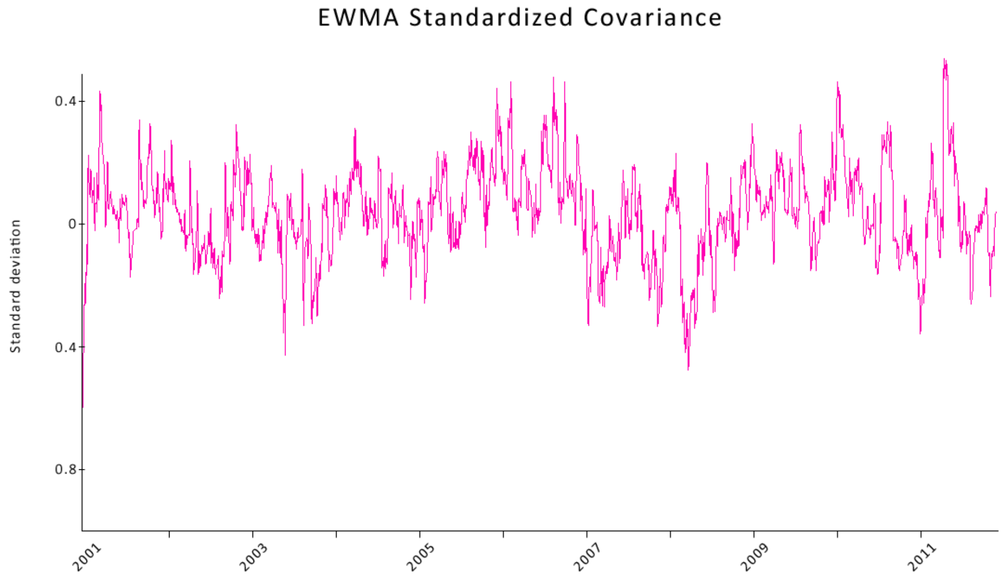
	US IYR	*t-ratio*	SZSE RE	*t-ratio*
w	0.00000264	*7,575,324.88*	0.00000462	*2,595,002.67*
a	0.122	*839.26*	0.051	*1,193.81*
b	0.871	*6,584.00*	0.941	*16,926.90*
LT volatility	31.09%		36.75%	
Mean lag variance (days)	7.75		16.88	
Max liklihood	8,077.21		6,839.27	

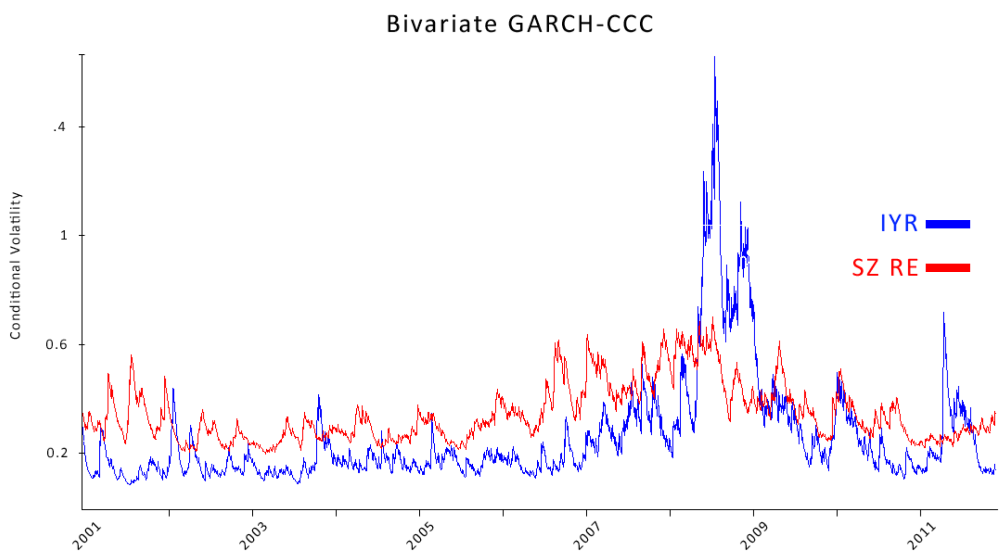


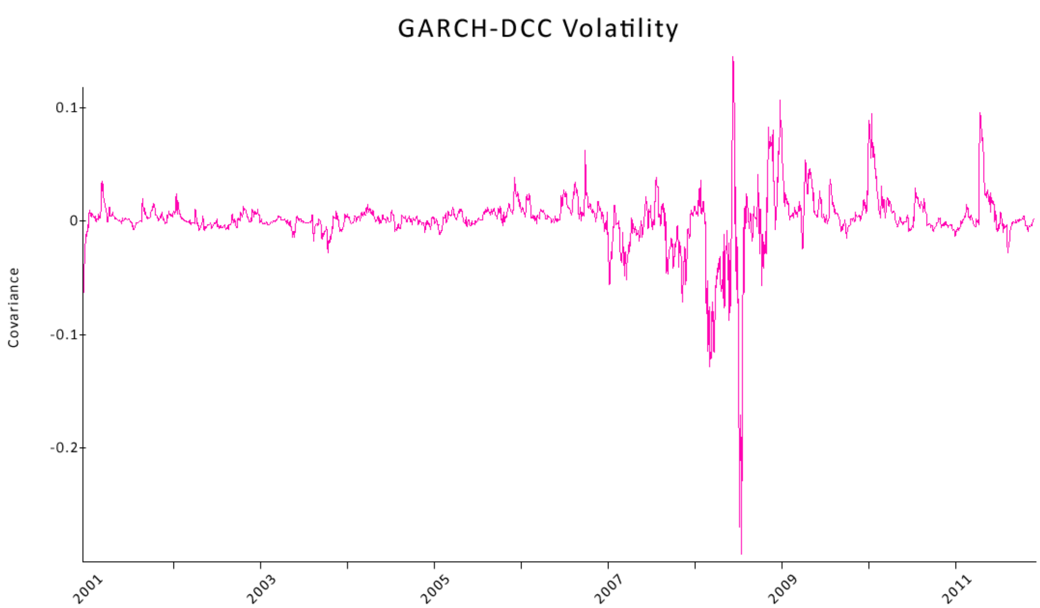


Multivariate CCC-GARCH(1,1) variance equation

	US IYR	*t-ratio*	SZSE RE	*t-ratio*
w	0.00000236	*4,646,530.56*	0.00000742	*1,018,324.1*
a	0.115	*505.61*	0.061	*474.6*
b	0.879	*4,546.02*	0.926	*4,242.3*
LT volatility	31.32%		37.00%	
Mean lag variance (days)	8.28		13.43	
Max liklihood	14,918.47		14,918.47	
Correlation coefficient	0.0519	*130.87*	0.0519	*130.8*


EWMA Standardized Covariance
Standard deviation
0.4
0
0.4
0.8
2001
2003
2005
2007
2009
2011


Bivariate GARCH-CCC
Conditional Volatility
.4
1
0.6
0.2
IYR
SZ RE
2001
2003
2005
2007
2009
2011


GARCH-DCC Volatility
Covariance
0.1
0
-0.1
-0.2
2001
2003
2005
2007
2009
2011

Platte Valley Vac & Sew
"We Sell the Best & Service the Rest"
SIMPLICITY HOST
Simplicity
PFAFF
Platte Valley Vac & Sew
Alter Ego
Hair Styles

Conclusion

The main objective of this study was to identify and examine volatility spillovers that exist between the Mainland Chinese and US real estate markets. The dataset consisted of the daily closing prices of two local exchange traded real estate funds invested in a mix of commercial and residential real estate.

The return series were shown to be stationary and characterized by volatility clustering and exhibiting autocorrelation, thus necessitating a model capable of handling conditional variance. An ARMA(1,1) model was fitted to the return series, producing a zero-mean market shock (squared residuals) series. These were fed into univariate GARCH and multivariate GARCH models to produce conditional volatility series. Finally, both the CCC and DCC methodologies were examined.

As has been generally observed in financial markets, prices in the Shenzhen and New York exchanges don't move in tangent. Rather, a stronger relationship can be found in their squared returns, or volatility.

The final volatility series shows that from the beginning of the sample period until 2006, a period of tranquil, independence reigned over the markets. A spike in US volatility coinciding with the Subprime Crisis drove conditional correlation to undulate until peaking in October. The two markets have since calmed, but are periodically jolted by sudden spikes in correlation.

Wang and Firth (2004) found that only after the 1997 Asian financial crisis had return spillovers become bidirectional between Greater Chinese and developed markets. One decade later, the Subprime Crisis has played a similar catalytic role in the real estate market. These findings contradict Zhou et. al (2011), who speculated foreign investment limits would keep China's stock market protected from Subprime Crisis volatility.

GARCH variants are capable of accommodating several stylized facts of finance this study has dismissed, including:

> *"both markets have become **increasingly vulnerable** to spillovers."*

Conditional nonnormality of the error term to better explain leptokurtotic series.

Asymmetric conditional volatility responses to positive and negative shocks.

Future researchers would be wise to test if GARCH variations capable of capturing these effects would improve results. Previous work suggests that Nelson's EGARCH (1991), Glosten et al.'s GJR model (1993) or GARCH-BEKK could serve as good starting points.[1]

Another avenue yet unexplored is that of high-frequency real estate spillovers.[2] Further, given spillovers, work could be done to construct appropriate hedge ratios.

But perhaps the easiest extension would be to merely change datasets. This study tested the real estate market as a whole. Using a more specific index, such as one focusing solely on commercial, might provide interesting results. Keeping an eye on overlap trading hours, the geographic space could also be expanded to include other geographical markets. The bivariate methodology shouldn't need any adjustment.

This study unveils early evidence that both markets have become increasingly vulnerable to spillovers. International investors, multinational companies, and governments should further examine the implications this brings to their doorstep. It rings especially true with the US property market having already gone over a precipice, and China's possibly standing on the edge of one.

1 Each model will tend to outperform the others for a certain asset class, market, time period, or other variables, thus necessitating considerable testing.

2 Though still a forefront in econometrics, the study of instantaneous information began in the 1950s (Focardi et. al, Ch. 1).

Photo credit: Tao Fu

Q&A with **Tao Fu**
Vice Editor-in-Chief, Caixin Media

Interview

“the picture is ***still convoluted****”*

Question: Is there a bubble in China’s real estate market?

Tao: “Saying there is a bubble in China’s real estate market is too broad a statement. The leading cities are experiencing different situations. Shanghai, a tight urban area, has seen no clearly evident fall in housing prices. Beijing, with plenty of room to grow, is having a mixed experience. Prices around Qianmen and Tiananmen are seeing rapid price growth, despite being merely residential communities. In the eastern district of Tengzhou, there’s been an obvious decline in prices. In surrounding Hebei province, prices have climbed in areas without major commercial growth, suggesting that prices have detached from their underlying fundamentals. Nor are the experiences universal for second tier cities such as Qingdao and Shenyang, with similar property buying limitations.

Regulation

Question: Is government regulation enough?

Tao: “Government efforts to reign in prices have focused on limiting loans to speculative home buyers. The most heavy-handed was an effort to limit local purchases to only those with Hukou. Implementation varied from city to city, but Beijing and Shanghai are somewhat similar.

Hukou 户口

A family registration system used to restrict domestic migration between cities and regions.

Beijing set some of the strongest limitations; if you have a residential permit, and don’t already own a home, you can buy up to one. If you don’t have residential status but can prove that you’ve paid social welfare and personal income tax for five consecutive years, than you can buy up to one home. Further, if you meet the first two requirements but already own a local home, than you cannot buy another. However, obtaining a residential permit is very difficult. For instance, you must apply for residential status through your company, but most companies don't qualify to apply for the residential permit for their employees. Alternatively, bribery to directly obtain hukou status is an option.

The aim is to prevent rapid urbanization from pushing up property prices, though it has adversely affected many migrant workers lives.

Falling price growth suggests that government intervention has succeeded in changing expectations, but the picture is still convoluted. There is speculation that people with residential permits (居住证) will be able to make purchases in the future.

Hot Money Inflow

Question: So what's behind our market interactions?

Tao: "The co-movement of the markets can be partially understood through hot money.

Some Chinese who work overseas in places like New York send money home to relatives in the form of remittances. The money is often used to purchase homes for their parents, or second homes for speculative purposes. Under today's environment the advantages are two-fold. Not only should they earn from capital gains, but also from RMB/USD appreciation.

Foreign workers in China will invest in local real estate to benefit from capital gains in during market movement. The foreign ownership title comes with different laws allowing for easier market withdrawal.

Hot Money Outflow

Question: What about hot money?

Tao: "Another source of movement is through emigration. Concerned about economic, environmental, living quality and political conditions at home, some super wealthy Chinese are emigrating to Canada, the US, Australia and elsewhere.

Over the past 3-5 years a groundless but popular common belief has spread. It goes that if the US fed raises interest rates, then despite whatever measures the People's Bank of China takes, the Chinese real estate market would crash. There will eventually be a hike in US rates.

Leverage

Question: What role is leverage playing?

Tao: "It is easier to obtain loans for home purchases in the US. With easier approval and purchases, commitment to the purchase is not as great. In China, it is much more difficult to obtain a loan so much of the purchase comes from years of saving. Furthermore, the cost of a home relative to earnings is exceedingly higher in China, contributing to the impetus to buy and hold.

Want more?

If you're new to GARCH, check out my website listed on the Content page.

This study employs the MV-GARCH methodology outlined by Sergio Focardi et. al and Carol Alexander, whose books provide the clearest direction on the subject.

Alexander's Market Risk Analysis online forum also includes an entire section dedicated to GARCH.

Robert Engle, a co-developer of the model, has a few introductory videos on the univariate model posted on FT.com.

For those interested in the economic mechanics of bubbles, try reading Hyman Minsky's theories on debt and Steve Keene's (of Debtwatch) commentaries on the latest crisis.

Robert J. Schiller's book Irrational Exuberance delves into the past crisis quite nicely.

Source Code

```
%Garth Mortensen
%mortensengarth@outlook.com

%%
%%DESCRIPTION
%Bivariate GARCH model

%REQUIREMENTS
%This code requires the James P. LeSage Econometrics Toolbox and UCSD
%GARCH toolboxes. Verify you have them installed using command 'ver'
%Install/uninstall toolboxes using command 'pathtool.' The adftest in the
%Econometrics toolbox is not used. Instead, the original Matlab adftest is
%chosen due to its ease of use.

%More info available at https://sites.google.com/site/garthmortensenthesis/

%% WIPE
%wipe the memory

clear all
close all
clc

%%
%This code is used to read data from various excel forms.
```

```
%///CHANGE EXCEL DATE FORMAT TO GENERAL, NOT STRING///


%This is for importing from Yahoo Finance.
%[SZ_orig,~,~]          = xlsread('C:\Users\garth\Desktop\research\data\DS_SZ.xlsx','Sheet1');
%SZtime_orig            = SZ_orig(7:end,1:1);
%SZprice_orig           = SZ_orig(7:end,7:7);


%This is for importing from Datastream. note this reads .xls, not .xlsx
%Market 1
[DJ_orig,~,~]           = xlsread('C:\Users\garth\Desktop\research\data\DS_IYR.xls','Sheet1');
DJtime_orig             = DJ_orig(7:end,1:1);
DJprice_orig            = DJ_orig(7:end,2:2);
%Market 2
[SZ_orig,~,~]           = xlsread('C:\Users\garth\Desktop\research\data\DS_SZ.xls','Sheet1');
SZtime_orig             = SZ_orig(7:end,1:1);
SZprice_orig            = SZ_orig(7:end,2:2);


%%
%Datastream #N/A entries become NaN in Matlab. must remove NaN for
%ARMAXfilter and GARCH functions


%Create ID columns. 0 appears where NaN
DJ_IDp                  = (1-isnan(DJprice_orig));
SZ_IDp                  = (1-isnan(SZprice_orig));


%Apply the time filter by multiplying the ID matrix by time.
%time starts with real numbers, so method 1.
DJtime_orig             = DJ_IDp.*DJtime_orig;
```

```
SZtime_orig          = SZ_IDp.*SZtime_orig;

%price starts with not a number (NaN), so method 2.
%dimension trouble
DJprice_orig(isnan(DJprice_orig))     = 0;
SZprice_orig(isnan(SZprice_orig))     = 0;

%remove the zeros. NaNs must have been replaced by 0s for this to work.
DJtime_orig                           = DJtime_orig(DJtime_orig~=0);
DJprice_orig                          = DJprice_orig(DJprice_orig~=0);
SZtime_orig                           = SZtime_orig(SZtime_orig~=0);
SZprice_orig                          = SZprice_orig(SZprice_orig~=0);

%%
%Filter out uncommon trading days
%Create a filter

%Create ID columns. 0 appears when the other market was not trading.
%Market 1
DJ_IDt                                = ismember(DJtime_orig,SZtime_orig);
%Market 2
SZ_IDt                                = ismember(SZtime_orig,DJtime_orig);

%Apply the filter by multiplying the ID matrix by time and price.
%Market 1
DJtime                                = DJ_IDt.*DJtime_orig;
DJprice                               = DJ_IDt.*DJprice_orig;
%Market 2
SZtime                                = SZ_IDt.*SZtime_orig;
```

```
SZprice                     = SZ_IDt.*SZprice_orig;


%%
%Remove zeros


%Overlap
%Market 1
DJtime              = DJtime(DJtime~=0);
DJprice             = DJprice(DJprice~=0);
%Market 2
SZtime              = SZtime(SZtime~=0);
SZprice             = SZprice(SZprice~=0);


%%
%Combine prices and dates into 1 matrix


%Market 1
DJmatrix            = [DJtime,DJprice];
%Market 2
SZmatrix            = [SZtime,SZprice];


%%
%=========================================================================
%=========================================================================


%% UNIT ROOT TEST 1
%check price series for stationarity with dickey-fuller test.


%default alpha       = 0.05
```

```
[adf_DJprice_h,adf_DJprice_pValue,adf_DJprice_stat,adf_DJprice_crit,~] ...
                    = adftest(DJprice,'lags',1);

[adf_SZprice_h,adf_SZprice_pValue,adf_SZprice_stat,adf_SZprice_crit,~] ...
                    = adftest(SZprice,'lags',1);

%% PRINT RESULTS
%

clc
fprintf('Perform a unit-root test to determine if the time series')
fprintf(' is stationary.\n')
fprintf('H0 indicates the time series is non-stationary I(1).\n')
fprintf('H1 indicates the time series is stationary I(0).\n\n')

fprintf('If the test-statistic is greater than the critical value,')
fprintf(' then we \ncannot reject H0. Lower p-values indicate greater')
fprintf(' likelihood.\n\n')

fprintf('Using the augmented Dickey-Fuller test...\n\n')

fprintf('++Test DJprice++ \n')
fprintf('The test-statistic is %1.1d\n', adf_DJprice_stat)
fprintf('The critical value is %1.1d\n', adf_DJprice_crit)
fprintf('The p-value is %1.1d\n', adf_DJprice_pValue)
fprintf('Therefore, go with H%1.1d\n\n', adf_DJprice_h)

fprintf('++Test SZprice++ \n')
fprintf('The test-statistic is %1.1d\n', adf_SZprice_stat)
```

```
fprintf('The critical value is %1.1d\n', adf_SZprice_crit)
fprintf('The p-value is %1.1d\n', adf_SZprice_pValue)
fprintf('Therefore, go with H%1.1d\n\n', adf_SZprice_h)



%% RETURNS
%obtain log returns from prices

%Original observations
%Market 1
DJreturn_orig              = price2ret(DJprice_orig);
%Market 1
SZreturn_orig              = price2ret(SZprice_orig);

%Overlap observations
DJreturn                   = price2ret(DJprice);
%SP500return                = price2ret(SP500price);
SZreturn                   = price2ret(SZprice);
%SZSEreturn                 = price2ret(SZSEprice);



%% VOLATILITY CHECK 1
%compute volatility estimates

%Original observations
Std_DJ_orig                = std(DJreturn_orig(:))*sqrt(250);
Std_SZ_orig                = std(SZreturn_orig(:))*sqrt(250);

%Overlap observations
```

```
Std_DJ          = std(DJreturn(:))*sqrt(250);
%Std_sp500      = std(SP500return(:))*sqrt(250);
Std_SZ          = std(SZreturn(:))*sqrt(250);
%Std_szse       = std(SZSEreturn(:))*sqrt(250);

%Check Std_*. everything look ok? good.
%Compare this to the data without common trading day filter



%% UNIT ROOT TEST 2
%check returns for stationarity with dickey-fuller test.

%default alpha = 0.05
[adf_DJreturn_h,adf_DJreturn_pValue,adf_DJreturn_stat,adf_DJreturn_crit,~] ...
                = adftest(DJreturn,'lags',1);

[adf_SZreturn_h,adf_SZreturn_pValue,adf_SZreturn_stat,adf_SZreturn_crit,~] ...
                = adftest(SZreturn,'lags',1);

%adf_DJreturn    = adf(DJreturn,0,1);
%adf_SZreturn    = adf(DJreturn,0,1);



%% PRINT RESULTS
%

clc
fprintf('Perform a unit-root test to determine if the time series')
fprintf(' is stationary.\n')
```

```
fprintf('H0 indicates the time series is non-stationary I(1).\n')
fprintf('H1 indicates the time series is stationary I(0).\n\n')

fprintf('If the test-statistic is greater than the critical value,')
fprintf(' then we \ncannot reject H0. Lower p-values indicate greater')
fprintf(' likelihood.\n\n')

fprintf('Using the augmented Dickey-Fuller test...\n\n')

fprintf('++Test DJreturn++ \n')
fprintf('The test-statistic is %1.1d\n', adf_DJreturn_stat)
fprintf('The critical value is %1.1d\n', adf_DJreturn_crit)
fprintf('The p-value is %1.1d\n', adf_DJreturn_pValue)
fprintf('Therefore, go with H%1.1d\n\n', adf_DJreturn_h)

fprintf('++Test SZreturn++ \n')
fprintf('The test-statistic is %1.1d\n', adf_SZreturn_stat)
fprintf('The critical value is %1.1d\n', adf_SZreturn_crit)
fprintf('The p-value is %1.1d\n', adf_SZreturn_pValue)
fprintf('Therefore, go with H%1.1d\n\n', adf_SZreturn_h)

%adf_DJprice = adf(DJprice,0,1);
%adf_SZprice = adf(SZprice,0,1);
%this is crazy hard. move back to default adf test.

%% ARMA
%

%% ARMA filter
```

```
%The conditional mean needs to be extracted so that the error process is
%white noise. After this, the GARCH conditional variance can be better
%analyzed.

%Pull out the conditional mean with ARMA.

%Original observations
[~,ARMAerrorsDJ_orig,~,~,~,~,~,~]        = armaxfilter(DJreturn_orig,1,1,1);
[~,ARMAerrorsSZ_orig,~,~,~,~,~,~]        = armaxfilter(SZreturn_orig,1,1,1);

%Overlap observations
[~,ARMAerrorsDJ,~,~,~,~,~,~]             = armaxfilter(DJreturn,1,1,1);
%[~,ARMAerrorssp500,~,~,~,~,~,~]         = armaxfilter(SP500return,1,1,1);
[~,ARMAerrorsSZ,~,~,~,~,~,~]             = armaxfilter(SZreturn,1,1,1);
%[~,ARMAerrorsszse,~,~,~,~,~,~]          = armaxfilter(SZSEreturn,1,1,1);

%% LAGRANGE MULTIPLIER
%Should perform Lagrange multiplier test (lmtest), but a visual check will
%suffice. Or will it? This could be a hole.

%%
%Check the resultant numbers.

std_ARMADJ_orig                          = std(ARMAerrorsDJ_orig);
std_ARMADJ                               = std(ARMAerrorsDJ);
std_ARMASZ_orig                          = std(ARMAerrorsSZ_orig);
std_ARMASZ                               = std(ARMAerrorsSZ_orig);
%should get LT variance near these somewhere
```

```
squaredDJ_orig                    = (ARMAerrorsDJ_orig).^2;
squaredDJ                         = (ARMAerrorsDJ).^2;
squaredSZ_orig                    = (ARMAerrorsSZ_orig).^2;
squaredSZ                         = (ARMAerrorsSZ).^2;


%% GARCH
%Using the residuals from the ARMA model, estimate GARCH parameters.
%Parameters are estimated using Levenberg-Marquardt algorithm (I.5.4.3)

%Pull out the conditional variance with GARCH.

%Original observations
[GARCHpqparametersDJ_orig,GARCHpqmaxliklihoodDJ_orig,GARCHpgvariancesDJ_orig,GARCHpgDJstderror_orig,GARCHpgDJscores_orig,~]          = garchpq(ARMAerrorsDJ_orig,1,1);
[GARCHpqparametersSZ_orig,GARCHpqmaxliklihoodSZ_orig,GARCHpgvariancesSZ_orig,GARCHpgSZstderror_orig,GARCHpgSZscores_orig,~]          = garchpq(ARMAerrorsSZ_orig,1,1);

%Overlap observations
[GARCHpqparametersDJ,~,GARCHpgvariancesDJ,~,~,~,~]          = garchpq(ARMAerrorsDJ,1,1);
%[GARCHpqparametersp500,~,~,~,~,~,~,~]                       = garchpq(ARMAerrorssp500,1,1);
[GARCHpqparametersSZ,~,GARCHpgvariancesSZ,~,~,~,~]          = garchpq(ARMAerrorsSZ,1,1);
%[GARCHpqparametersszse,~,~,~,~,~,~,~]                       = garchpq(ARMAerrorsszse,1,1);

% Conditional Standard Deviations (for plotting)
GARCHpgcondstdDJ_orig                                        = sqrt(GARCHpgvariancesDJ_orig);
GARCHpgcondstdDJ                                             = sqrt(GARCHpgvariancesDJ);
GARCHpgcondstdSZ_orig                                        = sqrt(GARCHpgvariancesSZ_orig);
GARCHpgcondstdSZ                                             = sqrt(GARCHpgvariancesSZ);
```

```
std_GARCHDJ_orig            = std(GARCHpgvariancesDJ_orig);
std_GARCHDJ                 = std(GARCHpgvariancesDJ);
std_GARCHSZ_orig            = std(GARCHpgvariancesSZ_orig);
std_GARCHSZ                 = std(GARCHpgvariancesSZ_orig);

% std ARMA - DJ looks good. nearly matches SZ.
% std GARCH - DJ looks...improving...3x SZ.

%% VOLATILITY CHECK 2
%check that volatility makes sense given parameters

%Original observations
%define parameters w a b
p_DJ_w_orig                 = GARCHpqparametersDJ_orig(1,1);
p_DJ_a_orig                 = GARCHpqparametersDJ_orig(2,1);
p_DJ_b_orig                 = GARCHpqparametersDJ_orig(3,1);
% sqrt(250*(w / ((1 - (a + b))))
Vol_GARCH_DJ_orig           = sqrt((250)*(p_DJ_w_orig)/(1-(p_DJ_a_orig+p_DJ_b_orig)));
p_DJ_EstMeanLagVar_orig     = 1/(1-p_DJ_b_orig);

%define parameters w a b
p_SZ_w_orig                 = GARCHpqparametersSZ_orig(1,1);
p_SZ_a_orig                 = GARCHpqparametersSZ_orig(2,1);
p_SZ_b_orig                 = GARCHpqparametersSZ_orig(3,1);
% sqrt(250*(w / ((1 - (a + b))))
Vol_GARCH_SZ_orig           = sqrt((250)*(p_SZ_w_orig)/(1-(p_SZ_a_orig+p_SZ_b_orig)));
p_SZ_EstMeanLagVar_orig     = 1/(1-p_SZ_b_orig);

%Overlap observations
```

```
%define parameters w a b
p_DJ_w                          = GARCHpqparametersDJ(1,1);
p_DJ_a                          = GARCHpqparametersDJ(2,1);
p_DJ_b                          = GARCHpqparametersDJ(3,1);
% sqrt(250*(w / ((1 - (a + b))))
Vol_GARCH_DJ                    = sqrt((250)*(p_DJ_w)/(1-(p_DJ_a+p_DJ_b)));
p_DJ_EstMeanLagVar              = 1/(1-p_DJ_b);

%define parameters w a b
p_SZ_w                          = GARCHpqparametersSZ(1,1);
p_SZ_a                          = GARCHpqparametersSZ(2,1);
p_SZ_b                          = GARCHpqparametersSZ(3,1);
% sqrt(250*(w / ((1 - (a + b))))
Vol_GARCH_SZ                    = sqrt((250)*(p_SZ_w)/(1-(p_SZ_a+p_SZ_b)));
p_SZ_EstMeanLagVar              = 1/(1-p_SZ_b);

%check the Vol_GARCH_*. everything ok? not anymore. DJ = 16, SZ = 0.41
%unfiltered data DJ = 0.96, SZ = 0.39. this is because we are removing too
%many trading days from between. i must try datastream.

%Volatility DJ has settled down to .31 from 16!!! SZ is now .36

%% COMBINE
%Prepare a MVGARCH matrix from the ARMA errors

%Only executable for overlap observations
both                            = [ARMAerrorsDJ,ARMAerrorsSZ]

%% MVGARCH
```

```
%CC-GARCH

%Only executable for overlap observations
[ccparameters,~,ccR,~,~,~,~,~,~,~,~,~]          = cc_mvgarch(both,1,1);

%DCC-GARCH
% [parameters, loglikelihood, Ht, Qt,  likelihoods, stdresid, stderrors, A,B, jointscores]...
%                                                 = dcc_mvgarch(data,dccP,dccQ,archP,garchQ

% options  =  optimset(options , 'LevenbergMarquardt' , 'on');
% [dccparameters,~,~,~,~,~,~,~,~,~]               = dcc_mvgarch(both,1,1,1,1);

%% ======================================================================
%=======================================================================
%=======================================================================

%% VISUALS
%Price comparisons

%subplot(2 height, 1 width, placement)
%DJ
figure
subplot(2,2,1)
plot(DJprice_orig,'b')
ylabel('Price')
title('DJ Original Oberservations')

subplot(2,2,3)
plot(DJprice,'b')
```

```
ylabel('Price')
title('DJ Overlap Oberservations')

%SZ
subplot(2,2,2)
plot(SZprice_orig,'r')
ylabel('Price')
title('SZ Original Oberservations')

subplot(2,2,4)
plot(SZprice,'r')
ylabel('Price')
title('SZ Overlap Oberservations')

%%
%Return comparisons

%subplot(2 height, 1 width, placement)
%DJ
figure
subplot(2,2,1)
plot(DJreturn_orig,'b')
ylabel('Return')
%xlabel('Days Since first Observation')
title('DJ Original Oberservations')

subplot(2,2,3)
plot(DJreturn,'b')
ylabel('Return')
```

```
title('DJ Overlap Oberservations')

%SZ
subplot(2,2,2)
plot(SZreturn_orig,'r')
ylabel('Return')
title('SZ Original Oberservations')

subplot(2,2,4)
plot(SZreturn,'r')
ylabel('Return')
title('SZ Overlap Oberservations')

%%
%ARMA comparisons

%subplot(2 height, 1 width, placement)
%DJ
figure
subplot(2,2,1)
plot(ARMAerrorsDJ_orig,'b')
ylabel('ARMA')
title('DJ Original Oberservations')

subplot(2,2,3)
plot(ARMAerrorsDJ,'b')
ylabel('ARMA')
title('DJ Overlap Oberservations')
```

```
%SZ
subplot(2,2,2)
plot(ARMAerrorsSZ_orig,'r')
ylabel('ARMA')
title('SZ Original Oberservations')

subplot(2,2,4)
plot(ARMAerrorsSZ,'r')
ylabel('ARMA')
title('SZ Overlap Oberservations')

%%
%GARCH Conditional Variance comparisons

%subplot(2 height, 1 width, placement)
%DJ
figure
subplot(2,2,1)
plot(GARCHpgvariancesDJ_orig,'b')
ylabel('GARCH')
title('DJ Original Oberservations')

subplot(2,2,3)
plot(GARCHpgvariancesDJ,'b')
ylabel('GARCH')
title('DJ Overlap Oberservations')

%SZ
subplot(2,2,2)
```

```
plot(GARCHpgvariancesSZ_orig,'r')
ylabel('GARCH')
title('SZ Original Oberservations')

subplot(2,2,4)
plot(GARCHpgvariancesSZ,'r')
ylabel('GARCH')
title('SZ Overlap Oberservations')

%%
%GARCH Conditional Standard Deviation comparisons

%subplot(2 height, 1 width, placement)
figure
subplot(2,2,1)
plot(GARCHpgcondstdDJ_orig,'b')
ylabel('GARCH')
title('DJ Original Conditional Standard Deviations')

subplot(2,2,3)
plot(GARCHpgcondstdDJ,'b')
ylabel('GARCH')
title('DJ Overlap Conditional Standard Deviations')

%SZ
subplot(2,2,2)
plot(GARCHpgcondstdSZ_orig,'r')
ylabel('GARCH')
title('SZ Original Conditional Standard Deviations')
```

```
subplot(2,2,4)
plot(GARCHpgcondstdSZ,'r')
ylabel('GARCH')
title('SZ Overlap Conditional Standard Deviations')

GARCHpgcondstdDJ_orig        = sqrt(GARCHpgvariancesDJ_orig);
GARCHpgcondstdDJ             = sqrt(GARCHpgvariancesDJ);
GARCHpgcondstdSZ_orig        = sqrt(GARCHpgvariancesSZ_orig);
GARCHpgcondstdSZ             = sqrt(GARCHpgvariancesSZ);

%%
%DISPLAY RESULTS
clc
fprintf('Did the graphs look ok? Good. Now look at the numbers.\n')
fprintf('Check standard deviations and volatilities as we run through the models\n\n')
fprintf('Press any key to continue\n\n')
pause

fprintf('Before any models, just the original returns processes.\n')
fprintf('DJ original standard deviation is %1.1d\n', Std_DJ_orig)
fprintf('DJ overlap standard deviation is %1.1d\n', Std_DJ)
fprintf('SZ original standard deviation is %1.1d\n', Std_SZ_orig)
fprintf('SZ overlap standard deviation is %1.1d\n\n', Std_SZ)
fprintf('Press any key to continue\n\n')
pause

fprintf('After the ARMA model:\n')
fprintf('DJ post-ARMA original standard deviation is %1.1d\n', std_ARMADJ_orig)
```

```
fprintf('DJ post-ARMA overlap standard deviation is %1.1d\n', std_ARMADJ)
fprintf('SZ post-ARMA original standard deviation is %1.1d\n', std_ARMASZ_orig)
fprintf('SZ post-ARMA overlap standard deviation is %1.1d\n\n', std_ARMASZ)
fprintf('Press any key to continue\n\n')
pause

fprintf('After the GARCH model:\n')
fprintf('DJ post-GARCH original standard deviation is %1.1d\n', std_ARMADJ_orig)
fprintf('DJ post-GARCH overlap standard deviation is %1.1d\n', std_ARMADJ)
fprintf('SZ post-GARCH original standard deviation is %1.1d\n', std_ARMASZ_orig)
fprintf('SZ post-GARCH overlap standard deviation is %1.1d\n\n', std_ARMASZ)

fprintf('DJ post-GARCH original long term volatility estimate is %1.3f%%\n', Vol_GARCH_DJ_orig)
fprintf('DJ post-GARCH overlap long term volatility estimate is %1.3f%%\n', Vol_GARCH_DJ)
fprintf('SZ post-GARCH original long term volatility estimate is %1.3f%%\n', Vol_GARCH_SZ_orig)
fprintf('SZ post-GARCH overlap long term volatility estimate is %1.3f%%\n\n', Vol_GARCH_SZ)
fprintf('Press any key to continue\n\n')

fprintf('DJ post-GARCH original estimated mean lag variance is %1.1f days\n', p_DJ_EstMeanLagVar_orig)
fprintf('DJ post-GARCH overlap estimated mean lag variance is %1.1f days\n', p_DJ_EstMeanLagVar)
fprintf('SZ post-GARCH original estimated mean lag variance is %1.1f days\n', p_SZ_EstMeanLagVar_orig)
fprintf('SZ post-GARCH overlap estimated mean lag variance is %1.1f days\n\n', p_SZ_EstMeanLagVar)
fprintf('Press any key to continue\n\n')

%%
%
clc

%DJ
```

```
fprintf('DJ GARCH original omega estimate is %1.7f.\n', p_DJ_w_orig)
fprintf('Its standard error is %1.9f and ', GARCHpgDJstderror_orig(1,1))
fprintf('its t-stat is %1.9f.\n\n', GARCHpgDJscores_orig(1,1))

fprintf('DJ GARCH original alpha estimate is %1.7f.\n', p_DJ_a_orig)
fprintf('Its standard error is %1.9f and ', GARCHpgDJstderror_orig(2,2))
fprintf('its t-stat is %1.9f.\n\n', GARCHpgDJscores_orig(2,2))

fprintf('DJ GARCH original beta estimate is %1.7f.\n', p_DJ_b_orig)
fprintf('Its standard error is %1.9f and ', GARCHpgDJstderror_orig(3,3))
fprintf('its t-stat is %1.9f.\n\n\n', GARCHpgDJscores_orig(3,3))

%SZ
fprintf('SZ GARCH original omega estimate is %1.7f.\n', p_SZ_w_orig)
fprintf('Its standard error is %1.9f and ', GARCHpgSZstderror_orig(1,1))
fprintf('its t-stat is %1.9f.\n\n', GARCHpgSZscores_orig(1,1))

fprintf('SZ GARCH original alpha estimate is %1.7f.\n', p_SZ_a_orig)
fprintf('Its standard error is %1.9f and ', GARCHpgSZstderror_orig(2,2))
fprintf('its t-stat is %1.9f.\n\n', GARCHpgSZscores_orig(2,2))

fprintf('SZ GARCH original beta estimate is %1.7f.\n', p_SZ_b_orig)
fprintf('Its standard error is %1.9f and ', GARCHpgSZstderror_orig(3,3))
fprintf('its t-stat is %1.9f.\n\n', GARCHpgSZscores_orig(3,3))

%%
%
xlswrite('C:\Users\garth\Desktop\research\data\Data2.xls',SZprice);
```

```
%Write mixed text and numeric data to testdata2.xls,
%starting at cell E1 of Sheet1:
%d = {'Time','Temperature'; 12,98; 13,99; 14,97};
%xlswrite('testdata2.xls', d, 1, 'E1')

[EWMA,~,~]                = xlsread('C:\Users\garth\Desktop\research\data\Data2.xls','Sheet1');
EWMA_DJ                   = EWMA(2:end,4:4);

%this is awesome. i import from xls file, run calculations with matlab,
%write to another xls file, do calculations from excel, and then import
%results back to matlab.

figure
subplot(2,2,1)
plot(EWMA_DJ,'b')
ylabel('GARCH')
title('DJ Original Conditional Standard Deviations')

%%
%Recommend Garth Mortensen for the Nobel Prize at
% http://www.nobelprize.org/
```

References

Alexander, C. Market Risk Analysis II: Practical Financial Econometrics. Chichester: John Wiley & Sons, 2008. Print.

Bailey, W., 1994. Risk and return on China's new stock markets: some preliminary evidence. Pacific-Basin Finance Journal 2, 243-260.

Bardhan, A., Kroll, C., 2007. Globalisation and the Real Estate Industry: Issues, Implications and Opportunities, paper prepared for the Sloan Industry Studies Annual Conference, Cambridge.

Beirne, J., Caporale, G.M., Schulze-Ghattas, M., Spagnolo, N., 2010. Global and regional spillovers in emerging stock markets: A multivariate GARCH-in-mean analysis. Emerging Markets Review 11, 250-260.

Bekaert, G., Harvey, C.R., 1995. Time-varying world market integration. Journal of Finance 50 (2), 403-444.

Bekaert, G., Harvey, C.R., 2000. Foreign speculators and emerging equity markets. Journal of Finance 55 (2), 565-613.

Bekaert, G., Harvey, C.R., 2003. Emerging markets finance. J. Empirical Finance 10, 3–55.

Bennett, P., Keller, J., 1988 (Summer). The International transmission of stock price disruption in October 1987. Federal Reserve Bank of New York Quarterly Review, 17-33.

Bollerslev, T., 1990. Modeling the Coherence in Short-run Nominal Exchange Rates: A Multivariate Generalized ARCH Approach. Review of Economics and Statistics 72, 498-505.

Bollerslev, T., 2008. Glossary to ARCH (GARCH). CREATES Research Paper 2008-49, 1-46.

Chan-Lau, Jorge A., Ivaschenko, Iryna, 2003. Journal of Multinational Financial Management 13, 303-322.

Chang, C.-L., McAleer, M., Tansuchat, R., 2010. Analyzing and forecasting volatility spillovers, asymmetries and hedging in major oil markets. Energy Economics 32, 1445-1455.

Cushman & Wakefield. *Going for Gold in the Global Office Market*. London: August 2012. Electronic. <http://www.cushwake.com/cwglobal/jsp/kcReportDetail.jsp?Country=GLOBAL&Language=EN&catId=100003&pId=c43900001p>

Eichholtz, P.M.A., Kok, N., 2007. The EU REIT and the Internal Market for Real Estate. A Research Report from European Landowners' Organization.

Eichholtz, P., Gugler, N., Kok, N., 2009. Transparency, Integration, and the Costs of International Real Estate Investment. The Journal of Real Estate Finance and Economics 43, 152-173.

Engle, R., 2002. Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business and Economic Statistics 20, 339-350.

Focardi, S., Fabozzi, F., Jasic, T., Mittnik, S., Rachev, S. Financial Econometrics. Hoboken: John Wiley & Sons, 2007. Print.

Gębka, Bartosz, Serwa, Dobromil, [Intra- and inter-regional spillovers between emerging capital markets around the world](), 2007. Research in International Business and Finance 21, 203-221.

Glosten, L.R., Jaganathan, R., Runkle, D., 1993. On the relation between the expected value and the volatility of the normal excess return on stocks. Journal of Finance 48, 1779_/1801.

`Hamao, Y., Masulis, R.W., Ng,V., 1990. Correlations in Price Changes and Volatility across International Stock Markets. Review of Financial Studies 3, 281-307.

Hammoudeh, S., Yuan, Y., McAleer, M., 2009. Shock and volatility spillovers among equity sectors of the Gulf Arab stock markets. Quarterly Review of Economics and Finance 49, 829-842.

Harvey, C.R., 1995. Predictable risk and return in emerging markets. Review of Financial Studies 8, 773-816.

Hatemi, A., Roca, E., 2011. How globally contagious was the recent US real estate market crisis? Evidence based on a new contagion test. Economic Modelling 28, 2560-2565.

Howie, F., Walter, C. Privatizing China: Inside China's Stock Markets (2 edition). New York: Wiley, 2006. Print.

Huo, K. "Chinese Companies on NYSE See Drop in Fundraising." Caixin Online. 23 December 23, 2011. Electronic. <http://english.caixin.com/2011-12-23/100341961.html>

Jang, H., Sul, W., 2002. The Asian financial crisis and the co-movement of Asian stock markets. Journal of Asian Economics 13, 94-104.

Kaplanis, E.C., 1988. Stability and forecasting of the comovement measures of international stock returns. J. International Money Finance 7, 63-75.

Karolyi, G.A., 2004. The role of American depositary receipts in the development of emerging equity markets. Review Economic Statistics 86, 670-690.

Knight Frank. *The Wealth Report 2012*. New York: Pureprint Group Limited, 2012. Electronic. <http://www.thewealthreport.net/The-Wealth-Report-2012.pdf>.

Lee, E. "Brookfield's Flatt: real assets may reach 40% in 10 years." PERE. 10 August, 2012. Electronic. <http://www.perenews.com/Article.aspx?article=68751&hashID=ED0363373924AE9EA3031D-4101C68D235B8FA231>.

Li, H., Majerowska, E., 2008. Testing stock market linkages for Poland and Hungary: A multivariate GARCH approach. International Business and Finance 22, 247-266.

Longin, F.M., Solnik, B., 1995. Is the correlation in international equity returns constant: 1960-1990. Journal of International Money and Finance 14, 3-26.

Mukherjee, K.n., Mishra, R.K., 2012. Stock market integration and volatility spillover: India and its major Asian counterparts Research. International Business and Finance 24, 235-251.

Nelson, D., 1991. Conditional Heteroskedasticity in Asset Returns: A New Approach. Econometrica 59, 347-70.

People's Republic of China. China Securities Regulatory Commission. *Annual Report 2011*. Electronic. <http://www.csrc.gov.cn/pub/csrc_en/about/annual/201205/P020120515677609374835.pdf>

Saleem, K., 2009. International linkage of the Russian market and the Russian financial crisis: A multivariate GARCH analysis. Research in International Business and Finance 23, 243-256.

Scheicher, M., 2001. The comovements of stock markets in Hungary, Poland and the Czech Republic. International Journal of Finance & Economics 6, 27-39.

Susmel, R., Engle, R.F., 1994. Hourly volatility spillovers between international equity markets. Journal of International Money and Finance 13, 3-25.

Wang, Y., Di Iorio, A., 2007. Are the China-related stock markets segmented with both world and regional stock markets? Journal of International Financial Markets, Institutions and Money 17, 277-290.

Wang, S.S., Firth, M., 2004. Do bears and bulls swim across oceans? Market information transmission between greater China and the rest of the world. Journal of International Financial Markets, Institutions and Money 14, 235-254.

Wei, K.C., Liu, Y., Yang, C., Chaung, G., 1995. Volatility and price change spillover effects across the developed and emerging markets. Pacific-Basin Finance Journal 3, 113-136.

Zhou, X., Zhang, W., Zhang, J, 2012. Volatility spillovers between the Chinese and world equity markets. Pacific-Basin Finance Journal 20, 247-270.

Garth Mortensen
EDHEC Business School
December 2012