Low-frequency Volatility of Real Estate Securities in Relation to Macroeconomic Risk

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Abstract

To explain long-run economic determinants of volatility in international property securities, we utilize the Spline-Generalized Autoregressive Conditional Heteroskedasticity (Spline-GARCH) model of Engle and Rangel (2008) to extract the 'low-frequency' volatility component from aggregate volatility shocks in 11 international securitized real estate markets over 1990-2014. The results show that the aggregate volatility of real estate securities can be decomposed into a long-run component (low-frequency) and a short-run component (high-frequency). In addition, the decomposition also allows the high-frequency financial data to be linked to the low-frequency macro data in a fixed-effect pooled regression framework. The analysis also reveals that the low-frequency volatility of real estate securities has strong and positive association with most of the macroeconomic risk proxies, including interest rate, inflation rate, GDP and foreign exchange rate. The property investment implications have also been highlighted.

Keywords: Real estate securities, Spline-GARCH, volatility, macroeconomic risk and international

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1: Introduction

Numerous studies have been undertaken to examine the volatility linkages between macroeconomic variables and asset prices. Most studies focused on general equities; relatively little attention has been devoted into securitized real estate despite real estate securities, in principle, could be more sensitive to macroeconomic risk. As discussed by Bredin et al. (2007), real estate securities, particularly REITs are highly cash flow dependent from the underlying real estate market. Importantly, the underlying private real estate market is strongly affected by general economy activities through a number of channels, such as rent, capitalization rate, occupational demand and property values in the underlying real estate market. Hence, the publicly listed real estate sector is far more heavily tied to their underlying asset base in comparison to mainstream equities. It also suggests that the response of real estate securities may differ from the general evidence regarding the overall equity market.

{Insert Figure 1}

Additionally, the global listed real estate sector has expanded tremendously over the last decade. The increasing popularity of real estate securities is illustrated by Figure 1. Despite the onset of the Global Financial Crisis (GFC), the total market capitalisation of the FTSE/EPRA NAREIT Developed Global Index has increased considerably from US$515billion in February 2005 to US$1,149 billion in September 2014. As of July 2014, there were 3,015 real estate stocks globally with a total market capitalization of US$3,060 billion (EPRA, 2014), suggesting that global real estate securities have been widely accepted by investors as an important asset class. With the unique characteristics of real estate securities and the rapid growth of the publicly listed real estate sector, institutional investors and pension fund managers have become increasingly interested in understanding the behavior of international real estate securities in relation to the broader economy. Particularly, the interest has intensified since the occurrence of the GFC in which the securitized real estate markets have responded rapidly to the GFC. This has had increased the volatility of real estate securities considerably. The challenges associated with high price volatility indicate the importance of identifying its determinants. In fact, a number of studies have identified the relationship between securitized real estate returns and macroeconomic variables (McCue and Kling, 1994,Chen et al., 1998,Ewing and Payne, 2005,Liow and Yang, 2005,Yunus, 2012). Nevertheless, many of these studies focus on the influence of macroeconomic variables on securitized real estate returns instead of securitized real estate market volatility.

In the finance literature, the importance of the state of the economy and stock market volatility has been a subject of interest in a number of papers. Many seminal studies such as Officer (1973),Roll (1988) and Schwert (1989) have demonstrated that stock price volatility cannot be explained solely by macroeconomic volatility. The weak link between macroeconomic volatility and stock price volatility can be partly attributed to misspecification of the financial market volatility (Jones et al., 1998). Specifically, aggregate volatility shocks have been largely employed to measure financial market volatility. However, aggregate volatility shocks may not accurately measure financial market volatility.

To enhance the accuracy of measuring the volatility of financial market, Engle and Rangel (2008) have suggested decomposing financial market volatility into two components: (1) high-frequency volatility and (2) low-frequency volatility. They developed a spline-GARCH model. The model introduces a quadratic spline to describe the low-frequency component of the volatility process associated with slowly varying deterministic conditions in the economy. More noteworthy, the model allows the high-frequency financial data to be linked with the low-frequency macro data. They also indicated a stronger relationship between macroeconomic risk and the volatility of financial market. While there have been a number of recent studies that have employed the spline-GARCH model to examine commodity- and interest rate-derivatives (Azad et al., 2011; Karali and Power, 2013), virtually no empirical work has been undertaken in the publicly listed real estate sector.

This study aims to fill in this gap in the literature and investigate the determinants and dynamics of price volatility in international securitized real estate markets by building on the spline-GARCH model of Engle and Rangel (2008). Specifically, it estimates the low-frequency volatility of international real estate securities. This allows us to shed more light on the volatility of real estate securities. An enhanced understanding of securitized real estate volatility has been of great interest to investors, policy makers and academics. An investigation of low-frequency volatility of real estate securities will enable more informed investment decision-making regarding the role of international real estate securities from an asset allocation perspective.

In addition, the study also investigates the linkages between securitized real estate price volatility and macroeconomic risk in a high-frequency setting without comprised of a reduced-form time series model. To bridge high-frequency real estate stock price volatility and its lower-frequency macroeconomic determinants, we use a two-stage approach. First, in the high-frequency data, we extracted the proportion of securitized real estate price volatility that is plausibly caused by macroeconomic variables. Thereafter, the extracted variation, namely low-frequency volatility, is constructed in the same sampling frequency as the macroeconomic variables. Then the importance of macroeconomic variables is gauged with using a fixed-effect pooled regression. Understanding how real estate stock volatility responds to chancing macroeconomic conditions will enable institutional investors and portfolio managers to better manage their risk exposure. This issue is obviously of enhanced importance in light of Cowen (2009) has argued that underestimation of macroeconomic risk is one of the major sources of GFC. Importantly, the findings are also expected to assist policy makers to have a better understanding of the volatility behavior of real estate securities.

This study contributes to the literature in a number of ways. Firstly, this study is the first real estate study to estimate and decompose aggregate volatility shocks into high- and low-frequency components in listed real estate markets. Specifically, the spline-GARCH model of Engle and Rangel (2008), in contrast to the traditional GARCH-related models, is applied for the first study in the real estate context. A rich body of literature has examined real estate price volatility (Cotter and Stevenson, 2006, 2008,Liow, 2009,Liow et al., 2009,Zhou, 2012), but no study utilizes the spline-GARCH model. This approach is unique. Unlike conventional GARCH or stochastic volatility models, it allows unconditional volatility to change over time by introducing a quadratic spline to provide a smooth and nonlinear long-run trend in the volatility time series (Engle and Rangel, 2008,Engle et al., 2013,Karali and Power, 2013).

The trend also describes the low-frequency volatility component. Recognizing the differences between high- and low-frequency volatility, the results are expected to offer critical information and enhance our understanding of the volatility dynamics in international real estate investing. Most importantly, Engle and Rangel (2008) have also documented that two-component volatility GARCH (spline-GARCH) model outperforms one component or aggregate volatility models. Although the model has been recently applied to various stock and derivatives markets, no study has analyzed the volatility nature of real estate securities. As discussed earlier, securitized real estate, particularly REITs exhibit some unique features compared to general stocks (i.e. high dividend payout). Due to the unique features, the listed real estate sector may respond to changes in interest rates and general economic activity differently from the general evidence regarding the stock market (Berdin et al., 2007). By considering these unique characteristics of securitized real estate, a specific investigation of real estate securities is essential to enable more informed and practical investment decision-making regarding the role of economic variables in influencing the volatility term structure of securitized real estate.

Secondly, this study, to the best of our knowledge, is the first formal attempt to examine the impact of macroeconomic risk on securitized real estate volatility in an innovative way. A large number of studies have assessed the linkages between securitized real estate and macroeconomic fundamentals (Darret and Glascock, 1989; McCue and Kling, 1994). Relative to these studies, the present paper focuses on applying a recently developed econometric technique, the spline-GARCH model, to evaluate the extent to which macroeconomic risks and securitized real estate are related in a high-frequency setting. One of the important features of the spline-GARCG model is that daily data of securitized real estate can be aggregated to a quarterly frequency for use, for example, in regressions over a set of macroeconomic variables for the first time. Therefore, this study is different from the abovementioned studies in the sense that we examined the impact of macroeconomic risk on real estate securities volatility in a high frequency setting.

Thirdly, we contributed to the limited studies in REIT volatility and macroeconomic risk. Prior studies have been limited to investigating the volatility linkages between US REIT and the US interest rates (Devaney, 2001; Cotter and Stevenson, 2006; Braiden et al., 2007). We extend the studies to eleven international securitized real estate markets. These are the most liquid and largest indirect property markets in the world, contributing 68.1% of the global total market capitalization (EPRA, 2014). This offers us a comprehensive dataset and provides more robust findings. The results and their implications will help to assess the role of macroeconomic shocks in explaining real estate stock volatility. Lastly, unlike abovementioned studies, we utilized a range of important economy indicators (i.e. GDP, inflation rate, exchange rate, interest rate) to gauge macroeconomic risk. This is the first attempt to comprehensively investigate the volatility linkages between real estate stock and macroeconomic risk. The finding is expected to assist policy makers to make an enhanced policy decision making.

The remainder of this paper is organized as follows. The following section provides a brief literature review on volatility modelling development. The impact of macroeconomic variables on the volatility of real estate securities is also reviewed. Section 3 details the data used and the methodological framework adopted. Section 4 reports and discusses the empirical findings, whilst the final section provides concluding comments.

2: Literature Review

The body of literature on the linkages between real estate securities and the general economy is vast. Several early studies such as Chen et al. (1986) and Darret and Glascock (1989) asserted that the term structure of interest rates, industrial production and the money base influence the performance of real estate securities. Moreover, McCue and Kling (1994) investigated the dynamics of REIT returns by using an unrestricted vector autoregression (VAR) model. They also illustrated that prices, nominal short term interest rates, inflation, output and investment influence REIT returns. Ewing and Payne (2005) extended the work of McCue and Kling (1994). They presented similar evidence that shocks to monetary policy, economic growth, inflation and default risk premium are critical determinants of US REIT returns. Downs et al. (2003) also reported that income component of Equity and Composite REITs in the US are sensitive to economic factors, while low sensitivity of Mortgage REITs to economic variables have been documented. This suggests that Mortgage REITs may be effective instruments for hedging economic risk.

However, Chen et al. (1998) adopted the methodology of Chen et al. (1986) in order to re-examine the relationship between REIT returns and economic variables. Their empirical results indicated that these economic and financial variables have minimal impact upon REIT return volatility. Mueller and Pauley (1995) and Liang et al. (1995) related the movement of REIT prices to interest rate cycles and they did not document a significant relationship between REIT prices and interest rates. In Asia-Pacific, Liow and Yang (2005) found that securitized real estate, stocks and several macroeconomic factors, including GDP, inflation, the money supply and the short-term interest rate are fractionally co-integrated. They attributed this relationship to the exposure of these markets to the same economic influences. Comparable findings are also illustrated by Quan and Titman (1999) based on the empirical evidence of 17 international real estate markets. Yunus (2012) extended the work of Liow and Yang (2005) by scrutinizing the dynamic interactions among securitized real estate, stock markets and key macroeconomic factors for ten international markets. They revealed that key macroeconomic variables such as GDP, M1, CPI and long-term bond rate systematically drive international real estate returns.

A large number studies have dedicated to assess the impact of interest rates on REIT returns. Chen et al. (2012) found REITs respond to monetary shocks differently under different stock market states, suggesting that asymmetric response of REIT returns to monetary policy shocks. Comparable evidence is also documented by Chang et al. (2011) in which the impacts of monetary policy changes are much stronger in high-volatility regimes than in low-volatility regimes. In line with the work of Bernanke and Kuttner (2005), Berdin et al. (2011) used futures markets to isolate unexpected changes in the policy rate. They found that unexpected monetary shocks have a significant impact on REIT returns. Importantly, dividend channel has been identified as a driving force behind this influence. They also illustrated important differences between the REIT market and the stock market. Anderson et al. (2012) assessed whether monetary shocks have an asymmetric effect on REIT returns during high- and low-variance regimes. They showed that the impacts of monetary policy are stronger during the high-variance periods associated with the recent recession and crisis events. In addition, they also demonstrated that REIT markets, in agreement with theory, respond twice as much as the broader equity market.

In a recent paper, Chou and Chen (2014) employed a Markov-switching model to examine whether US REIT returns response to monetary policy asymmetric. They illustrated strong evidence that monetary policy shocks have larger effects on REIT returns during boom markets than recessions. The results are in contrast to the empirical evidence of asymmetry related to output and stock returns, indicating that REITs' responses to monetary policy shocks are very different compared with stock returns. This also highlights the importance of a dedicated study of real estate securities.

Although the impact of macroeconomic fundamental has been intensely debated in the literature, no account has been explicitly taken for the linkages between macroeconomic volatility and the volatility of real estate securities. Devaney (2001) probably is one of the few studies to assess the impact of interest rates on REIT volatility. Although the estimated coefficients are largely of the anticipated signs, the coefficients are insignificant, suggesting that little linkages between interest rate volatility and REIT volatility. On the other hand, Cotter and Stevenson (2006) found that Treasury bill movements are significant determinants of both returns and volatility for Equity REITs. Bredin et al. (2007) examined the relationship between unexpected monetary shocks and REIT returns and volatility. Their results show a strong response in both REIT returns and volatility to unexpected policy rate changes. In the UK, Stevenson et al. (2007) presented evidence of interest rate volatility significantly impact upon property companies. They also asserted that the documented findings are not confined to periods of high and volatility interest rates.

Numerous real estate studies confirmed the importance of modelling of listed real estate volatility. Specifically, it has been established that the volatility series of real estate securities is time-varying (Stevenson, 2002,Jirasakuldech et al., 2009,Lee, 2009), highly persistent (Cotter and Stevenson, 2008,Liow, 2009), and contain critical information in the price discovery process (Michayluk et al., 2006,Liow et al., 2009,Hoesli and Reka, 2013,Lee et al., 2014). In addition, Cotter and Stevenson (2006) also confirmed the use of high-frequency data, that is, daily data in volatility modelling will shed new light on real estate volatility modelling.

Given the advancement of volatility modelling, numerous recent finance studies have asserted the conditional volatility of an asset price could be further decomposed into two components (i.e. long- and short-run components) and have advocated the use of two-factor volatility models (Pagan and Schwert, 1990,Nelson, 1991). For instance, Ding and Granger (1996) highlighted that the persistence of short-term component is very weak, although its impact could be severe. Engle and Lee (1999) proposed a Component-GARCH model with permanent and transitory components. They have also demonstrated that the C-CARCH model outperformed traditional GARCH models. In addition, Chernov *et al.* (2003) concluded that the use of two components volatility models are critical to adequately capture the dynamics of volatility.

More recently, Engle and Rangel (2008) relaxed parameter restrictions of the Engle and Lee (1999)'s C-GARCH model and introduced a spline-GARCH model. The spline-GARCH model introduces a trend in the volatility process of returns to describe the low-frequency component. Importantly, the low-frequency volatility is associated with slowly varying deterministic conditions in the econmy. They also reported empirical evidence to indicate a stronger relationship between marcoeconomic risk and the volatility of 48 stock markets. Supporting evidence was also presented by Adrian and Rosenberg (2008). The authors suggested that the high-frequency volatility component is related to market skewness risk or financial constraints, whereas the low-frequency component can be attributed to business cycle risk or macroeconomic risk. Therefore, they argued that both components captured different sets of information. Moreover, Azad et al. (2011) exhibited that the low-frequency volatility component of Japanese Yen interest rate swap has a strong and positive association with macroeconomic risk. Karali and Power (2013) also demonstrated that the impact of slowly-evolving aggregate variables on commodity price volatility is better captured by the spline-GARCH model.

In contrast to the large number of studies to have considered two components volatility modelling, specific literature concerning real estate has been limited. One of the only exceptions is Liow and Ibrahim (2010). They employed a C-GARCH model and demonstrated the existence of significant "permanent" and "transitory" components in the volatilities of international securitized real estate markets. Furthermore, significant differences between the "permanent" and "transitory" volatility movements at the international level were also evident. A C-GARCH model was also employed in housing markets (Karoglou et al., 2013,Lee and Reed, 2014).

Overall, there have been relatively few studies on the linkages between securitized real estate volatility and macroeconomic risk. In addition, there is no real estate study to examine how the low-frequency volatility of real estate securities is linked to macroeconomic risk despite the broader equity market has confirmed that the low-frequency volatility is a better volatility measure that is associated with slowly-evolving conditions in the general economy.

3: Data and Methodological Framework

3.1: Data

To assess the low-frequency volatility of publicly listed property securities, daily closing returns of property securities in 11 developed markets were collected. These markets are Australia, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, Switzerland, the UK and the US. The FTSE EPRA/NAREIT indices for these markets were utilized to measure the performances of these markets. Given the FTSE EPRA/NAREIT indices commenced only in January 1990, the study covers the period from 1st January 1990 to 31st March 2014, giving a total of 6,325 daily observations for each market. The summary statistics of the indices are presented in Table 1.

{Insert Table 1}

As can be seen from Table 1, real estate stocks commonly are very volatile. Property markets in Asia such as Japan (2.05%), Hong Kong (1.84%) and Singapore (1.89%) are more volatile compared with the listed real estate sectors in Europe such as Netherlands (1.04%), Switzerland (1.03%) and the UK (1.24%), and Australia (1.10%). A preliminary picture of the return distribution properties of each market, obtained by comparing skewness and kurtosis for each market, is also shown in Table 1. The normality statistics reveal that the return distributions of these indices are not normally distributed, implying the existence of volatility clustering effects. The LM tests further confirmed the time-varying characteristics with volatility clusters in the volatility series of these listed real estate sectors. This also validities the application of GARCH-related processes. Given that daily data is used in this study, strong persistence in the volatility series is to be expected. This is only largely consistent with the broader finance literature, but also listed real estate markets specifically (Cotter and Stevenson 2006, 2008; Jirasakuldech et al. 2009; Lee et al., 2014)[1].

A variety of macroeconomic variables have also been considered in the analysis. Following McCue and Kling (1994) and Liow and Yang (2005), these variables include Gross Domestic Product (GDP), Consumer Price Index (CPI), short-term interest rates, M2 money supply and exchange rates. GDP is an important indicator of the overall economy in a specific country as it measures the prosperity of the economy. CPI is used as a proxy of inflation rate. It is also an important macroeconomic variable in asset pricing. Short-term interest rates, 3 months treasury bills, are utilized to gauge the influence of interest rate. Money supply is a proxy of monetary policies in which it affects investment and direction of capital flows. It can also lead to greater changes in inflation and interest rate. Lastly, exchange rate is measure by the price of US$ in terms of local currency. The data were obtained from DataStream.

3.2: The Low-frequency Volatility of Listed Property Securities

The empirical analysis consists of two key components. The first examines the low-frequency volatility of listed property securities. The second is concerned with the linkages between the low-frequency volatility of real estate stocks and macroeconomic risk. To extract the low-frequency volatility of real estate securities, a Spline-GARCH model was performed. The

[1] Results from Augmented Dickey-Fuller and Phillips-Perron unit root tests show that all of the data is stationary. These results are available from the authors on request.

Spline-GARCH model was developed by Engle and Rangel (2008). To understand this two-component volatility model, we start with the familiar GARCH(1,1) model. It is specified as follows:

$$r_t - E_{t-1}r_t = \sqrt{h_t}\varepsilon_t \quad (1)$$
$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \quad (2)$$

where r_t represents the return of an asset at time t, $E_{t-1}(r_t)$ is the expected return at $t-1$, h_t characterizes the conditional volatility at time t and ε_t is the innovation term at time t.

Engle and Rangel (2008) argued that the ability of a GARCH(1,1) model to account for permanent and/or slow-moving patterns of volatility is limited. Therefore, they introduced a Spline-GARCH model that extends the GARCH(1,1) model, in an additive or multiplicative form, by offering a more flexible specification of low-frequency volatility. The spline-GARCH model introduces a trend in the volatility process of returns. The trend is captured using an exponential quadratic spline, which describes the low-frequency component of volatility. Importantly, it also guarantees that the low-frequency volatility is always positive. The Engle and Rangel's (2008) Spline-GARCH model can be estimated as follows:

$$r_t - E_{t-1}r_t = \sqrt{h_t}\varepsilon_t = \sqrt{\tau_t}g_t\varepsilon_t \quad (3)$$
$$g_t = (1-\alpha-\beta) + \alpha\left(\frac{(r_{t-1} - E_{t-2}r_{t-1})^2}{\tau_{t-1}}\right) + \beta g_{t-1} \quad (4)$$
$$\tau_t = c\exp\left(\omega_0 t + \sum_{i=1}^{k}\omega_i\left((t - t_{i-1})+\right)^2\right) \quad (5)$$

where g_t represents the high-frequency component of the conditional volatility, α characterizes the ARCH term, β indicates the GARCH term, τ_t represents the low-frequency component of the conditional volatility, c is a constant, $w_0 t$ is a time trend in the low-frequency volatility, $\sum_{i=1}^{k} \omega_i \left((t - t_{i-1}) + \right)^2$ denotes a low-order quadratic spline, $(t - t_{i-1})_+ = \max\{0, t - t_{i-1}\}$, and k is the number of knots in the spline model. It governs the cyclical pattern in the low-frequency trend of volatility. k is unspecified and the optimal value of k is determined by an information criterion. Large values of k imply more frequent cycles. The coefficients w_i govern the 'sharpness' of each cycle. Importantly, Engle and Rangel (2008) highlighted that τ_t can be estimated as direct function of macroeconomic risk.

3.3: Low-frequency Volatility of Real Estate Stocks and Macroeconomic Risk

The second part of the empirical analysis examines whether market volatility in real estate stocks can be explained by macroeconomic risk. We consider how macroeconomic risk (z_t) affects the low-frequency volatility of property securities by modelling low-frequency securitized real estate volatility as a function of macroeconomic and related policy variables[2]. This approach is consistent with Engle and Rangel (2008) and Azad et al. (2011). The empirical setting can be represented as follows:

$$Lowvol_{i,t} = c_{i,0} + \gamma_{i,1} IRVol + \gamma_{i,2} CPIVol + \gamma_{i,3} GDPVol + \gamma_{i,4} MSVol + \gamma_{i,4} FXVol + \mu_{i,t} \qquad (6)$$

where $Lowvol_{i,t}$ represents low-frequency volatility for securitized real estate market i for period t, $IRVol$ is the volatility of short-term interest rate, $CPIVol$ the volatility of consumer

[2] The study focuses on the macroeconomic determinants of low-frequency volatility of real estate securities. No consideration is given to the high-frequency volatility due to a variety of reasons. As noted by Adrian and Rosenberg (2008), the high-frequency volatility component is related to market skewness risk or financial constraints. Therefore, it is reasonable to hypothesise that the high-frequency volatility component is not affected by macroeconomic risk. However, a dedicated investigation of the linkages between the high-frequency volatility and macroeconomic risk is beyond the scope of this study.

price index, $CPDVol$ denotes the volatility of short-term interest rate, $MSVol$ is the volatility of money supply, and $FXVol$ is the volatility of foreign exchange.

Macroeconomic variables are only sampled at a quarterly frequency; direct modelling with the high-frequency (daily) dataset is not feasible. In other words, for each market, we should convert the daily low-frequency volatility series into a quarterly low-frequency volatility time series. Following Engle and Rangel (2008), the low-frequency volatility in a quarter can be computed as the following sample average:

$$Lowvol_{i,t} = \sqrt{\frac{1}{N_{i,t}} \sum_{d=1}^{N_{i,t}} \tau_{i,d,t}} \qquad (7)$$

where $Lowvol_{i,t}$ represents low-frequency volatility for securitized real estate market i in quarter t, $N_{i,t}$ is the number of trading days in a quarter t, $\tau_{i,d,t}$ denotes the daily low-frequency volatility observed in market i.

This step will allow us to match the quarterly low-frequency volatility time series with several macroeconomic time series. Macroeconomic risk can be represented by the absolute value of residuals from an autoregressive, AR(1), model. This can be represented as follows:

$$Z_t = \beta Z_{t-1} + e_t \qquad (8)$$

where Z_t is the relevant macroeconomic variable and $|\hat{\varepsilon}_t|$ is the estimate of volatility for macroeconomic variable Z_t.

4: Empirical Results and Discussion

4.1: The Low-frequency Volatility of Real Estate Stocks

Table 2 reports the estimated low-frequency volatility of real estate stocks through the estimation of the Spline-GARCH(1,1) model detailed previously. A standard GARCH(1,1) model was also performed in order to demonstrate the possible changes in the dependence structure of the spline-GARCH model.

{Insert Table 2}

The coefficients of α and β are positive and statistically significant, confirming that strong ARCH and GARCH effects in global real estate securities. This also justify the use of this form of specification in volatility modelling. Consistent with the finding of Engle and Rangel (2008), the mean values of α are 0.11 and 0.09 for the spline-GARCH model and the standard GARCH model respectively, reflecting little variation between the spline-GARCH model and the conventional GARCH model in terms of the ARCH effect. Nevertheless, the average values of β in the spline-GARCH model are 0.85, compared with the benchmark GARCH model of 0.90. This indicates that the GARCH effect is less persistence in the spline-GARCH model. This also reveals that the spline-GARCH model is less sensitive to *"old news"* in the sense that the coefficient of β relates to the lagged variance term. The results can be attributed to the advancement of the spline-GARCH model. As noted by Engle and Rangel (2008), volatility persistence computed from the spline-GARCH is lower in respect to the model allows the unconditional variance to be time-varying through the trend. Therefore, all previous shocks or *"old news"* would be less persistent than the suggested persistence level of a standard GARCH model. Similar argument has been also provided by (Lamoureux and Lastrapes, 1990).

Another important observation is the optimal number of knots. The number of knots range from 2 to 7 knots, reflecting the spline-GARCH model appears a preferable model as all markets exhibit more than one knot. As mentioned earlier, a larger value of k suggests more frequent business cycles. Therefore, the listed real estate markets in Australia (2 knots), France, the UK and the US (3 knots) have been seen as the markets with fewer but longer cycles in the low-frequency component of volatility. Coincidently, these four markets are the largest securitized real estate markets, accounting for 60 percent of the global listed real estate market. More importantly, REITs dominate the traded real estate sector in these markets. In addition, these REIT markets contribute 77 percent of the global REIT markets (EPRA, 2014). Traditionally, REITs have been viewed as a defensive asset. Despite the onset of GFC has increased the volatility of REITs significantly, the increased volatility of REITs could be related to short term or market skewness risk that is characterized by the high-frequency volatility component (Adrian and Rosenberg, 2008).

{Insert Figure 2}

This is further confirmed by Figures 2A, 2B, 2K and 2L. The figures provide some graphic evidence that the low-frequency component is associated with the slow-moving trend that characterizes the unconditional volatility. More specifically, the low-frequency volatility components are relatively smooth in spite of the impact of GFC on the conditional volatility series are significant. Hence, it is reasonable to expect that these markets have longer cycles but fewer in the low-frequency component of volatility. This also indicates the importance of taking into account for the low-frequency component and incorporating it into the model specification. Moreover, the results also show that indirect property market in Hong Kong is a very dynamic market. Although the listed property sector in Hong Kong is one of the largest and leading securitized real estate markets, the market is strongly characterized by property firms with strong development focus and real estate operating companies instead of REITs. This also implies that the firm structure of a real estate stock may have some impact on the low-frequency volatility component. Lastly, the AIC and HQIC statistics illustrated that the spline-GARCH model is a better model that the traditional GARCH model, confirming our finding earlier in which the spline-GARCH model is a clear improvement over a standard GARCH model.

To sum up, aggregated market volatility of real estate stocks can be decomposed into a high-frequency component and a low-frequency component. Importantly, an understanding of the low-frequency volatility is paramount in light of it characterizes the market fundamentals.

4.2: Macroeconomic Determinants of Low-frequency Volatility

The previous section provided some indication that the aggregate volatility of real estate equities should be modelled in a two-component model (low-frequency volatility and high-frequency volatility). Importantly, Engle and Rangel (2008) asserted that the low-frequency volatility captures the true volatility of market fundamentals. Hence it is hypothesized that there is a strong link between the low-frequency volatility and macroeconomic risk if the market fundamentals have been characterized by the low-frequency volatility. To extend this analysis we test whether there appears to be a relationship between the low-frequency volatility of real estate securities and the general economy, as proxied by a variety of macroeconomic variables. Using a fixed-effect pooled regression approach, we explore the linkages between the low-frequency volatility of real estate stocks and each individual variable individually. The results are exhibited in Table 3.

{Insert Table 3}

The preliminary results showed that the low-frequency volatility is positively and statistically associated with all macroeconomic volatilities, namely CPI volatility, short-term interest rate volatility, GDP volatility and exchange rates volatility. This suggests that these macroeconomic risks are strongly linked with the low-frequency volatility of listed property securities. The positive, but statistically insignificant, coefficient for money supply volatility indicates that whilst money supply volatility has some positive impact on the low-frequency volatility of real estate stocks, it does not do so to a statistically significant extent. Overall, these results are consistent previous recent mainstream finance work such as Engle and Rangel (2008), Azad et al. (2011) and Karali and Power (2013). The findings can also be interpreted as supporting the hypothesis that macroeconomic risk does have a discernible impact on the low-frequency volatility of securitized real estate. Nonetheless, the preliminary results should be further formally investigated.

To enhance the robustness of our findings, for the subsequent analysis, the macroeconomic determinants of traded real estate stocks are comprehensively inspected in which all explanatory variables are included in the models. The results are presented in Table 4.

{Insert Table 4}

A positive and statistically significant coefficient of interest rate volatility is documented from Model I to Model VI, reflecting interest rate volatility does have a significant influence on real estate stock volatility. Furthermore, the sign of the coefficients have the expected sign. Nonetheless, the results are contrary to the finding of Devaney (2001). This divergence in findings can be partly reiterated to the frequency of data that is used. Devaney (2001) analyzed monthly data instead of daily data. Importantly, Cotter and Stevenson (2006) have illustrated the differences in results when higher frequency daily data is tested. They also postulated the use of daily data in volatility modelling would offer further insights, implying the importance of incorporating daily data into the volatility model specification. This also supports our argument earlier that the spline-GARCH model is a preferable model in capturing macroeconomic risk with respect to it allows us to model in a high-frequency setting. Nevertheless, the results are still contrary to findings of low-frequency volatility studies from commodity futures and interest rate swaps markets (Azad et al, 2011; Karali and Power, 2013). This could attributed to previously reported results are sensitive to the exact sample analyzed.

In fact, the documented result of a strong contemporaneous connection between property stock volatility and interest rate volatility, in this study, do make strong intuitive sense in a number of respects. Firstly, as previously mentioned, listed property investment companies, particularly REITs are strongly characterized by the underlying private real estate market (Lee et al., 2008). Importantly, monetary policy changes will have a noticeable influence on occupational demand, capitalization rate, rental value and property value of the underlying private real estate market (Bredin et al., 2007). More specifically, property yields broadly follow interest rates; an increase in interest rates is expected to result an increase in property yields and a fall in the capital value of the company's underlying asset base. Consequently, this traded real estate market should be susceptible to interest rate movements. Furthermore, changes in interest rates should also influence the borrowing costs of listed property companies, particularly property development companies, in general, with high level of short-term debt (Stevenson et al., 2007). As a result, it would be expected to see a contemporaneous positive link between interest rate and securitized real estate volatilities, as found in paper such as Engle and Rangel (2008) in international general stock markets.

With respect to CPI volatility, we find, like Engle and Rangel (2008) Azad et al. (2011), that it has a positive impact on the low-frequency volatility, indicating that CPI volatility is also a critical macroeconomic determinant of real estate securities. A positive association is empirically appealing for publicly listed real estate stocks in respect to property securities in developed markets serve as a good hedge against expected inflation in the long run (Hoesli et al., 2008,Lee and Lee, 2014). In addition, real estate stocks do receive substantial income flows from rental markets. More importantly, rental incomes from the underlying direct markets are strongly correlated with CPI, particularly extensive studies have shown that commercial real estate in general represent a good hedge against inflation (Quan and Quigley, 1991,Glascock et al., 2002). Therefore, it is reasonable to document the finding of higher variability of CPI would increase the low-frequency volatility of securitized real estate.

Another result worth nothing is that GDP volatility always features in the models in which a positive and significant coefficient has been observed. This result also supports the Fama's

(1981) proxy hypothesis. As hypothesized, economic prospect and business expansion or contraction influences the demand of real estate and real estate stocks. The growth of an economy is expected to enhance the occupational demand of commercial property; thereby an increase in rental value and property value of the firms' underlying asset base is also expected. This also indicates that GDP volatility will be transmitted to the low-frequency of public traded real estate stocks; thereby it is not surprisingly to find that an increase in the volatility of GDP increases the low-frequency of indirect property. Similar results have also been documented in different financial markets (Officer, 1973,Engle and Rangel, 2008). This also asserts that low-frequency volatilities in countries with superior economic growth are lower compared with countries experiencing low or negative economic growth. The finding also echoes the argument of Hamilton and Lin (1996) that the business cycle as a major source of stock market volatility.

Some interesting observations are noted with regards to the coefficients of money supply volatility. Money supply volatility, in general, is positive, small in magnitude, and statistically insignificant. The results are at odd with the finding of Azad et al. (2011) in the Japanese interest rate swaps market. However, the results make intuitive sense in response to the money supply shock is normally transmitted to financial assets through interest rate and/or inflation (Azad et al., 2011). This is further confirmed by the strong correlation coefficients of money supply volatility with interest rate and inflation. Reference to foreign exchange volatility, it exhibits that the low-frequency volatility of real estate equities is high when the foreign exchange variable is volatile, suggesting the existence of a contemporaneous linear long-term volatility linkage between traded property companies and foreign exchange volatility. Although the results are not consistent with the finding of Engle and Rangel (2008) from the broader equities market, the results can be attributed to the active cross-border investment of real estate stocks. As discussed by Baum et al. (2013), the cross-border real estate investments have expanded significantly. Consequently, real estate companies are very sensitive to foreign exchange volatility. This also highlights the need of a dedicated study of real estate stocks.

The models have also been further controlled for the financial development of and the size of an economy. The economy size is measure by the log of nominal GDP in US dollars. The coefficient of log(GDPUS$) in the Model IV is positive and statistically significant, reflecting that large economics would have higher equity volatilities. One of the plausible explanations is that large economics have complex structures with extensive information flows and possibly leverage. On contrary, market development variables are negatively related to low-frequency volatilities. This suggests that more developed markets have advantages in terms of broader diversification; thereby it would lead to reduced market volatility. The results are largely consistent with wider equity markets (Engle and Rangel, 2008).

To enhance the specificity of the evidence, we also performed the abovementioned analysis with aggregated volatility of publicly traded property companies (estimated volatility from the GARCH model). The results support the view of a strong linkage between macroeconomic risk and volatility is only presented in the low-frequency volatility component. Specifically, little evidence is available to support a robust link between aggregated volatility and macroeconomic risk. This provides a broad confirmation of the view of the low-frequency volatility is driven by slowly-changing common macroeconomic factors. This also confirms the significance of the spline-GARCH model in volatility modelling[3].

Collectively, macroeconomic risk appears as the important determinants of real estate stock volatility. The results confirm the proposition of Engle and Rangel (2008) in that the low-frequency component of volatility is high when the macroeconomic risk factors (i.e. CPI, interest rate, GDP and foreign exchange) are volatile. More importantly, the findings also support the notion that the low-frequency volatility as opposed to aggregated volatility is strongly associated with slowly varying deterministic conditions in the economy.

4.3: Causality between Macroeconomic Determinants and Low-frequency Volatility of Real Estate Securities

After establishing the strong linkages between macroeconomic risk and low-frequency volatility of property securities in the previous section, this section investigates the pair-wise Granger causal relationship between macroeconomic risk proxies and the low-frequency volatility of listed real estate. An examination of the causal link is interest of a variety reasons. The results are expected to make an informed policy decision in that the finding facilities policy makers to implicate the market reactions (bi-directional causality/feedback effects) into subsequent policy decisions. In addition, if a uni-directional causality from the general economy to the low-frequency volatility of real estate stocks, real estate investors can

[3] The GARCH results are not reported for brevity. However, the results are available from the authors upon on request.

hedge their securitized real estate risk exposure via real estate derivatives[4] during the rise of macroeconomic risk. The causality results are presented in Table 5.

{Insert Table 5}

The results indicate that excluding foreign exchange volatility, none of the macroeconomic risk proxies have entirely one-way causality to low-frequency volatility of real estate securities. Specifically, there is evidence available to support that macroeconomic risk (IRVol, GDPVol, CPIVol, FXVol) Granger-caused the low-frequency volatility of listed property securities. Importantly, a bi-directional causality is also evident in which the hypothesis of low-frequency volatility does not Granger-cause macroeconomic risk is rejected for IRVol, GDPVol and CPIVol. This offers some indirect support to the assertion of Chen et al. (1986) and Schwert (1989) that there is no satisfactory theory to suggesting an entirely one way relationship between financial markets and macro economy. The implications from these findings are far-reaching and wide ranging, particularly for policy makers as they should regularly monitor and reflect the market reactions in enhancing their policy decision making. More importantly, the finding also confirms the finding of Kallberg et al. (2002) and Stevenson (2002) in that real estate volatility is an important measure. This also supports a widespread belief that financial market volatility contains useful information as it varies over time.

[4] Securitised real estate derivatives have been introduced in the US, Australia, Japan and Europe. Several studies such as Lee and Lee (2012) and Lee et al. (2014) have presented empirical evidence that these are effective instruments to hedge the market risk.

To sum up, a strong feedback effect has been documented between the low-frequency volatility of real estate stocks and macroeconomic risk. The results are supported earlier findings that a strong volatility linkage is evident between the low-frequency volatility and macroeconomic risk.

4.4: Robustness Checks

To enhance the robustness of the baseline findings, several robustness checks were performed. First, a sub-period analysis was performed in order to assess the volatility dynamics of publicly listed property companies. The full sample was equally decomposed into two sub-periods. The first period spans from January 1990 to December 2001, whilst the second period covers from January 2002 to March 2014. This first period contains, in historical terms, relatively stable listed real estate markets with much less negative returns compared with the second period that captures the effect of the GFC. The results are reported in Table 6.

{Insert Table 6}

By simply comparing the coefficients in Table 4 (the entire sample period) and Panel A of Table 6 (the sub-period 1), it is clearly shown that the macroeconomic determinants of real estate securities, in terms of the low-frequency volatility component, in Period 1 were broadly similar to the findings for the entire sample period. Results confirm the preceding findings in which a strong linkage between macroeconomic risk and the low-frequency volatility was evident in Period 1. Specifically, interest rate volatility, inflation volatility, GDP volatility and foreign exchange volatility are strongly associated with the low-frequency volatility of publicly traded property companies, reflecting that these are critical determinants of the market fundamental. Consistent with the baseline results, no noteworthy link was manifested between money supply volatility and the fundamental of the market, signifying that this is not a significant determinant. The lack of change exhibited in the sample period analysis is also consistent with the hypothesis of low-frequency captures the fundamental of the markets. Therefore, the documented relationships are expected to be much less sensitive to changes in the dynamics of market fundamental.

Panel B of Table 6 depicts the regression results in Period 2. The results with respect to the macroeconomic determinants of property securities in Period 2, in general, are comparable with the finding of the entire sample. A strong link is documented between the low-frequency volatility of property securities and GDP volatility and exchange rate volatility. This confirms that the low-frequency volatility is strongly associated with macroeconomic variables. Interestingly, a positive and significant coefficient of money supply volatility is demonstrated, suggesting that the increased of money supply volatility does increase the low-frequency volatility of real estate securities. The results here represent a departure from the findings for the entire sample period. This could be attributed to the GFC. Specifically, the GFC has had a strong negative impact on many economics. To stimulate the economic, a loose monetary policy has been widely implemented by many central banks by providing massive injections of money into economics. Therefore, it is not too surprisingly to find a greater role of money supply volatility in Period 2. In summary, the sub-period analysis clearly provides a broad confirmation of prior empirical work in which real estate stocks are linked in the long-run to macroeconomic risk.

Secondly, it should be noted the Engle and Rangel (2008) approach was performed in a seemingly unrelated regression framework, whereas this study was performed in a fixed-effect pooled regression framework. In this study, we also re-run our cross-sectional analysis with a seemingly unrelated regression model, random-effect pooled and no effect pooled regressions. However, the results suggest that the baseline results are robust.[5] No significant variation is documented, indicating that CPI volatility, interest rate volatility, GDP volatility and foreign exchange volatility are critical determinants of the low-frequency volatility of property companies. In short, empirical evidence is manifested to support the notion of macroeconomic risk does have a discernible impact on the low-frequency volatility of real estate stocks.

Lastly, we examined whether the above empirical results are robust to an alternative measure of long-term volatilities. Realized Volatility is used as an alternative measure of volatility of real estate securities. The realized volatility can be estimated as follows:

$$Rvol_{i,t} = \left(\sum_{d=1}^{N_{i,t}} r_{i,t,d}^{2} \right) \tag{9}$$

where $Rvol_{i,t}$ is the realized volatility in country i at year t, $N_{i,d}$ is the number of trading days observed for securitized real estate market i at year t and $r_{i,t,d}^{2}$ stands for the daily squared return observed in country i at day d of year t. Following Engle and Rangel (2008), realized volatility is also employed as a dependent variable instead of low-frequency volatility. Hence the realized volatility of real estate stocks is regressed with a variety of variables as discussed in equation 6. The results are broadly consistent with the documented

[5] The results are available from the authors upon on request.

findings in Table 6[6]. The only exception is GDP volatility. Contrasting with the low-frequency volatility from the spline-GARCH model, the realized volatility shows little responsiveness to GDP volatility, although the correct sign is documented. The discrepancy in the results between the spline and realized volatility might be due to the fact that the latter is a noisier measure of long-term volatility (Engle and Rangel, 2008; Azad et al., 2012). Nonetheless, a strong contemporaneous linear linkage between real estate securities and interest rate volatility, inflation volatility and exchange rate volatility is still identified. Results here confirm that the baseline results, in general, are robust to different long-run volatility measure.

5: Conclusion and Implications for Real Estate Securities

This study has addressed the lack of research into the volatility linkages between real estate securities and macroeconomic risk. Specifically, this study examines the issue whether the time variation in securitized real estate volatility can be linked to macroeconomic risk in an innovative framework, which is the spline-GARCH framework of Engle and Rangel (2008). The framework permits us to investigate the impact of macroeconomic risk on real estate equities in a high frequency setting for the first time.

The current study provides a number of important insights. Firstly, our results stimulate new research agenda in international real estate markets by providing strong empirical support for the importance of extracting the low-frequency component of real estate volatility. Importantly, the low-frequency volatility component appears as a critical component to

[6] The results are not reported for brevity. But the results are available from the authors.

describe the business cycle. The finding could also improve the risk management of institutional investors through the construction of better specified value a risk models. Secondly, strong linkages between the low-frequency volatilities of real estate securities and macroeconomic volatilities have also been illustrated. Furthermore, we found that computing quarterly volatility from the low-frequently component of volatility, rather than using aggregated volatility, exhibits more clearly the effect of macroeconomic indicators. The finding further enhances our understanding of real estate volatility, particularly the fundamental or true volatility of securitized real estate markets. This is a critical finding that should be recognized and considered in macroeconomic policy decisions and implementation. By recognizing this feature, policy makers will identify the true factors affecting the fundamental operation of securitized real estate.

Thirdly, a bi-directional relationship between macroeconomic risk and low-frequency volatility is also documented, indicating the ability of the low-frequency volatility to forecast macroeconomic risk. The finding also suggests that macroeconomic risk could serve as a good indicator for real estate investors, with using real estate derivatives, improving their risk management. Particularly, they would increase (reduce) the use of real estate derivatives in hedging the market risk at times of higher (lower) macroeconomic risk.

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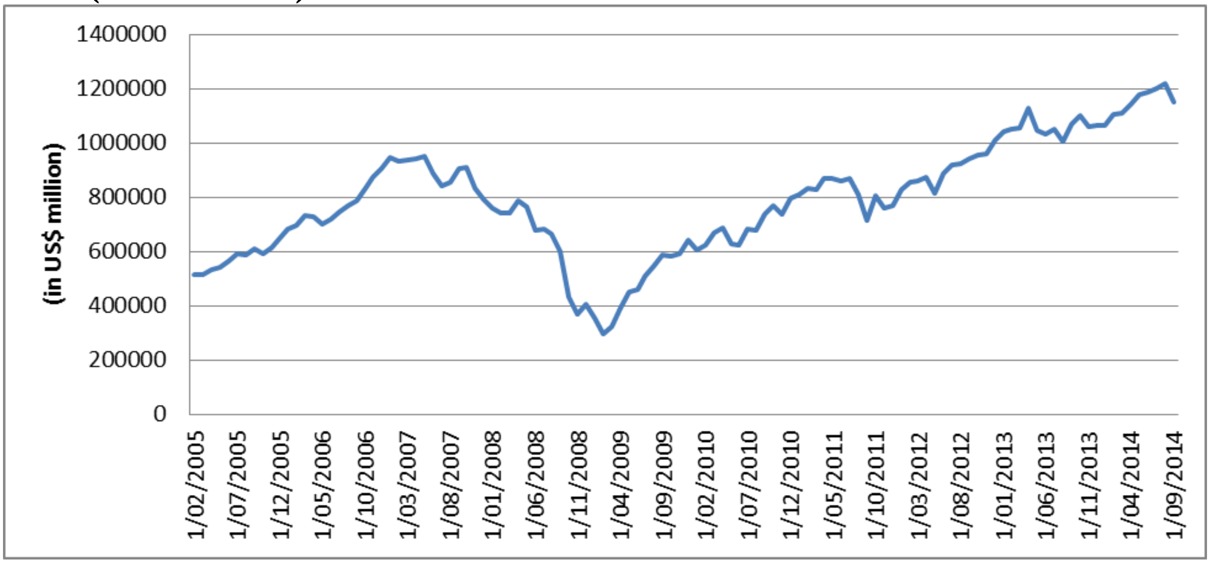
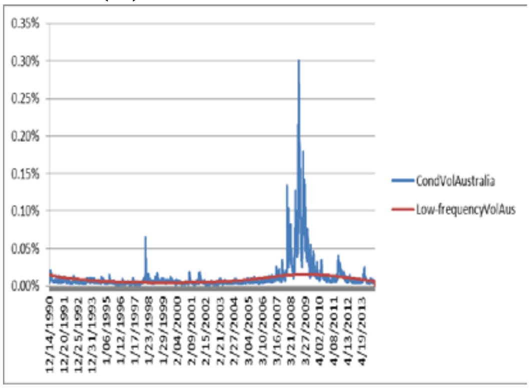
Figure 1: The Market Capitalization of the FTSE EPRA/NAREIT Global Developed Index (in US$ million)



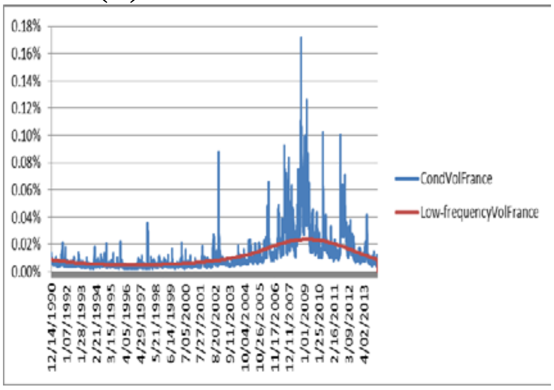
Source: DataStream (2014)

Figure 2: Low-frequency Volatility Components of International Securitized Real Estate Markets

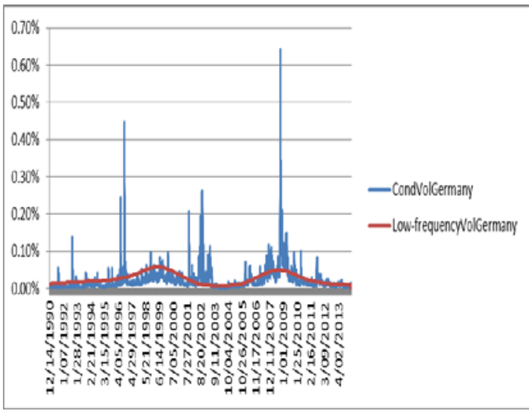
Panel 2(A): Australia



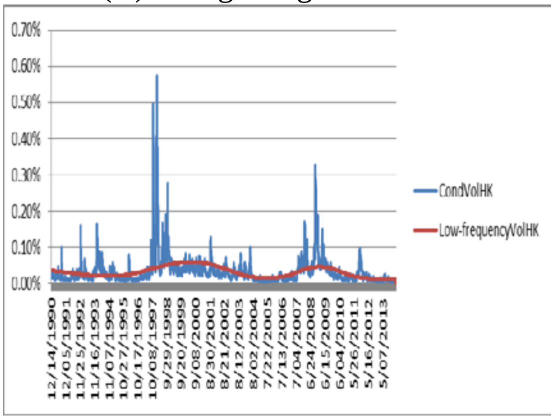
Panel 2(B): France



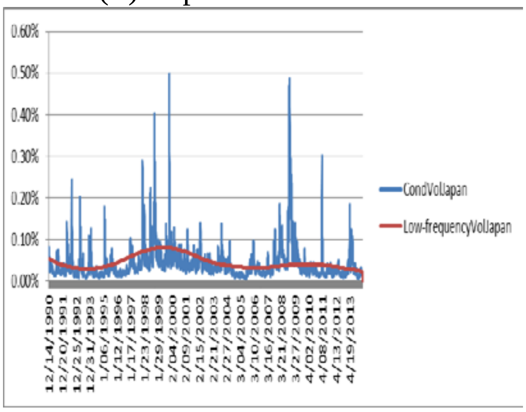
Panel 2(C): Germany



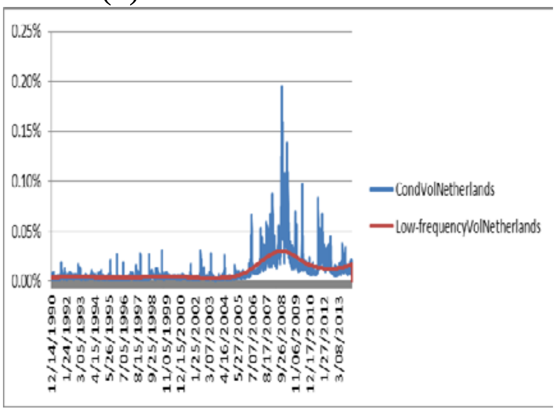
Panel 2(D): Hong Kong



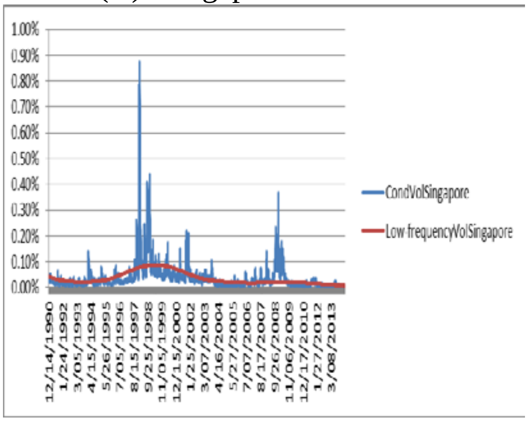
Panel 2(E): Japan



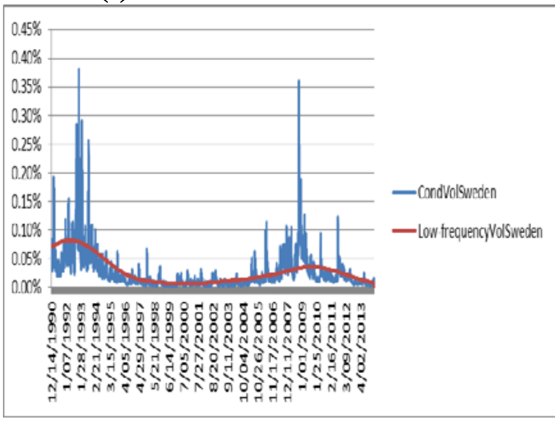
Panel 2(F): Netherlands



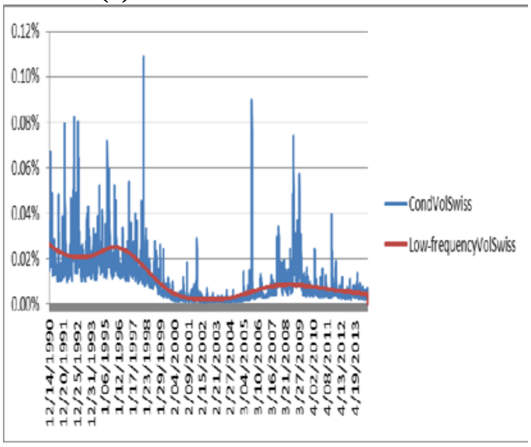
Panel 2(H): Singapore



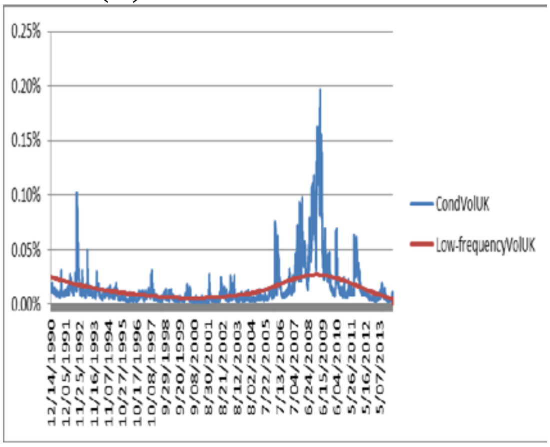
Panel 2(I): Sweden



Panel 2(J): Switzerland



Panel 2(K): UK



Panel 2(L): US

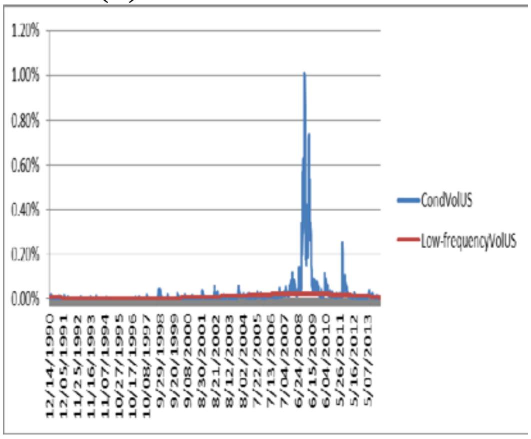


Table 1: Descriptive Summary

Market	Mean (%)	Standard Deviation (%)	Minimum (%)	Maximum (%)	Skewness	Kurtosis	Count
Australia	0.040	1.101	-11.347	8.242	-0.552	12.611	6325
France	0.046	1.119	-7.777	8.683	0.129	6.310	6325
Germany	0.026	1.485	-19.345	14.746	-0.214	15.235	6325
Hong Kong	0.054	1.838	-13.056	21.746	0.389	8.576	6325
Japan	0.024	2.010	-11.687	16.769	0.499	5.001	6325
Netherlands	0.024	1.036	-7.030	7.940	-0.108	8.239	6325
Singapore	0.031	1.892	-13.417	25.542	1.063	13.704	6325
Sweden	0.026	1.032	-6.674	8.053	-0.020	5.583	6325
Switzerland	0.029	1.613	-16.859	14.832	0.213	10.599	6325
UK	0.027	1.243	-13.417	25.542	1.063	13.704	6325
US	0.058	1.566	-19.499	18.351	0.422	28.497	6325

Notes: This table reports descriptive summary for 11 publicly traded real estate markets, namely Australia, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, Switzerland, the UK and US. The sample covers the daily observations from January 1990 to March 2014.

Table 2: Estimation Results of Spline-GARCH

Country	Knots	Alpha		Beta		Loglikehood		AIC		HQIC	
		SGARCH	GARCH	SGARCH	GARCH	SGARCH	GARCH	SGARCH	GARCH	SGARCH	GARCH
Australia	2	0.087	0.063	0.882	0.926	21253.79	21285.27	-6.718	-6.729	-6.715	-6.727
		(3.036)**	(0.541)**	(13.370)**	(69.630)**						
France	3	0.113	0.101	0.826	0.882	20750.80	20707.33	-6.559	-6.546	-6.555	-6.544
		(6.696)**	(5.766)**	(31.850)**	(43.710)**						
Germany	6	0.113	0.089	0.853	0.901	19023.17	18946.00	-6.011	-5.989	-6.007	-5.987
		(4.937)**	(4.668)**	(26.180)**	(39.870)**						
Hong Kong	7	0.089	0.087	0.884	0.903	17385.00	17353.35	-5.493	-5.486	-5.488	-5.484
		(8.028)**	(6.941)**	(57.920)**	(63.730)**						
Japan	4	0.111	0.111	0.863	0.874	16419.09	16403.73	-5.189	-5.185	-5.185	-5.184
		(7.669)**	(7.444)**	(49.250)**	(52.200)**						
Netherlands	6	0.135	0.115	0.780	0.868	21861.48	21787.15	-6.909	-6.888	-6.905	-6.886
		(4.727)**	(5.968)**	(14.580)**	(40.390)**						
Singapore	4	0.105	0.098	0.869	0.900	17641.99	17604.42	-5.575	-5.565	-5.572	-5.563
		(7.889)**	(6.413)**	(49.650)**	(58.640)**						
Sweden	4	0.099	0.086	0.873	0.915	18659.36	18595.27	-5.897	-5.878	-5.893	-5.876
		(5.705)**	(4.327)**	(36.590)**	(51.670)**						
Switzerland	5	0.126	0.051	0.787	0.947	21123.99	21007.33	-6.676	-6.641	-6.672	-6.639
		(7.221)**	(1.372)	(26.750)**	(23.810)**						
UK	3	0.086	0.078	0.893	0.914	20157.11	20143.58	-6.371	-6.368	-6.368	-6.366
		(6.701)**	(6.745)**	(54.370)**	(76.960)**						
US	3	0.119	0.117	0.852	0.882	21179.11	21136.67	-6.694	-6.682	-6.691	-6.680
		(8.871)**	(8.965)**	(56.120)**	(73.510)**						

Notes: This table reports estimated coefficients from a Spline-GARCH(1,1) model with Gaussian innovation and a traditional GARCH(1,1) model. The spline-GARCH(1,1) model specification is provided in Equations (3) through (5). The sample covers the daily observations from January 1990 to March 2014. Knots represent the optimal number of knots in the Spline-GARCH model. Figures in parentheses are robust standard errors. *, ** denotes significance at the 5% and 1% level respectively.

Table 3: Individual Panel Regressions

Variable	Coefficient	Standard Error	T-statistic
IRVol	0.004	0.001	2.782***
CPIVol	0.185	0.071	2.590***
GDPVol	0.078	0.078	3.615***
MSVol	0.011	0.011	0.618
FXVol	0.042	0.012	3.585***

Notes: This table reports estimated coefficients from a fixed-effect pooled regression. The model is estimated by

$$Lowvol_{i,t} = c_{i,0} + \gamma_{i,1}IRVol + \gamma_{i,2}CPIVol + \gamma_{i,3}GDPVol + \gamma_{i,4}MSVol + \gamma_{i,4}FXVol + \mu_{i,t}$$

where the dependent variable is the low-frequency volatility obtained from using equation (7). Volatility series for IR, CPI, GDP, MS and FX are obtained from the (absolute value of) residuals of AR(1) models. The sample covers the observations from 1990:Q1 to 2014:Q1. T-values are presented in parentheses. The White cross-section robust standard errors are utilized. *, ** denotes significance at the 5% and 1% level respectively.

Table 4: Low-frequency Volatilities and Macroeconomic Variables

Model	I	II	III	IV	V	VI
Constant	0.013	0.013	0.012	0.012	0.026	0.027
	(51.988)***	(48.648)***	(43.061)***	(76.245)***	(58.538)***	(16.395)***
IRVol	0.003	0.003	0.003	0.001	0.001	0.003
	(2.576)***	(2.562)**	(2.477)**	(2.883)***	(2.669)***	(2.246)**
CPIVol	0.149	0.149	0.135	0.031	0.021	0.090
	(2.149)***	(2.146)**	(1.948)**	(4.271)***	(2.973)***	(1.404)
GDPVol	0.071	0.071	0.069	0.016	0.012	0.064
	(3.180)***	(3.176)***	(3.074)***	(3.864)***	(2.972)***	(2.840)***
MSVol		0.002	-0.002	0.003	0.001	0.000
		(0.113)	(-0.091)	(1.087)	(0.512)	(0.003)
FXVol			0.038	0.006	0.004	0.034
			(3.322)***	(4.729)***	(3.274)***	(3.096)***
Log(GDP US$)				0.012		
				(76.245)***		
Log(Mkt Cap)					-0.001	
					(-27.812)***	
Log(Mkt Cap/GDP)						-0.009
						(-9.869)***

Notes: This table reports estimated coefficients from a fixed-effect pooled regression. The model is estimated by

$$Lowvol_{i,t} = c_{i,0} + \gamma_{i,1}IRVol + \gamma_{i,2}CPIVol + \gamma_{i,3}GDPVol + \gamma_{i,4}MSVol + \gamma_{i,4}FXVol + \mu_{i,t}$$

where the dependent variable is the low-frequency volatility obtained from using equation (7). Volatility series for IR, CPI, GDP, MS and FX are obtained from the (absolute value of) residuals of AR(1) models. The sample covers the daily observations from 1990:Q1 to 2014:Q1. T-values are presented in parentheses. The White cross-section robust standard errors are utilized. *, ** denotes significance at the 5% and 1% level respectively.

Table 5: Pair-wise Granger Causality Tests between Low-frequency Volatilities and Macroeconomic Variables

Model	Chi-Square Statistic
IRVol does not Granger cause Low-Vol	5.300***
Low-Vol does not Granger cause IRVol	9.912***
CPIVol does not Granger cause Low-Vol	7.356*
Low-Vol does not Granger cause CPIVol	18.630***
GDPVol does not Granger cause Low-Vol	10.498***
Low-Vol does not Granger cause GDPVol	9.923**
FXVol does not Granger cause Low-Vol	12.742***
Low-Vol does not Granger cause FXVol	3.615

Notes: This table reports the pair-wise Granger causality test results. The low-frequency is estimated via a Spline-GARCH(1,1) model with Gaussian innovation. The spline-GARCH(1,1) model specification is provided in Equations (3) through (6). Volatility series for IR, CPI, GDP, MS and FX are obtained from the (absolute value of) residuals of AR(1) models. The sample covers the observations from 1990:Q1 to 2014:Q1. *, ** denotes significance at the 5% and 1% level respectively.

Table 6: Low-frequency Volatilities and Macroeconomic Variables: Sub-period Analysis

Variable	Coefficient	Standard Error	T-statistic
Panel A: Period 1 (1990:Q1 to 2001:Q4)			
Constant	0.012	0.000	36.068***
IRVol	0.009	0.002	3.967***
CPIVol	0.257	0.075	3.412***
GDPVol	0.063	0.030	2.097**
MSVol	-0.027	0.015	-1.794*
FXVol	0.043	0.014	3.123***
Panel B: Period 2 (2002:Q1 to 2014:Q1)			
Constant	0.012	0.000	44.841***
IRVol	0.001	0.001	1.205
CPIVol	0.052	0.063	0.826
GDPVol	0.068	0.018	3.665***
MSVol	0.059	0.021	2.880***
FXVol	0.021	0.011	1.965**

Notes: This table reports estimated coefficients from a fixed-effect pooled regression. The model is estimated by

$$Lowvol_{i,t} = c_{i,0} + \gamma_{i,1}IRVol + \gamma_{i,2}CPIVol + \gamma_{i,3}GDPVol + \gamma_{i,4}MSVol + \gamma_{i,4}FXVol + \mu_{i,t}$$

where the dependent variable is the low-frequency volatility obtained from using equation (7). Volatility series for IR, CPI, GDP, MS and FX are obtained from the (absolute value of) residuals of AR(1) models. Period 1 covers the observations from 1990:Q1 to 2001:Q4, whereas Period 2 covers the observations from 2002:Q1 to 2014:Q1. T-values are presented in parentheses. The White cross-section robust standard errors are utilized. *, ** denotes significance at the 5% and 1% level respectively.