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

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Abstract

Real estate securities have a number of distinct characteristics that differentiate them from stocks generally. Key amongst them is that under-pinning the firms are both real as well as investment assets. The connections between the underlying macro-economy and listed real estate firms is therefore clearly demonstrated and of heightened importance. To consider the linkages with the underlying macro-economic fundamentals we extract the 'low-frequency' volatility component from aggregate volatility shocks in 11 international markets over the 1990-2014 period. This is achieved using Engle and Rangel's (2008) Spline-Generalized Autoregressive Conditional Heteroskedasticity (Spline-GARCH) model. The estimated low-frequency volatility is then examined together with low-frequency macro data in a fixed-effect pooled regression framework. The analysis reveals that the low-frequency volatility of real estate securities has strong and positive association with most of the macroeconomic risk proxies examined. These include interest rates, inflation, GDP and foreign exchange rates.

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

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1: Introduction

Numerous studies have examined the volatility linkages between macroeconomic variables and asset prices. In the main these papers have largely focused their attention upon the general stock market, with relatively little attention placed on individual industry sectors and specifically real estate securities. This is despite public real estate firms potentially displaying heightened sensitivity to macroeconomic risk. Papers such as Bredin et al. (2007) highlight how real estate securities, and in particular REITs (Real Estate Investment Trusts), are sensitive to cash flows dependent on the underlying real estate market. Due to a variety of channels, such as rental income, capitalization rates, occupational demand and capital values, the underlying property market is quite strongly and directly influenced and affected by general economic conditions. It is therefore arguable that the public real estate sector is more heavily and immediately tied, through their assets, to the macro-economy than stocks generally. This would also suggest that it is conceivable that the response of real estate firms to macro-economic variables may differ from in comparison to the overall equity market. Furthermore, papers such as Cowen (2009) argue that the underestimation of macroeconomic risk was one of the major contributory factors behind the 2007-9 financial crisis.

The mainstream finance literature has seen a number of papers consider how the state of the economy may impact stock market volatility. Seminal papers such as Officer (1973), Roll (1988) and Schwert (1989) demonstrate that equity market volatility cannot be explained solely by macroeconomic volatility. The weak link observed between volatility in macroeconomic variables and stocks can be partly attributed to the use of aggregate volatility shocks to measure financial market volatility (Jones et al., 1998). However, aggregate volatility may not be the most accurate measure of financial market volatility. Engle and Rangel (2008) suggest decomposing volatility into two components: (1) high-frequency volatility and (2) low-frequency volatility. Their Spline-GARCH 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. Their empirical analysis does indicate a stronger than previously observed 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 this gap in the literature and investigate the determinants and dynamics of volatility, and specifically low-frequency volatility, in 11 international public real estate markets using the Spline-GARCH model. The study investigates the linkages between public real estate volatility and macroeconomic risk in a high-frequency setting. In order to bridge high-frequency real estate stock price volatility and its lower-frequency macroeconomic determinants, we use a two-stage approach. First, from the high-frequency public real estate volatility we extract that which is plausibly caused by macroeconomic variables. The extracted component, namely low-frequency volatility, is estimated using the same sampling frequency as the macroeconomic variables. The importance of the macroeconomic variables is then gauged in a fixed-effect pooled regression framework. Understanding how real estate stock volatility responds to changing macroeconomic conditions will enable institutional investors and portfolio managers to better manage their risk exposure and to make more informed investment decisions from an asset allocation perspective.

This study contributes to the literature in a number of ways. Firstly, it is the first study to decompose aggregate volatility shocks in real estate stocks into their high and low frequency components. Whilst there is a rich literature that has now examined a variety of issues relating to real estate securities volatility (e.g. Cotter and Stevenson, 2006, 2008; Liow, 2009; Liow et al., 2009; Zhou, 2012), no study has utilized the Spline-GARCH model of Engle and Rangel (2008). Unlike conventional GARCH or stochastic volatility models, this modelling framework allows unconditional volatility to change over time through the introduction of 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). Secondly, it adds to the existing literature that has examined the impact of macroeconomic risk on public real estate volatility (e.g. Darret and Glascock, 1989; McCue and Kling, 1994). Relative to these studies, the current paper evaluates the extent to which macroeconomic risks and public real estate are related in a high-frequency setting. Thirdly, we contribute to a relatively limited number of studies that have examined the linkages between real estate security volatility and macroeconomic risk. This has been largely limited to studies examining interest rate sensitivity, the majority of whom examined the U.S. REIT sector (e.g. Devaney, 2001; Cotter and Stevenson, 2006; Bredin et al., 2007, 2011). In contrast the number of international studies is extremely limited (e.g. Stevenson et al., 2007; Xu & Yang, 2011; Akimov & Stevenson, 2014; Akimov et al., 2015). We examine the eleven largest and most liquid securitized property markets in the world, contributing 68.1% of the global total market capitalization (EPRA, 2014). Lastly, unlike the aforementioned studies that solely examine interest rates we extend the range of economy indicators to also include GDP, inflation and exchange rates.

The remainder of the paper is organized as follows. The following section provides a brief literature review on the development of volatility modelling and the impact of macroeconomic variables on the volatility of real estate securities. 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 examination of how the broad macro-economy impacts and affects the listed real estate sector has been a cornerstone of the academic literature on public real estate. Early studies, such as Chen et al. (1986) and Darret and Glascock (1989), clearly illustrated how variables such as the term structure rates, industrial production and the money base influence the performance of real estate securities. This work was expanded upon in papers such as McCue and Kling (1994) who illustrated nominal short term interest rates, inflation, output and investment all influence REIT returns. Ewing and Payne (2005) add to that body of evidence displaying that shocks to monetary policy, economic growth, inflation and default risk are all critical determinants of U.S. REIT returns. Studies such as Downs et al. (2003) have highlighted how the income return of Equity REITs are especially sensitive to economic factors. In contrast, Chen et al. (1998) find that economic and financial variables have minimal impact upon REITs. International evidence has frequently observed similar findings to those reported for the U.S. For example, Liow and Yang (2005) report evidence of fractional co-integration with several macroeconomic factors (GDP, inflation, money supply and short-term interest rates) across a variety of Asian markets[1]. Yunus (2012) extended this work by scrutinizing the dynamic interactions among public real estate, equities and key macroeconomic factors for ten international markets. They reveal that key macroeconomic variables such as GDP, money supply (M1), inflation (CPI) and long-term bond rates systematically drive public real estate returns.

As previously noted a large number of studies have specifically assessed the impact of interest rates on REIT returns. A number of key issues arise from this literature including variability in the sensitivity depending on the maturity of the interest rates concerned (e.g. Chen and Tzang, 1988; Devaney, 2001; He et al., 2003; Stevenson et al., 2007), although some early papers (e.g. Mueller and Pauley, 1995; Liang et al., 1995) fail to document a significant relationship between REITs and interest rates. A number of papers have also illustrated that he degree of interest rate exposure is not necessarily higher in periods of higher or more volatile rates. Lizieri and Satchel (1997), using a regime switching approach, report that U.K. property companies were particularly sensitive during a low interest rate regime. These results for the U.K. market are also supported by Stevenson et al. (2007) who analyse a period (1993-2005) that mostly saw low and stable rates. However, the papers reports significant sensitivity across most of the models and specifications examined. A number of recent papers have re-visited the interest rate sensitivity issue under different regimes. Chen et al. (2012) find that the response of REITs to monetary shocks under different stock market states does differ, a finding that would suggest a degree of asymmetry in the response. Both Chang et al. (2011) and Anderson et al. (2012) provide supporting evidence, however, of interest both papers note that that the response is stronger during high volatility regimes. This is contrary to the findings of Lizieri and Satchell (1997) in their examination of the U.K. market.

In a recent paper, Chou and Chen (2014) employ a Markov-switching model to examine whether U.S. REIT respond to monetary policy in an asymmetric manner, finding that monetary policy shocks have a larger effect during boom markets than recessions. The results are in contrast to the empirical evidence of asymmetry relating to output and stock returns, indicating that REITs' responses to monetary policy shocks are very different compared with stock returns. Bredin et al. (2011) also illustrate important differences between the REIT and broader stock markets. Drawing on the work of Bernanke and Kuttner (2005) the authors use the fed funds futures rate to isolate unexpected changes in U.S. interests rate. They report that unexpected monetary shocks have a significant impact on REIT returns. Importantly, the dividend channel is identified as a key driver behind this influence.

In conjunction with the aforementioned literature an increasing number of papers have considered the sensitivity to interest rates with respect to the volatility of public real estate. In common with later papers Devaney (2001) examine the issue in a GARCH (Generalised Autoregressive Conditional Heteroskedasticity) framework. Devaney's (2001) examination of U.S. REITs reports very significant linkages between interest rate volatility and REIT volatility. In contrast a number of significant findings are noted by Stevenson et al. (2007) in their examination of U.K. property companies, whilst Cotter and Stevenson (2006) report that Treasury bill movements are significant determinants of both returns and volatility for U.S. Equity REITs[2]. A recent paper by Akimov et al. (2015) extends the existing literature by not solely considering a single interest rate proxy but rather modelling the level, slope and curvature of the entire yield curve based on the Nelson-Siegel model of the term structure. Bredin et al. (2007) examine 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. Xu & Yang (2011) extend that analysis to consider whether foreign listed real estate markets are similarly affected by U.S. monetary shocks.

In addition to the papers that have specifically considered interest rate sensitivity in a GARCH framework over the last decade there has developed a large literature that has highlighted the importance of modelling of volatility in the context of public real estate. Specifically, it has been established that the volatility of real estate securities is time-varying (e,g, Stevenson, 2002; Cotter and Stevenson, 2006; Jirasakuldech et al., 2009; Lee, 2009), highly persistent (e.g. Cotter and Stevenson, 2008; Liow, 2009) and contains critical information concerning the price discovery process (e.g. Michayluk et al., 2006; Liow et al., 2009; Hoesli and Reka, 2013; Lee et al., 2014). In addition, Cotter and Stevenson (2006, 2007) confirm how the use of high-frequency data can shed new light and important insights into the modelling of REIT volatility. Given the advancement of volatility modelling, numerous recent finance studies have asserted that 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) highlight that the persistence of the short-term component is very weak, although its impact can be severe. Engle and Lee (1999) propose a Component-GARCH model, which has both permanent and transitory components, demonstrating that the C-CARCH model outperforms traditional GARCH models. In addition, Chernov *et al.* (2003) emphasises the benefits of using two component volatility models in capturing volatility dynamics.

More recently, Engle and Rangel (2008) relaxed parameter restrictions of the Engle and Lee (1999) 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, low-frequency volatility is associated with slowly varying deterministic conditions in the econmy. They report empirical evidence which indicate a strong relationship between marcoeconomic risk and the volatility of 48 stock markets[3]. The authors suggest that the high-frequency volatility component is related to market skewness risk and financial constraints, whereas the low-frequency component can be attributed to business cycle risk and macroeconomic risk. Therefore, both components capture different sets of information. Azad et al. (2011) support this premise by illustrating that the low-frequency volatility component of Japanese Yen interest rate swaps has a strong and positive association with macroeconomic risk. Furthermore, Karali and Power (2013) demonstrate that the impact of slowly-evolving aggregate variables on commodity price volatility is better captured by the Spline-GARCH model. In contrast, the number of studies to have specifically considered real estate has been notably limited. In the contexts of the public market in the exception is Liow and Ibrahim (2010) who employ a C-GARCH model, demonstrating the existence of significant “permanent” and “transitory” components in the volatilities of international securitized markets. Furthermore, significant differences between the “permanent” and “transitory” volatility movements at the international level were also found to be evident[4].

Although the impact of macroeconomic fundamental has been intensely debated in the literature, there have been relatively few studies that have explicitly considered the linkages between macroeconomic risk/volatility and the volatility of real estate securities. In addition, there is no real estate study that has examined how the low-frequency volatility of real estate securities is linked to macroeconomic risk. This is despite the empirical evidence from the broad finance literature that has illustrated how low-frequency volatility is a more appropriate measure of volatility when considering slowly-evolving macro-economic conditions.

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 global listed real estate sector has expanded considerably over the last fifteen years, as can be observed from Figure 1. Despite the Global Financial Crisis (GFC) the overall market capitalisation of the FTSE/EPRA NAREIT Developed Global Index increased 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), confirming the increased maturity of listed real estate and its place as a key industry sector within the broader equity markets. The rapid growth of the sector has contributed to an increased desire on the part of institutional investors and pension fund managers in understanding the behavior of international real estate securities in relation to the broader economy. This interest has intensified since the financial crisis in art due to the heightened volatility observed in public real estate markets. The challenges associated with high price volatility illustrate the importance of identifying its determinants. The summary statistics of the indices are presented in Table 1 and as can be seen real estate stocks display high volatility. Markets in Asia such as Japan (2.05%), Hong Kong (1.84%) and Singapore (1.89%) are more volatile compared with Australia (1.10%) and European sectors such as Netherlands (1.04%), Switzerland (1.03%) and the UK (1.24%). The normality statistics reveal that the return distributions are not normally distributed, implying the existence of volatility clustering effects. The LM tests further confirm the time-varying characteristics with volatility clusters in the volatility series of the listed real estate sectors. This also supports the rationale behind the use 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 not only consistent with the broader finance literature, but also those papers to have specifically considered listed real estate markets (e.g. Cotter and Stevenson 2006, 2008; Jirasakuldech et al. 2009; Lee et al., 2014)[5].

{Insert Figure 1 and Table 1}

A variety of macroeconomic variables are also 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 not only used as the proxy of inflation but 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 rates. Money supply is a proxy for the influence monetary policy. This may have a multitude of impacts in areas such as investment and capital flows as well as its link with inflation and interest rates. Finally, currency movements are proxied through the relevant US$ exchange rate. All of the data was obtained from Thompson-Reuters 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, as developed by Engle and Rangel (2008), is estimated. To understand this two-component volatility model, we start with the familiar GARCH(1,1) model. It is specified as follows:

$$r_t - E_{t-1} r_t = \sqrt{h_t}\varepsilon_t \tag{1}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{2}$$

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) argue that the ability of a GARCH(1,1) model to account for permanent and/or slow-moving patterns of volatility is limited. The proposed Spline-GARCH specification extends the GARCH(1,1) framework, in an additive or multiplicative form, by offering a more flexible specification of low-frequency volatility. The model introduces a trend in the volatility process of returns which is captured using an exponential quadratic spline. This element can be interpreted as describing 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 therefore be represented as follows:

$$r_t - E_{t-1}r_t = \sqrt{h_t}\varepsilon_t = \sqrt{\tau_t}\,g_t\varepsilon_t \tag{3}$$

$$g_t = (1-\alpha-\beta) + \alpha\left(\frac{(r_{t-1} - E_{t-2}r_{t-1})^2}{\tau_{t-1}}\right) + \beta g_{t-1} \tag{4}$$

$$\tau_t = c\exp\left(\omega_0 t + \sum_{i=1}^{k}\omega_i\left((t-t_{i-1})+\right)^2\right) \tag{5}$$

where g_t represents the high-frequency component of the conditional volatility, α characterizes the ARCH term, β is 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. k governs the cyclical pattern in the low-frequency trend of volatility, it is unspecified and its optimal value 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) highlight 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[6]. 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 rates, $CPIVol$ the volatility of consumer prices, $GDPVol$ denotes the volatility of GDP, $MSVol$ is the volatility of money supply and $FXVol$ the volatility of the foreign exchange rate. As the macroeconomic variables are only sampled at a quarterly frequency direct modelling with high-frequency (daily) data is not feasible. Therefore, for each market, we 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:

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

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 quarter t and $\tau_{i,d,t}$ denotes the daily low-frequency volatility observed in market i. This allows us to match the quarterly low-frequency volatility time series with the macroeconomic series'. Macroeconomic risk can be represented by the absolute value of residuals from an autoregressive AR(1) model. This can be represented as follows:

$$Z_t = \beta Z_{t-1} + e_t \tag{8}$$

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. The coefficients of α and β are positive and statistically significant, findings that both confirm strong ARCH and GARCH effects in global real estate securities and justifies 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 would indicate that the GARCH effect is less persistent in the Spline-GARCH model. It also illustrates that the Spline-GARCH model is less sensitive to *"old news"* given that the β coefficient relates to the lagged variance term. This finding can be attributed to the fact that the model allows the unconditional variance to be time-varying through the trend. Therefore, all previous shocks or *"old news"* will be less persistent than that suggested by a standard GARCH model[7]. The AIC and HQIC statistics would also indicate that the Spline-GARCH specification is a better model than the traditional GARCH model.

{Insert Table 2}

Another important finding from the initial estimations is the optimal number of knots observed, which range from 2 to 7. The fact that all markets exhibit more than one knot, which reflect the frequency of business cycles, does highlight one of the advantages behind adopting the Spline-GARCH framework. We can see that the listed markets in Australia (2 knots), France, the U.K. and the U.S. (3 knots) are those markets with fewer but longer cycles in the low-frequency component of volatility. Coincidently, these are four of the largest markets, accounting for 60% of the global listed real estate sector. Additionally, REITs today dominate the public real estate sector in each of these countries and in total the four comprise

77% of the global REIT market (EPRA, 2014). REITs have been traditionally viewed as a defensive sector. Although the onset of financial crisis was accompanied by a substantial increase in the volatility of REITs significantly this could have been due to short term or market skewness risk that is captured and characterized by the high-frequency volatility component (Adrian and Rosenberg, 2008).

This is further confirmed by Figures 2A, 2B, 2K and 2L. These figures provide some graphical 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 despite the impact of the financial crisis on the conditional volatility series being significant. Hence, it is reasonable to expect that these markets have longer cycles but fewer in the low-frequency component of volatility. This also highlights the advantages of taking into account the low-frequency component and incorporating it into the modelling framework.

{Insert Figure 2}

The results highlight some interesting characteristics with respect to the Hong Kong public real estate market. Specifically the results illustrate that the Hong Kong market is highly dynamic. Despite the introduction of REITs over a decade ago the listed sector is still dominated by corporates, many of whom have a strong development focus. The continued dominance of such firms in Hong Kong does in part reflect the development driven nature of the Hong Kong property market and the fact that REITs are not necessarily an appropriate vehicle for a development focused firm. In the context of our study it would however it may therefore be expected that the nature of the real estate stock underpinning the firms may have some impact on the low-frequency volatility component.

4.2: Macroeconomic Determinants of Low-frequency Volatility

The previous section provides some preliminary evidence concerning the advantages of decomposing volatility into its low and high frequency elements. As noted earlier in the paper Engle and Rangel (2008) argue that the low-frequency volatility captures the true volatility of market fundamentals. It can therefore be hypothesized that there may be a strong link observed between the low-frequency volatility and macroeconomic risk. We empirically examine this proposition using a variety of macro-economic variables (short-term interest rates, inflation, GDP and foreign exchange rates). Using a fixed-effect pooled regression 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 initial results show that the low-frequency volatility is positively and statistically associated with all of the macroeconomic volatilities. 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 with those from the mainstream finance literature (e.g. Engle and Rangel, 2008; Azad et al., 2011; Karali and Power, 2013). Whilst these findings can be interpreted as supporting the hypothesis that macroeconomic risk does have a discernible impact on the low-frequency volatility of securitized real estate they need to be formally investigated further. Specifically, we re-run the pooled regressions with all of the macroeconomic determinants included in the specification. 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 that interest rate volatility has a significant influence on real estate stock volatility. Furthermore, the sign of the coefficients have the expected sign. The results are however contrary to the finding of Devaney (2001). However, this divergence can be partly attributed to the use of monthly rather than daily data by Devaney (2001). Cotter and Stevenson (2006) illustrate the divergence that can be observed in results when higher frequency daily data is considered. They also postulate that the use of daily data in volatility modelling can offer further insights. This supports our argument that the Spline-GARCH model is preferable due to its use of high-frequency data. However, irrespective of that rationale it does need to be noted that the results with respect to interest rates are also contrary to those reported from low-frequency volatility studies that have considered both from commodity futures (Azad et al, 2011) and interest rate swaps markets (Karali and Power, 2013). This could, at least in part, be attributed to sensitivity with respect to the exact sample analyzed. The documented result of a strong contemporaneous connection between property stock volatility and interest rate volatility does make strong intuitive sense in a number of respects. Firstly, as previously mentioned, listed property investment companies, and especially REITs are strongly linked with and affected by events in the underlying private real estate market (Lee et al., 2008). Importantly, monetary policy changes will have a noticeable influence on occupational demand, capitalization rates, rents and capital values (Bredin et al., 2007). Whilst the relationship is not as strict or as rigid as in the bond market there does still remain a link between interest rates and property yields. Other factors may dominate but if interest rates do rise it will at least put upward pressure on property yields. Consequently, the traded real estate market should be susceptible to interest rate movements in terms of both asset values and income. Furthermore, changes in interest rates will also influence borrowing costs. This may be especially observed with respect to property development companies due to their greater use of short-term debt (Stevenson et al., 2007). As a result of these varied factors it would therefore be expected to see a contemporaneous positive link between interest rates and securitized real estate volatility, similar to that reported by papers such as Engle and Rangel (2008) in the context of the overall equity markets.

With respect to inflation we find that that CPI volatility is also a critical macroeconomic determinant. This finding is consistent with the results of Engle and Rangel (2008) and Azad et al. (2011). A positive association is empirically appealing for publicly listed real estate stocks. The evidence with respect to the ability of public real estate to act as an effective hedge is mixed (e.g. Liu et al., 1997; Simpson et al., 2007; Hoesli et al., 2008) and there is some recent work that has linked the relationship with the inflation illusion (Hardin et al., 2012; Hong & Lee, 2013). However, there are strong intuitive arguments as to the linkages between inflation and underlying property, especially with respect to income and there is considerable empirical evidence that the underlying assets can act as an effective hedge especially in the long-term[8]. Given that background it is reasonable to that we find that higher variability in consumer prices would increase the low-frequency volatility of public real estate.

Another result of note is the consistent positive and significant results with respect to GDP. This result can be viewed as being consistent with Fama's (1981) proxy hypothesis. As hypothesized, economic prospect and business expansion or contraction influences the demand of real estate and therefore real estate stocks. The growth of an economy is expected to enhance the occupational demand of commercial property; therefore an increase in rental and property values of a firms' underlying asset base is also to be expected. It is why in the vast econometric modelling literature in real estate GDP, or a similar proxy for economic activity, is a vital explanatory variable in explaining the behavior of occupier markets. These factors would imply that GDP volatility will be transmitted to the low-frequency volatility of the listed sector. Similar results have been documented in other financial markets (Officer, 1973,Engle and Rangel, 2008). This literature has also asserted that low-frequency volatilities in countries with superior economic growth are lower in comparison to those countries experiencing low or negative economic growth. The finding also echoes the argument of Hamilton and Lin (1996) in that the business cycle is a major driver of stock market volatility.

The coefficients with respects to money supply are of interest and worthy of further comment. Money supply volatility, in general, is positive, small in magnitude, and statistically insignificant. The results are at odds with the finding of Azad et al. (2011) in the context of the Japanese interest rate swap market. However, the results make intuitive sense in that money supply shocks are normally transmitted to financial assets through either interest rates or inflation (Azad et al., 2011). This is further confirmed by the strong correlation coefficients of money supply volatility with those for interest rates and CPI. The final variable considered is foreign exchange volatility. The results suggest the existence of a contemporaneous linear long-term volatility linkage with public real estate. Of interest these results are not in line with the general equity market findings of Engle and Rangel (2008).

We also add in control variables into the models that capture the relative economic size (log of nominal GDP in US dollars) and financial development. The second factor is proxied firstly by the log of the equity market capitalization and secondly by a ratio of stock market size relative to GDP. Specification IV reveals that GDP is positive and statistically significant, indicating that large economics have higher equity volatilities. A possible explanation in this regard is that large economics have complex structures with extensive information flows and possibly leverage. However, the market development variables are negatively related to low-frequency volatilities. This would suggest that more developed markets have advantages in terms of broader diversification leading to reduced market volatility. The results are largely consistent with wider equity markets (Engle and Rangel, 2008)[9]. Collectively, macroeconomic risk appears as an important determinant 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. inflation, interest rates, GDP and foreign exchange rates) are volatile. In addition, the findings also support the notion the low-frequency 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

The results thus far discussed have established a strong association between macroeconomic risk and low-frequency volatility. This section expands up that analysis to consider pair-wise Granger causality. An examination of the causal relationship is of interest for a variety of reasons, including enhancing the ability to make informed policy decisions. In addition, it may aid an investor's decision making and specifically their hedging decisions[10].

{Insert Table 5}

The results are presented in Table 5 and indicate that with the exception of foreign exchange volatility, all of the macroeconomic risk proxies display significant bi-lateral causality. Importantly, there is evidence available to support the view that macroeconomic risk (IRVol, GDPVol, CPIVol, FXVol) Granger-caused low-frequency volatility. The fact that there is significant bi-directional causality also reported in the majority of cases offers support to the assertions of Chen et al. (1986) and Schwert (1989) in that there is no satisfactory theory to suggest 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 the market in enhancing their policy decision making. The finding also support confirms the finding of Kallberg et al. (2002), Stevenson (2002) and numerous papers subsequently that financial market volatility contains highly useful information, in part due to its time-varying nature.

4.4: Robustness Checks

The final component of the empirical results involves a number of robustness checks. Firstly, a sub-period analysis is performed in order to assess the volatility dynamics of publicly listed firms. The full sample was split into two sub-periods. The first period extends from January 1990 to December 2001, whilst the second period covers the period January 2002 to March 2014. The first period contains, in historical terms, relatively stable market conditions. In contrast the second sub-period includes the financial crisis. 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 (sub-period 1), it can be clearly seen that the macroeconomic determinants of real estate securities, in terms of the low-frequency volatility component, were broadly similar to the findings for the entire sample period. The results confirm the preceding findings with a strong link between macroeconomic risk and the low-frequency volatility. Specifically, interest rate volatility, inflation volatility, GDP volatility and foreign exchange volatility are all strongly associated with the low-frequency volatility of public real estate firms. Consistent with the baseline results, no noteworthy link was noted with respect to money supply volatility. The results for the second sub-period, as reported in Panel B of Table 6, are also generally comparable. A strong link is documented with GDP and exchange rate volatility. Of interest we do report a positive and significant coefficient with respect to money supply. This may be due to the adoption of quantitative easing and a loose money policy in many countries following the financial crisis.

Our second robustness test is concerned with the use of fixed-effect pooled regression framework in comparison to the seemingly unrelated regression framework used by Engle and Rangel (2008). In order to ensure that the findings are not sensitive to the methodological framework adopted we re-run our analysis using a seemingly unrelated regression model, a random-effect pooled framework and a simple pooled regression. The results do however suggest that the baseline results are robust. 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[11].

Lastly, we examine whether the results are robust to an alternative measure of long-term volatility, namely *Realized Volatility*. This 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 market *i* in year *t* and $r_{i,t,d}^{2}$ is the daily squared return observed in country *i* for 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 in an equivalent specification of equation 6[12]. The results are broadly consistent with the documented findings in Table 6, the only exception being GDP volatility. In contrast to our base results the realized volatility shows little responsiveness to GDP volatility, although the anticipated sign is documented.

This may 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. The results therefore confirm that the baseline results, in general, are robust to the use of a different long-run volatility measure.

5: Conclusion and Implications for Real Estate Securities

Despite the evident importance of macroeconomic risk in both the private and listed real estate sectors there is currently a dearth of empirical research that has considered the linkages with respect to volatility. This study examines whether the time variation in public real estate volatility can be linked to macroeconomic risk through the Spline-GARCH framework of Engle and Rangel (2008). This framework allows 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 provide empirical evidence that highlights the benefits of extracting the low-frequency component of real estate volatility. Importantly, the low-frequency volatility component appears as a critical component in describing the business cycle. This finding may also improve the risk management of institutional investors through the construction of better specified value-at-risk models. Secondly, strong linkages between the low-frequency volatilities of real estate securities and macroeconomic series are identified. We find that computing quarterly volatility from the low-frequently component, rather than using aggregated measures of volatility, exhibits more clearly the impact of macroeconomic variables. The finding may aid and enhance our understanding of real estate volatility

Thirdly, a bi-directional relationship between macroeconomic risk and low-frequency volatility is also documented. The finding illustrates how macroeconomic risk serves as a good indicator for real estate investors, with potential application in the context of hedging. However, the result also highlights the importance of the financial markets, in this case specifically public real estate, in assessing macroeconomic risk.

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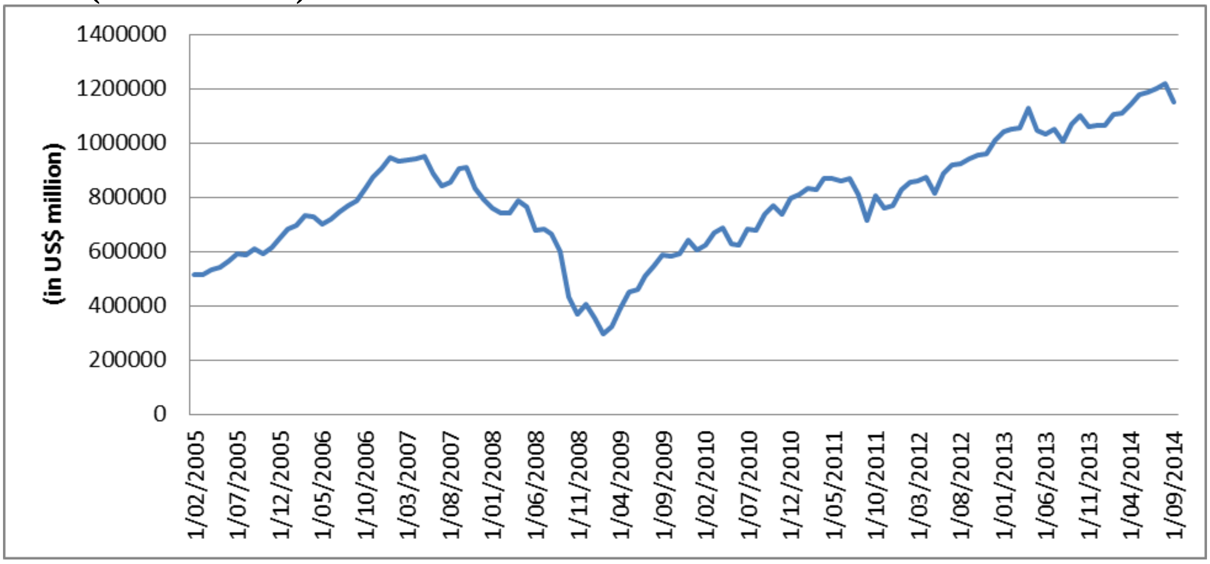
Tables and Figures

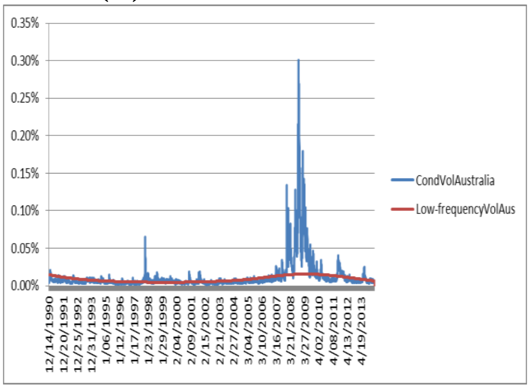
Figure 1: The Market Capitalization of the FTSE EPRA/NAREIT Global Developed Index (in US$ million)



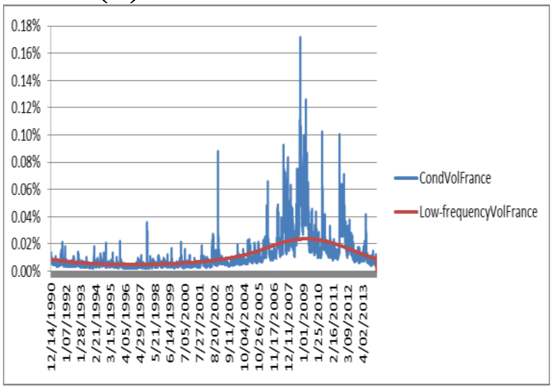
Source: DataStream (2014)

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

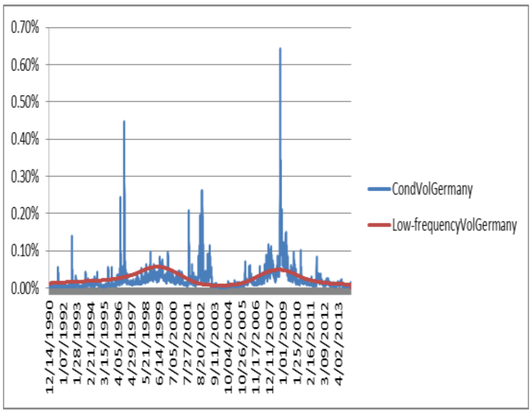
Panel 2(A): Australia



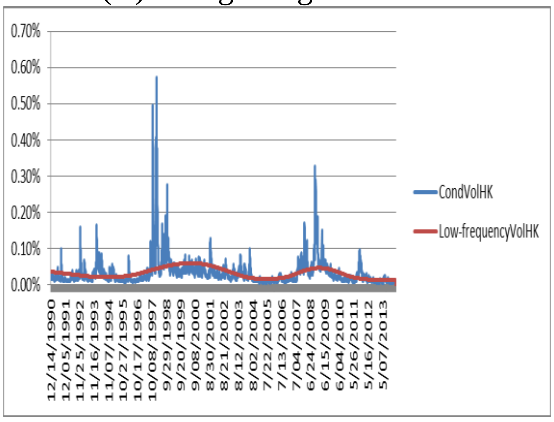
Panel 2(B): France



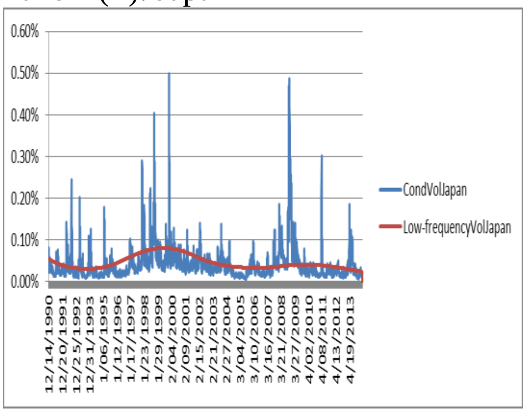
Panel 2(C): Germany



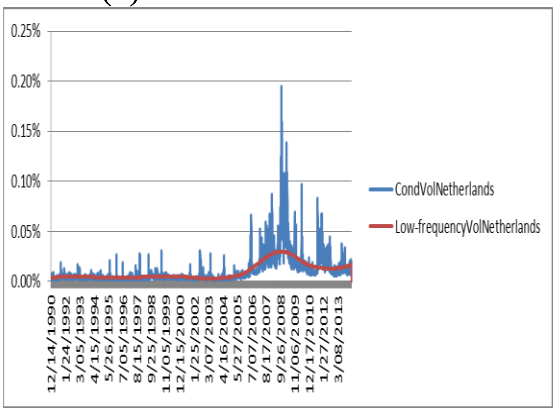
Panel 2(D): Hong Kong



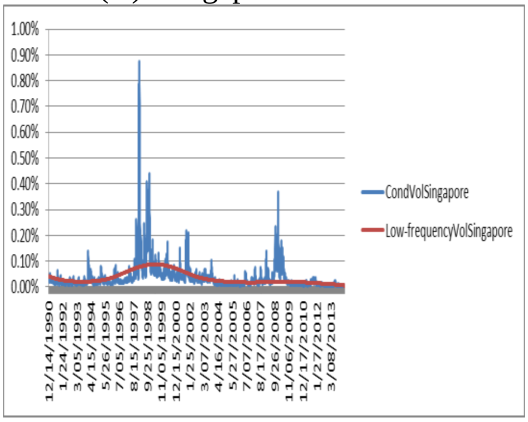
Panel 2(E): Japan



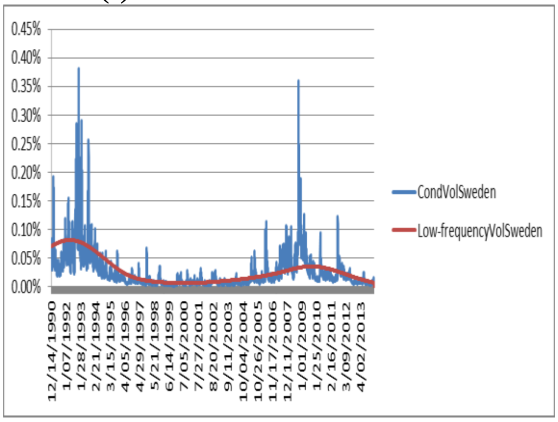
Panel 2(F): Netherlands



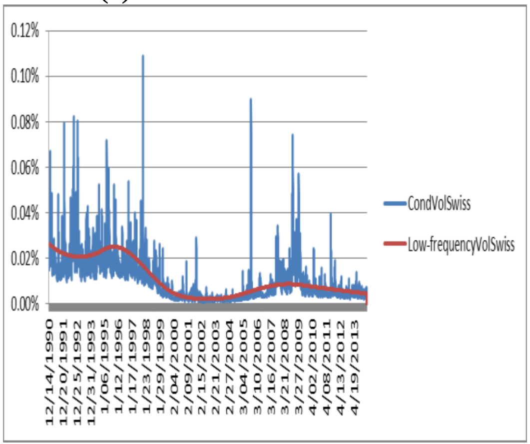
Panel 2(H): Singapore



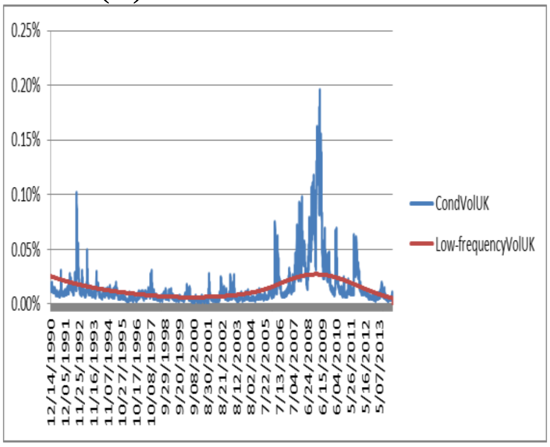
Panel 2(I): Sweden



Panel 2(J): Switzerland



Panel 2(K): UK



Panel 2(L): US

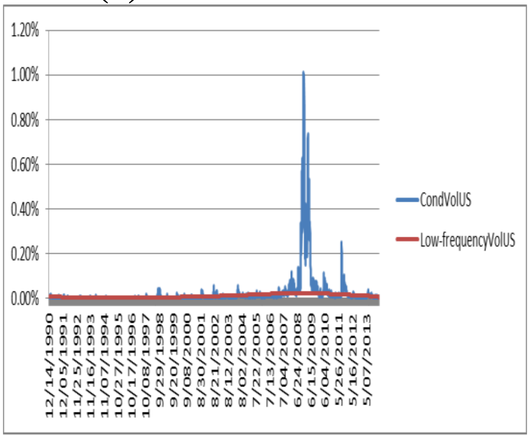


Table 1: Descriptive Summary

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: Table 1 reports descriptive summary statistics for the 11 publicly traded real estate markets (Australia, France, Germany, Hong Kong, Japan, Netherlands, Singapore, Sweden, Switzerland, the UK and US). The sample consists of 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 the estimated coefficients from the Spline-GARCH(1,1) model with Gaussian innovations and a traditional GARCH(1,1) model. The Spline-GARCH(1,1) model specification is described 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 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 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: Table 4 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: Table 5 reports the pair-wise Granger causality test results. The low-frequency volatility is estimated via a Spline-GARCH(1,1) model with a Gaussian innovation. The Spline-GARCH(1,1) model specification is shown in Equations (3) through (6). The 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 period 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 period 1990:Q1 through 2001:Q4, whereas Period 2 covers 2002:Q1 to 2014:Q1. T-values are presented in parentheses. White cross-section robust standard errors are utilized. *, ** denotes significance at the 5% and 1% level respectively.

Endnotes

[1] Comparable findings are reported by Quan and Titman (1999) based on empirical evidence from 17 international real estate markets.

[2] Liow et al. (2003) analyse the Singaporean market, finding that the pricing of risk is subject to market conditions.

[3] Supporting evidence is also presented by Adrian and Rosenberg (2008).

[4] C-GARCH models are also employed by Karoglou et al. (2013) and Lee and Reed (2014) in the context of housing markets.

[5] 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.

[6] 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.

[7] See also Lamoureux and Lastrapes (1990).

[8] See for example, Quan and Quigley (1991), Hoesli et al. (1997), Stevenson (2000), Glascock et al. (2002), Hoesli et al. (2008), and Amenc et al. (2009).

[9] To enhance the specificity of the evidence, we also perform the analysis with aggregated volatility using conditional volatility estimates obtained from conventional GARCH (1,1,) models. The results are available from the authors upon on request. They do however support the rationale behind adopting the Spline-GARCH specification. In contrast to the findings reported in the paper with find very little evidence of robust links between macroeconomic risk and aggregate volatility. These conflicting results therefore provide further support for the view that low-frequency volatility is driven by slowly-changing common macroeconomic factors.

[10] 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 market risk.

[11] The detailed results for the alternative econometric frameworks are available from the authors upon request.

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