Are Securitised Real Estate Markets Efficient?
New International Evidence Based on an Improved Automatic Portmanteau Test

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Abstract

We re-examine the efficiency of real estate markets based on the Escanciano-Lobato (2009) autocorrelation test which we improved by means of wild bootstrapping. Through Monte Carlo simulation, we find that the wild bootstrap based autocorrelation test has very good performance even in small samples. We apply the improved test to examine the efficiency of 14 international securitized real estate markets – Australia, Canada, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Singapore, Sweden, Switzerland, United Kingdom and the United States. Our results show that only six of these markets - Australia, Hong Kong, Italy, Japan, Sweden and the United States are efficient while the rest are inefficient. We also find that the degree of efficiency or inefficiency of each of these markets varies considerably across time. These findings indicate that real estate markets are relatively less efficient as compared to stock and bond markets in general and may also offer an explanation as to why existing studies on real estate market efficiency have mixed results.

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1. Introduction

This paper re-examines the issue of efficiency of the real estate markets based on the use of a new methodology – the automatic portmanteau test of Escanciano and Lobato (2009; EL, hereafter) for no autocorrelation, which we improve through wild bootstrapping. In doing so, this paper makes two contributions to the literature – first, to the financial economics literature and additionally, to the econometrics literature.

First, in relation to the economics and finance literature, we contribute by providing new and more robust evidence relating to market efficiency in the context of the real estate market. The issue of market efficiency is one that is very important and one that continues to be debated in the literature since it is at the core of financial economics theories and models. It has also very important practical implications. If markets are found to be efficient, then prices are not predictable and it is not possible to gain abnormal returns (Reilly and Brown, (2009)). If markets are efficient, it also means that resources are efficiently allocated since prices reflect rational and fundamental factors.

Ever since the issue of market efficiency was brought to the forefront by the work of Fama in the 1970 s, a voluminous amount of studies has been conducted on this issue in different financial and economic markets ever since. Overall, the evidence show that markets, particularly developed ones, are efficient, although some pockets of inefficiencies exist, especially in less developed markets (Reilly and Brown (2009)). The scale of research on this issue in the real estate markets, however, is still much less as compared to those in other markets (Schindler, Rottke and Füss (2010) and Schindler (2011)). Furthermore, the research on efficiency in this market has yielded mixed results depending on the specific real estate markets and time period covered and methodology used (Schindler (2011); Schindler et al (2010) and Serrano and Hoesli (2009)). Thus, there is a need for further research on market efficiency in the real estate market. Our paper therefore addresses this need in the literature.

It is well-accepted that real estate is very important as it can affect very significantly the performance of the economy and financial markets. The recent global financial crisis is a clear testimony to this. The crisis started as a real estate crisis but it then developed into a financial market and economic crisis (Hellwig (2008) and Greenlaw, Hatzius, Kashyap and Shin (2008)). Real estate is an important financial asset of households, particularly in developed countries but even in less developed economies (The Economist, March 5th-11th 2011 issue). It is one that differs from other economic commodities or investment products as it serves both as an investment and consumption good. Unlike other investments such as stocks, it is also lumpy and hence, is more illiquid. Investors are also not able to short sell it. There is now, however, the existence of securitised real estate markets which in a sense overcome some of the limitations associated with real estate. The behaviour of prices of these securitised real estate markets would still, of course, factor in the basic properties of real estate. Hence, prices in these markets would still reflect the nature of real estate to a certain extent. Given these unique properties of real estate, the real estate markets provide a good new laboratory for the testing of market efficiency.

Autocorrelation test is highly utilised as a test of market efficiency. If prices are random and exhibit no autocorrelation, then this is taken as an indication that the market is efficient (Fama (1970)). However, it is well-known in the econometric literature that standard autocorrelation tests could suffer from a number of problems due to, among others, heteroskedasticity and the need of (autocorrelation) lag selection (which can be quite arbitrary). Thus, as a result of these limitations, it is possible that the results of autocorrelation tests may show that markets are efficient (inefficient) when in fact they are inefficient (efficient). This situation could have been one of the major sources of the variation in evidence produced by existing studies on the efficiency of real estate markets as it is well-recognised that many economic and financial time series exhibit conditional heteroskedasticity or stochastic volatility (see Chunchachinda Dandapani, Hamid, and Prakash (1997); Liu, Longstaff and Pan (2003); Poon, Rockinger and Tawn (2004), among others).

The second contribution of this paper is to the econometric literature. As mentioned earlier, this paper examines the issue of market efficiency in real estate markets through the application of a new test - the EL (2009) automatic portmanteau test for no autocorrelation, which we improve through wild bootstrapping. As discussed in the methodology section, the EL autocorrelation test overcomes a number of limitations associated with standard autocorrelation tests, such as heteroskedasticity and the use of automatic (data-driven) lag selection. However, this test is subject to non-trivial over-rejection in small sample size applications under the null hypothesis of no autocorrelation (market efficiency). We show by Monte Carlo simulation evidence in this paper that the small sample properties of the test improve with wild bootstrapping. In particular, the wild bootstrap-based test has desirable size properties and shows a competitive power. The wild bootstrap is a re-sampling method that approximates the sampling distribution of a (test) statistic and has been found useful in econometrics – such as autoregressions with heteroskedasticity in Goncalves and Kilian (2004), multiple variance ratio test in Kim (2006), spectral tests for the martigale difference hypothesis in Escanciano and Velasco (2006) and unit root tests in Cavaliere and Taylor (2008). In theory, as shown in Liu (1988) and Davidson and Flachaire (2001), the wild bootstrap can yield asymptotic refinements in the distributions of pivotal statistics. Also, small-sample simulations in many studies such as Kim (2006) and Cavaliere and Taylor (2008) show that wild bootstrap based tests are accurate in size and with good power properties.

In this paper, we therefore address the gap that we have identified in the real estate markets efficiency literature through the use of an improved portmanteau test that overcomes the limitations associated with standard autocorrelation tests. We improve the small sample properties of the EL (2009) autocorrelation test by means of wild bootstrapping which we then utilise in our analysis of 14 securitised real estate markets - Australia, Canada, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Singapore, Sweden, Switzerland, United Kingdom and the United States. As far as we know, our paper is the first to apply this improved autocorrelation test in the study of market efficiency. Furthermore, in addition to the use of a more reliable test, we also utilised a more updated and longer data set as compared to recent studies on this issue such as those of Schindler, et al (2010) and Schindler (2011). Thus, the results from this paper provide new and more robust evidence on efficiency in real estate markets.

As an overview, first, our results show that by means of wild bootrstrapping, we were able to improve the small sample size properties of the EL (2009) autocorrelation test. When we applied this improved test to the analysis of the efficiency of 14 securitised real estate markets, we found that only six of these markets are efficient - Australia, Hong Kong, Italy, Japan, Sweden and the United States and the others are not. In line with Schindler et al (2011), our findings show that real estate markets seem to be less efficient as compared to stock and bond markets in general. We also find that the degree of efficiency (inefficiency) of each of the markets varies across time which may explain why existing studies on real estate market efficiency have mixed results.

The rest of the paper is organised as follows. Section 2 discusses the methodology while Section 3 presents the empirical results. Section 4 concludes the study.

2. Methodology

In this section, we discuss the EL (2009) test – its strengths as well as limitations and how we improve its small size properties through wild bootstrapping. We present the results of the Monte Carlo simulation which demonstrate the improvement. We then apply this improved test in the analysis of the efficiency of real estate markets.

Let us explore the shortcomings of standard autocorrelation tests. Take for example, the Box-Peirce Q_p test (cf. Box and Peirce (1970)), defined as $Q_p = n\sum_{j=1}^{p}\hat{\rho}_j^2$, which examines serial correlations ($\hat{\rho}_j$) up to p lags. In practice, performing the Q_p test requires the choice of a fixed lag number (p). On the one hand, choosing a p too small might cause inconsistency as the test may fail to detect serial correlation at lags higher than p; on the other hand, choosing a p too large could cost the power of the test as many unnecessary lags are brought in. Accordingly, the outcomes of the Box-Peirce test may possibly contradict to each other when different lags are considered.[1] Aside from the lag choice issue, tests for market efficiency may be subject to substantial size-distortion (usually, over-sized) when applied to series that are actually serially uncorrelated but with some kind of non-linear dependence, such as conditional heteroskedasticity.

Recently, the two aforementioned issues are simultaneously dealt in EL (2009). First, instead of using the standard measure of autocorrelation ($\hat{\rho}_j$) a hetroskedasticity-robust estimate of autocorrelation due to Lobato, et al (2001) is

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[1] Another commonly used test for market efficiency: the variance ratio test (cf. Cochrane (1988) and Lo and MacKinlay (1989)), also bears the same problem as it requires the choice of a fixed number – the holding period.

used in the construction of the test statistic. Second, an automatic (data-driven) lag selection is implemented to avoid the issue concerning an arbitrary choice of lag. According to the simulation results in EL (2009), the new automatic Box-Peirce test works well in terms of size and power when applied to series with relative large sample size (say, more than 1000). The test, however, tends to be over-sized if the sample size is only moderate or small (say, less than 300). This raises the question whether the critical values derived from the asymptotic distribution is valid for the cases with a smaller sample size.

<u>The EL (2009) Test</u>

Let Z_t be the asset price for t=1,...,n and $Y_t = \ln(Z_t) - \ln(Z_{t-1})$ be its log return. Define the j^th sample autocorrelation $\hat{\rho}_j = \hat{\gamma}_j / \hat{\gamma}_0$ where $\hat{\gamma}_j = (n-j)^{-1} \sum_{t=1+j}^{n} (Y_t - \bar{Y})(Y_{t-j} - \bar{Y})$ and $\bar{Y} = n^{-1} \sum_{t=1}^{n} Y_t$. EL (2009) suggest an automatic (data-driven) Box-Pierce Q test, defined as

$$AQ_{\tilde{p}} = n \sum_{j=1}^{p^*} \tilde{\rho}_j^2 , \qquad (1)$$

where

$$\tilde{\rho}_j = \frac{\hat{\gamma}_j}{\sqrt{\hat{\tau}_j}} \text{ where } \hat{\tau}_j = \frac{1}{(n-j)} \sum_{t=1+j}^{n} (Y_t - \bar{Y})^2 (Y_{t-j} - \bar{Y})^2 . \qquad (2)$$

As shown in Lobato et al (2001), $\tilde{\rho}_j$ is robust to heteroskedasticity. The lag parameter in (1) is selected as $p^* = \min\{m : 1 \le m \le p_n ; L_m \ge L_h, h = 1,2,\ldots,d\}$ where $L_p = Q_p - \pi(p,n,q)$ and $\pi(p,n,q) = p\ln(n)$ if $\max_{1 \le j \le d} \sqrt{n}|\tilde{\rho}_j| \le \sqrt{q\ln(n)}$ and

$\pi(p,n,q) = 2p$ otherwise. Here, d is a large fixed upper bound and q is a fixed number set as 2.4.[2] Note that $\pi(p,n,q)$ is a penalty term that is increasing in the number of autocorrelations (p) and the penalty function is based on either the Akaike Information Criterion (AIC) ($2p$) or the Bayesian Information Criterion (BIC) ($p\ln(n)$). To choose which criterion to use, EL (2009) develop a data-driven rule that depends on whether "$\max_{1\leq j\leq d}\sqrt{n}|\tilde{\rho}_j| \leq \sqrt{q\ln(n)}$" holds true. Unlike the usual Q_p test, the data-driven test is completely insensitive to the choice of d (the upper bound of lags). Under the null hypothesis of no serial correlation (i.e., market efficiency),

$$AQ_{\tilde{p}} \xrightarrow{d} \chi^2(1) \text{ as } n \to \infty \qquad (3)$$

and the test rejects the null hypothesis when the value of $AQ_{\tilde{p}}$ is large.

According to the simulation results in EL (2009), $AQ_{\tilde{p}}$ performs well when the sample is large but can be over-sized when the sample is small. This is because that the limiting null distribution ($\chi^2(1)$) does not approximate the test statistic's distribution well if the sample size is not large enough and results in over-rejection. In Table 1, we present the simulated distribution of $AQ_{\tilde{p}}$ under the null hypothesis with n=75, 150, 300, 1000, 2500, 5000 (assuming the series are iid N(0,1)) and $\chi^2(1)$. Obviously, $\chi^2(1)$ does not approximate well when n is smaller than 1000. Taking the 5% significance level (α=0.05) for example, the $\chi^2(1)$ critical value is 3.841 while for n=1000, 300 and 150 they are 4.200, 5.135 and 5.886, respectively. Comparing

[2] According to Escanciano and Lobato (2009), that q=2.4 is motivated from an extensive simulation study. Small q favors the Akaike Information Criterion, while a large q leads to the Bayesian Information Criterion. Moderate values, such as 2.4, give a switching effect that combines the advantages of the two model selection criteria.

to $\chi^2(1)$, the small sample distribution of AQ under the null is much right skewed and this could cause non-trivial over-rejection (Type I error).

Wild bootstrapping the EL (2009) Test

In this paper, we propose to approximate the small-sample distribution via the wild bootstrap.[3] The wild bootstrap based $AQ_{\tilde{p}}$ test is conducted in steps as follows.

(1) Form a bootstrap sample of n observations $Y_t^* = \eta_t Y_t$ (t=1,…,n) where η_t is a random sequence with $E(\eta_t) = 0$ and $E(\eta_t^2) = 1$.

(2) Compute $AQ_{\tilde{p}}$ based on $\{Y_t^*\}_{t=1}^n$ and label this new statistic $AQ_{\tilde{p}}^{wb}$.

(3) Repeat (1) and (2) sufficiently many times (say, m) to form a wild-bootstrap distribution of the $AQ_{\tilde{p}}$ statistic: $\{AQ_{\tilde{p}}^{wb}(j)\}_{j=1}^m$.

The p-value of the test can be obtained as the fraction of $\{AQ_{\tilde{p}}^{wb}(j)\}_{j=1}^m$ larger than $AQ_{\tilde{p}}$. Conditional on Y_t, Y_t^* is serially uncorrelated and therefore $AQ_{\tilde{p}}^{wb}$ should have the same asymptotic distribution as $AQ_{\tilde{p}}$. Moreover, since Y_t^* is serially uncorrelated no matter whether or not Y_t is serially correlated the wild bootstrapping distribution is able to approximate the sampling distribution under null hypothesis and this ensures that the bootstrapping test has power to reject the

[3] Kim (2006) suggests using the wild bootstrap for the multiple variance ratio test.

null hypothesis when it is not true. For the random sequence η_t, we consider two cases. The first case is the widely used two-point distribution suggested in Liu (1988) and Mammen (1993):

$$\eta_t = \begin{cases} \frac{1+\sqrt{5}}{2} & \textit{with probability } p = \frac{\sqrt{5}-1}{2\sqrt{5}} \\ \frac{1-\sqrt{5}}{2} & \textit{with probability } p = 1-p, \end{cases} \tag{4}$$

which meets the necessary requirements for wild bootstrapping (i.e. $E(\eta_t)=0$ and $E(\eta_t^2)=1$) and on top of this the third moment of η_t is equal to one ($E(\eta_t^3)=1$). We shall call the first approach WB[1] hereafter. The second case is the standard normal distribution (labelled as WB[2], hereafter) which meets $E(\eta_t)=0$ and $E(\eta_t^2)=1$ only (because the third moment of the standard normal distribution is zero). Hence, in WB[1] the first three moments of the bootstrap series coincide with the original series while in WB[2] only with the first two moments. See further discussions on the choice of η_t in Davidson, Monticini and Peel (2007).

Monte Carlo Simulation Results

The simulation design basically follows that of EL(2009). Specifically, we consider the following models under the null hypothesis: (i) a sequence of iid N(0,1) or Student-t(5) (ii) a GARCH(1,1) model $y_t = z_t * \sigma_t$ where z_t is a sequence of iid N(0,1) or Student-t(5) and $\sigma_t^2 = 0.001 + 0.05 y_{t-1}^2 + 0.90\sigma_{t-1}^2$ (iii) an EGARCH(1,1) model $y_t = z_t * \sigma_t$ where z_t is a sequence of iid N(0,1) or Student-t(5) and $\log(\sigma_t^2) = 0.001 + 0.5|z_{t-1}| - 0.2 z_{t-1} + 0.95\log(\sigma_{t-1}^2)$. Simulations are performed in

GAUSS with different sample sizes n=75, 150, 300 and to alleviate the initial condition effect the first 500 observations in each simulated path are dropped. The number of bootstrap iterations is set to 500 with 2,500 Monte Carlo trials. We set d=25, 50 and 75 for n=75, 150 and 300, respectively.[4] We report the result for the 5% nominal level in Table 2 where AQ stands for the test based on the asymptotic critical value and WB[1] and WB[2] are the tests based on the two wild-bootstrapping strategies given in the previous section.

Table 2 shows that the AQ test over-rejects the null hypothesis over all models considered and the scale of over-rejection lessens as the sample size increases. The size property is much improved when the wild bootstrap strategies are considered – the bootstrap with the two-point distribution in (4) (i.e. WB[1]) works particularly well in controlling size. Taking n=150 and with iid N(0,1) sequence for example, the rejection rate of AQ is 0.098 while they are 0.059 and 0.070 for WB[1] and WB[2], respectively.

Next, we examine the behaviour under the alternative. We consider an autoregressive process of order 1, AR(1), $y_t = \rho y_{t-1} + \mu_t$ where μ_t is generated by models as those under the null hypothesis. We consider ρ =0.1 and 0.2 and report the size-corrected power in Table 3.[5] Table 3 shows that the two bootstrap tests work well – WB[1] has very similar power as AQ while WB[2] appears to be somewhat more powerful than the others. Taking n=150 and with AR(1)-N(0,1)

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[4] Different values of d are considered and the results are insensitive to the values of d.

[5] Size-corrected power is obtained with critical values that make the rejection rate is actually 5% when the series is not autocorrelated (i.e. ρ =0).

sequence with ρ =0.2 for example, the (size-corrected) rejection rate of AQ is 0.472 while they are 0.478 and 0.482 for WB[1] and WB[2], respectively.

3. Empirical Analysis of Securitised Real Estate Markets

We apply the proposed wild bootstrap-based EL (2009) automatic portmanteau test for no autocorrelation to analyse the efficiency of 14 securitized real estate markets: Australia, Canada, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Singapore, Sweden, Switzerland, United Kingdom and United States. The results of existing studies on the issue of market efficiency in the real estate markets have yielded mixed results (Schindler et al, 2011 and Schindler et al, 2010).

Data

For each of the 14 securitised markets, we collect monthly indices (in local currency) from General Property Research (GPR) from 01/1984 to 01/2011 containing 325 monthly returns.[6] . Among the available real estate, the GPR index is considered as the most appropriate to examine the performance of the real estate market as it has the largest coverage in terms of market capitalisation (Serrano and Hoesli, 2009). The GPR index is a value-weighted index used to represent monthly price changes of the real estate stocks in the world. To be qualified for selection, a company must be a company of market capitalization over $50 million that derives

[6] Specifically, the data are the GPR General Index (Country Index History) obtained from the following link https://www.globalpropertyresearch.com/indices2.aspx?id=216.

at least 75% of its operational turnover from investment activities (property investment companies) or from investment and development activities combined (hybrid property companies). Selected stocks are assigned to six property sectors and they are office, residential, retail, industrial, hotel and diversified. The assignment is based on the principle that a company derives at least 60% of its operational turnover from a specific property sector. (See Serrano and Hoesli (2009) for a more detailed description of the index).

Empirical Results

The empirical results (p-values) are reported in Table 4. The null hypothesis of no serial correlation is rejected at the 10% significance level for eight indices (Canada, France, Germany, Netherlands, Norway, Singapore, Switzerland, United Kingdom) unanimously with all three tests, implying that these markets might not be efficient. On the other hand, there are five indices (Australia, Hong Kong, Japan, Sweden and United States) that the efficiency hypothesis cannot be rejected with any tests. Interestingly, in the case of Italy, the efficiency hypothesis is rejected by AQ but not by the two wild-bootstrap tests. Since the wild-bootstrapping approach is less over-sized, it is likely that the Italian real estate index is actually efficient.

We also run rolling tests with an eight-year window (each with 96 monthly returns) moving up by each year with a total 20 rolling results for the fourteen securitised real estate market. We report the testing result for US, UK and Australia markets in Table 5 and plot the result for all fourteen markets in Figure 1. From

Table 5, we can see that, although the three tests generally agree with each others, there are several sub-periods that AQ rejects the efficiency hypothesis (at either 5% or 10% significance level) but the wild bootstrap tests do not. Among the twenty subsamples, there are three sub-periods witness such inconsistency in the US and five sub-periods the UK and Australia, respectively. For example, the US real estate index during 1989-1996, the UK during 1997-2004, and the Australia during 1998-2005 are all rejected by AQ at the 10% significance level but none of them is rejected by the wild-bootstrap tests. Since AQ tends to over-reject with small samples, the wild-bootstrapping results (the one with two-point distribution (WB[1]) in particular) may be more reliable in these cases.

From Figure 1, we can see that the three tests generally agree with each others and, as expected, the AQ test tends to come with lower p-values than the wild-bootstrap based tests and sometimes this may lead to over-rejection. Interestingly, for all markets, our rolling result clearly shows that the degree of (in)efficiency can vary significantly over time and none of the markets is efficient (or inefficient) throughout all sub-periods. For example, France appears to be inefficient (i.e. with the p-value lower than 10%) more often than other markets: since 1988, the market never moves out from inefficiency. In contrast, the US market is inefficient only in a few early sub-periods. Also, we find that there is a tendency of moving from efficiency toward inefficiency in many markets (Australia, Canada, France, Germany, Hong Kong, Japan, Singapore, UK) since 2001. On the contrary, Sweden and Norway seem to become more efficient since 2001. The efficiency (inefficiency) of each market is therefore time varying. This is probably one of the major reasons why previous studies on market efficiency in the real estate markets yielded mixed results as these studies cover different time periods.

In order to provide further evidence as regards the robustness of our results and in particular, to allay concerns that our results could simply be a reflection of the efficiency of the stock market since our analysis are based on real estate equities data, we conducted the same tests based on data that is more focused on the real estate market – the GPR Real Estate Investment Trust (REIT)[7]. As can be seen in the Tables A1 and A2 in the Appendix of this paper, very similar results are obtained as regards which markets are efficient and inefficient although the level of efficiency for the markets which are efficient is higher as indicated by the bigger p-values. As the results from the REIT-based analysis are very similar to the previous results, we no longer discuss the new results in detail.

4. Conclusion

In this paper, we re-examine the issue of market efficiency using a wild-bootstrapping version of the EL (2009) automatic portmanteau test in the context of

[7] For consistency, we also use the GPR as the source of data for REIT. However, we were able to get complete data for only 11 out of the 14 markets and the time period of data availability is shorter and varies among the markets (see first column of Table A1), the longest being 01/1990 to 01/2011 (as against 01/1984 to 01/2011 for all markets in the case of the previous analyses). Based on this REIT data, we conduct the same tests for the 11 markets. In order to allow for comparison, we also perform the tests based on equities (GPR General Indices) data for each market using the same time period. The empirical results are presented in Table A1. These results are in line with the previous findings. Table A2 gives the rolling results for US and Australia based on the GPR REIT Indices. Again, these results are similar to those presented in Table 5.

14 different securitised real estate markets - Australia, Canada, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Singapore, Sweden, Switzerland, the United Kingdom and the United States. It is found that, via simulation, the wild bootstrap-based EL (2009) test has desirable size properties and shows a competitive power. Previous studies on this issue have yielded mixed results and to our knowledge, this paper is the first to use this improved new test. Thus, our paper provides more robust evidence on the issue of market efficiency in the real estate market which provides a contribution to the financial economics literature and additionally, through its improvement of an existing new method, also contributes to the econometrics literature.

Our results show that only six - Australia, Hong Kong, Italy, Japan, Sweden and the United States, of the 14 markets turned out to be efficient with the other eight being shown not to be efficient. These six markets are known to be the most liquid[8], globalised and with better standards of regulation that ensure a more transparent functioning of the market, when compared to the other eight markets (Serrano and Hoesli, 2009; Bardhan and Kroll, 2007). Hence, it appears that real estate markets, in line with Schindler et al (2011), are relatively less efficient as compared to stock and bond markets in general which could be a reflection of the nature of real estate. This implies that there are opportunities for international investors in the securitised

[8] The US has the largest securitised property market (known as Real Estate Investment Trusts or REITs), although, proportionately, the US securitised sector is smaller than some of the securitised property markets of Asia or Europe (Wilson and Zurbruegg, 2003). About 55% of all institutional grade real estate in Australia is listed, compared with 18% for the US, 17% for the the United Kingdom and 10% for Japan, (Steinert and Crowe , 2001).

real estate to earn excess returns in the inefficient markets using appropriate trading strategies. However, this could also mean that the market price mechanism in the inefficient real estate markets may not be able to allocate resources in the most productive way. Given the importance of the real estate sector to the economy, this provides a great challenge for policy makers.

Our results also show that the efficiency (inefficiency) of each market is time varying which may explain why previous studies have mixed results as they are based on different time periods. Again, this may be a reflection of the regulatory changes which have occurred in the real estate markets primarily after financial crises periods for both developed and less developed markets, although these reforms were more successfully implemented in the developed markets. Financial crises often had significant links with the real estate sector and hence, financial sector reforms arising out of these crises also spilled over into the real estate sector (IMF, 2001; Krinsman, 2007; Dell'Ariccia, and Laeven L., 2008). The recent global financial crises spurred a series of regulatory reforms worldwide which cut across financial as well as real estate markets. The Asian crisis in 1998 also led to significant structural changes in the financial markets of Asia which also involved the real estate sector.

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Table 1: Simulated AQ distribution versus $\chi^2(1)$

Sample Size	α=50%	α=25%	α=10%	α=5%	α=2.5%	α=1%
n=75	0.556	1.744	4.343	7.307	22.06	52.25
n=150	0.527	1.581	3.494	5.886	8.218	15.50
n=300	0.499	1.468	3.261	5.135	7.607	12.90
n=1000	0.469	1.362	2.882	4.200	5.928	8.826
n=2500	0.474	1.351	2.760	4.001	5.516	7.892
n=5000	0.462	1.330	2.738	3.913	5.208	7.375
Chi-Square (df=1)	0.469	1.323	2.706	3.841	5.024	6.635

Note: α stands for the significance level.

Table 2: Size at 5% significance level

	n=75			n=150			n=300		
Distribution	AQ	WB[1]	WB[2]	AQ	WB[1]	WB[2]	AQ	WB[1]	WB[2]
N(0,1)	0.115	0.064	0.080	0.098	0.059	0.070	0.080	0.057	0.068
t(5)	0.097	0.061	0.074	0.087	0.061	0.071	0.078	0.056	0.069
GARCH(1,1)-N(0,1)	0.120	0.069	0.084	0.101	0.066	0.085	0.081	0.061	0.068
GARCH(1,1)-t(5)	0.118	0.068	0.087	0.095	0.063	0.072	0.077	0.059	0.070
EGARCH-N(0,1)	0.102	0.061	0.079	0.088	0.060	0.076	0.072	0.058	0.071
EGARCH-t(5)	0.100	0.067	0.086	0.077	0.057	0.071	0.067	0.055	0.064

Note: AQ=The AQ test result with $\chi^2(1)$, WB[1] =The AQ test result with the two-point wild bootstrap, WB[2]=The AQ test result with the N(0,1) wild bootstrap.

Table 3: Power (size-adjusted) at 5% significance level

		n=75			n=150			n=300		
AR(1)	Distribution	AQ	WB[1]	WB[2]	AQ	WB[1]	WB[2]	AQ	WB[1]	WB[2]
0.1	N(0,1)	0.075	0.076	0.083	0.120	0.127	0.131	0.286	0.302	0.317
	t(5)	0.067	0.068	0.068	0.143	0.141	0.139	0.319	0.311	0.331
	GARCH(1,1)-N(0,1)	0.068	0.070	0.075	0.108	0.117	0.117	0.273	0.270	0.285
	GARCH(1,1)-t(5)	0.067	0.068	0.070	0.102	0.111	0.108	0.272	0.268	0.274
	EGARCH(1,1)-N(0,1)	0.084	0.079	0.081	0.086	0.083	0.094	0.118	0.127	0.135
	EGARCH(1,1)-t(5)	0.079	0.072	0.075	0.093	0.089	0.102	0.120	0.134	0.144
0.2	N(0,1)	0.165	0.163	0.171	0.472	0.478	0.482	0.860	0.870	0.881
	t(5)	0.177	0.170	0.177	0.478	0.482	0.488	0.879	0.877	0.881
	GARCH(1,1)-N(0,1)	0.155	0.159	0.170	0.419	0.422	0.424	0.831	0.824	0.835
	GARCH(1,1)-t(5)	0.153	0.151	0.164	0.416	0.415	0.423	0.848	0.836	0.842
	EGARCH(1,1)-N(0,1)	0.116	0.115	0.122	0.228	0.225	0.234	0.451	0.446	0.467
	EGARCH(1,1)-t(5)	0.110	0.108	0.112	0.210	0.225	0.224	0.439	0.440	0.456

Note: AQ=The AQ test result with $\chi^2(1)$, WB[1] =The AQ test result with the two-point wild bootstrap, WB[2]=The AQ test result with the N(0,1) wild bootstrap.

Table 4: Empirical result for monthly returns in 14 GPR Country Indices (p-values), 01/1984-01/2011

	AQ	WB[1]	WB[2]
Australia	0.112	0.118	0.104
Canada	**0.002**	**0.005**	**0.002**
France	**0.002**	**0.007**	**0.005**
Germany	**0.000**	**0.000**	**0.001**
Hong Kong	0.393	0.441	0.435
Italy	**0.093**	0.102	0.102
Japan	0.996	0.997	0.997
Netherlands	**0.016**	**0.021**	**0.015**
Norway	**0.003**	**0.009**	**0.006**
Singapore	**0.010**	**0.014**	**0.016**
Sweden	0.241	0.249	0.272
Switzerland	**0.001**	**0.002**	**0.002**
United Kingdom	**0.016**	**0.025**	**0.022**
United States	0.214	0.205	0.250

Note: AQ=The AQ test result with $\chi^2(1)$, WB[1] =The AQ test result with the two-point wild bootstrap, WB[2]=The AQ test result with the N(0,1) wild bootstrap. p-values less than 10% are in bold.

Table 5: Rolling results for monthly returns in US, UK and Australia indices (p-values)

	US			UK			Australia		
Subsample Period	AQ	WB[1]	WB[2]	AQ	WB[1]	WB[2]	AQ	WB[1]	WB[2]
01/1984-12/1991	**0.028**	**0.057**	**0.056**	0.614	0.654	0.668	0.857	0.867	0.871
01/1985-12/1992	**0.029**	**0.060**	**0.038**	0.205	0.248	0.231	0.779	0.785	0.804
01/1986-12/1993	**0.028**	**0.044**	**0.042**	0.111	0.132	0.132	0.689	0.686	0.767
01/1987-12/1994	**0.025**	**0.048**	**0.037**	**0.088**	0.111	**0.097**	0.516	0.546	0.566
01/1988-12/1995	0.125	0.162	0.132	**0.000**	**0.009**	**0.009**	0.919	0.938	0.940
01/1989-12/1996	**0.077**	0.120	**0.091**	**0.087**	0.136	0.112	0.676	0.720	0.718
01/1990-12/1997	0.170	0.214	0.185	**0.000**	**0.010**	**0.006**	**0.057**	**0.088**	**0.086**
01/1991-12/1998	0.593	0.659	0.631	0.112	0.167	0.150	**0.019**	**0.041**	**0.027**
01/1992-12/1999	0.680	0.713	0.721	0.121	0.144	0.164	**0.046**	**0.089**	**0.059**
01/1993-12/2000	0.855	0.864	0.877	0.358	0.415	0.407	**0.057**	**0.098**	**0.077**
01/1994-12/2001	0.973	0.983	0.976	0.971	0.987	0.973	**0.020**	**0.054**	**0.043**
01/1995-12/2002	0.719	0.765	0.771	0.497	0.536	0.555	**0.016**	**0.056**	**0.024**
01/1996-12/2003	0.430	0.461	0.493	0.140	0.187	0.200	**0.014**	**0.046**	**0.031**
01/1997-12/2004	0.802	0.834	0.837	**0.075**	0.115	0.110	**0.014**	**0.042**	**0.030**
01/1998-12/2005	0.677	0.737	0.710	**0.052**	**0.091**	**0.084**	**0.087**	0.144	0.105
01/1999-12/2006	0.410	0.487	0.463	0.136	0.206	0.173	0.777	0.801	0.787
01/2000-12/2007	0.813	0.835	0.855	0.118	0.165	0.138	0.734	0.756	0.769
01/2001-12/2008	0.532	0.604	0.675	**0.044**	**0.060**	**0.052**	**0.040**	**0.055**	**0.045**
01/2002-12/2009	0.418	0.461	0.538	**0.024**	**0.027**	**0.023**	**0.009**	**0.023**	**0.014**
01/2003-12/2010	0.451	0.529	0.568	**0.047**	**0.048**	**0.052**	**0.011**	**0.028**	**0.023**

Note: AQ=The AQ test result with $\chi^2(1)$, WB[1] =The AQ test result with the two-point wild bootstrap, WB[2]=The AQ test result with the N(0,1) wild bootstrap. p-values less than 10% are in bold.

Table A1: Empirical result for monthly returns in 11 GPR 250 REIT and General Indices (p-values)

	GPR-250-REIT			GPR-General		
Country (covering period)	AQ	WB[1]	WB[2]	AQ	WB[1]	WB[2]
Australia (01/1990~01/2011)	0.118	0.131	0.127	0.125	0.154	0.131
Canada (04/2000~01/2011)	**0.059**	**0.084**	**0.073**	**0.051**	**0.065**	**0.051**
France (01/2003~01/2011)	**0.033**	**0.082**	**0.058**	**0.045**	**0.081**	**0.056**
Hong Kong (12/2005~01/2011)	0.791	0.827	0.852	0.156	0.232	0.177
Japan (10/2001~01/2011)	**0.078**	**0.096**	**0.094**	**0.015**	**0.040**	**0.024**
Netherlands (01/1990~01/2011)	**0.006**	**0.011**	**0.012**	**0.014**	**0.018**	**0.016**
Singapore (10/2003~01/2011)	0.259	0.396	0.336	**0.048**	**0.088**	**0.057**
United Kingdom (01/2007~01/2011)	0.253	0.359	0.347	0.102	0.151	0.136
United States (01/1990~01/2011)	0.450	0.503	0.532	0.291	0.323	0.343

Note: AQ=The AQ test result with $\chi^2(1)$, WB[1] =The AQ test result with the two-point wild bootstrap, WB[2]=The AQ test result with the N(0,1) wild bootstrap. p-values less than 10% are in bold.

Table A2: Rolling results for monthly returns in US and Australia GPR 250 REIT indices (p-values)

	US			Australia		
Subsample Period	AQ	WB[1]	WB[2]	AQ	WB[1]	WB[2]
01/1990-12/1997	0.390	0.448	0.424	0.219	0.275	.257
01/1991-12/1998	0.801	0.840	0.831	**0.057**	**0.091**	**0.082**
01/1992-12/1999	0.995	0.997	0.995	0.139	0.174	0.175
01/1993-12/2000	0.821	0.832	0.850	0.129	0.187	0.138
01/1994-12/2001	0.477	0.537	0.519	**0.050**	**0.093**	**0.063**
01/1995-12/2002	0.627	0.660	0.666	**0.037**	**0.080**	**0.055**
01/1996-12/2003	0.832	0.878	0.858	**0.020**	**0.039**	**0.035**
01/1997-12/2004	0.276	0.352	0.330	**0.010**	**0.037**	**0.023**
01/1998-12/2005	0.246	0.300	0.320	**0.052**	**0.098**	**0.081**
01/1999-12/2006	0.211	0.287	0.271	0.729	0.758	0.751
01/2000-12/2007	0.518	0.566	0.577	0.848	0.865	0.863
01/2001-12/2008	0.616	0.693	0.764	**0.045**	**0.063**	**0.040**
01/2002-12/2009	0.479	0.518	0.595	**0.011**	**0.027**	**0.011**
01/2003-12/2010	0.496	0.563	0.592	**0.015**	**0.029**	**0.021**

Note: AQ=The AQ test result with $\chi^2(1)$, WB[1] =The AQ test result with the two-point wild bootstrap, WB[2]=The AQ test result with the N(0,1) wild bootstrap. p-values less than 10% are in bold.

Figure 1: Rolling test result (p-value) for 14 securitized real estate markets with rolling window 8 years (96 months)