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Are Securitized Real Estate Returns more Predictable than Stock Returns?

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Abstract This paper examines whether the predictability of securitized real estate returns differs from that of stock returns. It also provides a cross-country comparison of securitized real estate return predictability. In contrast to most of the literature on this issue, the analysis is not based on a multifactor asset pricing framework as such analyses may bias the results. We use a time series approach and thus create a level playing field to compare the predictability of the two asset classes. Forecasts are performed with ARMA and ARMA–EGARCH models and evaluated by comparing the entire empirical distributions of prediction errors, as well as with a trading strategy. The results, based on daily data for the 1990–2007 period, show that securitized real estate returns are generally more predictable than stock returns in countries with mature and well established REIT regimes. ARMA–EGARCH models are found to have portfolio outperformance potential even in the presence of transaction costs, with generally better results for securitized real estate than for stocks.

Keywords Predictability · Time series models · ARMA–EGARCH · REITs · Securitized real estate

JEL Classifications C53 · C22 · G15

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Introduction

After tripling in size over the past 5 years, the global market capitalization of real estate securities as measured by the FTSE EPRA/NAREIT Global Index amounts to \$794 billion as of the end of 2007. The strong growth experienced by real estate securities may be largely attributed to the adoption of REIT-like legislation, i.e. legislation providing for tax-transparency at the corporate level, in an increasing number of countries. In 1995, REITs were only present in six countries, but by 2007, over 30 countries had introduced REIT regimes and several others were considering such legislation. The explosion in REIT legislation reflects the increasing demand for securitized forms of real estate and the consolidation of securitized real estate as an independent asset class. As such, it is important to examine the predictability of securitized real estate returns, in particular whether these returns are more easily predictable than stock returns. This paper uses a time series approach to forecast securitized real estate returns and compares their forecasting properties to those of common stocks. For that purpose, we use daily returns for the 1990–2007 period.

Finding an asset class that is more predictable than another would change investors' perceptions concerning the uncertainty of future returns on that asset class, and therefore this could motivate important changes in terms of asset allocation. It is hard to determine *a priori* what results to expect from this study. On the one hand, it could be argued that securitized real estate returns may be easier to forecast due to the stable cash flows derived from the generally long-term leases. On the other hand, stock returns might seem more predictable than securitized real estate returns as the latter are constituted by mid and small-cap companies whose returns are generally more uncertain than those of larger companies.

Existing research has mainly compared the predictability of securitized real estate and stock returns by examining multifactor asset pricing models (Liu and Mei 1992; Mei and Liu 1994; Li and Wang 1995). However, two asset classes are not likely to be equally well specified by the same asset pricing model. Therefore, this type of comparison will not determine which asset class is more predictable *per se*, but which asset class is more predictable under the asset pricing model specified. In other words, when multifactor asset pricing models are used, it is uncertain whether the similarities or differences in predictability are due to similarities or differences in predictability between the two asset classes, or to differences in the explanatory power of the specified model for the two asset classes. To truly compare the predictability of two asset classes, a 'neutral' model that does not favor any asset class should be employed. Such is the case of time series models as they rely solely on past observations and do not require the specification of forecasting variables. To the best of our knowledge, Nelling and Gyourko (1998) are the only to have used a time series approach to compare the predictability between securitized real estate and stock returns.

This paper expands Nelling and Gyourko's (1998) work by enriching the autoregressive-based analysis with ARMA and ARMA–EGARCH models. Further, the comparisons made are not evaluated merely with statistical criteria, but also by examining entire empirical distributions as well as active trading strategies. This allows to conclude in a rigorous manner whether the returns of one of the two asset classes are in fact more predictable than those of the other asset class, but also if the results are economically significant. As the analysis covers ten countries, the contribution of the paper is thus to provide a better understanding of the predictability between securitized real estate and stock returns at an international level, but also a comparison of the predictability of securitized real estate returns across countries.

The results of this study suggest that the maturity of the securitized real estate market plays an important role in the predictability of its returns. In countries with mature and well established REIT regimes, securitized real estate returns are found to be more predictable than stock returns. Hence, the best forecasting accuracy is found in the United States, the Netherlands, and Australia; the countries with the oldest REIT regimes in our sample. Furthermore, active trading strategies, especially those based on ARMA–EGARCH forecasts, are found to outperform the buy-and-hold benchmark in all ten countries for both asset classes. When transaction costs are taken into account, this remains the case in half of our countries for real estate securities, but only in three for stocks.

The paper is structured as follows. The second section reviews the literature on the forecasting of securitized real estate returns. The next section discusses the data, while the fourth section covers the methodology. Results are presented in the fifth section and some concluding remarks follow.

Literature Review

Existing research on the forecasting of real estate returns (both direct and securitized) has relied on employing or comparing a number of univariate and/or multivariate models. Univariate models have been found to perform well with direct real estate, while multivariate models have generally been preferred for securitized real estate. Although there is conflicting evidence in the literature as to what forecasting technique works best, there is a general trade-off between the simplicity of the model and the forecasting accuracy.

Brooks and Tsolacos (2001) employ a number of time series techniques to assess the predictability of securitized real estate returns in the U.K. They find that a VAR model which incorporates financial spreads exhibits a better short-term out-of-sample forecasting performance than univariate time series models. However, after establishing trading rules with the forecasts, no excess returns are found over a buy-and-hold strategy once transaction costs are accounted for. In a follow-up paper, Brooks and Tsolacos (2003) compare the predictability of ARMA, VAR, and neural networks models in five European countries. They conclude that whilst no single technique is universally superior, the neural networks model generally makes the most accurate predictions for 1-month horizons.

In the U.S., Serrano and Hoesli (2007) examine the usefulness of using financial assets, direct real estate, and the Fama and French (1993) factors to forecast EREIT returns and compare the predictive potential of time varying coefficient (TVC) regressions, VAR systems, and neural networks models. Their results indicate that the best predictions are obtained with neural networks models and especially when the model includes stock, bond, real estate, size, and book-to-market factors. Similarly in Australia, Ellis and Wilson (2005) find that portfolios constructed with neural networks techniques consistently out-perform the market on both a nominal and risk-adjusted basis. In the direct real estate literature, the performance of neural networks is less conclusive. The quality of the house price predictions obtained with this technique is supported by some researchers (Nguyen and Cripps 2001; Limsombunchai et al. 2004; Peterson and Flanagan 2008), but criticized by others (Worzala et al. 1995; Lenk et al. 1997).

Existing research in the direct real estate market has addressed more thoroughly the comparison of different forecasting techniques, especially in the U.S. and the U.K. Brown et al. (1997) suggest that the U.K.'s housing market is better forecasted with a time-varying coefficient regression than with constant parameter ECMs, VAR systems or an autoregressive regression. In the U.S., Crawford and Fratantoni (2003) find that regime-switching models fit the data better than ARIMA or GARCH models. In spite of that, the performance of the simpler time-series models turns out to be as good or even better in out-of-sample tests. Analogously, Guirguis et al. (2005) compare the out-of-sample forecasts of six different estimation techniques. Their results indicate that the best forecasts are obtained with the rolling GARCH model and the Kalman filter with an autoregressive presentation (KAR) for the parameters' time variation. Miles (2008) considers several non-linear models and finds that generalized autoregressive (GAR) models generally do a better job at out-of-sample forecasting than ARMA and GARCH models, especially in markets with high home price volatility. In the Finnish office market, Karakozova (2004) compares the forecasting accuracy of a regression model, an ECM, and an ARIMAX. The ARIMAX provides the best predictions when it incorporates lagged values of capital growth and contemporaneous values of growth in service sector employment and in the gross domestic product.

The literature comparing the predictability of REIT returns versus that of other assets is filled with conflicting evidence. Liu and Mei (1992) use a multifactor latent variable model with time-varying risk premiums and conclude that expected excess returns are more predictable for EREITs than for stocks or bonds. These findings are also confirmed by Liao and Mei (1998). However, Mei and Lee (1994) include a real estate factor to an otherwise similar multifactor asset pricing model and find no evidence of higher predictability for EREIT returns. Li and Wang (1995) also use such a framework to compare the returns of EREITs and MREITs to the returns of stocks of other industries. Their findings suggest that the predictability of REIT returns is about the same as that of stocks. This multifactor asset pricing framework is examined out-of-sample by Mei and Liu (1994). They construct active trading strategies and find that larger profits and higher average risk-adjusted returns are generally obtained with EREITs than with other financial assets. Even though all of the preceding studies use the same framework, the lack of convergence in their results may be explained by the different model specifications employed. The three studies suggesting more predictability for EREITs use the same forecasting variables, i.e. the yield on a 1-month T-bill, the yield spread between AAA bonds and the T-bill, the dividend yield on an equally weighted portfolio, and the capitalization rate on EREITs, whereas the two studies suggesting similar predictability between the two asset classes use somewhat different forecasting variables in the specification of their models.

The returns of an asset class may only be defined as more predictable than those of another asset class if the framework used does not create a disparity between the two asset classes with respect to the model specification. As such, a time series approach creates the perfect conditions for such a comparison. This approach relies solely on past observations and does not require the choosing of forecasting variables that could bias the results by creating a model specification that is not equally fit for both asset classes. Nelling and Gyourko (1998) are the only authors to have addressed this issue using a time series approach. Using AR processes to make the forecasts and evaluating the out-of-sample predictability by employing a contrarian strategy, they find that small cap stocks are more predictable than EREITs, but that EREITs are equally predictable as mid caps. However, their results suggest that the predictability of monthly EREIT returns is limited as it is not large enough to cover transaction costs.

Performance continuation and reversals are also related to the time series properties of asset returns and have been the subject of many studies in the financial economics literature. For securitized real estate, Mei and Gao (1995) examine serial persistence of weekly returns and find that a contrarian-based strategy may be exploited only if transaction costs are ignored. Using a filter-based rule, Cooper et al. (1999) show that a contrarian strategy is in many cases more profitable than its associated execution costs. Graff and Young (1997) use different frequencies in their study and find positive momentum effects with yearly data, evidence of performance reversals with monthly data, and no evidence of momentum or reversals with quarterly data. Finally, Stevenson (2002) provides international evidence of momentum effects over short and medium term horizons, as well as little support for price reversals.[1]

In sum, the existing literature on the predictability of securitized real estate returns has concentrated on comparing the predictability of different forecasting techniques and on comparing the predictability of securitized real estate returns to that of other asset classes. Concerning the various forecasting techniques, no single technique has been found to be universally superior although a general trade-off between the simplicity of the model and the forecasting accuracy has been acknowledged. Concerning the comparisons of predictability between asset classes, the conclusions are mixed. This is not surprising since the research examining this issue uses variations of the multifactor asset pricing model of Liu and Mei (1992). Since a multifactor asset pricing model does not explain the returns of two asset classes to the same degree of accuracy due to the different factors driving the returns of each asset class, the conclusions reached by these studies are only valid for the multifactor asset pricing models being considered. Such criticism is not valid when time series models are considered as they do not favor one asset class over another as a result of the return generating model specified. Thus, this paper contributes to the literature by offering a more trustworthy comparison of the predictability of securitized real estate and stock returns.

Data

Whereas financial research customarily relies on daily data, empirical real estate research using securitized data has mainly concentrated on monthly, quarterly, and

[1] For studies related to these issues in the direct real estate literature, see Young and Graff (1996, 1997) for the U.S., Graff et al. (1999) for Australia, and Lee and Ward (2001) and Devaney et al. (2007) for the U.K.

yearly frequencies. However, the use of daily data is interesting for forecasting purposes as the cost and time needed to collect and process information in real estate markets may be such that the market may be inefficient at daily frequencies, but efficient at monthly or lower frequencies (Mei and Gao 1995). Therefore, this paper uses daily total return indices for the period January 1990–December 2007.[2]

The data employed in this study were obtained from *Thomson Datastream* and the period selected was dictated by the starting date of the FTSE EPRA/NAREIT database. We cover the ten largest real estate security markets according to the FTSE EPRA/NAREIT Global Index. The overall market value of firms encompassed by the index is $794 billion; with the ten largest constituent countries representing approximately 95% of the index. These countries are the U.S., Hong Kong, Japan, Australia, the U.K., France, Singapore, the Netherlands, Germany, and Sweden. For each country, we use the relevant FTSE EPRA/NAREIT index. For stocks, Datastream's total return indices are used and, for the risk free rate, the Euro-Currency 3-month middle rate is retained.[3] For Hong Kong, Australia and Sweden, the Euro-Currency rate is not available since 1990, so the Interbank 3-month middle rate is used for the former two countries and the Treasury Bill 90 day middle rate for the latter.

Since securitized real estate markets differ from country to country and such differences may have significant effects on the degree of predictability of returns, an overview of the markets is presented in Table 1. Albeit all the countries with the exception of Sweden had introduced REIT legislation by the end of 2007, only the U.S., the Netherlands, and Australia have REITs during the whole study period. Not surprisingly, these three countries also have the highest percentage of REITs and therefore the lowest percentage of non-REITs in their respective markets. As for the investment focus, rental investments dominate in North America (90%), Europe (94%), and Australia (80%), while non-rental investments are privileged in Asia (61%). In fact, securitized real estate markets in Asia are mainly dominated by property developers (Liow 1997; Newell and Chau 1996). Finally, it is important to acknowledge that real estate securities in North America tend to be sector specific, whereas they are generally diversified into various sectors in Europe and in Asia.[4]

Summary statistics are presented in Table 2. A substantial variation in performance is observed across countries both for securitized real estate and for stocks. However, it is worth noting that real estate securities present higher Sharpe ratios than stocks in the U.S., Japan, Australia, and France, while the opposite occurs in the remaining six countries. Mei and Liu (1994) also document higher risk-adjusted returns for EREITs than for other financial assets in the U.S. The volatility of securitized real estate is relatively similar to that of stocks in all countries except for Hong Kong, Japan, and Singapore where they are considerably higher. This finding is not surprising as low initial yields associated with prime real estate located

[2] We also performed preliminary analyses using monthly data but the autocorrelation functions suggest that the data do not follow ARMA processes. Hence, time series forecasts could not be devised at this frequency.

[3] The correlation of Datastream's total return indices and MSCI's total return indices is around 95% in all the countries. However, the MSCI total return indices are only available since January 2001.

[4] EPRA Monthly Statistical Bulletin, December 2007.

Table 1 Overview of securitized real estate markets as of December 2007

Country	Acronym and year enacted	% of the FTSE EPRA/NAREIT global index	# of stocks	% of REITs in the market (vs Non-REITs)	Investment focus (% of rental vs non-rental)
U.S.	US-REIT 1960	28.65	103	96.10	88.77
Hong Kong	HK-REIT 2003	23.50	21	4.27	12.68
Japan	JREIT 2000	11.58	23	29.18	31.17
Australia	LPT 1985	10.05	23	94.78	79.63
U.K.	UK-REIT 2007	6.74	36	82.51	95.34
France	SIIC 2003	5.40	10	91.87	N/A
Singapore	SREIT 1999	3.62	11	45.23	N/A
Netherlands	FBI 1969	1.57	7	100.00	N/A
Germany	G-REIT 2007	1.29	9	5.39	N/A
Sweden	Non-existent	0.85	6	0.00	N/A

The FTSE EPRA/NAREIT Global Index has a market value of $794 billion. The ten largest countries in the index account for approximately 95% of the index. Canada represents 2.95% of the index and Austria 0.93%, but they are not included in our study because the series are not available throughout the whole period

in major cities in Asia have mainly attracted investors in search of potential capital gains rather than rental income. Hence, the focus on capital growth partially explains why securitized real estate in Asia has been more volatile than in the U.S. or other industrialized economies (Ooi and Liow 2004). As mentioned above, the return and risk figures of Asian real estate securities are also influenced by the fact that these companies largely engage in development and construction activities.

Methodology

The effect of past realizations and past changes in volatility are used to forecast securitized real estate and stock returns. The two forecasting methodologies applied

Table 2 Summary statistics (daily data for the period January 1990–December 2007)

Country	Securitized real estate				Stocks			
	Market capitalization ($ bn)	Total returns		Sharpe ratio	Market capitalization ($ bn)	Total returns		Sharpe ratio
		Mean (%)	Std. Dev. (%)			Mean (%)	Std. Dev. (%)	
U.S.	272	0.06	0.81	0.05	15,921	0.05	0.98	0.03
Hong Kong	124	0.07	1.83	0.03	1,669	0.07	1.48	0.04
Japan	95	0.02	2.00	0.01	4,280	0.00	1.21	−0.01
Australia	96	0.06	0.77	0.05	1,188	0.05	0.80	0.04
U.K.	61	0.03	0.99	0.01	3,723	0.04	0.92	0.02
France	33	0.05	0.87	0.03	2,572	0.05	1.12	0.02
Singapore	20	0.04	1.96	0.01	412	0.03	1.11	0.02
Netherlands	14	0.03	0.72	0.02	777	0.05	1.05	0.03
Germany	8	0.03	1.35	0.01	2,020	0.04	1.09	0.02
Sweden	7	0.01	1.55	−0.01	499	0.05	1.39	0.02

are: ARMA and ARMA–EGARCH models. Then, the out-of-sample performance of the two forecasting techniques employed is compared and their usefulness for investment decision making is determined.

Forecasting Techniques

ARMA Models

The autoregressive-moving average (ARMA) model is a univariate model which assumes that the behavior of a stationary process follows repeating patterns. Since their creation by Box and Jenkins (1976), these models have been widely used in finance. ARMA specifications aim to model a series by using its autoregressive (AR) and moving average (MA) components. More precisely, the AR component consists of the lagged values of the variable of interest and the MA component consists of the lagged values of the error term.

The ARMA model to be estimated is:

$$r_{i,t} = \mu + \sum_{j=1}^{p} \phi_{i,j} r_{i,t-j} - \sum_{k=0}^{q} \theta_{i,k} u_{i,t-k} \tag{1}$$

where $r_{i,t}$ is the return on the asset class for day t in country i, and $\sum_{j=1}^{p} \phi_{i,j} r_{i,t-j}$ and $\sum_{k=0}^{q} \theta_{i,k} u_{i,t-k}$ are the AR and MA components, respectively. To satisfy the stationarity condition imposed when using ARMA models, the stationarity of all raw series is examined with the Augmented Dickey-Fuller (ADF) unit root test. The ADF test is a parametric test based on the estimation of an AR(p) model, in which the null hypothesis of a unit root is tested against the alternative that the coefficients of the lagged dependent variables are strictly less than one. The null hypothesis is rejected at the 1% level for all the return series, therefore implying that all the series are stationary, I(0).

The orders p of the AR and q of the MA are determined using the Schwarz Bayesian information criterion (SBC). The SBC is a statistic commonly used to select between competing models.[5] It takes into account the goodness-of-fit of each model and it penalizes models in relation to the number of parameters. The model chosen, i.e. the orders of p and q, is that for which the SBC is minimized. The SBCs are calculated for models with p and q up to five lags for each series to account for a week of data. The orders of the models are re-defined every year to adapt the forecasts to the medium-term dynamics of the series (these are reported in Tables 3 and 4). The short-term dynamics are captured by performing 1 day ahead out-of-sample forecasts resulting from the estimation of the model with the previous 60 observations (i.e., data for approximately one quarter). The size of the rolling window is chosen in accordance with McGough and Tsolacos (1995) and Tse (1997) who suggest that the minimum number of observations needed for generating an ARMA model is 50 observations. The sample is rolled forward by including a new

[5] Akaike's information criterion (AIC) is often also used to select between competing models, but as noted by Mills (1990), the AIC can result in the selection of an over-parametrized model.

Table 3 ARMA(p,q)–EGARCH(x,y) model specifications used to forecast securitized real estate returns

Year	Model	U.S.		Hong Kong		Japan		Australia		U.K.		France		Singapore		Netherlands		Germany		Sweden	
		Spec	SBC	Spec	SBC	Spec	SBC	Spec	SBC	Spec	SBC	Spec	SBC	Spec	SBC	Spec	SBC	Spec	SBC	Spec	SBC
1992	ARMA	(0,1)	−7.04	(4,4)	−5.83	(0,1)	−5.42	(3,3)	−6.90	(4,4)	−6.54	(0,3)	−6.84	(5,5)	−5.75	(4,4)	−7.23	(3,0)	−6.96	(3,3)	−5.03
	EGARCH	(5,5)	−15.63	(3,3)	−12.15	(3,3)	−12.70	(3,3)	−15.20	(5,5)	−13.11	(4,4)	−15.02	(1,0)	−11.12	(5,5)	−15.26	(1,1)	−13.61	(3,3)	−10.61
1993	ARMA	(0,1)	−7.72	(0,2)	−5.42	(4,1)	−4.99	(0,1)	−7.16	(5,1)	−5.63	(0,1)	−7.08	(1,0)	−6.04	(0,1)	−7.54	(0,1)	−6.78	(5,0)	−4.11
	EGARCH	(3,3)	−16.96	(5,5)	−7.19	(1,0)	−10.18	(5,5)	8.23	(5,5)	−0.07	(2,2)	−15.74	(5,5)	13.58	(1,1)	−14.90	(1,1)	−11.60	(1,1)	16.89
1994	ARMA	(1,4)	−7.62	(2,0)	−5.48	(0,1)	−5.15	(0,4)	−7.02	(3,0)	−6.23	(2,2)	−7.59	(3,3)	−6.04	(1,0)	−7.60	(2,2)	−6.71	(1,5)	−4.35
	EGARCH	(1,1)	−16.46	(5,5)	−11.45	(2,2)	−9.04	(3,3)	−15.54	(5,5)	1.03	(5,5)	−14.17	(1,1)	−11.12	(1,1)	−16.74	(2,2)	−13.40	(1,1)	−10.15
1995	ARMA	(1,0)	−7.91	(3,0)	−4.87	(4,4)	−5.84	(2,1)	−6.94	(5,5)	−6.37	(1,1)	−6.87	(4,4)	−5.30	(3,3)	−7.42	(0,1)	−6.61	(5,5)	−5.30
	EGARCH	(5,5)	−14.35	(3,3)	−12.29	(2,2)	−10.48	(2,2)	−15.04	(5,5)	−13.60	(5,5)	11.79	(1,0)	−6.75	(5,5)	−16.54	(3,3)	−13.47	(5,5)	−11.46
1996	ARMA	(1,0)	−8.50	(5,5)	−5.79	(5,5)	−5.21	(4,0)	−7.30	(5,5)	−6.68	(5,0)	−7.06	(5,5)	−5.71	(0,4)	−7.79	(0,3)	−6.91	(4,4)	−5.97
	EGARCH	(5,5)	−18.20	(2,2)	2.59	(1,0)	−8.89	(5,5)	−15.35	(1,1)	−13.40	(5,5)	−14.18	(2,0)	−10.65	(5,5)	7.56	(3,3)	−12.86	(4,4)	−11.91
1997	ARMA	(1,1)	−8.30	(0,2)	−6.11	(3,3)	−5.84	(3,3)	−7.44	(2,0)	−7.26	(3,3)	−7.91	(5,5)	−5.62	(5,5)	−7.98	(3,0)	−4.96	(3,3)	−6.38
	EGARCH	(1,0)	−16.62	(5,0)	−12.54	(2,1)	−9.64	(1,1)	−15.33	(5,5)	12.23	(3,1)	−15.01	(4,4)	−2.69	(2,2)	−14.51	(5,5)	−9.04	(3,3)	−11.70
1998	ARMA	(0,1)	−7.55	(3,3)	−4.77	(4,4)	−4.66	(4,0)	−6.66	(0,5)	−6.33	(4,4)	−7.10	(1,0)	−4.93	(5,5)	−7.07	(4,4)	−6.61	(0,4)	−6.32
	EGARCH	(1,1)	−15.21	(3,3)	−6.97	(5,5)	−9.21	(5,5)	9.12	(5,0)	−14.28	(1,1)	21.40	(1,1)	7.27	(1,1)	−10.01	(4,4)	−12.72	(5,5)	12.01
1999	ARMA	(0,1)	−6.63	(5,5)	−3.84	(2,2)	−4.12	(4,4)	−6.58	(3,3)	−6.88	(2,2)	−7.09	(5,5)	−3.33	(5,0)	−7.40	(0,5)	−5.56	(4,4)	−6.53
	EGARCH	(2,1)	−13.83	(1,0)	−7.97	(5,5)	14.68	(4,4)	−13.89	(1,1)	−13.37	(2,2)	−12.95	(5,5)	−8.73	(1,1)	−7.95	(1,1)	−10.20	(3,3)	−13.76
2000	ARMA	(0,1)	−7.38	(4,4)	−5.11	(0,2)	−4.47	(0,4)	−6.78	(5,5)	−6.95	(4,4)	−7.15	(4,4)	−4.58	(4,4)	−7.24	(5,5)	−5.35	(4,4)	−7.30
	EGARCH	(3,3)	−15.18	(5,5)	8.44	(2,2)	−9.04	(5,5)	−14.21	(5,5)	−13.19	(1,0)	−14.17	(5,5)	−9.95	(5,5)	−15.30	(4,0)	−11.49	(3,0)	−12.77
2001	ARMA	(4,4)	−7.07	(3,3)	−5.01	(2,2)	−4.78	(5,5)	−7.14	(1,0)	−7.06	(0,1)	−7.01	(2,2)	−4.79	(0,3)	−7.79	(4,4)	−5.61	(3,3)	−6.39
	EGARCH	(2,1)	−15.34	(1,0)	−9.46	(2,2)	−10.53	(1,0)	−14.77	(3,3)	−14.13	(1,0)	−14.07	(5,5)	−8.99	(2,1)	−15.54	(1,1)	−0.78	(1,1)	9.12
2002	ARMA	(0,3)	−6.83	(3,3)	−5.06	(3,3)	−5.04	(5,5)	−6.89	(4,1)	−7.12	(2,2)	−7.12	(5,5)	−4.59	(5,5)	−7.47	(4,4)	−5.55	(4,0)	−6.45
	EGARCH	(1,1)	14.61	(5,5)	−11.07	(2,2)	−9.93	(4,0)	−14.24	(1,1)	−15.51	(1,0)	−15.19	(2,1)	−9.26	(1,0)	−16.44	(1,1)	21.93	(1,1)	−12.37
2003	ARMA	(4,2)	−6.48	(4,4)	−5.50	(5,5)	−4.88	(3,3)	−7.90	(5,5)	−6.62	(4,0)	−6.27	(5,5)	−5.30	(1,0)	−7.13	(0,3)	−4.65	(2,2)	−6.52
	EGARCH	(1,1)	−12.89	(1,1)	−11.04	(5,5)	−10.38	(2,2)	−15.20	(2,0)	18.90	(1,1)	−11.83	(5,5)	−10.54	(2,2)	−13.21	(3,3)	−8.59	(3,3)	−14.54
2004	ARMA	(0,5)	−6.91	(3,1)	−5.28	(0,1)	−4.93	(0,1)	−7.29	(1,0)	−6.63	(1,1)	−7.22	(3,3)	−5.05	(5,5)	−7.44	(0,5)	−5.29	(4,4)	−7.16
	EGARCH	(5,5)	−13.25	(2,1)	−9.07	(1,0)	−9.36	(5,5)	−14.74	(4,4)	−12.25	(1,0)	−15.59	(1,1)	−10.05	(1,0)	−15.22	(4,4)	−11.93	(2,2)	−13.95
2005	ARMA	(4,4)	−6.21	(4,4)	−5.46	(2,2)	−5.42	(5,5)	−7.33	(0,5)	−7.22	(3,3)	−6.98	(5,5)	−6.60	(4,4)	−7.42	(4,4)	−7.47	(0,2)	−6.97
	EGARCH	(5,5)	−12.33	(5,5)	−12.23	(5,5)	−12.68	(1,1)	−15.23	(5,5)	−15.50	(1,0)	−13.84	(3,1)	−11.58	(3,3)	−13.48	(3,3)	−13.05	(5,5)	−12.85
2006	ARMA	(3,3)	−6.42	(5,5)	−6.54	(5,5)	−5.95	(4,4)	−7.08	(0,4)	−6.90	(5,5)	−6.58	(5,5)	−6.48	(5,5)	−7.17	(3,0)	−6.58	(2,0)	−5.95
	EGARCH	(1,0)	−12.92	(5,5)	−11.47	(1,1)	−9.98	(4,4)	−14.69	(2,2)	−12.63	(1,1)	−5.77	(5,5)	−9.72	(2,2)	−13.44	(2,1)	−12.01	(4,4)	−12.96
2007	ARMA	(0,1)	−6.56	(5,5)	−6.18	(5,5)	−5.36	(0,3)	−6.84	(5,5)	−5.93	(0,3)	−6.04	(0,1)	−5.88	(4,0)	−6.33	(2,2)	−5.77	(0,3)	−5.57
	EGARCH	(5,5)	1.50	(5,5)	7.71	(2,2)	−11.31	(2,0)	−12.40	(1,0)	−12.38	(3,0)	−11.64	(5,5)	−0.99	(5,5)	−3.87	(1,1)	3.20	(2,2)	−12.47

The SBC (Schwarz Bayesian information criterion) is calculated every year for all models up to five lags. This table reports the models used to make the forecasts, i.e. the models for which the SBC is minimized in the previous year

Table 4 ARMA(p,q)−EGARCH(x,y) model specifications used to forecast stock returns

Year	Model	U.S.		Hong Kong		Japan		Australia		U.K.		France		Singapore		Netherlands		Germany		Sweden	
		Spec	SBC	Spec	SBC	Spec	SBC	Spec	SBC	Spec	SBC	Spec	SBC	Spec	SBC	Spec	SBC	Spec	SBC	Spec	SBC
1992	ARMA	(3,3)	−6.68	(3,0)	−6.17	(5,5)	−6.25	(2,0)	−6.51	(5,5)	−6.94	(5,5)	−6.35	(5,5)	−6.55	(3,3)	−7.28	(3,0)	−6.33	(5,5)	−5.85
	EGARCH	(4,4)	−14.84	(4,4)	−10.99	(3,3)	−12.77	(1,1)	−13.69	(4,3)	−14.52	(5,5)	10.98	(2,2)	−7.27	(1,1)	−14.47	(5,5)	−11.61	(4,4)	−12.52
1993	ARMA	(2,2)	−7.43	(0,3)	−5.74	(0,1)	−5.62	(0,1)	−7.02	(0,1)	−6.52	(4,0)	−6.41	(0,5)	−7.07	(4,4)	−7.56	(3,3)	−7.17	(0,1)	−5.26
	EGARCH	(1,0)	−13.53	(3,3)	−13.01	(5,3)	−10.57	(2,0)	−15.98	(5,5)	0.31	(1,1)	−10.84	(1,1)	−13.69	(3,3)	−15.15	(5,5)	−15.07	(2,2)	−9.92
1994	ARMA	(2,2)	−7.63	(1,0)	−5.79	(0,1)	−6.07	(0,1)	−7.00	(4,4)	−7.54	(5,5)	−6.86	(1,0)	−7.33	(1,0)	−7.64	(0,1)	−7.19	(0,1)	−6.32
	EGARCH	(4,4)	−15.14	(1,1)	−12.07	(5,5)	−12.79	(5,5)	−15.65	(1,1)	4.25	(1,1)	−14.58	(1,1)	−14.09	(5,5)	−14.95	(3,3)	−14.35	(4,4)	−14.36
1995	ARMA	(5,0)	−7.39	(4,4)	−5.27	(3,3)	−6.75	(5,5)	−6.61	(3,3)	−6.95	(5,5)	−6.60	(4,4)	−6.36	(4,4)	−7.19	(0,5)	−6.82	(5,5)	−6.32
	EGARCH	(1,0)	−15.62	(1,1)	−11.12	(1,1)	−13.46	(2,2)	−15.09	(1,1)	−5.86	(4,4)	−13.46	(5,5)	−13.75	(5,5)	−15.79	(1,1)	−15.75	(3,0)	−9.50
1996	ARMA	(5,0)	−7.79	(5,5)	−6.07	(4,4)	−6.18	(0,1)	−7.17	(5,5)	−7.60	(0,5)	−6.65	(0,1)	−6.84	(3,3)	−7.75	(0,5)	−7.31	(0,5)	−6.60
	EGARCH	(4,4)	−16.39	(2,2)	−5.27	(5,5)	−12.59	(5,0)	−13.86	(1,0)	−14.71	(4,4)	−13.14	(1,1)	7.27	(5,5)	−13.74	(3,3)	−15.87	(3,1)	−12.44
1997	ARMA	(1,0)	−7.03	(0,2)	−6.38	(5,5)	−7.06	(5,5)	−6.96	(0,5)	−7.67	(5,5)	−7.21	(5,5)	−6.82	(0,4)	−7.17	(0,1)	−7.24	(3,3)	−6.79
	EGARCH	(2,0)	−16.12	(5,5)	−13.73	(1,1)	−13.36	(1,1)	−14.58	(5,5)	−15.57	(1,1)	−14.43	(5,0)	−10.42	(4,4)	−12.29	(3,1)	−15.19	(5,5)	−13.95
1998	ARMA	(0,2)	−6.23	(3,3)	−4.75	(2,0)	−5.83	(3,3	−6.37	(3,3)	−6.76	(4,4)	−6.02	(0,4)	−5.90	(4,0)	−5.78	(4,0)	−5.94	(0,4)	−5.92
	EGARCH	(1,0)	−13.49	(1,1)	−8.95	(5,5)	−11.89	(5,5)	13.03	(1,1)	−14.31	(1,1)	13.28	(4,4)	−10.47	(1,1)	−13.05	(2,1)	−13.19	(5,5)	−6.54
1999	ARMA	(5,5)	−5.93	(5,5)	−4.46	(5,0)	−5.81	(0,1)	−6.35	(0,1)	−6.05	(0,1)	−5.63	(5,5)	−4.99	(0,1)	−5.46	(2,0)	−5.51	(4,4)	−5.21
	EGARCH	(4,4)	−12.73	(2,2)	−9.01	(1,1)	−13.42	(1,1)	−12.14	(5,5)	−11.64	(1,1)	−10.31	(1,1)	−10.95	(1,1)	−12.92	(1,1)	−12.87	(1,1)	−11.47
2000	ARMA	(4,4)	−6.16	(4,4)	−5.48	(0,3)	−6.07	(0,4)	−6.76	(4,4)	−6.44	(4,4)	−6.30	(4,4)	−5.70	(4,4)	−6.26	(1,1)	−6.05	(4,4)	−6.00
	EGARCH	(1,1)	−12.59	(4,1)	−10.15	(4,4)	−13.28	(2,2)	−15.39	(3,3)	−12.28	(3,3)	−9.72	(5,5)	14.64	(1,1)	−10.93	(4,1)	−13.51	(1,1)	−11.29
2001	ARMA	(4,4)	−7.07	(3,3)	−5.01	(2,2)	−4.78	(5,5)	−7.14	(1,0)	−7.06	(0,1)	−7.01	(2,2)	−4.79	(0,3)	−7.79	(4,4)	−5.61	(3,3)	−6.39
	EGARCH	(2,1)	−9.56	(2,1)	−9.49	(1,0)	−11.80	(1,0)	−13.09	(2,1)	−11.66	(5,5)	−11.22	(5,5)	−9.77	(5,5)	−13.44	(5,3)	−12.23	(5,5)	−5.97
2002	ARMA	(5,5)	−5.76	(3,3)	−5.41	(4,0)	−5.58	(3,3)	−6.81	(2,2)	−5.94	(4,4)	−5.56	(3,0)	−5.84	(2,2)	−5.63	(4,4)	−5.53	(5,5)	−4.90
	EGARCH	(5,5)	2.52	(1,1)	−10.96	(1,0)	−10.63	(1,1)	−13.37	(1,1)	−13.79	(1,0)	−11.90	(2,2)	19.57	(1,1)	−12.45	(5,5)	3.14	(5,5)	−9.17
2003	ARMA	(0,4)	−5.44	(4,4)	−6.14	(5,5)	−5.77	(0,4)	−7.08	(0,3)	−5.50	(3,3)	−5.07	(5,5)	−6.22	(3,3)	−5.02	(5,5)	−5.31	(5,5)	−4.99
	EGARCH	(5,5)	13.74	(5,5)	0.62	(5,2)	−13.88	(2,1)	−14.02	(1,1)	−10.59	(5,5)	−10.25	(1,1)	−12.73	(1,1)	−8.78	(2,0)	−10.78	(1,1)	−9.53
2004	ARMA	(5,5)	−6.33	(0,3)	−6.32	(4,4)	−6.00	(5,5)	−7.35	(5,5)	−6.21	(5,5)	−5.72	(0,1)	−6.25	(5,5)	−5.55	(4,4)	−5.75	(5,5)	−5.93
	EGARCH	(4,4)	−14.78	(5,0)	−11.51	(4,4)	−11.83	(1,1)	−15.36	(5,5)	−14.69	(4,4)	−11.97	(4,4)	−12.11	(5,5)	−8.47	(4,4)	−12.59	(5,5)	−12.52
2005	ARMA	(1,1)	−7.13	(5,5)	−6.33	(4,4)	−6.34	(3,3)	−8.14	(0,2)	−7.37	(5,5)	−6.89	(4,4)	−7.12	(5,5)	−6.90	(5,5)	−6.88	(2,0)	−6.48
	EGARCH	(3,1)	−13.07	(5,5)	−14.17	(1,1)	−3.80	(1,1)	−15.75	(1,1)	−14.30	(3,3)	−13.21	(2,0)	−15.71	(5,5)	−13.43	(5,5)	−14.10	(5,5)	−13.69
2006	ARMA	(3,3)	−7.29	(5,5)	−7.19	(5,5)	−6.86	(4,4)	−7.37	(4,0)	−7.62	(3,3)	−7.32	(4,4)	−7.45	(5,5)	−7.39	(3,0)	−7.47	(2,2)	−7.04
	EGARCH	(3,3)	−15.28	(1,1)	−13.09	(5,5)	0.24	(3,3)	−14.16	(3,0)	−16.79	(4,4)	−14.15	(5,5)	−0.20	(4,4)	15.57	(5,5)	1.66	(1,1)	−14.68
2007	ARMA	(2,0)	−7.29	(4,4)	−6.64	(3,3)	−6.09	(0,1)	−6.81	(3,0)	−6.85	(3,3)	−6.67	(5,0)	−6.79	(0,3)	−6.71	(3,3)	−6.74	(3,0)	−6.05
	EGARCH	(1,0)	−13.33	(5,0)	−12.37	(5,5)	6.96	(3,1)	−13.29	(5,0)	−15.28	(2,2)	−12.59	(5,5)	12.17	(1,1)	−13.08	(5,5)	−14.06	(1,0)	−11.92

The SBC (Schwarz Bayesian information criterion) is calculated every year for all models up to five lags. This table reports the models used to make the forecasts, i.e. the models for which the SBC is minimized in the previous year observation and dropping the last one. Parameters are re-estimated at each step and new forecasts are produced until the sample is exhausted.

ARMA–EGARCH Models

Financial markets are characterized by having periods that are more volatile than others. ARMA processes cannot model this fact as they assume a constant variance, but autoregressive conditional heteroscedastic (ARCH) processes can do so as they capture time-varying but persistent volatility (Engle 1982). In ARCH models, the variance of the error term $h_{i,t}$ is a function of the variances of the previous time periods' error terms. An ARCH model may be described as follows:

$$u_{i,t} = \sqrt{h_{i,t}} v_t, \tag{2}$$

where $h_{i,t} = V\left[u_{i,t} \middle| u_{i,t-1}, \ldots, u_{i,t-x}\right] = c + \sum_{l=1}^{x} a_{i,l} u_{i,t-l}^2$, $a_{i,l}$ represents the ARCH coefficients, and $v_t \sim N(0,1)$.

The generalized autoregressive conditional heteroscedastic (GARCH) models constitute a generalization of the ARCH models in which the variance of the error term is assumed to follow an ARMA process (Bollerslev 1986). Therefore, the autoregressive components are chosen in accordance with the ARMA analysis in the previous section. A GARCH model may be described as follows:

$$u_{i,t} = \sqrt{h_{i,t}} v_t, \tag{3}$$

where $h_{i,t} = V\left[u_{i,t} \middle| u_{i,t-1}, \ldots, u_{i,t-x}\right] = c + \sum_{l=1}^{x} a_{i,l} u_{i,t-l}^2 + \sum_{m=1}^{y} b_{i,m} h_{i,t-m}$, $b_{i,m}$ represents the GARCH coefficients, c, $a_{i,l}$, and $b_{i,m}$ are positive to ensure that the conditional variance is positive, and $v_t \sim N(0,1)$.

Even though numerous variations and extensions of these models have been developed, the only extension we will consider is the exponential generalized autoregressive conditional heteroscedastic (EGARCH) models (Nelson 1991). The benefits of EGARCH models have been pointed out by Pagan and Schwert (1990), Hentschel (1995), and Brandt and Jones (2006).[6] EGARCH models capture the most important stylized features of stock return volatility, i.e. time series clustering, negative correlation with returns, lognormality, and with certain specifications, long memory (Andersen et al. 2001). The logarithmic transformation of this specification guarantees that the conditional variance will be positive without having to impose any constraints on the coefficients. Other extensions (TARCH, SWARCH, QTARCH, etc.) could provide better forecasts, but with additional assumptions our approach could loose the 'neutrality' that we are looking for. An EGARCH model may be described as follows:

$$u_{i,t} = \sqrt{h_{i,t}} v_t, \tag{4}$$

[6] For a review of the volatility forecasting literature, see Poon and Granger (2003). They summarize the methodologies and empirical findings of 93 papers that study the forecasting performance of various volatility models and find that the choice of a model is to some extent data and period specific.

where $\ln(h_{i,t}) = c + \sum_{l=1}^{x} a_{i,l} g(v_{t-l}) + \sum_{m=1}^{y} b_{i,m} \ln(h_{i,t-m})$, $g(v_t) = \theta v_t + \lambda[|v_t| - E|v_t|]$, and $v_t \sim N(0, 1)$.

The model estimated in this paper is an ARMA–EGARCH model so that we can forecast the level of the series, $r_{i,t}$, as well as its variance. The ARMA–EGARCH model is simply an ARMA model where the residual term, $u_{i,t}$, is assumed to be Gaussian white noise with variance denoted by the EGARCH model. The ARMA–EGARCH model used is:

$$r_{i,t} = \mu + \sum_{j=1}^{p} \phi_{i,j} r_{i,t-j} - \sum_{k=0}^{q} \theta_{i,k} u_{i,t-k} \tag{5}$$

where $u_{i,t} \sim N(0, h_{i,t})$.

Table 3 reports the chosen ARMA and ARMA–EGARCH models for each year and country for securitized real estate, while Table 4 does the same for stocks. As expected, the model specifications and parameter estimates (not reported) for both asset classes vary somewhat over time in all the countries.[7] This highlights the need of using a dynamic method in which we adapt the models (at a yearly frequency) and the parameter estimates (at a daily frequency) as new observations are made available.

Predictability Comparisons

Prediction Errors and Excess Returns

The comparison of the predictability of securitized real estate and stocks, but also the cross-country comparisons, are undertaken by examining the entire empirical distributions of prediction errors (PEs). First, a graphical comparison is depicted by estimating the probability density functions (PDFs) of the PEs with a kernel-smoothing method. The kernel density estimate of series $r_{i,t}$ at point x_i is estimated by:

$$\widehat{f}_i(x_i) = \frac{1}{Th} \sum_{t=1}^{T} K\left(\frac{r_{i,t} - x_i}{h}\right) \tag{6}$$

where $K\left(\frac{r_{i,t}-x_i}{h}\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{r_{i,t}-x_i}{h}\right)^2}$ is the Gaussian kernel, T is the number of observations, and h is the smoothing parameter or bandwidth, estimated with the following rule of thumb $h = \widehat{\sigma} T^{-1/5}$. Then, the Kruskal-Wallis test is employed to determine if the differences between the empirical distributions of the PEs are significant.

The Kruskal-Wallis test is a straightforward generalization of the Wilcoxon Rank-Sum or Mann-Whitney test where K independent samples can be tested. The Wilcoxon test is a non-parametric test for determining whether two independent samples come from the same distribution. The null hypothesis tested is that the two samples are drawn from a single population, and therefore that their probability distributions are equal. This test is based on the idea that the sum of the ranks for the

[7] Since we do not perform our forecasts with a single, static model, but with a model that evolves and adapts itself through time, we do not use other diagnostic tests as we are already using the SBC criterion to choose the most appropriate specification.

samples above and below the median should be similar. In the Kruskal-Wallis test, the K independent samples of sizes $n_1,\ldots,n_K$ are all combined into one large sample, they are sorted from smallest to largest and ranks are assigned (assigning the average rank to any observation in a group of tied observations). Then, the average of the ranks of the observations in the i-th sample, $\overline{R}_i$, is obtained and the test statistic is calculated as follows:

$$KW = \frac{12}{N(N+1)}\sum_{i=1}^{K} n_i\left(\overline{R}_i - \frac{N+1}{2}\right)^2 \tag{7}$$

where the null hypothesis that all K distributions are the same is rejected if $KW > \chi^2_{K-1}$. Since we believe that forecasting performance should not focus on the forecasts *per se*, but on the outcomes of the investment decisions taken with those forecasts, the same procedure is repeated, but instead of using PEs, we use the excess returns of an active trading strategy (to be described below) over a buy-and-hold investment.

Trading Strategies

To evaluate the performance of the predictions both across asset classes and across countries, we use the forecasts to construct active trading strategies and benchmark them against a buy-and-hold strategy. Under the assumption that an investor takes a long position either on real estate securities or on the risk free asset, the following trading rules are applied. If securitized real estate return forecasts are higher than the risk free asset's mean return for the previous 60 days, the investor will go long on real estate securities; otherwise the investor will go long the risk free asset. The same procedure is employed for stocks. At this point, no transaction costs are taken into account, but we also calculate the round-trip transaction costs that would equate the active strategy to the passive one. Note that benchmarking with a buy-and-hold investment entails that the active strategy will outperform the passive strategy if market downturns can be accurately predicted in a bull market whereas in a bear market, a passive strategy can be outperformed by being long the risk free asset and/or by accurately predicting market upturns; when short selling is not allowed. Therefore, outperforming a buy-and-hold investment is more difficult in bull markets than in bear markets.

Predictability Results

Comparisons based on Prediction Errors and Excess Returns

The predictability of securitized real estate and stock returns is first compared in each country with the PDFs of the prediction errors obtained with ARMA and ARMA–EGARCH forecasts. Such comparisons are illustrated in Figs. 1 and 2, respectively. Both figures show that securitized real estate PDFs dominate stock PDFs in the U.S. and the Netherlands. Inversely, both figures also show that stock PDFs dominate securitized real estate PDFs in Japan, Australia, the U.K., Singapore,

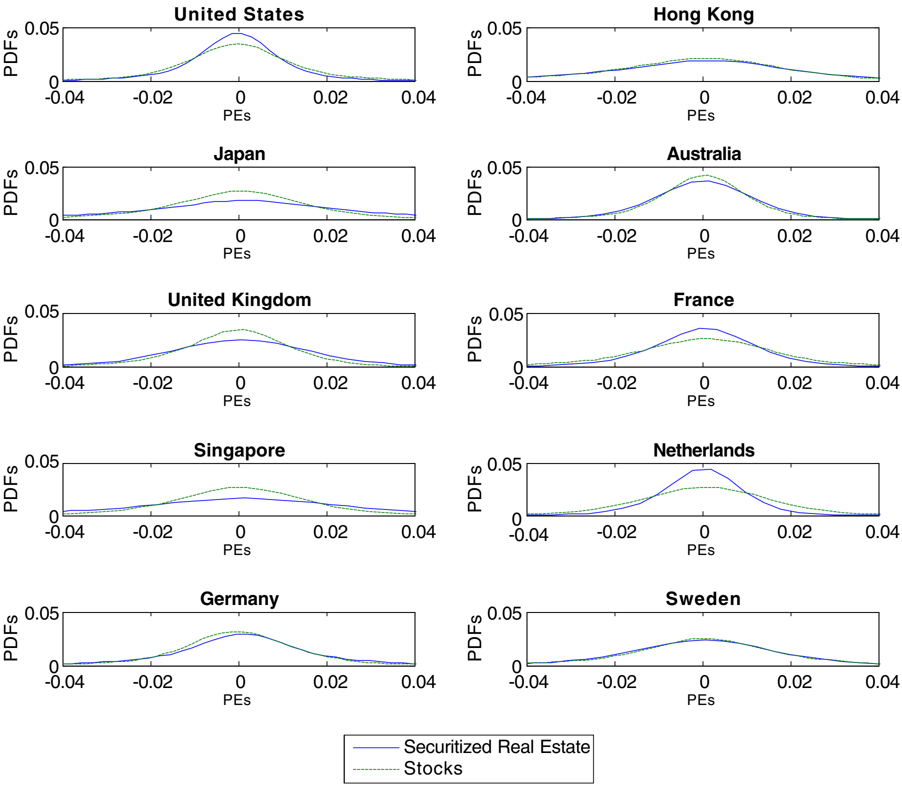

Fig. 1 Probability density functions of the ARMA prediction errors

Germany, and Sweden. In Hong Kong and France, the results depend on the forecasting technique used.

The differences between two PDFs might be difficult to establish graphically in some cases, so the Kruskal-Wallis test is used to determine if the differences between each pair of empirical distributions are significant (second column of Table 5).[8] Based on the ARMA forecasts, securitized real estate returns appear more predictable than stock returns in the Netherlands (at the 1% level), whereas stock returns appear more predictable than securitized real estate returns in Japan, the United Kingdom, and Germany (at the 1% level). Based on the ARMA–EGARCH forecasts, securitized real estate returns appear more predictable than stock returns in France (at the 10% level). The opposite conclusion holds for Sweden (at the 5% level). For the remainder of countries, both asset classes appear to be equally predictable. For the U.S., our results thus differ from the findings of Liu and Mei (1992) and Liao and Mei (1998), but are consistent with those of Mei and Lee

[8] Table 5 makes it possible to assess the significance of differences, but the determination of which asset class is more predictable is based on graphical inspection of the distributions (Figs. 1 and 2).

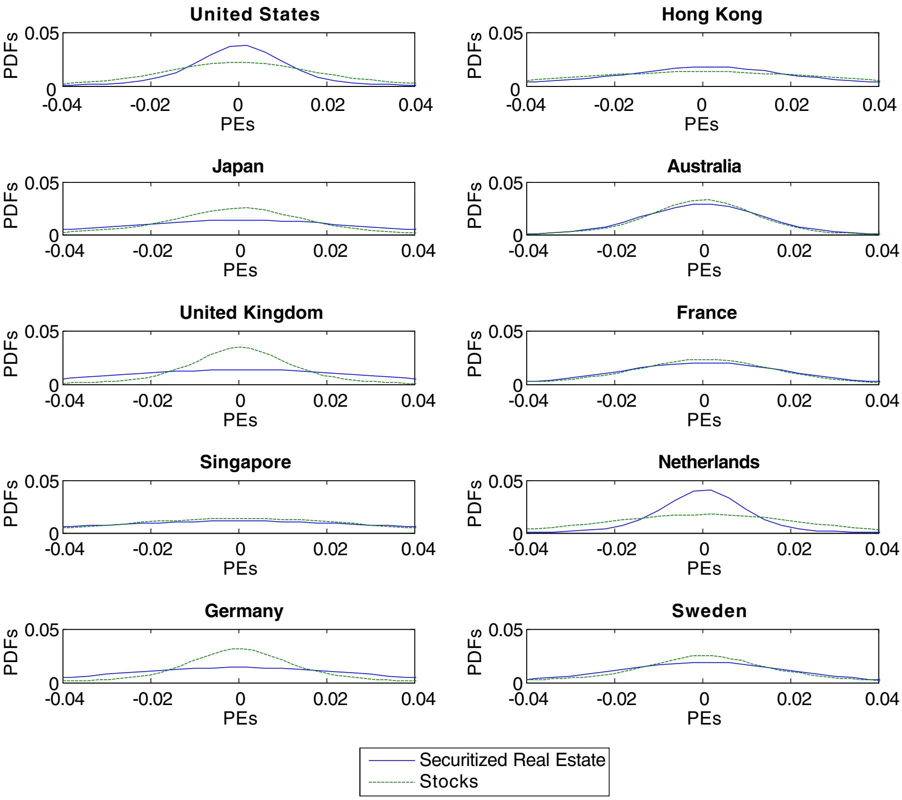

Fig. 2 Probability density functions of the ARMA–EGARCH prediction errors

Table 5 *P*-values of the Kruskal-Wallis test

Country	Prediction errors		Excess returns	
	ARMA	ARMA–EGARCH	ARMA	ARMA–EGARCH
U.S.	0.25	0.69	0.12	0.07[a]
Hong Kong	0.20	0.54	0.04[b]	0.04[b]
Japan	0.00[c]	0.99	0.16	0.03[b]
Australia	0.95	0.90	0.97	0.88
U.K.	0.00[c]	0.32	0.17	0.27
France	0.87	0.09[a]	0.28	0.02[b]
Singapore	0.97	0.38	0.03[b]	0.01[c]
Netherlands	0.01[c]	0.77	0.01[c]	0.01[c]
Germany	0.00[c]	0.37	0.00[c]	0.01[c]
Sweden	0.48	0.04[b]	0.56	0.11

The null hypothesis tested is that the probability distributions of both asset classes are equal
[a] Rejection of the null hypothesis at the 10% level
[b] Rejection of the null hypothesis at the 5% level
[c] Rejection of the null hypothesis at the 1% level

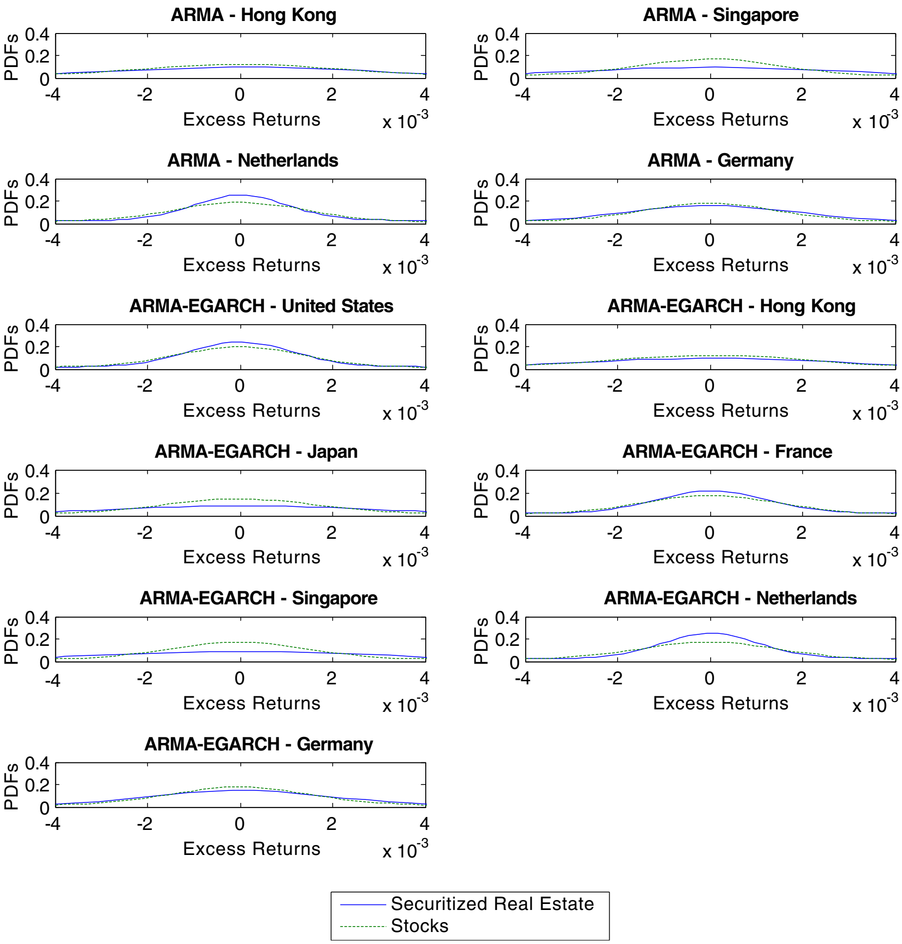

Fig. 3 Significantly different probability density functions of ARMA and ARMA–EGARCH excess returns

(1994) and Li and Wang (1995), even if the framework used in these studies might bias their conclusions in this regard.

From an investment point of view, the accuracy of a forecast is not as important as the outcome of the investment decision made with the forecast. Therefore, the predictability of the two asset classes in each country is compared in a more pragmatic manner by replacing the prediction errors in the analysis by the excess returns of the active trading strategy over the buy-and-hold investment. Using excess returns enriches the analysis as the results show if the differences in predictability are economically significant. The last column of Table 5 contains the results of the Kruskal-Wallis test for differences in the distributions of excess returns. Only the significantly different PDFs of ARMA and ARMA–EGARCH excess returns are presented in Fig. 3. Overall, the results show that the predictability of securitized real estate and stock returns differs in some countries. Securitized real estate appears to be more predictable in the Netherlands with the two forecasting techniques, and in the U.S. and France with the ARMA–EGARCH models.[9] Stocks appear to be more predictable with the two forecasting techniques in Hong Kong, Singapore, and Germany, and with the ARMA–EGARCH models in Japan.

Hence, some differences exist between the results obtained with prediction errors and excess returns of an active strategy over a buy-and-hold investment. In line with Gerlow et al. (1993), our results show that statistical criteria may be misleading for determining the potential profitability of a forecast in a trading strategy. However, a common result that emerges from the different methodologies is that securitized real estate returns are generally more predictable than stock returns in countries with well established REIT regimes. Securitized real estate returns are indeed more predictable than stock returns in the U.S. and the Netherlands, countries where REIT regimes exist since 1960 and 1969, respectively. On the other hand, stock returns are more predictable than securitized real estate returns in some of the countries that have only established REIT regimes in the recent past.

The greater predictability of securitized real estate returns in mature REIT markets is intuitively appealing as such vehicles have more stable income returns (cash flows) as their investment focus is on income producing real estate and are required to distribute at least 90% of their income as dividends to qualify for tax transparency in the U.S. (100% in the Netherlands). Related to this issue, Pagliari et al. (2005) show that there is no difference from a statistical point of view between REIT and direct real estate returns in the U.S. once REIT returns have been deleveraged, direct real estate returns desmoothed, and portfolio composition effects corrected for. Evidence thus emerges for tax transparent real estate vehicles to behave more like direct investments, in particular with respect to a regular income stream.

It is further worthwhile to perform some cross-country comparisons; these pertain to securitized real estate only. The predictability of ARMA models across countries is assessed in Fig. 4, Panel A. The properties displayed by the PDFs of the prediction errors show that differences in predictability exist across countries. The best forecasts using ARMA models are obtained in the Netherlands, the U.S., and Australia. According to the Kruskal-Wallis test (not reported for the cross-country comparisons), the top three countries have empirical distributions which are significantly different from those of the other countries at the 5% level. The results regarding the ARMA–EGARCH forecasts (Fig. 4, Panel B) are similar to those of the ARMA forecasts, but lack statistical significance.

Figure 5 displays securitized real estate's empirical distributions across countries using excess returns instead of prediction errors. Since excess returns evaluate the decisions made with the forecasts, whereas prediction errors evaluate the accuracy of the forecasts, it is not surprising that the PDFs of the former are steeper than those of the latter (note that the *x-axes* have different units). Indeed, with the trading strategy, there will only be an 'error' when the decision being made is to go long the risk free investment as else the two strategies will be identical. Both time series techniques reveal similar results. The Kruskal-Wallis tests identify two groups of countries with different predictability patterns. Australia, the Netherlands, the U.S., France, the U.K., Germany, and Sweden belong to the group with higher predictability, while

[9] The ARMA results are consistent with Nelling and Gyourko's (1998) findings for the United States as their AR models reveal that EREITs and mid caps are equally predictable.

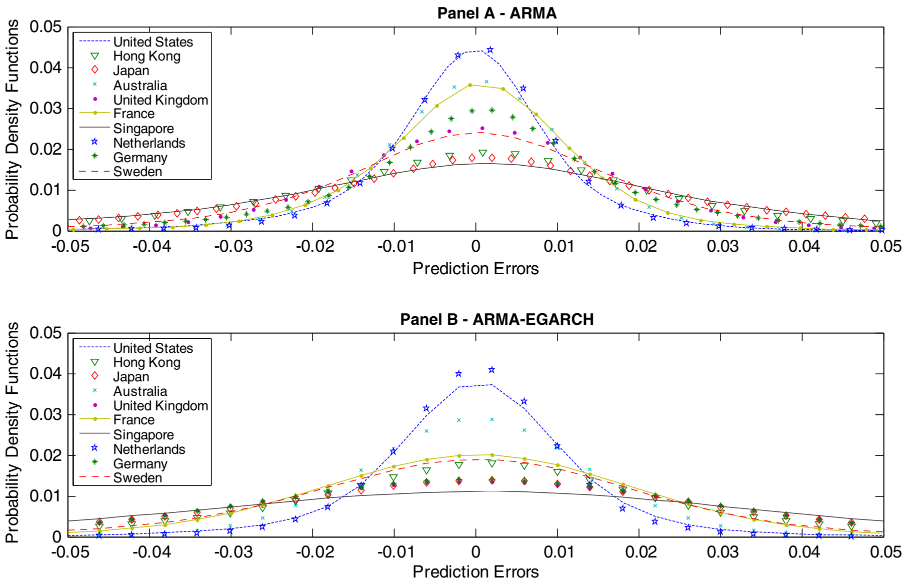

Fig. 4 Securitized real estate's probability density functions of the prediction errors

Singapore, Hong Kong, and Japan are in the one with lower predictability. The contrasting results for Asia are not surprising as a different continental environment and performance behavior have been documented (Ooi and Liow 2004; Hoesli and Serrano 2007). In sum, the results obtained with the cross-country comparisons confirm those obtained with the across asset comparisons; the predictability of

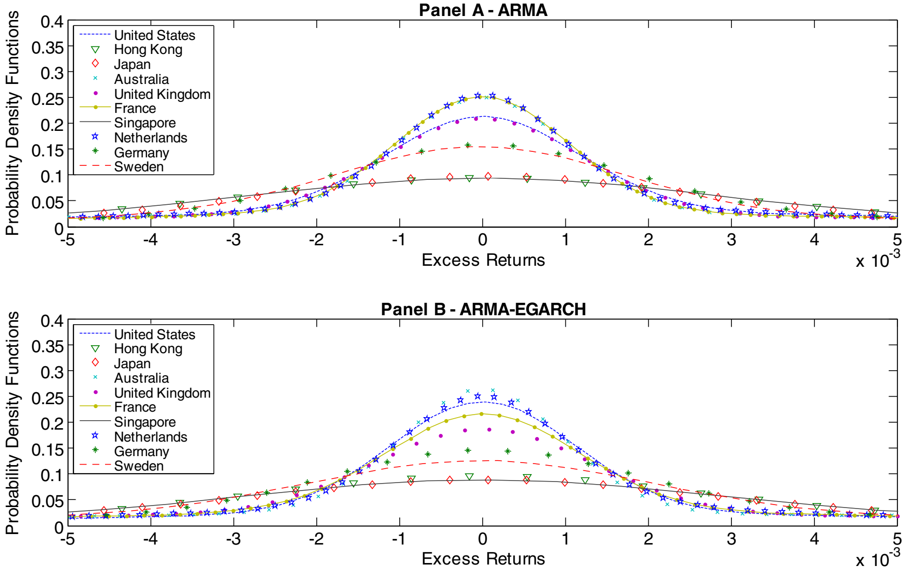

Fig. 5 Securitized real estate's probability density functions of the excess returns

securitized real estate returns is greater in the countries with the more established REIT regimes (i.e. the U.S., the Netherlands, and Australia).

Trading Strategy Comparisons

The results of the trading strategies using the ARMA and ARMA–EGARCH forecasts without taking transaction costs into account are shown in Table 6. For comparison purposes, we also report the results of buy-and-hold strategies. The initial wealth in each case is 1,000 units of local currency. A buy-and-hold investment on securitized real estate outperforms a buy-and-hold investment on stocks in the U.S., Japan, Australia, and France. On the other hand, a buy-and-hold investment on stocks outperforms a buy-and-hold investment on securitized real estate in Hong Kong, the U.K., Singapore, the Netherlands, Germany, and Sweden. These results obviously highlight the varying average returns on the asset classes. The two active trading strategies outperform the buy-and-hold benchmark in all countries for both asset classes. With the exception of Germany for securitized real estate and of France for stocks, the ARMA–EGARCH forecasts outperform the ARMA forecasts in all the countries for the two asset classes. This results from the fact that the ARMA–EGARCH model is more complete as it takes into account the variance of returns in addition to mean returns. Overall, the trading strategies work very well, but gains need to be put into perspective with the costs associated with such strategies.

Table 7 displays the transaction costs that would render the active strategy equivalent to a passive one. Such a focus is interesting as institutional and private investors will have different transaction costs and can thus assess the usefulness of the reported strategies. These figures show that the active trading strategies generally produce better results for real estate securities than for stocks. In fact, the active trading strategies allow for higher transaction costs for securitized real estate than for stocks in seven out of ten countries when ARMA models are used and in eight out of

Table 6 Terminal wealth for trading strategies vs buy-and-hold policies (January 1992–December 2007)

Country	Securitized real estate			Stocks		
	Trading strategy		Buy-and-hold policy	Trading strategy		Buy-and-hold policy
	ARMA	ARMA–EGARCH		ARMA	ARMA–EGARCH	
U.S.	19,940	26,614	9,606	11,363	14,787	5,237
Hong Kong	40,093	109,838	7,567	41,614	96,646	10,896
Japan	7,448	25,012	2,029	6,868	8,401	1,131
Australia	12,423	14,518	8,617	11,832	15,191	7,429
U.K.	17,238	17,873	4,779	14,988	19,912	5,154
France	9,347	17,532	9,213	7,820	6,645	6,515
Singapore	24,754	26,100	3,046	11,810	11,945	3,515
Netherlands	13,963	14,491	4,852	19,114	23,753	6,986
Germany	14,814	12,257	1,740	23,529	36,510	4,955
Sweden	32,606	49,623	4,378	24,893	30,769	10,667

The initial investment is 1,000 units in local currency. No transaction costs are considered

Table 7 Transaction costs rendering trading profits equal to buy-and-hold profits

Country	Round-trip transaction costs (basis points)			
	Securitized real estate		Stocks	
	ARMA	ARMA–EGARCH	ARMA	ARMA–EGARCH
U.S.	18	23	12	16
Hong Kong	25	43	23	38
Japan	22	39	26	30
Australia	6	9	9	14
U.K.	21	23	19	22
France	0	12	3	0
Singapore	33	33	20	22
Netherlands	18	20	16	20
Germany	40	37	26	35
Sweden	33	39	14	17

ten countries when ARMA–EGARCH models are used; the ARMA–EGARCH models generally outperforming the ARMA models.

To determine if profits may be made with the forecasts, a possible benchmark to use is round-trip transaction costs amounting to 30 basis points (Chan and Lakonishok 1993; Aitken and Frino 1996). With such a benchmark, the buy-and-hold investment is outperformed by active strategies net of transaction costs with both forecasting techniques in Singapore, Germany, and Sweden for securitized real estate. Additionally, active strategies based on ARMA–EGARCH models outperform the passive strategy in the presence of transaction costs in Hong Kong and Japan for securitized real estate and in Hong Kong, Japan, and Germany for stocks. Thus, active trading strategies outperform the buy-and-hold benchmark in five countries for real estate securities and in three for stocks, reinforcing the conclusion that securitized real estate is generally more predictable than stocks.

Since the trading strategy is based on the time series forecasts, our approach is akin to that employed in studies of serial persistence. Therefore, our results support the good results of momentum strategies as reported by Cooper et al. (1999) and by Stevenson (2002), whereas they contrast the findings of Mei and Gao (1995). Overall, the results indicate that time series forecasts help achieve higher profits than those obtained with a buy-and-hold investment once transaction costs are accounted for in a number of countries.

Concluding Remarks

Although previous research has compared the predictability between securitized real estate and stock returns, the use of a multifactor asset pricing framework has resulted in potentially spurious conclusions due to the possible specification biases introduced in such comparisons. The time series approach followed in this paper creates a level playing field that allows to truly compare the predictability of returns between the two asset classes. Therefore, our methodology provides the answers to a question that has been somewhat wrongfully addressed in the literature.

Empirical distributions of the prediction errors reveal differences in predictability between securitized real estate and stock returns. So is the case when excess returns of an active strategy over a passive investment are used in the analysis. The latter results, however, allow for the economic significance of the results to be assessed. These analyses show that the maturity of the securitized real estate market plays an important role in the predictability of its returns. In particular, we find that in countries with established REIT regimes, securitized real estate returns are more predictable than stock returns as the rental focus of REITs generates more predictable income returns. Stated differently, tax transparency is likely to lead real estate securities to behave more like the underlying real estate assets. This finding is confirmed with the cross-country comparisons of securitized real estate return predictability. Hence, the best forecasting accuracy is found in the U.S., the Netherlands, and to a lesser extent Australia; the countries with the three oldest REIT regimes in our sample.

Active trading strategies based on ARMA and especially on ARMA–EGARCH forecasts outperform the buy-and-hold benchmark in all the countries for both asset classes. When transaction costs are taken into account, this remains the case in half of our countries for real estate securities, but only in three for stocks. Given that ARMA–EGARCH models forecast the variance of returns in addition to mean returns, they are generally more effective in devising investment strategies.

Further research could aim to find models and forecasting variables that lead to economically significant outcomes. The use of more complex active trading strategies could also contribute to this objective. Nonlinear models are also worth exploring, as well as using forecasting variables related to the well documented hybrid nature of securitized real estate, i.e. the fact that real estate stocks encompass stock, bond, and real estate dimensions. A multivariate framework could be employed to compare the predictability of securitized real estate and stock returns provided that an appropriate model driving the returns of each asset class could be devised. Finally, future research could aim to further explain the factors that make REITs more predictable than non-REITs.

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