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The Long Term Relation Between Indirect and Direct Real Estate

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THE LONG TERM RELATION BETWEEN INDIRECT AND DIRECT REAL ESTATE

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Executive Summary

Using a panel of eight countries, this thesis presents a cointegration relation between direct real estate and indirect real estate in the long run. The presence of cointegration implies that two assets are substitutes for investors in the long run. As a consequence, diversification benefits of holding both assets are no longer possible so that only one asset category should appear in the mixed asset portfolio in the long run. On the other hand, two assets are not substitutable in the short run because of their different characteristics in terms of valuation, leverage effects and liquidity. Due to their valuation techniques a lead-lag relation between two assets is observed in the short run. Since the direct real estate index reflects the appraiser valuations which are determined approximately once a year, it falls behind the value of the indirect real estate which can be detected through daily supply and demand behaviour of the market. Panel vector error correction results confirm that while lagged indirect real estate returns have a predictive power on current value of direct real estate returns the reverse is not true which implies that indirect real estate is leading and direct real estate is following variable.

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CHAPTER I: INTRODUCTION

This thesis mainly aims to investigate whether direct real estate and indirect real estate differ from each other in the long-run. If a cointegration relationship exists between two assets, they adjust to equilibrium in the long-run so that both assets may be used interchangeably as a measure of real estate in the long run analyses. Furthermore, investors can hold real estate in their portfolio either in the form of a property or real estate security in the long run because both assets would imply the same level of risk and return characteristics in the long-run once a cointegration relation is detected.

Direct real estate can be defined as properties that are purchased directly whereas indirect real estate refers to shares of real estate companies listed on the stock exchanges. Although the prices of direct real estate and indirect real estate are fundamentally determined by the value of bricks or buildings there are still other factors that cause one asset class to behave differently from another over time. For instance, the value of a listed real estate company is driven not only by its property holdings but also by its management quality and usage of financial leverage. Moreover, prices of two assets are determined based on different valuation techniques at different frequencies. For instance, share price of the listed real estate companies is based on current demand and supply behaviour of the market on a daily basis. On the other hand, the price of direct real estate is determined by the appraisers who tend to assign a value to a property on a quarterly or annually basis. Due to these factors, direct real estate and indirect real estate may not be perfectly substitutable assets for the investors.

Previous research on the relationship between direct real estate and indirect real estate suggests that these two assets are weakly correlated. This result creates an incentive for the investors to hold both assets in their portfolio to benefit from diversification. If two assets are cointegrated, however, short term contemporaneous correlations are expected to increase so that diversification benefits of investing in both assets are no longer possible over long horizons.

In practice, long term investors such as pension funds use Asset Liability Models (ALM) in deciding their optimal strategic asset allocations. ALM models apply scenario analysis to determine risk and return characteristics of the optimal investment strategies. Scenarios generated by these models are based on historical time series of variables of interest and these scenarios are used to make long term strategic policy decisions. In this context, pension funds might observe short term correlations between direct real estate and indirect real estate looking at historical time series and they might use this input to generate scenarios regarding risks and returns of a portfolio which includes both types of assets at the same time. However, observed short term correlations tend to increase in the presence of a cointegration relationship between two assets meaning that diversification benefits are no longer possible and, as a result, only one asset class can have a place in the mixed asset portfolio in the long run. As a consequence, scenarios generated by short term correlations might be misleading for pension funds to make long term strategic policy decisions. Therefore, it is worth investigating whether two assets form a cointegration relation in the long-run.

The cointegration studies in the literature that examined the long run relationship between direct and indirect real estate all used time series data. A common problem associated with time series analysis is insufficient number of observations due to data limitations. Since the direct real estate data is recently available for most of the countries and it is measured quarterly or annually, the cointegration analysis between direct and indirect real estate might suffer from the insufficient number of observations in country by country analysis. At this stage, using panel data which combines cross-sections and time series might solve the problem. Therefore, this thesis will apply a panel-based framework to analyze the existence of a long-run relationship between direct real estate and indirect real estate.

Once a cointegration relationship is detected, one can employ a vector error correction mechanism to analyze short term behaviour of direct and indirect real estate in detail. This mechanism incorporates an error correction term which is known as speed of adjustment parameter. This parameter explains that once a deviation from long run relationship occurs, which variable or variables make adjustments to restore the long run relation. Vector error correction estimation also includes both lagged dependent and independent variables as explanatory variables to observe Granger causality in the short run. The possibility of a lead-lag structure between direct real estate and indirect real estate has been widely discussed in the literature. Since the direct real estate index reflects appraiser valuations which are determined every six to twelve months, it falls behind the value of the indirect real estate which can be detected through daily supply and demand behaviour of the market. Therefore, it is worthwhile to investigate the Granger causality between lagged returns of listed real estate companies and appraisal-based real estate indices.

The structure of this thesis is organized as follows: Section 2 describes characteristics of direct real estate and indirect real estate. Section 3 presents the previous studies in the literature. Data sources and methodology are explained in Section 4. Estimation results regarding panel unit root and panel cointegration tests, long run and short run model are presented in Section 5. Finally, Section 6 gives concluding remarks.

CHAPTER II: CHARACTERISTICS OF REAL ESTATE

Investors can hold real estate in their portfolio either directly, by purchasing a property, or indirectly, by buying the shares of real estate companies listed on the stock exchanges.[1] Direct and indirect real estate are valued in different markets so that they mainly have different characteristics in terms of valuation, leverage effects and liquidity. These characteristics can be summarized as follows:

Valuation: Direct real estate series are determined by appraisal valuations which are conducted approximately once a year. That is, direct real estate is valued initially by the purchase price at the time of acquisition and its value updated by periodic appraiser valuations and its final value depends on sale price at the time of sale. Knowing the past values of a property, appraisers tend to assign a current value to this property similar to its value in previous period which causes the direct real estate series to follow a smooth behaviour over time. On the other hand, the value of indirect real estate series is determined by daily demand and supply behaviour of the stock market and share price of real estate companies are affected by the investor sentiment regarding stock market. Different valuation techniques of two assets result in that one asset shows higher volatility than another. In other words, the volatility of direct real estate returns is underestimated compared to indirect real estate returns as a consequence of appraisal smoothing and volatility of indirect real estate returns is overestimated compared to direct real estate returns due to market sentiment.

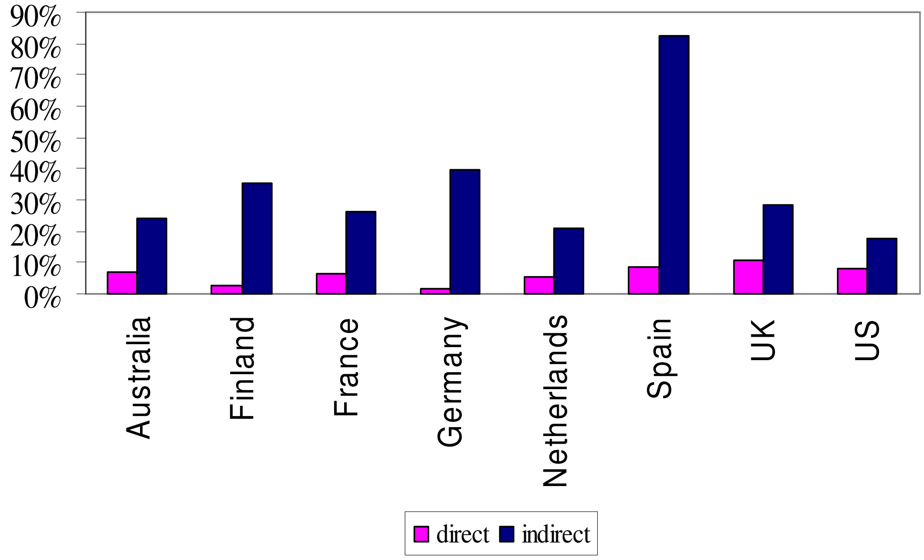
[1] Non-listed indirect real estate investments are also available for investors but this category is beyond the scope of this paper.

Leverage: Direct real estate indices are reported exclusive of leverage whereas indirect real estate series include financial leverage used by listed real estate companies. Leverage can be defined as using borrowed money to increase the profit of an investment. If asset returns of the listed real estate company are higher than its cost of debt, securitized real estate returns tend to be higher than that of direct real estate as leverage level increases. Moreover, returns of indirect real estate are more volatile than those of direct real estate since leverage is exposed to interest rate risk and due to leverage factor.[2]

Liquidity: Direct real estate has generally perceived less liquid than indirect real estate because buying and selling direct real estate requires a longer time period compared to indirect real estate. The longer time period stems from the fact that direct real estate incurs high transaction costs and its value is determined at a low frequency whereas price of indirect real estate is available in daily stock exchanges and its transactions costs are low. Due to liquidity considerations, direct real estate is generally attractive for long term investors whereas indirect real estate is attractive for both short term and long term investors.

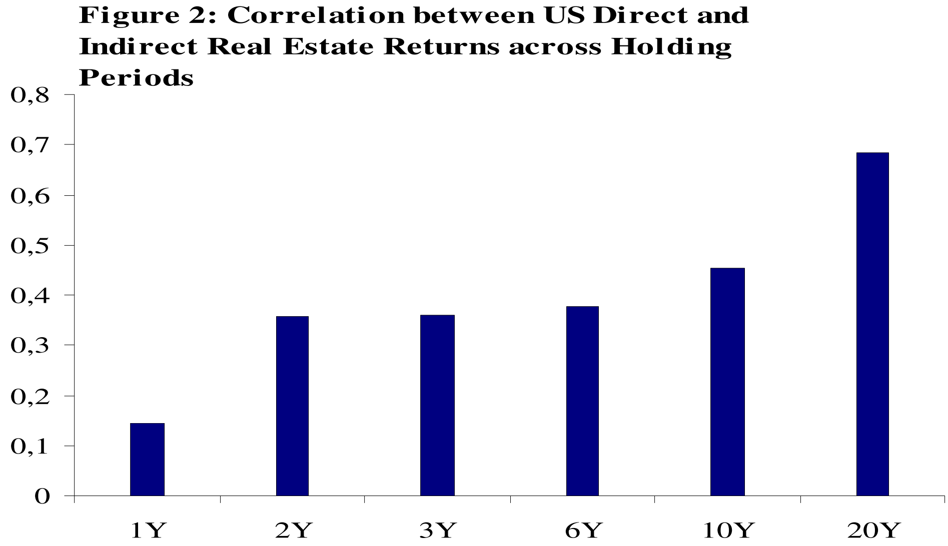
[2] Property returns are multiplied by the leverage factor which is the reciprocal of one minus the loan-to-value ratio.

Figure 1: Standard Deviation of Yearly Asset Returns



Source: Table 1: Data Summary in Chapter IV

Figure 1 presents the standard deviation of yearly returns for direct and indirect real estate across countries. Note that calculations are based on data availability of each country so that some countries cover long periods whereas short series are available for the others. As a consequence, it may not be possible to compare volatility of two assets across countries by looking at Figure 1. One can only make comparisons about the level volatility of two assets in each country separately. Obviously, the volatility of direct real estate returns is lower than that of indirect real estate returns for all countries in Figure 1. As mentioned above, the reason behind that observation can be appraisal valuation of direct real estate and market valuation and of indirect real estate. High volatility of the indirect real estate returns may also be influenced by leverage effects.



Source: Table 1: Data Summary in Chapter IV

Figure 2 indicates contemporaneous correlation between direct and indirect real estate returns across various holding periods. For a one-year holding period, the two assets are correlated with a coefficient of 0.14 and the size of correlation steadily rises as the holding period increases and it becomes 0.68 for twenty years. This observation roughly says that the relationship between direct and indirect real estate is weaker in short periods but it becomes stronger as the holding period increases. This observation suggests the possibility of cointegration relationship at first glance, since the correlation coefficient between two asset returns converges to one in the presence of cointegration by definition. In the short run real estate companies are exposed to risk generated by stock market movements but in the long run their share price is mostly determined by their property holdings which is in line with the adage that “bricks are bricks”.

CHAPTER III: LITERATURE REVIEW

The relationship between direct real estate and indirect real estate has been widely studied in the literature. Earlier studies generally focused on the contemporaneous correlation between the two assets and most of them observed that they are weakly correlated. Goetzmann and Ibboston (1990) and Ross and Zisler (1991) were among the first to emphasize that the two assets behave differently in terms of risk and return characteristics using time series data. According to their results, low correlation might stem from the fact that two assets have different valuation techniques and only one asset category, indirect real estate, is influenced by leverage effects.

Giliberto (1990) emphasized that the low correlation between the two assets becomes stronger once a one-period lag of indirect real estate is added into the estimation. He found this result reasonable since appraisal-based valuations have low frequencies and follow the daily market conditions after a lag. Similarly, the lead-lag structure between the two assets also examined by Myer and Webb (1993) through Granger causality tests and they concluded that indirect real estate prices lead direct real estate prices. Barkham and Geltner (1995) investigate whether a price discovery mechanism exists in public and private real estate markets using Granger causality tests after correcting the securitized real estate series for leverage. They conclude that price information regarding public real estate market does not fully transmit to private real estate market for about one year or longer.

The studies mentioned above utilize short-term investment horizons in analyzing the possible relationship between direct and indirect real estate. A recent study by Morawski et al. (2008) points out the importance of the length of investment horizon since direct real estate is a long-term investment in nature so that the correlation between two assets is likely to be stronger as the investment horizon increases. In this context, they apply cointegration analysis to determine whether two asset classes move together in the long run using quarterly data from 1978 to 2006. Their results suggest that there exists a cointegration relationship between direct real estate and indirect real estate for the United States and United Kingdom even though indirect real estate tends to lead the direct one in the short-run.

Another recent study by Oikarinen et al. (2009) examines the relationship between indirect and direct real estate series both in the short-run and in the long-run. They emphasize that the presence of leverage in indirect real estate series might disrupt a one-to-one relationship between two assets in the long run. The reason is that indirect real estate returns grow faster than direct real estate returns over long horizons assuming that asset returns of the listed real estate company are higher than its cost of debt. As a consequence, they find that the long run cointegration coefficient of indirect real estate is about 0.65 which is consistent with 35 percent leverage level for indirect real estate companies in the United States.

In the literature, empirical studies on long term relationship between direct real estate and indirect real estate are limited. Moreover, all of these studies utilize time series analysis to investigate such a long-run relation. This thesis intends to investigate this relation through a panel based framework which combines cross section and time dimensions so that the sample size becomes larger compared to a single country analysis. As a consequence, problems arising from data limitations regarding direct real estate series are overcome and an increased number of observations leads to increased accuracy of the estimation results.

CHAPTER IV: EMPIRICAL ANALYSIS

4.1. DATA

The available data for direct real estate and indirect real estate across countries are summarized in Table 1.

Table 1: Data Summary

Countries	Direct Real Estate-Non-listed	Indirect Real Estate-Listed
Australia	1986-2009- Quarterly	1989-2009- Monthly
Finland	1997-2009- Annually	1992-2009- Monthly
France	1997-2009- Annually	1989-2009- Monthly
Germany	1995-2009- Annually	1989-2009- Monthly
Netherlands	1977-2009- Annually	1989-2009- Monthly
Spain	2000-2009- Annually	1989-2009- Monthly
UK	1986-2009- Quarterly	1989-2009- Monthly
US	1977-2009- Quarterly	1972-2009- Monthly

Sources: European Public Real Estate Association (EPRA), Investment Property Databank (IPD), ROZ-IPD, and National Council of Real Estate Investment Fiduciaries (NCREIF), Property Council of Australia, and KTI.

As a measure of direct real estate, NCREIF, ROZ-IPD, Property Council of Australia, KTI indices are used for United States, the Netherlands, Australia, and Finland, respectively. IPD index is used for all of the remaining countries. Direct real estate data constructed by the aforementioned institutions are reported as exclusive of leverage effects and they include all type of real estate (All Property). Indirect real estate is measured by NAREIT equity index for the US and EPRA index is used for all of the remaining countries and it is reported as inclusive of leverage effects by these organizations. Both direct and indirect real estate indices are total return indices specified as the base year of 2002 equals to 100 and they are measured in local currency of the respective countries.

Table 2: Sample Size

Countries	Covered Period	Number of Observations
Australia	1989-2009	21
Finland	1997-2009	13
France	1997-2009	13
Germany	1995-2009	15
Netherlands	1989-2008	20
Spain	2000-2009	10
UK	1989-2009	21
US	1977-2009	33
Total Number of Observations: 146		

Source: Table 1: Data Summary

The sample size is arranged based on data availability across countries and the sample is unbalanced by construction. Annual data is used because previous literature suggests that even if direct real estate series are available at quarterly for Australia, UK and US, they are generally valued at the end of fourth quarter.[3] As a consequence, using quarterly data for these countries may be misleading and incorporates high degree of stale pricing effects. Moreover, IPD data is available only annually for the remaining countries. In order to increase the sample size, these countries are added into the estimation. Finally, both direct and indirect real estate indices are estimated in natural logarithms.

[3] See Geltner (1993).

Figure 3 and Figure 4 below report both direct and indirect real estate total return indices in levels and in first differences across countries, respectively. According to Figure 3, direct real estate series show smoothing behaviour over time due to appraisal valuation of property index whereas indirect real estate series are volatile over years due to market valuation and leverage included in real estate companies' total return indices. Both indices are growing in levels generally, except the sudden drop in indirect real estate series in 2007. Figure 3 confirms the possible lead-lag relationship between two assets. For instance, indirect real estate index has experienced a peak around 2006 in each country whereas direct real estate index still continues to increase for some countries, Germany and Finland or it has experienced a peak after 2006 for the other countries. This observation suggests that indirect real estate is leading whereas direct real estate is following variable.

According to Figure 4, both direct and indirect real estate show fluctuations around a positive mean and they look stable over time. In 2007, there is a sudden drop in the value of indirect real estate index in each country which can be explained by the negative effect of financial crisis all around the world.

Figure 3: Real Estate in Levels (2002=100)

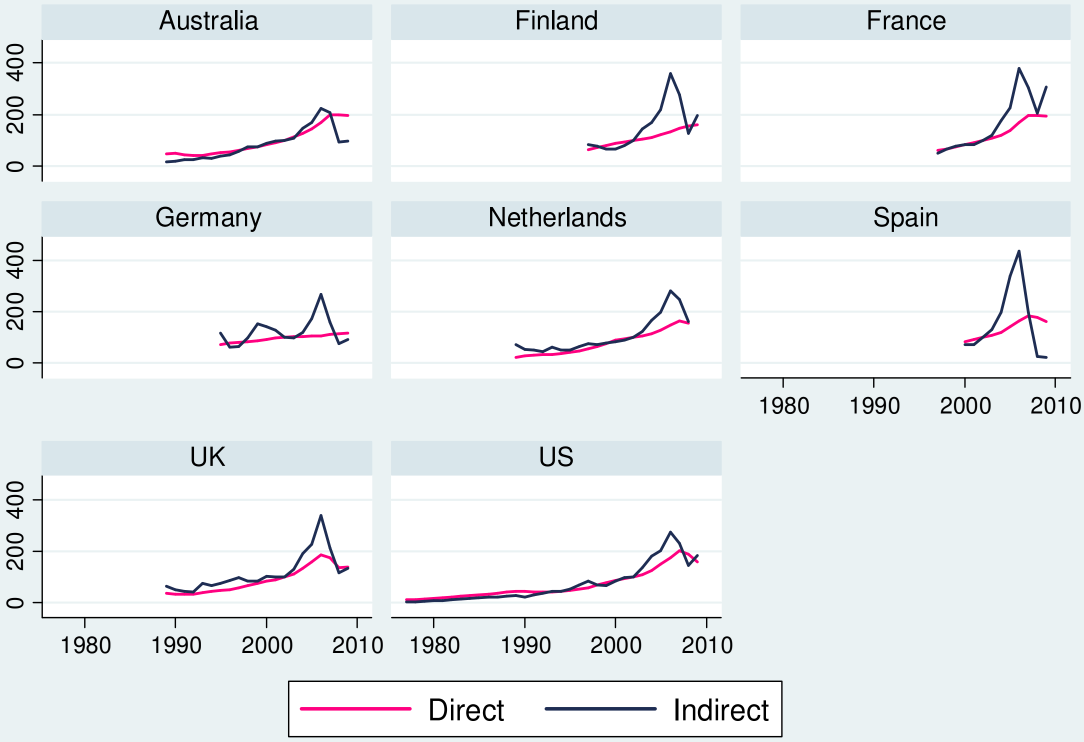
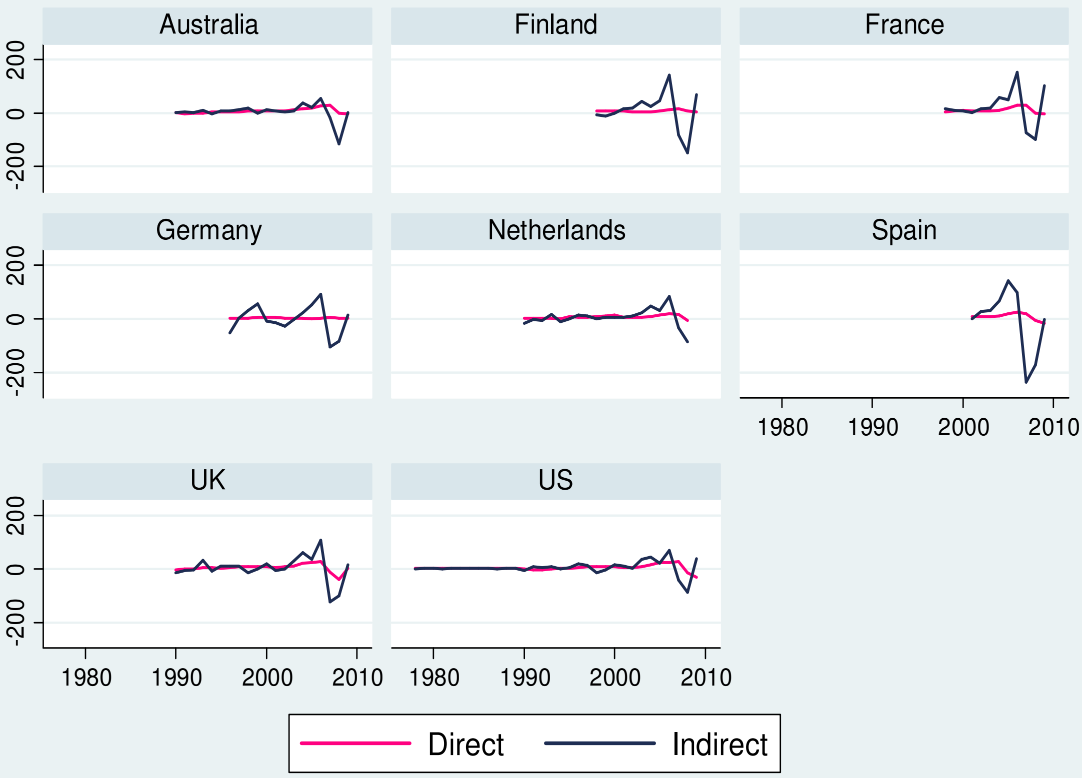


Figure 4: Real Estate in First Differences (2002=100)



4.2. METHODOLOGY

4.2.1. THE LONG TERM

4.2.1.1. Panel Unit Roots

Similar to macroeconomic and financial time series, real estate series are generally found to be nonstationary in the literature. Therefore, it is necessary to check the integration properties of direct and indirect real estate series before performing cointegration analysis. If a series is stationary, it is called integrated of order zero, I(0). If a series is nonstationary in the level but it is stationary in the first difference, then this series is said to be integrated of order one, I(1).

Dickey-Fuller (DF) or Augmented Dickey-Fuller (ADF) tests have been traditionally used to test for the presence of unit roots in time series. Similarly, in the panel literature, Levin, Lin and Chu (2002), Im, Pesaran and Shin (2003), Hadri (2000), Maddala and Wu (1999), Choi (2001) have developed panel-based unit roots tests which are derived from the tests in the time series literature. Levin, Lin and Chu (2002) and Hadri (2000) tests are designed to be used if the sample is balanced. When the time dimension of the sample varies country to country, sample is unbalanced, tests developed by Im, Pesaran and Shin (2003), Maddala and Wu (1999), Choi (2001) are suitable for testing integration properties of the variables of interest in the cointegration analysis.

The power of panel unit root tests is considered to be higher compared to individual unit root tests since the information in the time series is enhanced by that contained in the cross-section data. Moreover, in contrast to individual unit root tests with complicated limiting distributions, panel unit root test statistics have normal limiting distributions.[4] Panel unit root tests developed by Im et al. (2003), Maddala and Wu (1999) and Choi (2001) can be summarized as follows:

Im et al. (2003) (IPS) uses Augmented Dickey Fuller (ADF) specification by considering the following two models:

$$\Delta y_{it} = \rho_i y_{i,t-1} + \sum_{L=1}^{p_i} \theta_{iL} \Delta y_{i,t-L} + \alpha_{mi} d_{mt} + \varepsilon_{it} \qquad (1)$$

where y_{it} is a series with cross-section dimension $i = 1,2,....,N$ and with time-series dimension, $t = 1,2,....,T$, $m = 1, 2$, d_{mt} indicates the vector of deterministic variables such as intercepts and time trends and α_{mi} denotes the corresponding vector of coefficients for model $m = 1, 2$, p_i is the individual specific lag order, and ε_{it} is an error term which is distributed independently across cross-sections and it may contain serial correlation. For model 1, $d_{1t} = \{1\}$, and for model 2, $d_{2t} = \{1, t\}$. The null hypothesis of IPS for both models is that each series in the panel contains a unit root, i.e., $H_0 : \rho_i = 0$ for all i and the alternative hypothesis allows for some (but not all) of the individual series to have unit roots, i.e.,

$$H_1 : \begin{cases} \rho_i < 0 \text{ for } i = 1, 2, \ldots, N_1 & \text{(No unit root)} \\ \rho_i = 0 \text{ for } i = N_1 + 1, \ldots, N & \text{(Unit root)} \end{cases}$$

[4] The distribution of DF and ADF test statistics converges to a function of Brownian motion which is a non-standard limiting distribution. The power of these tests is very limited especially for small samples. See Levin et al. (2002) and Baltagi (2005).

where N is the total number of cross-sections units. The testing procedure of the IPS test is based calculating individual ADF statistics for each cross section separately and then taking the average of them to find an averaged t-statistic for the entire panel. The IPS test is distributed asymptotically standard normal as $T \to \infty$ followed by $N \to \infty$.

To provide an asymptotic distribution, IPS test makes an assumption regarding the size of N and T, such as $N/T \to 0$, implying that N should be relatively smaller than T. As an alternative to the IPS test, Maddala and Wu (1999) and Choi (2001) suggest a Fisher test which combines the significance levels from individual unit root tests using Fisher's (1932) results.

Fisher's test can be used with any individual unit root test in time series literature. For instance, Fisher-ADF unit root test first calculates the significance of individual ADF tests, namely, p-values. Based on the property of continuous individual test statistics, π_i's, p-values, have an independent uniform distribution and $-2\log_e \pi_i$ is χ^2 distributed with two degrees of freedom. By applying the additive property of the χ^2 distribution, one can find the combined p-values are also χ^2 distributed with 2N degrees of freedom as $T \to \infty$, i.e,

$$-2\sum_{i=1}^{N}\log_e \pi_i \to \chi^2_{2N}.$$

The null and the alternative hypotheses of Fisher-ADF test are the same as for the IPS test but Fisher's test is not an asymptotic test; it is an exact test. The assumption of the IPS test regarding the size of N and T is no longer needed to guarantee asymptotic validity of the Fisher test. As a consequence, finite sample properties of the Fisher test are superior compared to those of the IPS test. According to Monte Carlo simulations of Choi (2001), the Fisher test has greater power compared to the IPS test even if the sample size is small whereas the power of both the IPS and the Fisher test increases as the number of cross sections becomes large implying that one can benefit from increased power by adding more cross sections to the sample.

4.2.1.2. Panel Cointegration

The concept of cointegration has been widely used in the time series literature to test the presence of long run relationships among variables. According to Engle and Granger (1987), if two nonstationary variables with the same order of integration have a linear combination with a lower order of integration then cointegration exists between two nonstationary variables. For instance, if both direct real estate and indirect real estate series are I(1) and a linear combination of them is I(0), one can conclude that the two variables are cointegrated and form a long run relationship in the sense that the discrepancy between the two variables is not an ever growing amount, namely it is stationary in the long run.

Similar to individual unit root tests, cointegration tests in the time series literature suffer from low power when the time horizon is short. Panel techniques may be better in detecting cointegration relationships since a pooled levels regression combines cross-sectional and time series information in the data when estimating cointegrating coefficients.

Kao (1999), and Pedroni (1999, 2004) proposed panel cointegration tests similar to the Engle and Granger (1987) framework, which includes testing the stationarity of the residuals from a levels regression. Kao's test is based on the following model:

$$y_{it} = \alpha_i + \beta x_{it} + e_{it} \tag{2}$$

$$y_{it} = y_{i,t-1} + u_{it} \tag{3}$$

$$x_{it} = x_{i,t-1} + v_{it} \tag{4}$$

where $i = 1,.......,N$ and $t = 1,......,T$, α_i denotes individual intercepts, β is the common slope across i, e_{it} is error term and both y_{it} and x_{it} contain a unit root.[5] Kao's test is designed to find whether y_{it} and x_{it} are cointegrated. Equation (2) is estimated using Least Square Dummy Variable (LSDV) and the residuals are tested based on the following ADF equation:

$$\hat{e}_{it} = \rho \hat{e}_{i,t-1} + \sum_{j=1}^{p} \gamma_j \Delta \hat{e}_{i,t-j} + v_{itp} \tag{5}$$

where p denotes number of the lags chosen to make the residuals in Equation (5) serially uncorrelated. ADF test statistic is expressed as usual t-statistic when $\rho = 1$ in Equation (5) which is distributed standard normal asymptotically. To test whether x_{it} and y_{it} are cointegrated based on the ADF test statistic, the null and the alternative hypotheses can be written as $H_0 : \rho = 1$ and $H_1 : \rho < 1$, respectively.

[5] Note that Kao (1999) also checks the test results when a time trend is added to Equation (3) but his simulations show that asymptotic variances are different compared to model without a trend. Eviews can only test the model without a trend.

Pedroni (1999, 2004) develops an alternative residual based cointegration test under the null of no cointegration for heterogeneous panels. Pedroni's test differs from Kao's test in the sense that it assumes ρ to be heterogeneous across cross-sections in Equation (5). The test statistic is based on calculating cointegration test statistics for each cross section separately and then averaging them to find a cointegration test for the entire panel so that it performs well if the sample size has a sufficiently large time dimension for each cross section.[6]

4.2.1.3. Estimation of the Long Run Equation

In the cointegrated panels, using the ordinary least squares (OLS) method to estimate the long-run equation leads to a biased estimator of the parameters unless the regressors are strictly exogenous, so that the OLS estimators cannot generally be used for valid inference. Pedroni (2000) proposes fully modified ordinary least square (FMOLS) estimation while Kao and Chiang (2000) and Mark and Sul (2001) recommend the dynamic ordinary least squares (DOLS) as alternative methods of panel cointegration estimation.

FMOLS estimation corrects for endogeneity and serial correlation to the OLS estimator. To correct for the endogeneity bias and to obtain an unbiased estimator of the long-run parameters, DOLS uses a parametric adjustment to the errors by augmenting the static regression with leads, lags, and contemporaneous values of the regressors in first differences. Both FMOLS and DOLS provide consistent estimates of standard errors that can be used for inference. According to Kao and Chiang (2000), FMOLS and DOLS estimators have normal limiting properties, and the DOLS estimator outperforms the FMOLS estimator

[6] Since the time dimension is very short for most of the countries our sample, Pedroni's test is excluded from the empirical part of the study.

in small samples. On the basis of the earlier findings in favor of panel DOLS estimation, the DOLS method is employed to estimate long-run cointegration equation which relates direct real estate with indirect real estate. DOLS estimation is given in the following equation:

$$D_{it} = \alpha_i + ID_{it}\beta + \sum_{j=-q}^{q} c_j \Delta ID_{i,t+j} + \varepsilon_{it} \tag{6}$$

where $i = 1, \ldots\ldots N$ and $t = 1, \ldots\ldots\ldots T$, D and ID stand for the natural logarithms of direct real estate and indirect real estate return indices, respectively, β is a homogenous coefficient across cross-sections, α_i are individual fixed effects, ε_{it} are the error terms, and q stands for number of leads and lags of the first differenced indirect real estate index.

When using panel data estimation, choosing between fixed effects and random effects is crucial. The intercepts, α_i's, in Equation (6) stand for the parameters that are estimated for each cross-section in fixed effects estimation whereas they are assumed to be randomly drawn from a certain distribution in random effects estimation. When the sample size consist of a specific set of countries, like a sub-sample of Organization for Economic Co-Operation and Development (OECD) countries, fixed effect estimation is appropriate while the sample size includes randomly chosen countries all around the world representing the population, random effect estimation is more suitable.[7] Therefore, this thesis chooses fixed effects to estimate the parameters in Equation (6).

[7] Baltagi (2005).

4.2.2. THE SHORT TERM

The existence of a cointegration relationship between direct and indirect real estate series implies that these series move together in the long run. Even if the two series deviate from the long run relationship in some periods, there exists a mechanism that makes the variables turn back to their long run equilibrium. In other words, one can analyze the short run dynamics of the two variables knowing that these variables are cointegrated in the long-run.

4.2.2.1. Panel Vector Error Correction Model

According to the Granger representation theorem, if two I(1) series are cointegrated, they can be characterized as being generated by an error correction mechanism.[8] However, the presence of a cointegration relationship cannot explain the direction of causality among the variables. In order to analyze the direction of causality, a panel-based vector error correction model (VECM) should be performed. This model can be estimated based on the two-step Engle-Granger procedure. In the first step, the long-run relationship is estimated through Equation (6) to construct an error correction term (ECT) for the second step. ECT is defined as one-period lagged residuals of long run equation and the sign of the ECT indicates whether one or two variables make adjustments to deviation from long run relationship. In the second step, the VECM is estimated by means of bias-corrected least square dummy variable (LSDV) estimation suggested by Bruno (2005).

[8] Engle and Granger (1987).

For the second step, the two-equation VECM can be written as follows:

$$\Delta D_{it} = \theta_{1i} + \lambda_1 \varepsilon_{i,t-1} + \sum_{k=1}^{m} \theta_{11k} \Delta D_{i,t-k} + \sum_{k=1}^{m} \theta_{12k} \Delta ID_{i,t-k} + u_{1it} \qquad \lambda_1 < 0 \tag{7a}$$

$$\Delta ID_{it} = \theta_{2i} + \lambda_2 \varepsilon_{i,t-1} + \sum_{k=1}^{m} \theta_{21k} \Delta ID_{i,t-k} + \sum_{k=1}^{m} \theta_{22k} \Delta D_{i,t-k} + u_{2it} \qquad \lambda_2 > 0 \tag{7b}$$

where Δ denotes first differences, $\varepsilon_{i,t-1}$ denotes the ECT estimated in the first step, u_{1it}, and u_{2it} are serially uncorrelated error terms, θ_{1i} and θ_{2i} stand for unobserved fixed effects, and m denotes the maximum number of lags included in the estimation. If indirect real estate returns do not Granger cause direct real estate returns in the short run, all the coefficients of θ_{12k} should be insignificant. Similarly, if direct real estate returns do not Granger cause indirect real estate returns, one should conclude that all of θ_{22k}'s do not statistically differ from zero. The coefficients of the ECT, λ_1 and λ_2, can be interpreted as the speed of adjustment parameters to the long run equilibrium and they are tested using t-statistics.

The signs of λ_1 and λ_2 are expected to be negative and positive, respectively. This can be explained as follows: When $\varepsilon_{i,t-1}$ is positive direct real estate index is higher than indirect real estate index in the last period. To make the long run relationship hold, either direct real estate index should decrease or indirect real estate index should increase in this period. Otherwise, when both variables deviate from their long run relationship in the short run, a mechanism that makes them turn back to their long run equilibrium does not exist. Moreover, at least one of the variables should react to a deviation from the long run equilibrium so that at least one of the adjustment parameters should be significant if a long run relationship exists between direct real estate and indirect real estate.

Equations (7a) and (7b) suffer from an endogeneity problem because lags of dependent variables appear as explanatory variables on the right hand side in each equation and all lags of dependent variable include unobserved fixed effects, θ_{1i} and θ_{2i}. Even if in the fixed effect estimation, the within transformation eliminates θ_{1i} and θ_{2i}, the endogeneity problem still exists.[9] The Endogeneity is a common problem for dynamic panel data models and it leads to biased coefficient estimates of lags of dependent variables, θ_{11k}'s and θ_{21k}'s, for this case. In order to estimate unbiased coefficients, instrumental variable (IV) estimation suggested by Anderson-Hsiao (1981) or generalized method of moments (GMM) estimation developed by Arellano-Bond (1991) can be used. These estimation techniques are based on transforming the model (7a)-(7b) by first differencing to eliminate individual fixed effects and then they use past values of dependent variables as instruments for endogenous variables. One drawback of these techniques is that their properties hold only when N is very large and T small so that they are generally applied to micro panel studies.

For macro panels, when T$\rightarrow\infty$, the LSDV estimator is consistent and it is biased up to a negligible degree.[10] However, when T is smaller than 30, Judson and Owen (1999) show that

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[9] For a simple dynamic panel data model, $y_{it} = \mu_i + \delta y_{i,t-1} + \beta x_{it} + v_{it}$. After within transformation, lagged dependent variable becomes $(y_{i,t-1} - \bar{y}_{i.-1})$ where $\bar{y}_{i.-1} = \sum_{t=2}^{T} y_{i,t-1} / (T-1)$ and error term is ($v_{it} - \bar{v}_{i.}$) where $\bar{v}_{i.} = \sum_{t=1}^{T} v_{it} / T$ so that $y_{i,t-1}$ is correlated with $\bar{v}_{i.}$ because $\bar{v}_{i.}$ includes $v_{i,t-1}$ by construction.

[10] See Nickell (1981).

the LSDV estimator has a bias up to 20 percent of the true value coefficient of interest. For T smaller than 30, they showed that a bias-corrected LSDV performs well compared to instrumental variable or GMM estimation techniques for a balanced panel. However, for that time when Judson and Owen (1999) wrote their paper, applicability of bias-corrected LSDV was limited because nobody has developed a method to implement it for unbalanced panels so that they recommended using one-step GMM of Arellano Bond (1991) or AH estimator of Anderson-Hsiao (1981) as the second best alternatives when T is around 20. Their results based on Monte Carlo simulation are summarized in Table 3.

Table 3: Judson and Owen (1999):

	$T \leq 10$	$T = 20$	$T = 30$
Balanced Panel	Bias-corrected LSDV	Bias-corrected LSDV	Bias-corrected LSDV
Unbalanced Panel	One-step GMM	One-step GMM or AH	LSDV

Bruno (2005) has derived bias approximation formulae of LSDV estimator for unbalanced panels and he suggested a bias-corrected LSDV estimator for unbalanced panels when N is small and average T across cross sections is more than and equal to 20.[11] Since the LSDV estimator is inconsistent unless T goes to infinity, the bias-corrected LSDV uses an initial consistent estimator such as IV or GMM and then accounts for more than 90 percent of the actual bias of the LSDV estimator.

[11] While short run estimation results of this thesis are based on the bias-corrected estimator, one can also check the Appendix for the results based on one-step GMM and AH estimators suggested by Judson and Owen (1999).

CHAPTER V: EMPIRICAL RESULTS

5.1. Fisher-ADF and IPS Unit Root Tests

This thesis employs Fisher-ADF and IPS panel unit root tests in order to investigate integration properties of direct real estate and indirect real estate return indices. The other panel unit root tests mentioned in Chapter IV are excluded from the estimation since all of the other tests are designed to be used only for balanced panels. Table 4 presents test statistics and associated p-values for Fisher-ADF and IPS tests.[12]

Table 4: Panel Unit Root Tests

H0: All individual series contain a unit root

Ha: Some individual series are stationary

Model: $$\Delta y_{it} = \rho_i y_{i,t-1} + \sum_{L=1}^{p_i} \theta_{iL} \Delta y_{i,t-L} + \alpha_i + \varepsilon_{it}$$

	Fisher-ADF		**IPS**		
Variables	Test Statistic	p-value	Test Statistic	p-value	Conclusion
D	11.136	0.801	1.666	0.952	I(1)
ID	22.251	0.135	-0.382	0.351	I(1)
ΔD	35.643***	0.003	-4.731***	0.000	I(0)
ΔID	70.596***	0.000	-9.349***	0.000	I(0)

Notes: D and ID stand for logarithms of direct real estate and indirect real estate return indices, respectively. Similarly, ΔD and ΔID are the same variables in first differences. Both IPS and Fisher-ADF test statistics include an individual intercept. Lag lengths are chosen by the Bayesian Information Criterion (BIC). *** denotes level of significance at 1 percent.

[12] Note that in both tests a deterministic trend is excluded from the ADF equation since a trend is found to be insignificant for differenced direct and indirect real estate series across all countries our sample.

According to Table 4, the null hypothesis of both tests cannot be rejected at the 1 percent significance level for direct and indirect real estate return indices so that both variables contain a unit root, and they are non-stationary in levels. Similarly, for the differenced variables one can reject the null hypothesis of both tests at the 1 percent significance level meaning that both variables do not contain unit roots and they are stationary in first differences. Panel unit root tests confirm that both direct real estate and indirect real estate series are I(1) which is a prerequisite before performing cointegration analysis.

5.2. Kao Cointegration Test

Kao residual based cointegration tests results are given in Table 5:

Table 5: Kao Cointegration Test

H0: No Cointegration

Ha: Cointegration

Model: $D_{it} = \alpha_i + ID_{it}\beta + \varepsilon_{it}$

ADF - t-statistic	p-value
-2.772***	0.002

Notes: *** denotes level of significance at 1 percent. Lag length for residuals is chosen based on BIC.

The results indicate that the null hypothesis of no cointegration is rejected at the 1 percent significance level which implies that there exists a cointegration relation between direct real estate and indirect real estate. As a consequence, the two assets are substitutes for the investors in the long run and diversification benefits of holding both assets in the long run portfolio are no longer possible because the correlation between two assets converges to one in the long run.

5.3. Dynamic Ordinary Least Square Estimation

After detecting the cointegration relationship, the long run model in logarithms is estimated using DOLS estimation by imposing a homogeneous slope coefficient of indirect real estate, β, and heterogeneous intercepts across countries, α_i's. The assumption of constant slope coefficient across countries is reasonable when the time dimension of the sample is taken into account. As described before, half of the countries in the sample have short series like less than twenty years. In order to perform cointegration analysis, one needs a long time dimension because cointegration is designed to find a long run relationship by construction. Since the time dimension of the sample is not suitable to estimate country by country cointegrating coefficients, β_i, an average cointregration coefficient is estimated across countries by imposing a homogeneity assumption. On the other hand, real estate markets might have different characteristics in each country so that some degree of heterogeneity might be present across countries. In order to account for unobserved country specific effects, the long run equation is estimated by assuming different constant terms for each country.

The estimated long run cointegration coefficient of indirect real estate and country specific intercepts are given in Table 6 and Figure 5, respectively.

Table 6: DOLS Estimation

Long Run Equation: $D_{it} = \alpha_i + ID_{it}\beta + \varepsilon_{it}$

$\hat{\beta}$	p-value
0.701***	0.000

F-test: H0: All fixed effects are equal to zero

F(7, 101) = 6.52 Prob>F = 0.00

R^2=0.919

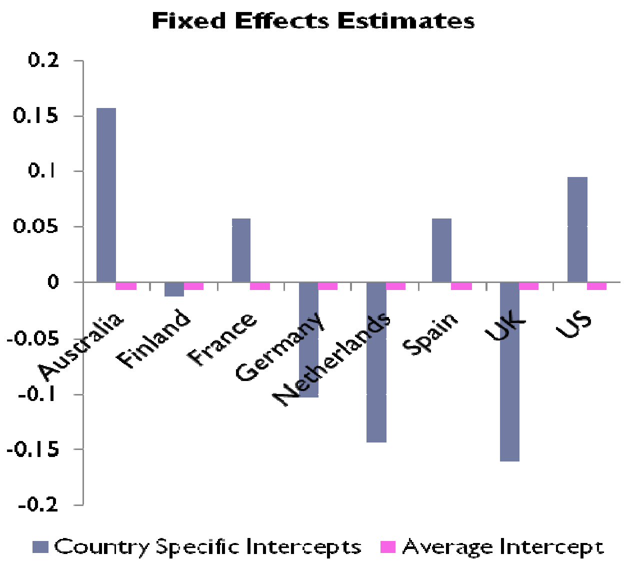
Notes: Model is estimated using fixed effects estimation. *** denotes level of significance at 1 percent. Two lags and one lead of differenced indirect real estate are included to long run equation based on BIC.

According to Table 6, the long run coefficient on indirect real estate is equal to 0.701 and it is statistically significant at the 1 percent level. The reported F test also shows that fixed effects are jointly significant across countries. Since the equation is estimated in logarithms, 0.701 indicates the elasticity of direct real estate with respect to indirect real estate and it can interpreted such that return index for direct real estate rises by 0.701 percent as the return index for indirect real estate increases by 1 percent in the long run. One reason that cointegrating coefficient is not equal to one might be that indirect return indices include leverage level of real estate companies across eight countries in the sample. Assuming that asset returns of the listed real estate company are higher than its cost of debt, indirect real estate returns tend to be higher than those of direct real estate as leverage level increases. Another reason for a cointegrating coefficient unequal to one may be that the indices have different weights in property-types that differ in risk and return levels. Pagliari *et al.* (2005) report that direct indices have been more office and retail property-oriented whereas indirect indices have been more exposed to retail and residential property for the United

States during the period of 1981-2001. On a risk-adjusted basis, Pagliari *et al.* (2001) also show that the office sector is historically the worst performing property sector in direct indices while residential sector is the best performing sector for the United States. After restating direct indices with the property weights of indirect indices which are less office-oriented compared to direct indices, Pagliari (2005) show that the risk of direct indices decreases while the return of them increases. In sum, the worst performance of office sector has a dominant effect on direct indices and, as a consequence, direct returns fall behind the indirect returns in the long run.

The observed amount of leverage is reported as 40 percent by study of Pagliari et al. (2005) whereas an implied leverage is found to be 35 percent by Oikarinen et al. (2009) for real estate companies in United States. This thesis finds about 30 percent implied leverage for the eight countries on average which is close to the leverage level of reported by aforementioned studies for the United States.[13]

Figure 5: Estimated Fixed Effects



[13] The confidence interval for $\hat{\beta}$ at the 1 percent significance level is between 0.768 and 0.632 and this interval includes 36 percent implied leverage level for the eight countries on average.

Figure 5 presents estimated country specific intercepts and average intercept across eight countries in the sample. Results show that each country's own intercept is slightly different from the average intercept of entire panel meaning that there are unobserved country specific effects that make real estate markets behave differently from country to country.

5.4. Panel Vector Error Correction Estimation

Equations in 7(a) and 7(b) are estimated using bias-corrected LSDV. Both equations include the error correction term, one and two period lagged dependent and independent variables.

Table 7: Panel Vector Error Correction Results: Bias-corrected LSDV: initiated by Anderson Hsiao (AH) estimator

	ε_{it-1}	ΔD_{it-1}	ΔD_{it-2}	ΔID_{it-1}	ΔID_{it-2}
ΔD_{it}	-0.0353 (0.37)	**0.7202** **(0.00)**	**-0.3905** **(0.00)**	**0.0455** **(0.126)**	**-0.0563** **(0.06)**
Granger Causality				**Wald test: 5.93** **p-value: 0.05**	
ΔID_{it}	**0.4905** **(0.02)**	-0.1483 (0.88)	-1.2513 (0.27)	**0.6007** **(0.00)**	**-0.433** **(0.06)**
Granger Causality		**Wald test: 1.71** **p-value: 0.42**			

Notes: The results are based on biased corrected LSDV estimation which utilizes Anderson Hsiao estimator initially. Bias is corrected up to first order, O(1/T), and 100 replications are used in bootstrap procedure to find asymptotic variance-covariance matrix of estimators. Lag length is chosen as two based on BIC.

Table 8: Panel Vector Error Correction Results: Bias-corrected LSDV: initiated by Arellano Bond (AB) estimator

	ε_{it-1}	ΔD_{it-1}	ΔD_{it-2}	ΔID_{it-1}	ΔID_{it-2}
ΔD_{it}	-0.0204 (0.49)	**0.8087** **(0.00)**	**-0.4102** **(0.00)**	**0.0507** **(0.02)**	**-0.0559** **(0.01)**
Granger Causality				**Wald test: 10.37** **p-value: 0.00**	
ΔID_{it}	**0.4819** **(0.00)**	-0.1735 (0.76)	-1.0555 (0.11)	**0.6791** **(0.00)**	**-0.4556** **(0.00)**
Granger Causality		**Wald test: 3.93** **p-value: 0.14**			

Notes: The results are based on biased corrected LSDV estimation which utilizes Arellano Bond estimator initially. Bias is corrected up to first order, O(1/T), and 100 replications are used in bootstrap procedure to find asymptotic variance-covariance matrix of estimators. Lag length is chosen as two based on BIC.

Table 7 and Table 8 have similar results in terms of estimated parameters and corresponding p-values but bias-corrected LSDV estimation initiated by AB estimator, Table 8, has smaller p-values compared to the one which uses AH initially, Table 7, since Arellano Bond estimator is more efficient than Anderson Hsiao estimator.[14]

The first row in Table 8 gives the estimation results for Equation 7(a). The results show that the estimated coefficient of the error correction term has the correct sign, negative, but it is insignificant which implies that when a deviation from the long run relationship occurs, direct real estate does not make any adjustments to restore the long run relationship. The estimated coefficients of both the first and second lag of direct real estate returns are significant at the 1 % significance level with opposite signs. Last year's return on direct real

[14] See Baltagi (2005).

estate has a positive effect on this year's return whereas return from direct real estate two years ago negatively affects its current return, which implies that direct real estate markets experience peaks and troughs over time. Similarly, the estimated coefficients of both the first and second lag of indirect real estate returns are jointly significant at the 1 % significance level based on a Wald test. In other words, indirect real estate returns from the last two years have significant predictive power on this year's return on direct real estate, which implies that indirect real estate Granger causes direct real estate. This result confirms the lead-lag relationship of both assets in the short run. Indirect real estate is a leading variable due to market valuation whereas direct real estate is a following variable due to appraisal valuation.

The second row in Table 8 shows the estimation results for Equation 7(b). The results indicate that the estimated coefficient of the error correction term has an expected sign, positive, and it is significant. This means that indirect real estate responds to a deviation from the long run relationship and it adjusts 0.48 percent of disequilibrium per year. The Wald test cannot reject the null hypothesis which means that direct real estate does not Granger cause indirect real estate. Similar to direct real estate returns, indirect real estate returns follow a cyclical pattern such that this year's return is influenced by the last two year's returns in opposite directions. The significant coefficients of last two year's indirect real estate returns show that indirect real estate returns are predictable from their own past values which might be interpreted as the inefficiency of indirect real estate markets. However, as Elton *et al.* (2007) emphasizes, the significant autocorrelation coefficients do not necessarily contradict with the Efficient Market Hypothesis as long as investors can benefit from trading strategy once transaction costs are taken into account.[15] Hence, further analysis regarding the benefits of trading strategies in comparison to buy and hold strategy should be investigated for the countries in the sample.

The study by Schindler et al. (2009) finds that weekly indirect real estate returns are predictable based on their historical values for Australia, France, the Netherlands, and UK, whereas they are independent from their past values for Germany and the United States for the period from 1990 to 2006. After finding predictability of indirect real estate returns for some countries, they also performed trading strategies based on moving averages and they conclude that, for a given amount of transactions costs, investors can earn risk-adjusted returns with trading strategies compared to buy-and-hold strategy for the countries in which returns are predictable. The results of this thesis show that indirect real estate returns are predictable on a yearly basis for the entire panel. Before making inferences about the inefficiency of the indirect real estate markets across eight countries, country by country analyses are needed to check whether investors can capitalize the predictability of the returns by taking transaction costs into account.

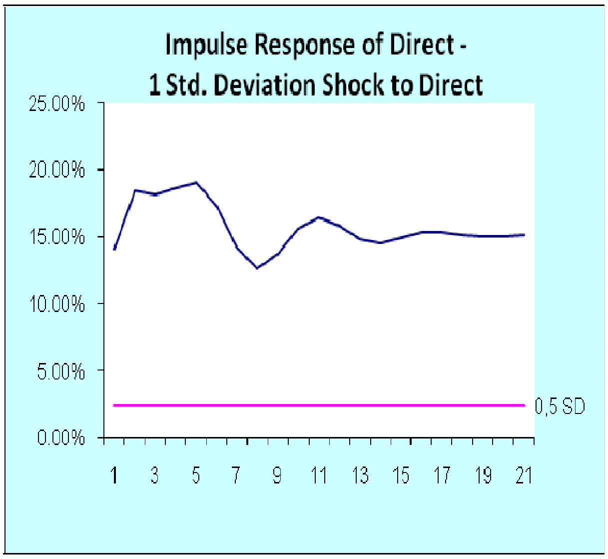
5.5. Impulse Response Functions

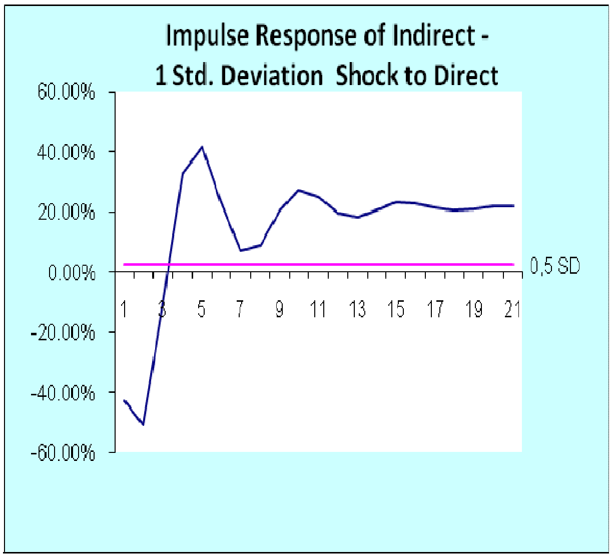
An impulse function shows the behavior of one variable in response to a one-time exogenous change in another variable as a function of time. Impulse response functions are

[15] One of the forms of Efficient Market Hypothesis is called as weak-form efficiency which states that investors cannot consistently achieve excess market returns knowing the historical values of a given asset.

calculated based on coefficient estimates of the panel vector error correction model which is estimated using biased-corrected LSDV-initial AB in Table 8.[16]

Figure 6: Shock to Direct Real Estate





According to Figure 6, a one standard deviation shock to direct real estate at time t+1, increases its expected return on the same period by 14 percent. At time t+4, the expected return on direct real estate rises by 19 percent and the impact of shock becomes stable in the long run. Indirect real estate returns are also influenced by one standard deviation to direct real estate. At time t+1, the expected return on indirect real estate decreases by 43 percent, and then it increases by 41 percent after four years. Following a positive shock to direct returns, the expected return on indirect real estate reaches its peak after five years which may be interpreted such that investors can have a long position on indirect real estate

[16] The average of country specific intercepts is added into the calculation and insignificant coefficients are taken as zero. The effect of shocks becomes stable in the long run but returns do not converge to zero because the average of country specific intercepts of Equations 7(a) and 7(b) determines the initial value of the graphs and they are positive and negative, respectively. In the Appendix, impulse response functions are calculated based on Arellano Bond estimation which eliminates fixed effects by first differencing. The effect of shocks dies out in the long run for the graphs based on the AB estimator.

today and they can have a short position on it after 5 years since indirect real estate is a liquid asset. Although lagged values of direct real estate returns do not have predictive power on indirect real estate returns, the latter is influenced by a shock to direct real estate because of a significant speed of adjustment parameter, 0.48, reported in Table 6. As the pink line in Figure 6 indicates, half of the shock is eliminated in two years by the adjustment of indirect real estate returns.

Figure 7: Shock to Indirect Real Estate

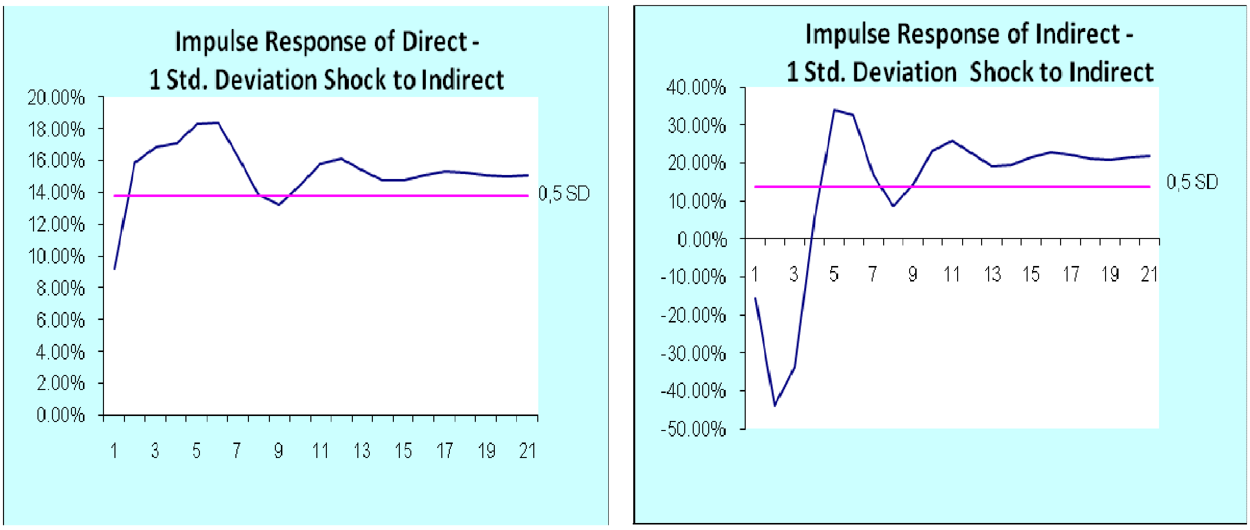


Figure 7 shows impulse responses of both asset returns after a one standard deviation shock to indirect real estate. Direct real estate returns are positively influenced by the shock initially. They increase by 9 percent at time t+1, they experience 18 percent increase at time t+6 and they become stable at 15 % in the long run. If a positive shock to indirect real estate is materialized, the expected return on direct real estate reaches its maximum after 6 years. However, investors may not immediately alter the portfolio weight of direct real estate since direct real estate is an illiquid asset. Since direct real estate does not respond to a deviation from the long run relation, its response to the shock can be interpreted as returns on direct real estate being predictable from lagged returns of indirect real estate. As the pink line in Figure 6 indicates, half of the shock is eliminated in two years by the adjustment of indirect real estate returns. Indirect real estate responds negatively its own shock and then returns increase by 34 percent after four years. The line of 0.5 standard deviation shows that half of the shock is eliminated in three years by the adjustment of indirect real estate returns.

CHAPTER VI: CONCLUSION

This thesis investigates the relationship between direct and indirect real estate both in the short run and in the long run in a panel based framework. Panel cointegration analysis confirms the presence of a cointegration relation between the two assets which means that they are substitutes for investors in the long run. As a consequence, investors should treat the two real estate categories as a single asset class in the long run since they imply the same level of risk and return characteristics over long horizons and diversification benefits of holding both assets are no longer possible in the long run.

Long run equation estimation results show that there is not a one-to-one relation between the two assets. In other words, when indirect real estate indices increase by one percent, direct real estate indices arise by less than one percent. The inelastic behavior of direct real estate with respect to indirect real estate may stem from two factors: The first one is that real estate companies use leverage which is included in indirect real estate indices and the second one is that two asset return indices have different weights in property-types that differ in risk and return levels. If the first factor dominates the second one, it can be concluded that for an average country in our sample, the implied leverage level is about 30 percent which is close to the leverage level reported by real estate companies in the United States by the studies of Pagliari et al. (2005) and Oikarinen et al. (2009). As a further research, one can employ firm-level studies in order to find out actual leverage level real estate companies across countries.

Short run estimation results and the corresponding impulse response functions suggest that the long run relationship between two variables is restored by the adjustments of indirect real estate whereas direct real estate does not respond to deviations from the long run relationship. The observed lead-lag structure between the two variables is confirmed in a panel based framework. While lagged indirect real estate returns have predictive power on the current value of direct real estate returns, the reverse is not true implying that indirect real estate is the leading and direct real estate is the following variable. The impulse response of indirect real estate to a positive shock to direct real estate suggests that investors can make money in the short run by overweighing the indirect real estate when its expected return is low and by underweighting the indirect real estate when its expected return is high by ignoring the trading costs which may dominate profits in reality.

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APPENDIX

Table A1: Panel Vector Error Correction Results: AH Estimator
Instrumental Variables-2SLS

	ε_{it-1}	ΔD_{it-1}	ΔD_{it-2}	ΔID_{it-1}	ΔID_{it-2}
ΔD_{it}	-0.1624 (0.06)	1.1516 (0.06)	-0.5283 (0.00)	-0.0978 (0.18)	-0.132 (0.03)
ΔID_{it}	2.6109 (0.00)	-1.8658 (0.00)	-1.6188 (0.02)	1.3539 (0.00)	0.4655 (0.02)

Notes: For the first equation, second lag of dependent variable, ΔD_{it-2}, is used as an instrument for first differenced lag of dependent variable, $\Delta(\Delta D_{it-1})$. Similarly, for the second equation, second lag of dependent variable, ΔID_{it-2}, is used as an instrument for first differenced lag of dependent variable, $\Delta(\Delta ID_{it-1})$.

Table A2: Panel Vector Error Correction Results: Arellano Bond Estimator

	ε_{it-1}	ΔD_{it-1}	ΔD_{it-2}	ΔID_{it-1}	ΔID_{it-2}
ΔD_{it}	-0.0339 (0.2)	**0.7194** **(0.00)**	**-0.3938** **(0.00)**	**0.0465** **(0.02)**	**-0.0556** **(0.02)**
Granger Causality				**Wald Test: 9.59** **p-value: 0.00**	
AB second order serial correlation test: H0: no autocorrelation z = -0.50 Pr > z = 0.61					
ΔID_{it}	**0.4904** **(0.00)**	-0.1495 (0.8)	-1.2484 (0.06)	**0.6007** **(0.00)**	**-0.4331** **(0.00)**
Granger Causality		**Wald Test: 6.58** **p-value: 0.04**			
AB second order serial correlation test: H0: no autocorrelation z = -0.037 Pr > z = 0.96					

Notes: For the first equation, second lag of dependent variable, ΔD_{it-2}, is used as an instrument for first differenced lag of dependent variable, $\Delta(\Delta D_{it-1})$. Similarly, for the second equation, second lag of dependent variable, ΔID_{it-2}, is used as an instrument for first differenced lag of dependent variable, $\Delta(\Delta ID_{it-1})$.

Impulse Response Functions after AB estimation in Table A2: