Spatial Externalities in Segmented Asset Markets: Evidence from International Commercial Real Estate

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Abstract

This paper provides the first study on international private commercial real estate markets. Despite their geographic segmentation arising from the immobility of the asset, we find evidence of cross-sectional dependence of property market excess returns. We attribute this effect to the strategic interaction of informed and uninformed investors who are confronted with limited market transparency. Transparency risk differentials serve as a measure of information acquisition costs for market entry and are identified as transmission channel. Using an extensive dataset we estimate a spatial econometric model. We derive a spatial multiplier and show empirically that market-specific shocks and changes in macroeconomic fundamentals spill over to property markets with similar degree of transparency risk and are amplified via feedback loop effects.

Keywords: *Asymmetric information; commercial real estate; market segmentation; spatial econometrics; transparency risk.*

JEL-Classification: *C33, D82, D83, G15, R30*

1 Introduction

Institutional-grade commercial real estate has become an important asset class in the portfolio of large international investors over the last decades. With 12.9 trillion U.S. dollars (USD) invested stock worldwide and total transaction volume of 518 billion USD in 2013, trading in direct properties has already reached its pre-financial crisis value from 2006 (Money into Property, DTZ Research, 2014). However, capital growth in commercial property investments is unequally distributed across the globe and trading activity is concentrated in a few markets.[1] Prices exceed their fundamental value due to exaggerated demand of investors in some locations, while other property markets suffer from limited market liquidity. Furthermore, with commercial real estate held as a collateral asset in the business and banking sector, the performance of property markets can have a significant impact to the real economy and the global financial stability. For instance, the value of commercial real estate shows a large co-movement with the investment behavior of firms (see, e.g., Liu et al., 2013; Chaney et al., 2012).

To the best of our knowledge, this is the first paper with focus on international commercial real estate markets. Compared to other financial assets, such as bonds, equity, and foreign exchange, commercial real estate is specific. First, property markets are geographically segmented due to the immobility of the traded asset. The fundamental value is driven by local economic factors and supply restrictions, e.g., land scarcity (Saiz, 2010) or land use regulations (Glaeser et al., 2005). Second, heterogeneous properties are privately traded over-the-counter (OTC) and transaction prices depend on the asymmetric information as well as the bargaining

[1] Money in Property, DTZ Research (2014) reports growth of invested stock in commercial real estate of 9% in Asia Pacific, 4-5% in Germany, France, and Nordic European countries, and 3% in North America in 2013. Similarly, transaction volumes increased by 26% to 185 billion USD in Europe, by 22% to 98 billion USD in Asia, and by 19% to 235 billion USD in North America in 2013.

power of buyers and sellers. Third, efficient market prices are unobservable because of infrequent trading and lack of market transparency limits publicly available information on international property prices. Compared to centralized trading platforms, the incorporation of information into prices and the disclosure to other market participants is slow in private markets and investing in commercial real estate is particularly perceived as risky for foreign investors.

We show empirically that limited transparency causes heterogeneous property markets to be cross-sectionally dependent. This trading friction leads to co-movements in excess returns across internationally segmented commercial real estate markets. We identify the economic distance in transparency risk as main transmission channel of amplified feedback loops and spillover effects across property markets. Furthermore, we argue that the transmission of shocks is related to the strategic interaction of informed and uninformed investors. Large institutional traders invest in private markets which are similarly transparent as their home market since this reflects lower information acquisition costs to enter foreign property markets. Therefore, informed investors bear the market entry costs of foreign investments, while uninformed traders can avoid these costs by following the trading strategy of the first-mover. This herding behavior leads to higher market activity as well as learning externalities where investors can learn from bids and offers of their counterparties (e.g., Duffie et al., 2014) and transform their knowledge about the relationship between fundamentals and the observed transaction price in one market to thinly traded private markets with similar transparency risk.

Using an extensive dataset of annual market indices for the property sectors logistic/industrial, office, and retail in 26 countries at city-level from 2001 to 2013, we estimate different specifications of a spatial model. We explicitly capture the source of spatial interaction among international excess returns in a pre-specified weighting matrix that is connected to transparency risk among direct property markets. We use transparency risk differentials as spatial weights to reflect the cross-sectional dependence between excess returns. Based on this specification, we test for cross-sectional correlation and we find evidence of local spillover effects across segmented asset markets. A large portion of variation over time in international property excess returns can be explained by potential spillover effects from similarly transparent markets. Disentangling country-specific market fundamentals from global systematic risk factors, we show that spillover effects prevail, even conditioning on common systematic risk. Furthermore, we derive a spatial multiplier based on the reduced-form representation of our model. Market-specific shocks and changes in macroeconomic fundamentals are transmitted across private markets via this multiplier effect and are amplified by feedback loops captured in our weighting matrix.

We extend the literature in several directions: First, we contribute to the understanding of information transmission and price determination in OTC markets. Several studies analyze the implication of search costs finding a trading counterparty on asset pricing (e.g., Duffie et al., 2005, 2007) and market illiquidity (e.g., Lagos and Rocheteau, 2007, 2009). This paper focuses on limited transparency as an additional cost component in segmented asset markets. Transparency is an even more important risk factor in thinly traded private real estate markets. For instance, Eichholtz et al. (2001, 2011) show that the outperformance of local investors relative to foreign investors in domestic markets is negatively related to the degree of transparency.

Second, we contribute to the literature on information-based home bias. For instance, Gehrig (1993) develops a pricing model in which investors deviate from the global market portfolio by holding a dominant share of domestic assets for which they have superior information. Brennan and Cao (1997) and Brennan et al. (2005) predict a positive relation between domestic returns and capital inflows caused by herding behavior of uninformed foreign investors. Van Nieuwerburgh and Veldkamp (2009) argue that investors have an incentive to acquire information solely about domestic assets. Empirical studies, e.g., Seasholes and Zhu (2010), Malloy (2005), and Coval and Moskowitz (2001) focus on geographic distance as private information proxy. We extend the idea of information-based home bias to a multi-market setting in which traders invest in multiple markets which are similar transparent as their home market.

Third, we also contribute to the empirical literature of panel data under cross-sectional correlation. Depending on whether the correlation structure is caused by common systematic risk or due to cross-sectional dependence, the literature distinguishes between multi-factor models and spatial econometric methods. The multi-factor approach as proposed by e.g., Pesaran and Tosetti (2011), Chudik et al. (2011), as well as Pesaran (2006) is robust against cross-sectional dependence if unobserved factors commonly affect all cross-sectional units. However, this strategy does not identify the true underlying economic mechanism in case of spatial correlation. In our approach, we follow Corrado and Fingleton (2012) and specify a time-varying weighting matrix which is directly linked to the underlying economic transmission process instead of using a mere geographic distance measure.

Our results provide important implications for institutional investors. If local risk factors dominate, investors might benefit from diversification in international real estate. However, we show that trading frictions lead to concentrated allocation of capital in international commercial real estate markets causing co-movements in excess returns which act as a counter-effect to potential diversification benefits. Furthermore, the results of this paper are particularly relevant for financial market regulation. Unlike the recent financial crisis during which financial products, e.g., commercial mortgage backed securities (CMBS) systematically and commonly affected economies across the globe, the danger in case of commercial real estate lies in their potential instability because of the spillover of shocks to segmented property markets which are only linked via similar transparency risk. This requires policy makers to establish and enforce transparency standards in international property markets.

The remainder of the paper is structured as follows. Section 2 discusses the general theoretical setup. Our methodological framework is presented in Section 3. In Section 4 we discuss our data and the definition of the spatial weight matrix. The empirical results are presented in Section 5. Section 6 concludes.

2 Economic Framework and Related Literature

The economic implications of our empirical framework are based on the strategic interaction of large informed as well as uninformed investors leading to spatially correlated private markets. Foreign investors are confronted with adverse selection costs due to the information advantage of domestic market-makers.[2] Therefore, large institutional traders have an incentive to invest in information acquisition costs before they enter foreign property markets. They are willing to bear the market entry costs to obtain private information as long as they are smaller than potential adverse selection costs arising from trading with informed brokers and local real estate agents. This framework is illustrated in Figure 1. We assume that information acquisition costs of a hypothetical investor are positively related to the transparency risk

[2] For instance, domestic investors are better informed about regional market conditions and geographic amenities such as local infrastructure. Similarly, international investors are less familiar with domestic legal restrictions as well as regulatory requirements. They must trade with better informed local counterparties or intermediaries and are therefore exposed to potential adverse selection and agency costs (e.g., Levitt and Syverson, 2008; Garmaise and Moskowitz, 2004).

differential between a foreign and her home market. Foreign investors enter only property markets which are similar to their domestic market in terms of transparency risk. Thereby, we presume that investors have an advantage in obtaining private information because of the acquaintance with the foreign market structure. Our argumentation is in line with Pasquariello (2007) who extends the strategic interaction framework of informed and uninformed agents to a multi-market setup and shows that foreign investors strategically enter multiple markets in order to hide their private information. Therefore we deviate from the empirical home bias literature, e.g., Brennan et al. (2005), Brennan and Cao (1997), and Gehrig (1993) arguing that investors trade only in domestic markets because of superior information.

However, it can be optimal for some investors to remain uninformed and to follow the first-mover (see, e.g., Conslik, 1980). In our setup, this herding behavior leads to concentrated trading and higher market activity in these markets and uninformed investors can learn from private information revealed by observed bid and offer prices of the first-moving counterparty.[3] By using property prices as a source of information in one market, investors can learn about the relationship between unobservable property prices and their fundamentals. For instance, this is in line with papers, such as Cespa and Foucault (2014) as well as Pasquariello (2007) who argue that markets are connected via the cross-market learning of international investors. These learning externalities lead to spillover and feedback loop effects in commercial real estate markets with similar degree of transparency.

<< Figure 1 about here >>

[3] Our argumentation for herding incentives in imperfectly competitive property markets differs from the perfect financial market framework of Brennan and Cao (1997). They argue that uninformed investors overestimate private information signals in foreign markets which cause more aggressive trading compared to domestic investors.

We contrast our transmission channel with other theories: For instance, Karolyi et al. (2012) find evidence of market-wide co-movements in liquidity which might commonly affect the pricing in international asset markets due to tightening funding constraints (Brunnermeier and Pedersen, 2009), wealth restrictions (Kyle and Xiong, 2001), or correlated trading (Kamara et al., 2008) of large institutional investors. However, since commercial real estate is traded in segmented private OTC markets, we follow the idea of Cespa and Foucault (2014) and argue that higher market liquidity arises mainly endogenously as a spillover effect accompanied by higher price informativeness due to traders' herding behavior. Furthermore, we rule out spatial correlation of private markets mainly to be driven by real economic transmission channels as proposed e.g., by Asgharian et al. (2013). They argue that stock market linkages might be caused by economic relationships such as similar interest rates as proxy for capital mobility, convergence in inflation expectations provoking investors no longer to hedge domestic inflation risk (Adler and Dumas, 1983), or bilateral trade measures to foster business cycle synchronization. However, this argumentation might hold for integrated stock markets but is less valid in case of internationally segmented markets with trading distortions caused by market frictions and limited transparency.

3 Methodology

In this section, we discuss our methodology. First, we give a brief overview of estimation strategies to model cross-sectional dependence in general and then we focus on the merits of spatial econometrics. Based on this, we discuss the identification of our transmission mechanism across international property market excess returns.

3.1 Weak versus Strong Cross-Sectional Dependence

The econometric literature on panel data proposes two different strategies to model cross-sectional dependence. The need for specific estimation strategies has emerged because of the violation of the residual independence assumption and potential inconsistency of standard panel estimators.[4] One approach attempts to approximate common latent factors by a multi-factor structure. In its simplest form, unobserved factors can be represented by a two-way fixed effects model (Sarafidis and Wansbeek, 2012).[5] If the interest lies only in robust inference against any form of cross-sectional dependence, the common factor approach is sufficient.

However, this estimation strategy is inappropriate if the focus lies on the modeling of spatial interaction between cross-sectional observations. The literature on spatial econometrics accounts for local cross-sectional correlation of endogenous variables in terms of a weighting matrix. By defining distance-decaying spatial weights between the observations, the cross-sectional weighted average of endogenous variables is added as additional explanatory variable in the model

$$y_t = \lambda W y_t + X_t \beta + \varepsilon_t \,, \tag{1}$$

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[4] For instance, the within-estimator is inconsistent if explanatory variables are potentially correlated with unobserved common factors which are captured in the error term (see, e.g., Andrews, 2005).

[5] The error term is then specified as $\varepsilon_{it} = \lambda' \phi_t + v_{it} = \eta_i + \tau_t + v_{it}$, where a combination of time-invariant fixed effect η_i and time-fixed effect τ_t approximate the factor structure. Furthermore, Pesaran (2006) evolves a consistent Common Correlated Effects (CCE) estimator in which a finite unobserved common factor structure is approximated by cross-sectional averages of endogenous and explanatory variables as additional regressors. This framework is extended to the case of infinite latent factors (e.g., Chudik et al., 2011) as well as when residual cross-sectional dependence is left in the error term (Pesaran and Tosetti, 2011). However, this approach comes along with poor finite sample properties. In this paper, we focus on estimators suited for a small time dimension. We refer the reader to Chudik and Pesaran (2013) who provide an overview of panel models with large time dimension.

with vector y_t of n cross-sectional observations, $n \times k$ matrix X_t of covariates, $1 \times k$ parameter vector β, a $n \times n$ weighting matrix W with weights w_{kl} between observations k and l, as well as an error vector ε_t at period $t = 1,...,T$. Parameter λ measures the degree of spatial dependence. Rewritten in its reduced-form

$$y_t = \left(I_n - \lambda W\right)^{-1}\left(X_t\beta + \varepsilon_t\right), \tag{2}$$

this represents a general equilibrium representation of the endogenous variables after changes in explanatory variables and idiosyncratic shocks have been transmitted such that the economic system is adjusted to the new steady state. Spillover effects can be directly modeled by the simultaneous feedback loop mechanism through the spatial multiplier $\left(I_n - \lambda W\right)^{-1}$.

3.2 Spatial Framework

Our baseline regression model is specified as

$$Y_{nt} = \lambda_0 W_{nt} Y_{nt} + X_{nt}\beta_0 + \eta_n + e_{nt}, \tag{3}$$

where Y_{nt} is a $n \times 1$ vector of endogenous variable pooled cross-sectionally over all $j = 1,...,J$ property sectors (industrial, office, and retail) and $i = 1,...,M$ cities in all $k = 1,...,K$ countries. Matrix X_{nt} contains a set of country-specific and global regressors. We determine the cross-sectional dependence in terms of the weighting matrix W_{nt} with distance-decaying spatial weights $\omega_{kl,t}$ between observation k and l in each time period t. Using the weighted average of endogenous variables as additional regressor leads to the potential reflection problem as proposed by Manski (1993) which arises from the fact that spillover effects captured via the spatial lag parameter cannot be identified and clearly disentangled from potentially spatially correlated observed or unobserved variables captured in the error term (see, e.g., Gibbons and Overman, 2012).

We attempt to resolve the identification problem to identify the economic transmission process. First, we disentangle weak-form cross-sectional dependence from common exogenous factors by controlling for country-specific and global state variables in order to isolate the spatial effect. Second, we provide a theoretical rationale for using an endogenous spatial lag Wy since the transmission mechanism of spillover effects is directly linked to observable market prices and not to country-specific fundamentals. Therefore, we justify the exclusion restriction of the exogenous spatial lag WX to achieve identification of our spatial effect. This assumption is crucial because the exclusion restriction allows us to use WX as instrument for Wy. Third, we assume that the economic distance in our weighting matrix is correct and we impose the reduced-form specification to reflect the true underlying data generating process of our sample.[6]

The fixed-effects specification (η_{ij}) arises from the need to control for time-invariant individual-specific effects that are correlated with explanatory variables and therefore cause an omitted variable bias. Following Mundlak (1978) we specify an auxiliary regression term denoted as

$$\eta_{ij} = \overline{x}_{ij}\xi + \alpha_{ij}\,, \tag{4}$$

with time-averages of explanatory variables $\overline{x}_{ij} = T^{-1}\sum_{t=1}^{T} x_{ijt}$ to account for this source of endogeneity. Using the conditional expectation representation, α_{ij} is uncorrelated with

[6] The spatial literature is criticized for modeling spatial correlation of the sample rather than of the underlying population from which the sample is drawn (see Gibbons and Overman (2012) and Manski (1993) for a critical discussion). However this criticism can be mitigated in case of commercial real estate since opaque markets for which no data is available are not attractive for international investors. We therefore interpret our data sample as a close approximation to the underlying population of private markets which are most relevant for investors.

exogenous regressors by construction since $E\left(\varepsilon_{ij} = \alpha_{ij} + e_{ij} \mid x_i\right) = 0$, such that it can be treated as a random effect. The estimates are identical to the results obtained by the within-estimator (Mundlak, 1978). Furthermore, we use a joint significance test of $H_0 : \xi = 0$ as a simple Hausman (1978) test of fixed effects in a spatial context. We also impose parameter homogeneity $\left(\beta_{ij} = \beta, \forall i, j\right)$, because of the limited data availability in international private property markets. However, the parameter vector β can be interpreted in terms of a population average effect in our sample.[7]

The structural equation of our model is therefore specified as

$$Y_{nT} = \lambda_0 W_{nT} Y_{nT} + X_{nT} \beta_0 + K_{nT} X_{nT} \pi_0 + \varepsilon_{nT}\,, \tag{5}$$

with a vector of cross-sectional endogenous variables $Y_{nT} = \left(Y'_{n1}, ..., Y'_{nT}\right)'$, a vector of covariates $X_{nT} = \left(X'_{n1}, ..., X'_{nT}\right)'$, and a residual vector $\varepsilon_{nT} = \left(\varepsilon_{n1}{}', ..., \varepsilon_{nT}{}'\right)'$ for $t = 1, ..., T$. The Mundlak (1978) correction term $\left(\frac{l_T l'_T}{T} \otimes I_n\right) X_{nT} = K_{nT} X_{nT}$ is added as additional regressor variable and we allow for a time-varying weighting matrix $W_{nT} = \begin{pmatrix} W_{n1} & & \\ & \ddots & \\ & & W_{nT} \end{pmatrix}$.

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[7] We assume an underlying unit-specific coefficient $b_{ij} = \beta + d_{ij}$, where parameter d_{ij} is defined as zero-mean deviation of β_{ij} from its average effect $E\left(\beta_{ij}\right) = \beta$. The population mean effect is identified under the sufficient condition $E\left(\beta_{ij} \mid \left(x_{ij} - T^{-1} \sum_t x_{ij}\right)\right) = E\left(\beta_{ij}\right) = \beta$ and it can be shown that the within-estimator is consistent under some standard regularity conditions (see Wooldridge, 2010).

Wang and Lee (2013a,b) derive an estimation strategy for spatial models in the context of randomly missing endogenous data based on imputation. Latent dependent observations are replaced by predicted values based on own and spatially correlated covariates. Using a selection matrix D_{nt} to capture all $n_t^{(o)}$ observable endogenous variables from the cross-sectional vector Y_{nt} at period *t*, the $n_t^{(u)} = n_t - n_t^{(o)}$ missing dependent variables $\left(I_n - D_{nt}\right)Y_{nt}$ are replaced by predicted values obtained from the reduced-form $\left(I_n - D_{nt}\right)S_{nt}^{-1}\left(\hat{\lambda}\right)\left[X_{nt}\hat{\beta} + K_{nt}X_{nt}\hat{\pi}\right]$, using the inverse of matrix $S_{nt} = I_n - \lambda_0 W_{nt}$. This strategy is empirically valid since we assume that the endogenous variable is missing completely at random (MCAR), which implies that the probability of private market excess returns being missing is unrelated to the value of related fundamentals (see, e.g., Wooldridge, 2002). In our context, returns are unobserved in some years because of the nonexistence of a transparent asset market to reveal the inherent market value.

Following Wang and Lee (2013b), we apply the GMM estimator to account for the unbalanced data structure in our sample.[8] We estimate the parameter vector $\theta_0 = \left(\lambda_0, \beta_0', \pi_0'\right)'$ by minimizing $\hat{g}_{nT}^*(\theta)\hat{\Omega}_{nT}^{-1}\hat{g}_{nT}^*(\theta)$.[9] The moment function $g_{nT}(\theta) = Q_{nT}'U_{nT}$ is defined as

[8] We refrain from estimating the parameters by maximum likelihood (ML) in order to avoid potential misspecifications. ML is based on the assumption, that the true data generating process of the spatial process is known as well as that the weighting matrix is correctly specified and does not contain measurement errors (see, e.g., Conley (1999), Gibbons and Overman (2012) for more details). Estimates based on GMM require less restrictive assumptions about the functional form.

[9] Without knowing the true structure of the variance-covariance matrix $Var\left(U_{nT}\right) = T_{nT}Var\left(\varepsilon_{nT}\right)T_{nT}'$, the optimal weighting matrix, i.e., the inverse of $\Omega_{nT} = Var\left(g_{nT}\left(\theta_0\right)\right) = Q_{nT}'Var\left(U_{nT}\right)Q_{nT}$, is not identified and a feasible best GMM estimator with smallest variance cannot be achieved. However, the optimal GMM estimator can be obtained using the vector of best instruments $Q_{nT}^* = T_{nT}'^{+}C_{nT}^m = \left[W_{nT}S_{nT}^{-1}\left(X_{nT}\beta_0 + K_{nT}X_{nT}\pi_0\right), X_{nT}, K_{nT}X_{nT}\right]$

orthogonality condition of the $nT \times k$ instrumental matrix Q_{nT} and the disturbance vector of the structural equation which is defined as

$$U_{nt} = S_{nt}\left[D_{nt}Y_{nt} + \left(I_n - D_{nt}\right)S_{nt}^{-1}\left(X_{nt}\beta_0 + K_{nt}X_{nt}\pi_0\right)\right] - X_{nt}\beta_0 - K_{nt}X_{nt}\pi_0 \,. \tag{6}$$

We apply a heteroscedasticity and autocorrelation consistent (HAC) estimator of the variance covariance matrix $\Omega_{nT} = Var\left(g_{nT}\left(\theta_0\right)\right)$. The elements of the matrix $n^{-1}\hat{\Omega}_{nT} = \left(\hat{\psi}_{rs,nT}\right)$ are computed as $\hat{\psi}_{rs,nT} = n^{-1}\sum_{i=1}^{nT}\sum_{j=1}^{nT} Q_{nT,ir}Q_{nT,js}\hat{u}_{i,nT}\hat{u}_{j,nT}K\left(d_{ij,nT} / d_{nT}\right)$, with residuals $\hat{u}$ from our model as proposed by Kelejian and Prucha (2007). We use the Bartlett kernel for $K_v\left(d_{ij} / d_{nT}\right)$ to ensure that the estimated variance-covariance matrix is positive semi-definite in small finite samples. The bandwidth parameter is specified as $d_{nT} = \left(n \times T\right)^{1/4}$ and we assume that the distance between spatial observations is non-zero only in the same time period. We use our transparency based spatial weighting matrix with elements smaller than the cut-off value of the median restricted to zero.[10] The required additional regularity assumptions are discussed in more detail in Wang and Lee (2013b) as well as Kelejian and Prucha (2007).

For comparison reason, we also estimate the structural parameters using spatial versions of the 2SLS- and the NLS-estimator as proposed by Wang and Lee (2013b).[11]

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where $T_{nT} = S_{nT}D_{nT}S_{nT}^{-1}$ arises from the missing data structure, and $T_{nT}'^{+}$ is defined as the Moore-Penrose inverse of T_{nT}'.

[10] Note that our results are similar if we do not impose any cut-off value or restrict it to the 25%-quantile.

[11] Similar to GMM, the 2SLS estimator is based on imputation of predicted estimates of the reduced-form $\left(I_{nT} - D_{nT}\right)S_{nT}^{-1}\left(\tilde{\lambda}\right)\left[X_{nT}\tilde{\beta} + K_{nT}X_{nT}\tilde{\pi}\right]$, however predicted values are based on simple NLS estimates $\tilde{\theta} = \left(\tilde{\lambda}, \tilde{\beta}', \tilde{\pi}'\right)'$. Alternatively, the NLS estimator uses only observable dependent variables to estimate the parameters. Wang and Lee (2013b) show that all three estimators are consistent, asymptotically normal, and

4 Panel Data

This section discusses our panel data which ranges over the period from 2001 to 2013, including the recent financial crisis period. First, we focus on our proxies for international property market returns. We then describe global systematic risk factors, country-specific fundamentals, and additional control variables.

4.1 Property Market-Specific Returns

We use a data set of annual total market returns on commercial real estate from 2001 to 2013 disaggregated at city-level and for the three sectors logistic/industrial, office, and retail in 26 countries. The data is provided by Property Market Analysis (PMA). To our knowledge this dataset provides the most comprehensive panel of international commercial property markets including cities in the largest global markets for institutional-grade properties such as the U.S., Japan, China, Germany, and the U.K., but also markets in Asia-Pacific such as Hong Kong, Singapore, and South Korea.[12] We provide an overview of the variation of commercial real estate markets in our sample from 2001 to 2013 averaged over all sectors and cities for each country in Figure 2.

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asymptotically equivalent even in case of unknown heteroskedasticity and correlation structure. In Appendix B, we provide a more detailed discussion of HAC-robust versions of the Wang and Lee (2013b) NLS- and 2SLS estimators.

[12] As reported by Prudential Real Estate Investors (2012) market activity is mostly concentrated in the U.S. with an institutional-grade real estate transaction volume of 6.8 trillion USD and estimated global market size of 25.4%, followed by Japan with 2.7 trillion USD (10.1%), China with 1.9 trillion USD (7%), Germany with 1.6 trillion USD (6.1%), as well as the U.K. with 1.4 trillion USD (5.2%).

Table C.1 in Appendix C indicates the market coverage of cities in our sample. Periodic nominal total returns reflect net cash flows and capital appreciation earned by international investors. In order to isolate the cross-sectional dependence between segmented property markets from potential common exchange rate effects, we measure total returns in local currency. Excess returns are calculated relative to the risk-free rate, for which we use the three-month U.S. Treasury Bill rate. Table 1 provides a descriptive summary of private market excess returns for each country, aggregated over all cities and all sectors. Mean excess returns vary from 15.6% (Hong Kong) and 11.8% (South Korea) to 2.27% (Switzerland), and 2.26% (Spain). Property market volatility is highest in Ireland (with standard deviation of 23.6), Hong Kong (21.4%), Singapore (20.7%) and Greece (15.2%). The current transparency level as published by the Jones Lang Lasalle (JLL) in 2012 is provided in the seventh column. Following JLL we differentiate between property markets classifications "highly transparent", "transparent", and "semi-transparent". Index values have been stable in most countries, although Eastern European countries, e.g., Czech Republic, Hungary, and Poland increased their market transparency from semi-transparent to transparent. Our sample is equally distributed between highly transparent and transparent markets, with exceptions of semi-transparent markets in China, Greece, and South Korea. Commercial real estate data are unavailable for opaque private markets. Less transparent or even opaque markets do not provide information on e.g., the performance measure such as price indices or market fundamentals and cannot *per se* be included in our analysis.

<< Table 1 and Figure 2 about here >>

Figure 3 illustrates the common time trend of all property markets pooled across all three sectors and all cities from 2001 to 2013. We find evidence of a common downward behavior across all private markets during the aftermath of the recent financial crisis in the years 2008 and

2009. Similarly, we also observe a recovery afterwards which is slightly below the average excess returns of the pre-financial crisis periods.

<< Figure 3 about here >>

Commercial real estate is traded in illiquid private markets and the underlying market value is unobservable. Because of the infrequent trading of heterogeneous properties, the estimated market value is based on observed transaction prices. Using PMA returns as proxies for the unknown true value, we define the potential measurement error v_{ijt} of sector $j = 1,...,M$ for city $i = 1,...,N$ at time t as the difference between the true latent market return y'_{ijt} and its observable proxy $y_{ijt} = y'_{ijt} + v_{ijt}$. We assume that the measurement error is uncorrelated with the explanatory variables. If this assumption is valid, then the measurement error is captured by the disturbance term in the regression without causing inconsistency of our estimates.

4.2 Explanatory Variables

We use global and country-specific explanatory variables as proxies for common systematic risk factors. The data are obtained from different providers.[13] All variables are determined in nominal values, are measured in local currency. In order to ensure stationarity of our country-specific covariates, we apply the Im et al. (2003) panel unit root test.[14] The correlation matrix among all explanatory variables is shown in Table 2. Country-specific factors

[13] Data are obtained from Thomson Reuters Datastream, as well from the Worldbank database. Appreciation in housing is used from the Bank of International Settlement (BIS). We refer the reader to Table C.2 in the Appendix C, where we list all our data used and provide a detailed discussion of their sources.

[14] The Im et al. (2003) panel unit root test can be applied to unbalanced data and accounts for cross-sectional dependence in panels.

are only moderately correlated, so that there is no evidence of potential multicollinearity, however, some common global risk factors are highly correlated.

<< Table 2 about here >>

Country-Specific Fundamentals: Country-specific macroeconomic state variables systematically affect local commercial real estate markets. Based on MSCI equity indices we compute excess returns on each *national market portfolio (STOCK ER)* to capture financial conditions in the asset market. Investors holding real estate in their portfolio require a risk premium as compensation for sacrificed stock returns. Therefore, we expect a positive correlation of property excess returns with the local market portfolio. Furthermore, expected discounted cash flows from property investments are driven by macroeconomic conditions in the economy. We use log changes in *personal consumption expenditures (Δ CONSUMPTION)*, measured per capita, to account for demand factors. The level effect of the *term spread (SPREAD)* proxies macroeconomic supply conditions. The spread is measured as the difference between long-term government bond yields and short-term interbank interest rates and reflects investors' expectation of future interest rates. Higher expected refinancing costs and lower payoffs from future discounted cash flows of income-producing properties cause investors to demand higher compensating returns. We do not use the nominal long-term interest rate directly since government bonds are not stationary. We also calculate log changes in CPI to proxy *expected inflation (Δ CPI)*. As commercial real estate is considered as a hedge against inflation, we expect a positive correlation with inflation. Furthermore, we add *aggregated commercial investments growth* (*INVESTMENT*) for the USA, Western Europe, Central and Eastern Europe, and Asia-Pacific as well as market-specific *changes in property stocks* (*Δ CONSTRUCTION*) for the sectors office and retail obtained from PMA. Please note that construction data for the sector logistic/industrial is unavailable.

Common Global Systematic Risk: We compute *excess return*s on a *world market portfolio (GLOBAL STOCK ER)* proxied by Morgan Stanley Capital International (MSCI) world equity index returns relative to the three-month U.S. Treasury Bill rate to test the global CAPM specification for segmented property markets. The *three-month Eurodollar rate (EURODOLLAR)* captures investors' expectation about the global economy as proposed by, e.g., Bekaert and Harvey (1995). We use the *TED spread (TED SPREAD)* computed as difference between the three-month LIBOR rate and the risk-free three-month U.S. Treasury Bill rate, to reflect global funding liquidity as well as credit risk, which was high during the recent financial crisis (e.g., Brunnermeier, 2009).

Control Variables: Currency risk is a relevant priced factor in international segmented markets (see, e.g., Adler and Dumas, 1983; and Dumas and Solnik; 1995). Deviations in the purchasing power parity (PPP) lead to a home bias in investors' portfolio choice to hedge inflation risk. We refrain from controlling for each possible currency pair to save degrees of freedom in our estimation and use *real exchange rate changes (Δ REAL XR)* relative to the USD as risk factor. Following the definition of the PPP, we compute log changes as a linear approximation of changes in the nominal exchange rate measured as USD per unit of foreign currency and adjust for differences in the inflation rate between both countries. Our variable is in line with the perspective of an U.S. investor who translates nominal returns earned in foreign currency into real returns denominated in USD (see, e.g., Adler and Dumas, 1983).

Additionally, we control for *unemployment rate* (*Δ UNEMPLOYMENT*), which affects the demand for commercial real estate. *Credit supply* provided by the banking sector (*FINANCIAL*

DEPTH) reflects country-specific funding liquidity, while *foreign direct investment inflows* (*FDI INFLOWS*) capture capital inflows from other countries. Both variables are measured in percentage of GDP. We also control for country-specific *money supply* (*Δ MONEY SUPPLY*). Furthermore, we include appreciation in local *housing market prices* (*Δ HOUSING*). In equilibrium, commercial and residential real estate sectors are exposed to same construction costs and compete for common production factors, such as capital, available land, and labor costs (Roback, 1982). In order to avoid potential simultaneity biases, we use lagged values as instruments for appreciation in the residential housing market. We also control for the market duality and potential information adjustment processes or arbitrage opportunities between private and public property markets by using *excess returns on real estate investment trusts (REIT ER)*. REITs invest in commercial real estate, providing liquidity to the private market and are traded in more liquid public stock markets.

4.3 Economic Distance Measure

As elements of the weighting matrix we use country-specific differentials of the global real estate transparency index published by Jones Lang LaSalle (JLL). This index reflects uncertainty due to institutional regulations, information frictions, and trading barriers as perceived by international investors.[15] We use the economic distance in transparency risk between two property markets as measure for market entry cost of a foreign investor located in one market to invest in another. The closer the risk differentials between a foreign property market and the

[15] The Jones Lang Lasalle (JLL) Transparency index consists of five sub-indices to proxy the degree of information disclosure on performance measurement, market fundamentals, financial disclosures, legal frameworks, as well as fairness and efficiency of the transaction process in international real estate markets. The index values constitute an ideal indicator for the level of market transparency and potential information acquisition costs in international private property markets. We provide a more detailed discussion of the components in the Appendix A.

home market, the more familiar is the home investor about the foreign private market as she has to invest less in information acquisition costs.

For each time period t, we use an inverse distance to specify the elements of the $N \times N$ weighting matrix, W_t, based on the transparency index. Each element of the matrix is computed as

$$w_{kl,t} = d_{kl,t}^{-1} \quad for\ k,l = 1,...,N\ , \tag{7}$$

where $d_{kl,t}$ measures the distance between the index values of cross-sectional units k and l. A smaller distance corresponds to a larger spatial weight. Spatial units are all property markets and we pool across all sectors and cities in all countries. The diagonals of the time-varying weighting matrices are restricted to zero in order to rule out that spatial units can influence themselves. We row-normalize the W_t matrices to unit sum, such that each elements of the weighting matrix are defined as

$$w_{kl,t}^{*} = \frac{w_{kl,t}}{\sum_{l}^{N} w_{kl,t}}\ . \tag{8}$$

Our proximity measure fulfills several properties: First, the weighting matrix is exogenous from investors' perspective and independent of the covariates. This exogeneity assumption is required for identification of the spatial lag coefficient (Manski, 1993).[16] Second, we use an economic distance measure as proxy for the true economic transmission channel to explain the spatial correlation rather than following the concept of simple geographic distance. Finally, we allow for time-varying weighting matrices as the JLL transparency index is released every second year. However, the index is country-specific. We therefore normalize the distance

[16] Identification strategies in case of endogenous weighting matrices have been only recently discussed by Qu and Lee (2015) as well as Kelejian and Piras (2014).

between two cities or sectors within a country to the smallest distance in our sample, such that $d_{k'l',t} < \min\left(d_{kl,t}\right)\ for\ k', l'$ being different sectors/cities in the same country. This is in line with our economic intuition that potential diversification benefits across sectors or cities within a country should be obtained by investors without significant additional information acquisition costs. Furthermore, please note that we assume symmetric weights. Therefore, we do not differentiate in terms of the economic distance to high or low transparent markets. Although rational investors located in low transparent countries are confronted with lower entry costs to invest in high transparent markets, we assume that they use their information advantage due to the proximity to similarly low transparent markets to gain from higher expected returns. Note further that we abstain from including transparency risk as additional regressor variable as the index is not available prior to 2004. The index values do not show much variation over time and their effect on property excess returns are likely to be swept away by fixed effects.

We also test for a broader set of economic distances as control measures: We use differences in political risk reflected by the Heritage Foundation Index of Economic Freedom as well as the Economist Intelligence Unit (EIU). For instance, Pástor and Veronesi (2013) show that international investors require a risk premium for holding assets in countries with high political uncertainty. Similarly, we control for the Transparency International Corruption Perception Index and the EIU Country Risk index. These weighting matrices are used as a robustness check since we assume similar effects compared to the JLL transparency index.

5 Empirical Results

In this section we show our empirical results. In section 5.1 we identify country-specific factors, which drive the performance of private commercial real estate markets. We test for market integration and show that cross-sectional dependence in segmented commercial real estate markets remains, even when we control for common global systematic risk. In section 5.2 we provide the results of our spatial regression models. International property markets are cross-sectionally dependent via the transparency risk channel as implied by our spatial weighting matrix. In section 5.3 we conduct several robustness tests, which confirm and extend our main results.

5.1 Country-Specific Fundamentals

A large portion of variation in nominal excess returns within international property markets over time can be explained by country-specific systematic risk factors. We present the results in Table 3. FEs capture time-invariant market frictions arising, e.g., from capital controls, policy restrictions, but also from inelastic supply factors, such as land scarcity.[17] As proposed by Petersen (2009) we calculate clustered-robust standard errors to ensure robust inference.[18] The main driving fundamentals are identified in Model I. The coefficient signs are in line with our economic intuition. Private market excess returns are positively related with stock market excess returns and changes in household consumption expenditures. For instance, Bardhan et al. (2008) and Ling and Naranjo (1997) find similar results in case of publicly traded REIT shares. A well-

[17] We follow Wooldridge (2002: 288) and apply a robust Hausman (1978) test by estimating an auxiliary regression using clustered-robust standard errors. Running a simple OLS regression $y_{ijt} - \lambda T^{-1} \sum_t y_{ijt} = \left(x_{it} - \lambda T^{-1} \sum_t x_{it}\right)' \beta + \left(x_{it} - T^{-1} \sum_t x_{it}\right)' \gamma + \varepsilon_{ijt}$ with $\hat{\lambda} = 1 - \left[1 / \left(1 + T \left(\hat{\sigma}_\eta^2 / \hat{\sigma}_\varepsilon^2 \right) \right) \right]^{1/2}$, we use a Wald test of random effects. The *t*-statistic rejects the null hypothesis of random effects, i.e., $H : \gamma = 0$, and we apply the within-estimator to control for endogeneity arising from potential omitted variables biases.

[18] Standard errors as proposed by Driscoll and Kraay (1998) would be more appropriate to be fully robust against cross-sectional dependence. However, we cannot apply this approach because of their poor finite sample properties in panels with small time dimension.

performing, and liquid asset market ensures easy access to financing opportunities for investment trusts to buy direct real estate, while at the same time higher expected returns are required for alternative investments in income-producing properties. Rising consumption expenditures lead to a higher demand for retail space, warehouses, but is also reflected in economic growth, triggers increasing investments in the office and industrial property sector. We identify consumption expenditures as main fundamental factor.[19]

We also estimate a positive coefficient for inflation close to one, which can be interpreted as perfect hedge. Considering properties as inflation hedge, we confirm Fama and Schwert (1977) finding similar results for residential housing. The positive relation to the term spread and private market excess returns can be explained by different economic channels: First, higher refinancing costs due to increasing long-term interest rates relative to short-term rates causes a higher required risk premium on commercial real estate. Second, higher expected returns are driven by investors' increasing risk-aversion to future economic prospects as indicated by higher term spreads (see, e.g., Chen et al., 1986). Applying the Pesaran (2004) CD test of cross-sectional error dependence, we reject the null hypothesis of independence, finding evidence of residual dependence, which cannot be explained by the covariates.

<< Table 3 about here >>

We include time-fixed effects in Model II to control for time-varying common factors. Using a two-way fixed effects specification to approximate a multi-factor structure, the remaining error dependence is absorbed. Note, however, that this specification cannot uncover the true economic transmission channel of spatial interaction between segmented markets. In our

[19] Alternatively, we also test for model specifications using growth in GDP as main fundamental variable. However, growth in GDP and consumption expenditures shows a high correlation of 88% and we find similar results.

estimation of the spatial model in section 5.2, we replace missing endogenous variables by estimated values from the reduced-form by including country-specific factors. Therefore, the precision of the estimates depends on the quality of chosen risk factors as predictor variables. To test their robustness, we add control variables and re-estimate the regressions in Models III to V. Estimates do not change if we control for unemployment rate and funding liquidity (Model III), at a national as well as international level. We control for market duality between private and public property markets as well as for the housing sector in Model IV. Please not that we exclude China from our sample in Model IV as we do not observe Chinese housing data. Appreciation in the residential sector does not affect excess returns on commercial real estate, while excess returns on REITs are positively correlated with private market excess returns. REITs invest in income-producing properties, therefore providing funding liquidity and capital flows into illiquid private commercial real estate markets. This funding channel ensured by the securitized real estate sector provides higher market liquidity (see, e.g., Bond and Chan, 2012; and Ling et al., 2013). The TED spread is negatively correlated with our endogenous variable (Model V). Higher credit risk, and more restrictive global funding liquidity has a negative impact on private commercial real estate, particularly during the recent financial crisis 2007/08 (see Brunnermeier, 2009). A positive relationship with the three-month Eurodollar rate can be interpreted as investors' expectation of the world business cycle (see, e.g. Bekaert and Harvey, 1995) reflected in higher expected excess returns.

Table 4 indicates the test results for market integration. We show that residual dependence is not explained by common systematic risk factors. The Pesaran (2004) *t*-statistic remains significantly different from zero. We control for potential exchange rate effects if the exogenous variable is denominated in USD. Conditional on fixed effects, excess returns on income-producing properties are positively correlated with the global market portfolio (Model I). Our results are in line with studies such as Bond et al. (2003) who find a similar relationship for publicly traded REIT shares. However, as indicated by the low adjusted R^2 of 8.50%, private market excess returns cannot be explained by the global market portfolio. Investors do not perceive the same global market risk to be priced in heterogeneous commercial real estate markets. Using global consumption growth, measured as first latent factor form a principal component analysis of international consumption data as explanatory variable (Model II), we find a low explanatory power of 6.4%. Our result provides further evidence of segmented property markets and is in line with Backus et al. (1992) who show that consumption growth is only weakly correlated across countries. Similar results are obtained testing for global funding liquidity and expectations of global economic prospects (Models III and IV). However a large portion of variation in private market excess returns can be explained by excess returns on U.S. REITs as leading indicator as well as by global investment activity in international commercial real estate (Model V), indicated by an adjusted R^2 of 31.4%.

<< Table 4 about here >>

5.2 Spatial Dependence and Spillover Effects

In this section, we estimate the effect of the underlying spillover mechanism of private property markets using a spatial lag model. The weighting is based on country-specific transparency differentials. Panel A of Table 5 provides the results of our model. The estimates are similar for all three estimators (GMM, 2SLS, and NLS), although the estimators propose different strategies to account for unbalanced panels. From this, we conclude that missing data do not affect the estimates. The signs of the state variables are in line with the estimates in Table

3 and the coefficients differ only slightly. The estimated spatial lag is positive and significant, ranging from 0.603 for NLS to 0.539 for the GMM-estimator. We find evidence of spatial correlation and co-movement of private market excess returns with similar transparency risk. Investors from high transparency countries invest in foreign markets with similar level of transparency because of smaller information acquisition costs. Similarly, investors familiar with less transparent property markets have an information advantage by investing in low-transparent private markets.[20]

The estimated spatial lag can be interpreted as multiplier effect of the reduced-form specification and indicates the magnitude of how shocks and fundamentals changes in one market are transmitted to other private markets. As indicated by our weighting matrix we interpret this transmission channel in terms of trading barriers and potential market entry costs. This causes cross-sectional dependence in excess returns and distorted capital allocation concentrated in private markets which are similarly transparent. When investors learn from observed bid and offers from the first-mover in one market about unobservable efficient property prices in other markets, their increasing demand for commercial real estate drives property prices up only in markets with similar transparency risk.

In a second step, we compute average direct and total impact measures in Panel B of Table 5 to summarize the dependence structure of our model. Both measures are derived from the implicit reduced-form specification. Because of the connectivity of segmented markets captured by the transparency distance, country-specific shocks and changes in fundamental not only spill over to other markets but are amplified via potential feedback loop effects and are mediated through the equilibrium price adjustment to a new steady-state. The strength of shocks thereby

[20] Please note that despite the small numerical differences between high and low transparent private markets as indicated by the JLL index, the difference is economically relevant.

depends on the degree of spatial correlation as well as the cross-sectional weights. The average direct impact measures the effect of a unit change in country-specific fundamentals, e.g., a unit change in consumption expenditures, on its own property market taking into account potential feedback loops and the average total impact can be interpreted as a change in the endogenous variable caused by a hypothetical unit change in all other markets by the same amount.[21] Compared to the immediate country-specific effect, the direct impact is higher due to amplified feedback loops. We also find evidence of positive average total impact effects for all estimated coefficients with the largest impact caused by growth in consumption expenditures. A hypothetical 1%- increase of consumption expenditures increases excess returns in one market by up to 274.9% (for NLS) and to 258.8% (for 2SLS).

<< Tables 5 about here >>

The results are similar when we control for changes in common global factors. Table 6 provides the empirical results. Including the TED spread in our model specification, we control for global funding liquidity risk and we take into account the drop in global liquidity during the recent financial crisis. The estimated effect of the TED spread is negative and significant. Average direct and total impact measures of the TED spread are larger compared to the estimated immediate effect since the change in TED spread is commonly transmitted and amplified through the private market system. Coefficients of the fundamentals are similar in sign and magnitude to the baseline model in Table 5. Conditional on the common factor, we find

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[21] We follow LeSage and Pace (2009: 33-35) and calculate the average direct impact, $(nT)^{-1} trace(S_r(W))$ of parameter $\beta_r, r = 1,...,k$, using $S_r(W) = (I_{nT} - \lambda W)^{-1} I_{nT}\beta_r$. The average total impact to an observation is calculated as average of the row sums from the reduced form, $(nT)^{-1} \iota'_{nT} S_r(W) \iota_{nT}$. Le Sage and Pace (2009) also compute the average total impact from an observation which measures the average influence of a unit change in fundamentals on all other markets. They show that both average total impact measures are numerically the same.

evidence of co-movements in international segmented private markets caused by spatial interaction and not by commonality in liquidity (see e.g., Karolyi et al., 2012). The degree of spatial dependence is slightly smaller compare to the spatial lag in Table 5 since spatial dependence is absorbed by the common factor. By conditioning on global risk factors, we disentangle the spatial interaction effect imposed by the weight matrix from common factors.[22]

<< Tables 6 about here >>

In Table 7 we additionally control for new development in the commercial property sector. Accounting for construction added to the invested stock, we attribute price co-movements among institutional-grade commercial real estate markets to rising capital values caused by increasing demand of international investors. The sample ranges from 2006 to 2013 for which no missing data are observed to show that the unbalanced panel does not affect the results. We find similar estimates of the spatial lag, e.g., 0.593 based on GMM, compared to the baseline model in Table 5. Positive changes in construction lead to an increase in the supply of properties and therefore negatively affect expected returns of investors. Based on the Average Total Impact, a hypothetical 1%-change in construction in all markets decreases property excess returns in one market by -104.8% (estimate from GMM).

<< Table 7 about here >>

5.3 Robustness Tests

[22] The challenge to separate weak-form spatial spillover effects from strong global common factors is discussed in the spatial literature. For instance, Bailey et al. (2015) propose a testing procedure to identify weak-form spatial effects versus cross-sectional dependence arising from common factors. However, their test requires a large time dimension in the panel and therefore cannot be applied to our sample. Bailey et al. (2015) propose a two-step approach in which the endogenous variable is first regressed on common factors and the obtained residuals are then used as endogenous variable to estimate a spatial model. Our approach is more in line with Bai and Li (2013) who jointly estimate interaction effects and common factors using quasi-MLE.

In this section we apply several robustness checks. First, we re-estimate our spatial model separately for each sector to test for potential sector-specific heterogeneity. Second, we compare our results with models using a different data set for international commercial real estate markets which is based on Investment Property Databank (IPD). Finally, we compare our baseline results of Table 5 with model specifications using alternative weighting matrices.

Sector-Specific Heterogeneity: Table 8 indicates similar estimates of the spatial lag for the sectors office (0.611) and retail (0.532), but a slightly smaller estimate of the spatial lag (0.321) for logistic/industrial. All three models are estimated using GMM. We conclude that the industrial sector is more heterogeneous and less affected by trading of international investors than the markets for retail and office for which more data are available. We identify growth in consumption expenditure as main fundamental driver for all three property sectors. We find no significant effect of inflation rate and the term spread on excess returns in the office market. However, we conclude that our baseline results in Tables 5 are not biased by potential heterogeneity when pooling over all three sectors.

<< Table 8 about here >>

IPD Commercial Real Estate Indices: For robustness, we re-estimate our models using a different data set of annual property market returns from 1998 to 2013 of 25 countries provided by IPD. For each country we collect returns for the three sectors logistics/industrial, office, and retail, with exception of South Korea for which no industrial data is available. In contrast to the PMA sample which is based on city-level data, returns are aggregated at sector-level for each country. IPD also includes data from Canada, New Zealand, and South Africa. However, the IPD coverage does not include private markets in Asia-Pacific, e.g., China, Hong Kong, and Singapore, and data availability is limited for emerging markets, particularly for Eastern

European countries, such as Hungary, Poland, and the Czech Republic, leading to an unbalanced panel. Table 9 provides a descriptive summary of country-specific excess returns, aggregated over all three sectors. The current transparency level as published in 2012 is indicated in the seventh column. The IPD coverage is equally distributed between highly transparent and transparent markets and only markets in South Korea are semi-transparent. We re-estimate the spatial model using a time-aggregated weighting matrix since the sample starts in 1998 but the JLL index starts in 2004. Table 10 highlights the results of the spatial lag model for all three estimators. Estimates of the country-specific fundamentals are similar compared to the results in Table 5. Using excess returns from IPD coverage, the estimated spatial lag is smaller in magnitude compared to disaggregated city-level data provided by PMA. The level of spatial dependence ranges from 0.403 for GMM to 0.456 for 2SLS. In all three specifications, the effect of the term spread is insignificant.

<< Tables 9 and 10 about here >>

Model Specifications with Alternative Weighting Matrices: We compute different specifications of the weighting matrix to test for robustness. The results are indicated in Table 11. We use different indices to specify the weight matrix which should provide results similar in magnitude to the baseline model based on the JLL transparency index. The construction of the weighting matrices is analogous to the procedure described in section 4.2. Model I is based on country-specific economic freedom, reflecting investors' overall risk in terms of property rights, economic and political stability and investment freedom. Compared to the baseline model in Table 5 the estimated degree of spatial dependence is smaller in magnitude (0.460 based on 2SLS). Using differentials based on country-specific corruption perception (Model II), we observe a spatial lag of 0.625. Similar results can be found using political risk (Model III), as well as a broader index to account for country-specific risk (Model IV) based on different aspects reflecting the banking sector, political, structural, as well as economic risk. The estimated results are in line with our economic intuition since all weighting matrices are based on index values which are similar to the JLL transparency index and can be used as proxies for potential trading frictions and information acquisition costs. We do not include weighting matrices which are directly based on the economic performance of a country such as GDP, or international trade indicators, e.g., capital flows or foreign direct investments between countries as these weighting matrices might endogenously depend on the set of our covariates.

<< Table 11 about here >>

6 Conclusion

Despite the importance as additional asset class and as well as the potential impact on the performance of the real economy as well as stability of the financial sector, international commercial real estate has not been the focus of recent studies. This paper contributes to the literature and accomplishes to provide the first analysis of international private property markets. Using an extensive dataset of city-level data for the three sectors logistic/industrial, office, and retail, we find evidence of cross-sectional dependence of excess returns on geographically segmented commercial real estate markets.

Applying a spatial panel approach, we explicitly model the cross-sectional dependence in terms of a spatial weighting matrix. As economic distance measure in our matrix we use transparency risk differentials. The proximity of the transparency between property markets reflects potential information acquisition costs an investor has to invest in order to enter foreign property markets. We assume that large institutional traders invest in private markets which are similar in terms of transparency risk compared to their home market as a higher familiarity with the market structure is related to lower market entry costs. While informed investors bear these costs, uninformed investors rationally follow the first-mover. The herding behavior triggers concentrated trading in private property markets. We argue that this strategic interaction of informed and uninformed investors leads to cross-market learning externalities. Informed investors reveal their private information by bid and offers to their uninformed trading counterparties who can learn about the relationship between fundamentals and unobserved prices in other thinly traded property markets. Thereby, we argue that transparency risk differential serve as transmission channel through which segmented private markets are dependent.

We empirically show the following results: First, we disentangle macroeconomic fundamentals from global systematic risk factors. By testing for market integration, we show that international property markets are segmented and can be best explained by country-specific state variables. Growth in consumption expenditures is identified as main explanatory variable. Second, we estimate a spatial model and find evidence of co-movements in private market excess returns. The estimated spatial lag coefficient is significant and measures the degree of cross-sectional dependence. This effect prevails even conditional on common systematic risk. Third, we propose a reduced-form specification and derive a spatial multiplier based on the weighting matrix. Local shocks and changes in country-specific macroeconomic fundamentals are transmitted to property markets with similar transparency risk and the magnitude is amplified via feedback loop effects.

Our results provide important insights for institutional investors as well as policy makers. First, limited market transparency causes trading frictions and co-movements in segmented markets and acts as counter effect to potential diversification strategies. Second, the allocation of capital as well as the transmission of shocks to property markets with similar degree of transparency risk leads to potential instability in the commercial real estate sector and requires the regulation and enforcement of transparency standards in international commercial real estate markets.

Appendix A: The Jones Lang LaSalle Transparency Risk Index

Subindices	Topic Areas	Transparency Components
Performance Measurement (25%)	Direct Property Indices	• Existence of direct property index • Reliability of the index and extent to which it is used as a benchmark of performance • Type of index (valuation-based vs. notional) • Length of direct property level returns index time series • Size of institutional invested real estate market • Market coverage of direct property index
	Listed Real Estate Securities Indices	• Dominant type of listed real estate securities (i.e. long term holders of real estate vs. homebuilders and conglomerates) • Use of listed real estate securities data on the real estate market • Years since the first commercial real estate company was listed • Value of public real estate companies as % of GDP • Existence of a domestic listed real estate index and its use as a benchmark existence of an international listed real estate index and its use as a benchmark • Length of public real estate index time series
	Private Real Estate Fund Indices	• Existence of a domestic fund index and its use as a benchmark • Existence of international fund index and its use as a benchmark • Length of unlisted fund index time series
	Valuations	• Independence and quality of third-party appraisals • Use of market-based appraisal approaches • Competition in the market for valuation services • Frequency of third party real estate proposals

Market Fundamentals (20%)	Market Fundamentals Data	• Existence and length of time series on property rents (office, retail, industrial, and residential) • Existence and length of time series on take-up/absorption (office, retail, industrial, and residential) • Existence and length of time series on vacancy (office, retail, industrial, and residential) • Existence and length of time series on yields/cap rates (office, retail, industrial, residential, and hotels) • Existence and length of time series on capital values (office, retail, industrial, residential, and hotels) • Existence and length of time series on investment volumes (office, retail, industrial, residential, and hotels) • Existence and length of time series on revenue per available room for hotels • Existence of a comprehensive database of individual buildings (office, retail, industrial, residential, and hotels) • Existence of a comprehensive database of leases (office, retail, industrial, residential, and hotels) • Existence of a comprehensive database of property transactions (office, retail, industrial, residential, and hotels)
Governance and Listed Vehicles (10%)	Financial Disclosure	• Stringency of accounting standards • Level of detail in financial statements • Frequency of financial statements • Availability of financial reports in English
	Corporate Governance	• Manager compensation and incentives • Use of outside directors and international corporate governance best practice • Free float share of the public real estate market

Legal and Regulatory (30%)	Regulation	• Extent to which the tax code is consistently applied for domestic investors • Extent to which real estate tax rates are predictable for domestic investors • Extent to which the tax code is consistently applied for foreign investors • Extent to which real estate tax rates are predictable for foreign investors • Existence of land use rules and zoning • Predictability of changes in land use and zoning • Enforcement of land use rules and zoning • Existence of building codes and safety standards for buildings • Enforcement of building codes and safety standards for buildings • Simplicity of key regulations in contract law • Efficiency of the legal process • Level of contract enforceability for domestic investors • Level of contract enforceability for foreign investors
	Land and Property Registration	• Existence of land registry • Accessibility of land registry records to public • Availability of title insurance • Accuracy of land registry records • Completeness of land registry records on ownership • Completeness of public records on transaction prices • Completeness of public records on liens and easements
	Eminent Domain / Compulsory Purchase	• Notice period given for compulsory purchase • Fairness of compensation to owners in compulsory purchase • Ability to challenge compulsory purchase in court of law
	Debt Regulation	• Availability of data on real estate debt outstanding • Availability of data on maturities and originations of real estate loans • Depth and length of real estate debt data • Data on delinquency and default rates of commercial real estate loans • Regulatory requirements for lenders to monitor property collateral values and cash flow • Regulatory requirements for lenders carry out appraisals • Strength of regulatory enforcement

Transaction Process (15%)	Sales Transactions	• Quality and availability of pre-sale information • Fairness of the bidding process • Confidentiality of the bidding process • Professional and ethical standards of property agents • Enforcement of professional and ethical standards of property agents
	Occupier Services	• Providers of property management services known to occupiers • Service expectations for property management clear to occupiers • Alignment of occupier and property manager interests • Frequency of service charge reconciliation • Accuracy and level of detail in service charge reports • Ability for tenants to audit landlord's accounts and challenge discrepancies

Source: Jones Lang Lasalle http://www.jll.com/greti/transparency/technical-note; See more at: http://www.jll.com/greti/transparency/technical-note#sthash.zzAn241k.dpuf; (13 Topics and 115 Factors).

Appendix B: Estimation of the Spatial Model using GMM, 2SLS, and NLS

In this part of the appendix we briefly describe the nonlinear least squares (NLS), and the two-stage least squares (2SLS) estimators which are proposed by Wang and Lee (2013b). We use both estimators as alternative estimation strategies to the GMM approach for our spatial model under missing data. First, we focus briefly on each estimator and then show that all three estimators are consistent and asymptotically equivalent under the unknown structure of the variance-covariance matrix.

2SLS-estimator: The 2SLS-estimator is based on imputation of missing dependent values by an implicit reduced-form specification $(I_n - D_{nt})S_{nt}^{-1}(\tilde{\lambda})\left[X_{nt}\tilde{\beta} + K_{nt}X_{nt}\tilde{\pi}\right]$ using initial estimates $\tilde{\theta} = (\tilde{\lambda}, \tilde{\beta}', \tilde{\pi}')'$ from a non-weighted NLS approach. The structural equation $\tilde{Y}_{nt} = \lambda_0 W_{nt}\tilde{Y}_{nt} + X_{nt}\beta_0 + K_{nt}X_{nt}\pi_0 + \tilde{U}_{nt}$ can be estimated with vector of dependent variables $\tilde{Y}_{nT} = D_{nt}Y_{nT} + (I_n - D_{nt})S_{nt}^{-1}(\tilde{\lambda})\left[X_{nt}\tilde{\beta} + K_{nT}X_{nT}\tilde{\pi}\right]$. With $\tilde{Z}_{nT} = \left[W_{nT}\tilde{Y}_{nT}, X_{nT}, K_{nT}X_{nT}\right]$, and using $Q_{nT}^{*} = \left[W_{nT}S_{nT}^{-1}(X_{nT}\beta_0 + K_{nT}X_{nT}\pi_0), X_{nT}, K_{nT}X_{nT}\right]$ as best instrument variable matrix of dimension $nT \times k_x$ IV, the 2SLS-estimator is computed as

$$\hat{\theta}_{2SLS} = \left[\tilde{Z}_{nT}{}'\left(H_{nT}\Sigma_{\varepsilon,nT}H_{nT}{}'\right)^{+}Q_{nT}\left(Q_{nT}'\left(H_{nT}\Sigma_{\varepsilon,nT}H_{nT}{}'\right)^{+}Q_{nT}\right)^{-1}Q_{nT}'\left(H_{nT}\Sigma_{\varepsilon,nT}H_{nT}{}'\right)^{+}\tilde{Z}_{nT}\right]^{-1}$$
$$\times\tilde{Z}_{nT}{}'\left(H_{nT}\Sigma_{\varepsilon,nT}H_{nT}{}'\right)^{+}Q_{nT}\left(Q_{nT}'\left(H_{nT}\Sigma_{\varepsilon,nT}H_{nT}{}'\right)^{+}Q_{nT}\right)^{-1}Q_{nT}'\left(H_{nT}\Sigma_{\varepsilon,nT}H_{nT}{}'\right)^{+}\tilde{Y}_{nT},$$

with $\Sigma_{\varepsilon,nT} = Var(\varepsilon_{nT})$ and $\left(H_{nT}^{m}\Sigma_{\varepsilon,nT}H_{nT}^{m}{}'\right)^{+}$ is defined as Moore-Penrose generalized inverse of $\left(H_{nT}^{m}\Sigma_{\varepsilon,nT}H_{nT}^{m}{}'\right)'$, with vector $H_{nT} = T_{nT} + (I_{nT} - T_{nT})C_{nT}\left[C_{nT}{}'R_{nT}'R_{nT}C_{nT}\right]^{-1}C_{nT}{}'R_{nT}'R_{nT}$ and $T_{nT} = S_{nT}D_{nT}S_{nT}^{-1}$. As the true specification of $\Sigma_{\varepsilon,nT} = Var(\varepsilon_{nT})$ is unknown, we follow Wang and

Lee (2013b) and choose $\left(H_{nT}^{m}H_{nT}^{m\prime}\right)^{+}$ instead of the generalized inverse of $H_{nT}^{m}\Sigma_{\varepsilon,nT}^{m}H_{nT}^{m\prime}$ in order to weight the IV matrix.

NLS-estimator: The NLS-estimator ignores missing dependent variables in the parameter estimation of the structural model $Y_{nT}^{(o)} = h_{nT}\left(X_{nT}, K_{nT}X_{nT}, \theta_0\right) + U_{nT}$, where $U_{nT} = J_{nT}^{(0)}S_{nT}^{-1}\varepsilon_{nT}$. The parameter vector $\theta_0 = \left(\lambda_0, \beta_0', \pi_0'\right)'$ is estimated from minimizing the following object function

$$\min_{\theta}\left(Y_{nT}^{(o)} - h_{nT}\left(X_{nT}, K_{nT}X_{nT}, \theta_0\right)\right)' \Omega_{u,nT}^{-1}\left(Y_{nT}^{(o)} - h_{nT}\left(X_{nT}, K_{nT}X_{nT}, \theta_0\right)\right), \tag{B1}$$

where the time-varying selection matrix $J_{nt}^{(o)}$ captures observable data from the vector of endogenous variables $Y_{nT}^{(o)} = \left[\left(J_{n1}^{(o)}Y_{n1}\right)', \ldots, \left(J_{nT}^{(o)}Y_{nT}\right)'\right]'$. In order to estimate the Mundlak (1978) fixed effects specification, we define the moment condition of error terms derived from the reduced-form specification $h_{nT}\left(X_{nT}, K_{nT}X_{nT}, \varsigma_0\right) = R_{nT}\left(\lambda_0\right)\left[X_{nT}\beta_0 + K_{nT}X_{nT}\pi_0\right]$, where we denote matrix $R_{nT}\left(\lambda_0\right) = \begin{pmatrix} J_{n1}^{(o)}S_{n1}^{-1}\left(\lambda_0\right) & & \\ & \ddots & \\ & & J_{nT}^{(o)}S_{nT}^{-1}\left(\lambda_0\right) \end{pmatrix}$, using $S_{nt} = I_n - \lambda_0 W_{nt}$ for $t = 1, \ldots, T$.

The true structure of the optimal weighting matrix cannot be identified as the variance-covariance matrix $\Omega_{v,nT} = R_{nT}\Sigma_{\varepsilon,nT}R_{nT}'$ is unknown. A heteroscedasticity and autocorrelation (HAC)-robust version of the NLS estimator can be implemented by using $\left(R_{nT}R_{nT}'\right)^{-1}$ as weighting matrix instead.

Asymptotic equivalence of GMM, 2SLS, and NLS: Using the optimal instrument matrix $Q_{nT}^{*} = T_{nT}'^{+}\left[W_{nT}S_{nT}^{-1}\left(X_{nT}\beta_0 + K_{nT}X_{nT}\pi_0\right), X_{nT}, K_{nT}X_{nT}\right]$, the optimal GMM-estimator

$\hat{\theta}_{gmm} = \left(\hat{\lambda}, \hat{\beta}', \hat{\pi}'\right)'$ has the asymptotic distribution $\sqrt{n}\left(\hat{\theta}_{gmm} - \theta_0\right) \to N\left(0, \Sigma_{bgmm}\right)$, where the asymptotic variance-covariance matrix is denoted as

$$\Sigma_{bgmm} = \lim_{n\to\infty} n\left(C'_{nT}T'_{nT}T'^{+}_{nT}C_{nT}\right)^{-1} C'_{nT}T^{+}_{nT}T_{nT}\Sigma_{\varepsilon,nT}T'_{nT}T'^{+}_{nT}C_{nT}\left(C'_{nT}T'^{+}_{nT}T'_{nT}C_{nT}\right)^{-1}, \tag{B2}$$

with $C_{nT} = \left[W_{nT}S_{nT}^{-1}\left(X_{nT}\beta_0 + K_{nT}X_{nT}\pi_0\right), X_{nT}, K_{nT}X_{nT}\right]$. Similarly, the 2SLS-estimator is consistent with asymptotic variance-covariance matrix

$$\begin{aligned}\Sigma_{2SLS} = n&\left(C_{nT}{}'H_{nT}{}'H_{nT}C_{nT}\right)^{-1} C_{nT}{}'H_{nT}{}^{+}H_{nT}\Sigma_{\varepsilon,nT}H_{nT}{}'H_{nT}{}^{+\prime} \\ &\times C_{nT}\left(C_{nT}{}'H_{nT}{}^{+\prime}H_{nT}{}^{+\prime}C_{nT}\right)^{-1}\end{aligned}. \tag{B3}$$

The practical weighted NLS estimator is consistent with the asymptotic distribution $\sqrt{n}\left(\hat{\theta}_{nls} - \theta_0\right) \to N\left(0, \Sigma_{nls}\right)$, where

$$\begin{aligned}\Sigma_{nls} = \lim_{n\to\infty} n&\left(C_{nT}{}'R'_{nT}\left(R_{nT}R'_{nT}\right)^{-1}R_{nT}C_{nT}\right)^{-1} C_{nT}{}'R'_{nT}\left(R_{nT}R'_{nT}\right)^{-1}R_{nT}\Sigma_{\varepsilon,nT}R'_{nT}\left(R_{nT}R'_{nT}\right)^{-1}R_{nT}C_{nT} \\ &\times\left(C_{nT}{}'R'_{nT}\left(R_{nT}R'_{nT}\right)^{-1}R_{nT}C_{nT}\right)^{-1}.\end{aligned}$$

Wang and Lee (2013b) show that the HAC-robust versions of the estimators do not have the smallest variance. However, they prove that using a simple NLS as plug-in estimator all three estimators are consistent and asymptotically equivalent even under unknown heteroscedasticity. For further technical details we refer to Wang and Lee (2013a,b).

Appendix C: Additional Tables

In this part of the appendix we show additional tables which provide a more in-depth discussion of the market data we use and extend the empirical analysis of section 5.

- Table C.1 provides an overview of the PMA market coverage. For all three regions North America, Asia-Pacific, and Europe we list all covered cities for each country and each of the three sectors logistic/industrial, office, and retail separately.
- Table C.2 depicts a descriptive summary of the IPD market coverage averaged over all sectors and cities for each country. We provide mean, standard deviation, as well as minimum and maximum values. Furthermore, we illustrate the total number of observations and the level of transparency for each country.
- Tables C.3 and C.4 illustrate the fixed effects regression results of country-specific and global multi-factor models using the IPD market coverage. These tables are analogous to Tables 3 and 4, respectively.
- Finally, Table C.5 contains a detailed description of the data we use in our sample as well as their sources.

Table C.1: PMA Market Coverage

This table provides the market coverage of the PMA database. We list all sectors and cities for which we have aggregated total returns on commercial real estate. In Panel A we list all cities of the USA, in Panel B we list all cities in Asia-Pacific, and in Panel C we list all cities of the European property market in our sample.

Panel A: North America

Country	**City**	**Logistic**	**Office**	**Retail**
USA	Atlanta	Yes	Yes	Yes
	Boston	Yes	Yes	Yes
	Chicago	Yes	Yes	Yes
	Dallas	Yes	Yes	Yes
	Houston	Yes	Yes	Yes
	Inland Empire	Yes	No	No
	Los Angeles	Yes	Yes	Yes
	Miami	Yes	Yes	Yes
	New York	Yes	Yes	Yes
	Philadelphia	Yes	No	No
	Phoenix	Yes	No	No
	Seattle	No	Yes	No
	San Francisco	No	No	Yes
	Washington	No	Yes	Yes

Panel B: Asia-Pacific

Country	**City**	**Logistic**	**Office**	**Retail**
Austalia	Brisbane	No	Yes	No
	Melbourne	yes	Yes	Yes
	Perth	No	Yes	No
	Sydney	yes	Yes	Yes
China	Beijing	yes	Yes	Yes
	Guangzhou	No	Yes	Yes
	Shanghai	yes	Yes	Yes
Hong Kong	Hong Kong	yes	Yes	Yes
Japan	Nagoya	No	Yes	Yes
	Osaka	No	Yes	Yes
	Tokyo	yes	Yes	Yes
Singapore	Singapore	yes	Yes	Yes
South Korea	Seoul	No	Yes	Yes

Table continues on the next page.

Table continued.

Panel C: Europe

Country	**City**	**Logistic**	**Office**	**Retail**
Austria	Vienna	No	Yes	Yes
Belgium	Antwerp	Yes	No	No
	Brussels	No	Yes	Yes
Czech Republic	Prague	Yes	Yes	Yes
Denmark	Copenhagen	Yes	Yes	Yes
Finland	Helsinki	No	Yes	No
France	Lille	Yes	Yes	Yes
	Lyon	Yes	Yes	Yes
	Marseille	Yes	Yes	Yes
	Paris	Yes	Yes	Yes
Germany	Berlin	Yes	Yes	Yes
	Cologne	No	Yes	Yes
	Dusseldorf	Yes	Yes	No
	Frankfurt	Yes	Yes	Yes
	Hamburg	Yes	Yes	Yes
	Munich	Yes	Yes	Yes
	Stuttgart	No	Yes	No
Greece	Athens	No	Yes	Yes
Hungary	Budapest	Yes	Yes	Yes
Ireland	Dublin	Yes	Yes	Yes
Italy	Milan	Yes	Yes	Yes
	Naples	No	No	Yes
	Rome	Yes	Yes	Yes
Netherlands	Amsterdam	Yes	Yes	Yes
	Rotterdam	Yes	Yes	No
Norway	Oslo	No	Yes	No
Poland	Warsaw	Yes	Yes	Yes
Portugal	Lisbon	Yes	Yes	Yes
Spain	Barcelona	Yes	Yes	Yes
	Madrid	Yes	Yes	Yes
Sweden	Stockholm	Yes	Yes	Yes
Switzerland	Zurich	No	Yes	No
UK	Birmingham	Yes	Yes	Yes
	Edinburgh	Yes	Yes	No
	Glasgow	Yes	Yes	Yes
	London	Yes	Yes	Yes
	Manchester	Yes	Yes	Yes

Table C.2: Summary Statistic of Property Market Excess Returns based on IPD

This table shows mean, standard deviation, minimum, and maximum value of market excess returns on income-producing properties for 25 countries from 1998 to 2013 based on the IPD coverage. Excess returns are aggregated over all sectors for each country. We indicate the total number of observations in column 6 to illustrate the coverage in each country. Column 7 shows the transparency level as published by Jones Lang Lasalle (JLL) in 2012.

Country	Mean	Std. Dev	Min	Max	Obs.	Transparency
Australia	0.079	0.047	-0.052	0.168	48	Highly Transparent
Austria	0.036	0.027	-0.047	0.074	30	Transparent
Belgium	0.050	0.317	0.003	0.117	27	Transparent
Canada	0.089	0.048	-0.046	0.154	41	Highly Transparent
Czech Rep.	0.022	0.073	-0.209	0.153	26	Transparent
Denmark	0.054	0.023	0.008	0.104	42	Transparent
Finland	0.049	0.019	0.011	0.114	45	Highly Transparent
France	0.077	0.053	-0.039	0.195	48	Highly Transparent
Germany	0.018	0.027	-0.053	0.069	48	Transparent
Hungary	0.048	0.166	-0.211	0.424	25	Transparent
Ireland	0.049	0.171	-0.516	0.314	48	Transparent
Italy	0.041	0.022	0.001	0.086	33	Transparent
Japan	0.035	0.046	-0.084	0.102	29	Transparent
Netherlands	0.055	0.033	-0.028	0.106	48	Highly Transparent
New Zealand	0.080	0.053	-0.040	0.181	48	Highly Transparent
Norway	0.074	0.055	-0.078	0.270	39	Transparent
Poland	0.062	0.093	-0.074	0.272	26	Transparent
Portugal	0.046	0.039	-0.029	0.149	40	Transparent
South Africa	0.121	0.070	-0.031	0.270	48	Transparent
South Korea	0.078	0.038	0.041	0.196	14	Semi-Transparent
Spain	0.039	0.069	-0.123	0.154	39	Transparent
Sweden	0.062	0.048	-0.041	0.170	48	Highly Transparent
Switzerland	0.051	0.024	0.006	0.136	36	Highly Transparent
UK	0.055	0.097	-0.257	0.164	48	Highly Transparent
USA	0.064	0.089	-0.224	0.151	45	Highly Transparent

Table C.3: Results on Country-Specific Risk Factors based on IPD Coverage

This table shows regression results of international direct property excess return on country-specific risk factors. Estimations are based on the within-estimator accounting for market-specific fixed effects. We apply the Pesaran (2004) CD test and show *t*-statistics and corresponding *p*-values of the null hypothesis of cross-sectional residual independence. The unbalanced panel consists of the three sectors logistic/industrial, office, and retail in cities of 25 countries over the years 1998 to 2013. Clustered-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Model I	**Model II**	**Model III**	**Model IV**	**Model V**
STOCK ER	0.048***	0.009	0.052***	0.048**	0.030
	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)
∆ CONSUMPTION	1.816***	1.801***	1.699***	1.777***	1.870***
	(0.207)	(0.263)	(0.216)	(0.230)	(0.241)
∆ CPI	0.942***	0.972***	0.896***	0.981***	1.020***
	(0.236)	(0.260)	(0.254)	[0.244]	(0.220)
SPREAD	0.478***	0.073	0.678***	0.510**	0.103
	(0.184)	(0.158)	(0.193)	(0.206)	(0.166)
∆ REAL XR			0.005	0.021	-0.018
			(0.030)	(0.021)	(0.028)
REITS ER				0.011	
				(0.008)	
∆ HOUSING				-0.039	
				(0.035)	
FDI INFLOW			0.014		
			(0.044)		
FINANCIAL DEPTH			0.021		
			(0.013)		
∆ MONEY SUPPLY			0.033		
			(0.024)		
∆ UNEMPLOYMENT			-0.414***		
			(0.103)		
EURODOLLAR					-0.246**
					(0.147)
TED SPREAD					-0.919***
					(0.337)
Observation	969	969	963	957	969
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time-Fixed Effects	No	Yes	No	No	No
Pesaran CD	17.063***	1.929*	16.491***	15.068***	20.490***
Adj. R^2	0.271	0.176	0.264	0.284	0.289

Table C.4: Results on Common Global Systematic Risk based on IPD Coverage

This table shows regression results of international direct property excess returns on global risk factors. As proxies for the global market portfolio we use the MSCI world index (Global Stock ER). Growth in global consumption expenditures (Δ GLOBAL CONS.) is based on the first factor of a Principal Component Analysis. TED SPREAD is measured as difference between long- and short-term interest rates. Estimates are based on the within-estimator including property-specific fixed effects. The three-month Eurodollar rate is denoted as EURODOLLAR. REIT US ER indicates excess returns on US MSCI REIT index. We apply the Pesaran (2004) CD test and show *t*-statistics of the null hypothesis of cross-sectional independence in residuals. The unbalanced panel consists of the three sectors industrial, office, and retail in 25 countries over the years 1998 to 2013. Clustered-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Model I	**Model II**	**Model III**	**Model IV**
GLOBAL STOCK ER	0.054***			
	(0.014)			
Δ GLOBAL CONS.		0.021***		
		(0.003)		
TED SPREAD			-2.305***	
			(0.457)	
EURODOLLAR			0.744***	0.699***
			(0.189)	(0.168)
REIT US ER				0.112***
				(0.016)
Δ REAL XR	-0.007	-0.018	0.022	0.001
	(0.026)	(0.034)	(0.027)	(0.027)
Observation	969	866	969	969
Fixed Effects	Yes	yes	yes	yes
Pesaran CD	44.53***	41.62***	35.696***	27.065***
Adj. R^2	0.028	0.062	0.087	0.121

Table C.5: Definition of Global and Country-Specific Data

This table gives a more detailed discussion and overview of the data used in the paper. We list all variables and indicate the data sources. We differentiate between endogenous market-specific variables, exogenous variables used to construct the weighting matrix, as well as common global and national fundamentals and controls.

Variables	**Description**	**Source**
Endogenous Variable (Market-Specific)		
Property Market Excess Returns	Total returns on commercial real estate are computed from property market indices at annual basis for three sectors (logistic/industrial, office, and retail). The PMA coverage contains city-level data in 26 countries from 2001 to 2013. The IPD coverage contains 25 countries from 1998 to 2013. Some indices start at a later time period. Returns are computed in excess to the U.S. three-month Treasury Bill.	PMA/IPD
Exogenous Variables used for the Weighting Matrix (Country-Specific Differentials)		
Property Market-specific Transparency Risk	Transparency differentials are computed as inverse distance measure, based on cross-sectional country-specific transparency indices. The transparency index is released in 2004, 2006, 2008, and 2012.	Jones Lang LaSalle
Economic Freedom	As proxy for political risk, we use the index of economic freedom which is released each year. Based on our sample from 2001 to 2013, we compute time-varying weighting matrices with cross-sectional inverse distance measures.	Heritage Foundation
Corruption Perception	We use the corruption perception index which is released each year from 2001 to 2013. Based on the index values for each country, we construct time-varying weighting matrices with cross-sectional inverse distance measures.	Transparency International
Country Risk	The Country risk index is released each year. We use index values for 26 countries from 2001 to 2011. For the missing values in the years 2012 and 2013 we use lagged values.	Economist Intelligence Unit (EIU)
Political Risk	The index is released at an annual basis. We compute inverse distance for each time-varying weighting matrix. Our data ranges from 2001 to 2011. For the missing values in the years 2012 and 2013 we use lagged values, since the index does not reveal much variation over time.	Economist Intelligence Unit (EIU)

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Explanatory Variables (Global Factors)		
Global Market Portfolio (*GLOBAL STOCK ER*)	This variable is based on the MSCI world index as proxy for a global market portfolio. We compute excess returns relative to the thee-year U.S. Treasury Bill rate, ranging from 1998 to 2013.	Datastream
Three-Month Eurodollar Rate (*EURODOLLAR*)	The three-month Eurodollar rate reflects changes in investors risk aversion. The sample ranges from 1998 to 2013.	Datastream
TED Spread (*TED SPREAD*)	The TED spread is computed as difference between the three-month LIBOR rate and the three-month U.S. Treasury Bill rate. We use this variable as proxy for global funding liquidity and credit risk.	Own construction
Investment (*INVESTMENT*)	This variable is based on global investment of international investors in the commercial real estate sector. We compute aggregated investment flow variables for Western Europe, Eastern Europe, Asia-Pacific, as well as the USA.	PMA
Excess Returns on Securitizes Real Estate (*REIT US ER*)	We use the NAREIT/MSCI US REIT index to construct returns relative to the risk-free rate. The variable ranges from 1998 to 2013. We use US REIT excess returns as global leading indicator in commercial real estate.	Datastream
Explanatory Variables (Country-Specific Factors)		
Spread (*SPREAD*)	Computed as difference between long-term interest rate (10 years) and three month short-term interbank rate for each country from 1998 to 2013. We use 6 month interest rates as long term interests for China, Czech Republic, Greece, Hungary, and Poland.	Own Calculation
Expected Inflation Rate (Δ *CPI*)	Expected inflation is proxied by log changes of CPI for all countries from 1998 to 2013. We use data from Datastream.	Datastream
Stock Market Excess Returns (*STOCK ER*)	We use country-specific stock market indices provided by MSCI from 1997 to 2013 as proxy for national market portfolios.	Datastream
Excess Returns on REITS (*REIT ER*)	We compute country-specific excess returns on securitized real estate based on NAREIT/MSCI REIT. We use FTSE EPRA REIT for Finland and Ireland. We compute AR(1)-forecasts to fill missing values for Hungary, South Korea, and Poland.	Datastream

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Changes in Consumption Expenditure (Δ *CONS*)	For each country, we collect consumption data from 1997 to 2013, on which we compute log changes. Changes in consumption expenditure are measured per capita.	Datastream
Changes in GDP (Δ *GDP*)	We also compute log changes of GDP (in per capita values) for each country from 1998 to 2013. We find a correlation of 88% between growth in GDP and consumption expenditures. GDP is measured in constant prices, except for China (current prices).	Datastream
	Controls (Country-Specific)	
Changes in Real Exchange Rate (Δ*REAL XR*)	We compute log changes of the real exchange rate as a linear approximation of changes in nominal exchange measured as USD per unit of foreign currency (direct quotation) and adjust for differences in log changes of price levels (CPI) between both countries. The values range from 1998 to 2013.	Own Calculation
Unemployment Rate (Δ*UNEMPLOYMENT*)	We collect unemployment rates from 1998 to 2013 for all countries in our sample.	Datastream
Foreign Direct Investment Inflows (*FDI INFLOWS*)	We use net inflows of foreign investments in domestic firms, measured in current USD. We compute values denominated in local currencies by dividing by the exchange rate. The sample ranges from 1998 to 2013.	Worldbank
Financial Depth (*FINANCIAL DEPTH*)	As proxy for financial depth we use domestic credit provided by the banking sector (including monetary authorities, deposit money banks, and other financial corporations). The variable is measured in percentage to GDP. We compute AR(1) forecast to replace missing values for Canada, New Zealand, and Norway.	Worldbank
Residential Housing Appreciation (Δ *HOUSING*)	We use log changes in residential property price indices for all 25 countries in our sample with the exception of China. The data range from 1998 to 2013. As sources we use the BIS Residential Property Price database.	Bank of International Settlement
Additional Construction in Commercial Real Estate Sector (Δ *STOCKS)*	This variable is computed as log change in the stock of commercial real estate stocks for 26 countries based on the PMA databank.	PMA
Changes in Money Supply (Δ *MONEY SUPPLY*)	For each country in our sample, we use changes in money supply, based on M0. Please note that we use M1 for China.	Worldbank

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Additional Variables		
Long-Term Interest	Country-specific 10-year government bonds. Long-term interest rates range from 1998 to 2013. We use six month interest rates as long term interests for China, Czech Republic, Greece, Hungary, and Poland.	Datastream
Short-Term Interest	This variable is based on three-month interbank rates since short-term Treasury bills are not available for some countries in our sample.	Datastream
Risk-Free Rate	Three-month U.S. Treasury Bill rate is used as proxy for the risk-free rate.	Datastream
Changes in Nominal Exchange Rate (Δ *XR*)	Log changes of nominal exchange rates are computed for all countries in our sample relative to the USD. The data ranges from 1998 to 2013.	Datastream
Changes in Total Population (Δ *POP*)	We compute log changes of total population for each country from 1998 to 2013. Total population values are based on mid-year estimates. This variable is used to compute per capita values of GDP and consumption expenditures.	Worldbank
Three-Month LIBOR Rate	This variable ranges from 1998 to 2013 and is used to construct the TED spread.	Datastream

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Figure 1: Information Acquisition Costs and Transparency Risk Differentials

This figure illustrates the conceptual framework of the trade-off between information acquisition costs (market entry costs) and costs due to adverse selection. International investors have incentives to obtain costly information in order to enter property markets if the acquisition costs are lower than the costs from trading with informed domestic investors. We assume that information acquisition costs are positively related to the transparency risk distance between the foreign private market and the investors' due to similarities in both markets with respect to regulation, information disclosure, ect. They enter multiple markets which are similar in terms of transparency risk until the costs of obtaining private information exceeds the adverse selection costs from trading with better privately informed agents.

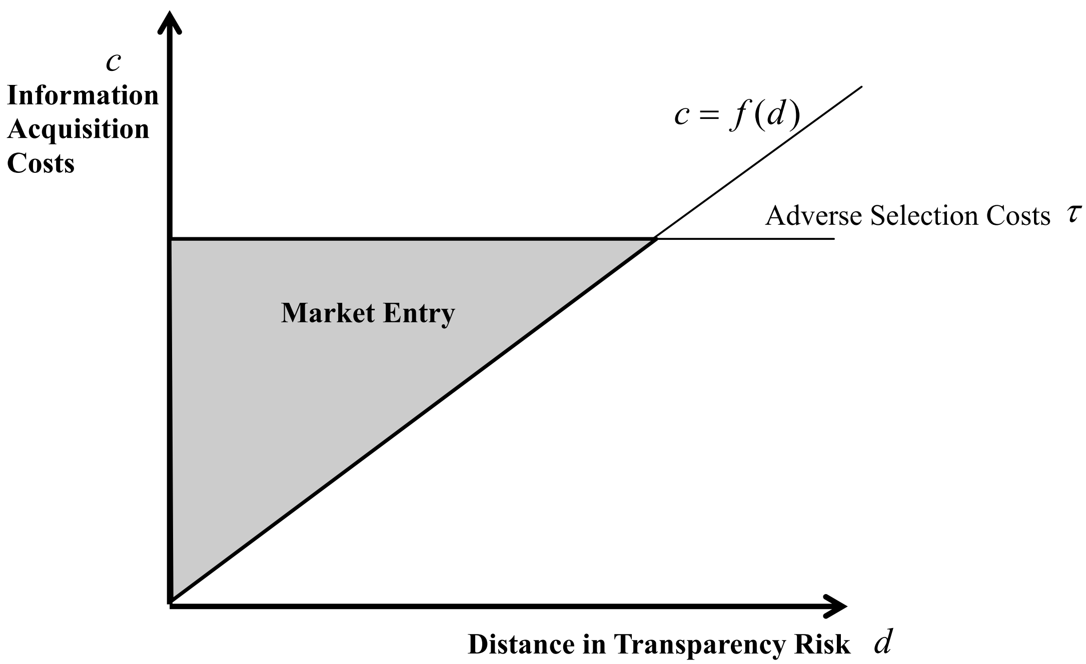
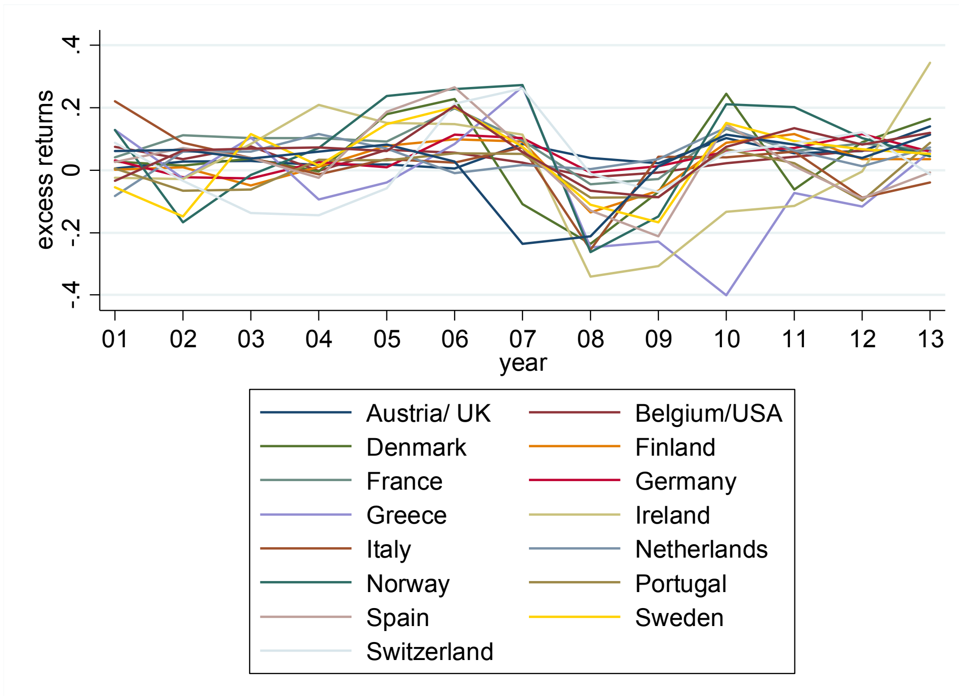


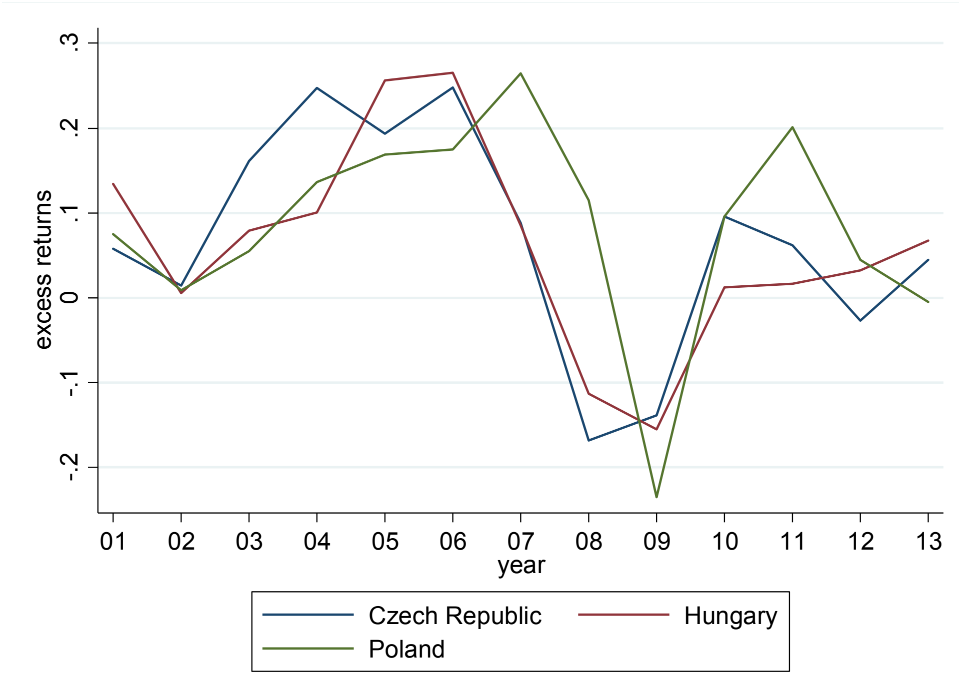
Figure 2: Performance of Commerial Real Estate Markets

This figure depicts country-specific excess returns averaged across all sectors and cities from 2001 to 2013. Panel A illustrates the performance of commercial real estate for Western Europe and the USA. Panels B and C show averaged variation over time for Central and Eastern Europe and Asia-Pacific, respectively.

Panel A: Commercial Real Estate in Western Europe and USA



Panel B: Commercial Real Estate in Central and Eastern Europe



Panel C: Commercial Real Estate in Asia-Pacific

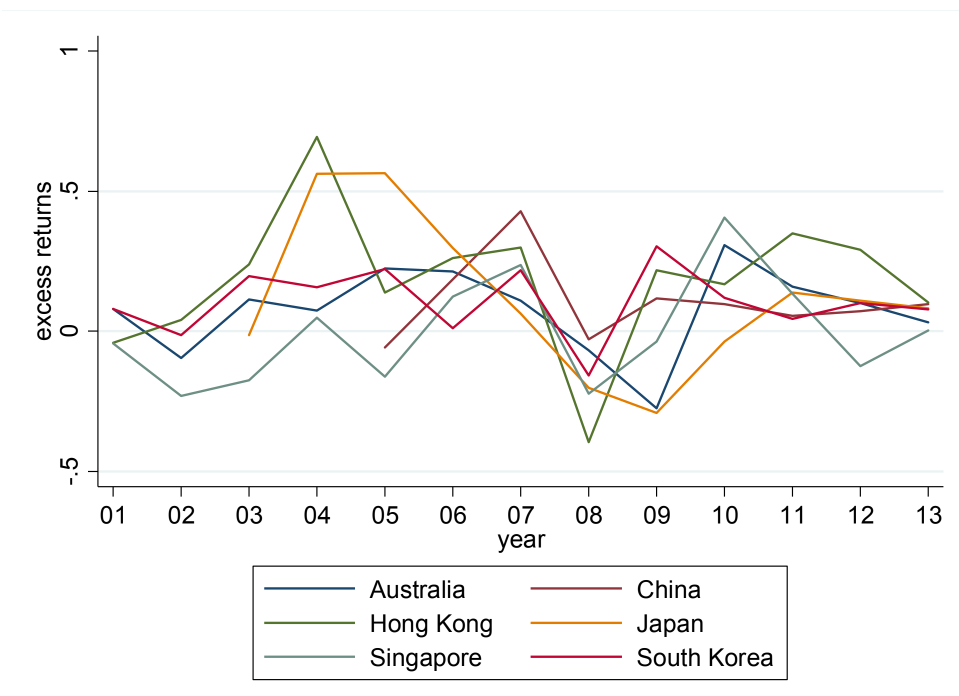


Figure 3: Illustration of Time-Varying Effects

This figure shows the plots and averages of property excess returns pooled across all cities and sectors over the years from 2001 to 2013. The data are based on the PMA market coverage. We see a drop in average return during the financial crisis period in the years 2008 and 2009. A recovery in the year 2010 leads to an average return which is slightly below the average excess return of the pre-crisis period 2007 to 2008.

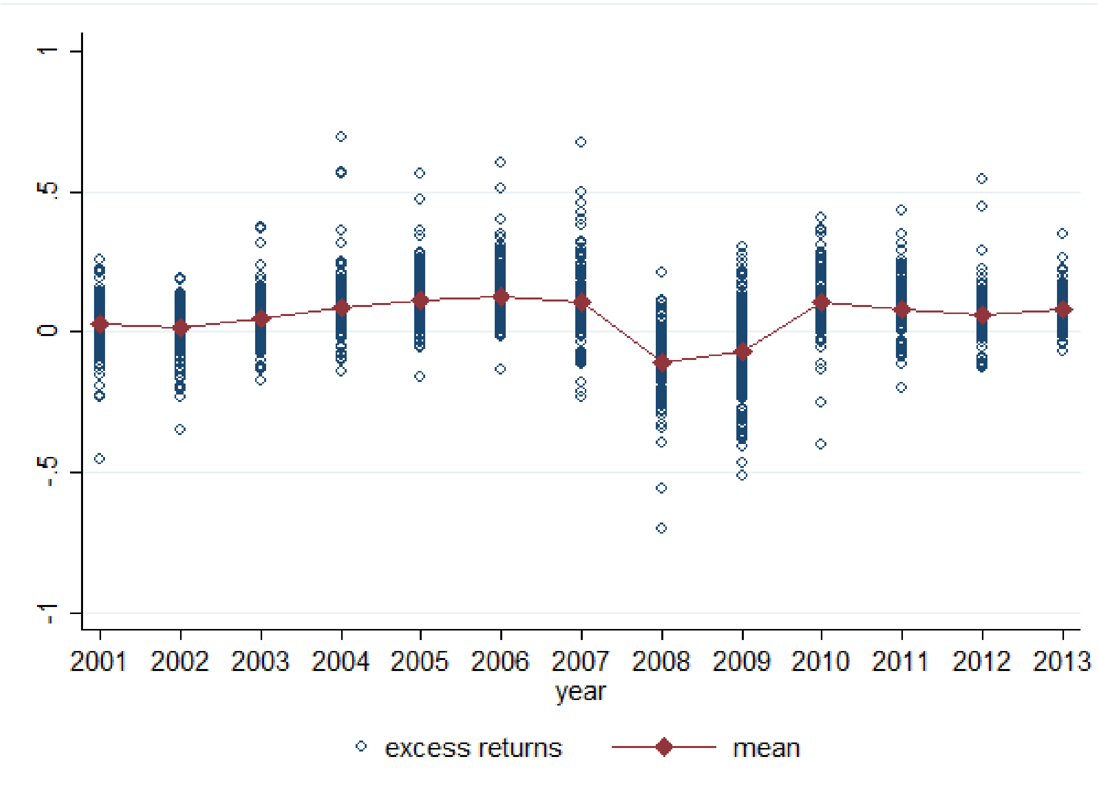


Table 1: Summary Statistic of Property Market Excess Returns

This table shows mean, standard deviation, minimum, and maximum value of country-specific market excess returns on income-producing properties for 26 countries from 2001 to 2013. Values are based on the PMA market coverage. Excess returns are aggregated over all sectors and all cities for each country. We indicate the total number of observations in column 6 to illustrate the coverage for each country in the panel. Column 7 shows the transparency level as published by Jones Lang Lasalle (JLL) in 2012.

Country	Mean	Std. Dev	Min	Max	Obs.	Transparency
Australia	0.081	0.125	-0.275	0.605	104	Highly Transparent
Austria	0.042	0.080	-0.121	0.299	26	Transparent
Belgium	0.039	0.064	-0.112	0.215	52	Transparent
China	0.098	0.115	-0.170	0.432	68	Semi-Transparent
Czech Republic	0.064	0.096	-0.170	0.432	39	Transparent
Denmark	0.038	0.115	-0.237	0.312	39	Transparent
Finland	0.024	0.074	-0.135	0.117	13	Highly Transparent
France	0.061	0.088	-0.301	0.247	156	Highly Transparent
Germany	0.035	0.069	-0.204	0.236	221	Transparent
Greece	-0.039	0.152	-0.400	0.268	26	Semi-Transparent
Hong Kong	0.156	0.214	-0.396	0.693	39	Transparent
Hungary	0.038	0.122	-0.278	0.265	39	Transparent
Ireland	-0.095	0.236	-0.704	0.399	39	Transparent
Italy	0.033	0.083	-0.255	0.285	91	Transparent
Japan	0.058	0.187	-0.377	0.566	73	Transparent
Netherlands	0.037	0.065	-0.141	0.286	65	Highly Transparent
Norway	0.072	0.176	-0.263	0.273	13	Transparent
Poland	0.084	0.110	-0.235	0.319	39	Transparent
Portugal	-0.004	0.077	-0.175	0.136	39	Transparent
Singapore	0.055	0.207	-0.382	0.677	35	Transparent
South Korea	0.118	0.098	-0.158	0.304	23	Semi-Transparent
Spain	0.026	0.131	-0.330	0.358	91	Transparent
Sweden	0.038	0.115	-0.234	0.204	39	Highly Transparent
Switzerland	0.027	0.124	-0.144	0.261	13	Highly Transparent
UK	0.043	0.115	-0.288	0.351	182	Highly Transparent
USA	0.058	0.125	-0.516	0.457	416	Highly Transparent

Table 2: Correlation Matrix of State Variables

This table shows the correlation of all explanatory variables in our sample. The panel consists of 26 countries over the years 2001 to 2013.

	STOCK ER	ΔCONSUMPTION	SPREAD	ΔCPI	ΔUNEMPLOYMENT	ΔREAL XR	REIT ER	FINANCIAL DEPTH	ΔMONEY SUPPLY	FDI INFLOWS	ΔHOUSING	EURODOLLAR	TED SPREAD	GLOBAL STOCK ER	INVESTMENT	ΔCONSTRUCTION
STOCK ER	1.000															
Δ CONSUMPTION	0.126	1.000														
SPREAD	0.040	-0.314	1.000													
Δ CPI	-0.373	0.151	-0.225	1.000												
Δ UNEMPLOYMENT	0.001	-0.342	0.435	-0.083	1.000											
ΔREAL XR	0.015	0.146	-0.034	0.051	-0.068	1.000										
REIT ER	0.156	0.347	-0.139	-0.008	-0.085	0.062	1.000									
FINANCIAL DEPTH	0.034	-0.294	0.162	-0.248	-0.256	-0.143	-0.022	1.000								
ΔMONEY SUPPLY	-0.027	0.074	0.017	-0.038	-0.070	0090	0.056	-0.031	1.000							
FDI INFLOW	-0.053	0.217	-0.203	0.149	0.155	0.002	0.061	-0.027	0.027	1.000						
Δ HOUSING	0.227	0.396	-0.137	0.073	-0.041	0.152	0.154	-0.245	0.033	0.107	1.000					
EURODOLLAR	-0.115	0.310	-0.375	0.147	-0.228	0.038	0.231	-0.133	-0.011	0.140	0.128	1.000				
TED SPREAD	-0.596	-0.029	-0.272	0.316	-0.205	-0.055	0.231	-0.0003	-0.058	0.114	-0.165	0.460	1.00			
GLOBAL STOCK ER	0.778	-0.020	0.186	-0.493	0.154	0.087	-0.172	0.056	-0.032	-0.045	0.147	-0.272	-0.704	1.00		
INVESTMENTS	0.381	0.352	0.064	-0.103	0.066	0.135	0.069	-0.067	-0.003	-0.010	0.266	0.067	-0.565	0.396	1.000	
ΔCONSTRUCTION	-0.025	0.380	0.436	0.090	-0.019	0.034	0.109	0.569	-0.035	-0.160	-0.007	0.334	0.158	-0.577	0.409	1.000

Table 3: Results on Country-Specific Systematic Risk Factors

This table shows regression results of international direct property excess return on country-specific risk factors. Estimations are based on the within-estimator accounting for market-specific fixed effects. We apply the Pesaran (2004) CD test and show *t*-statistics of the null hypothesis of cross-sectional residual independence. The unbalanced panel pools the three sectors logistic/industrial, office, and retail and all cities in 26 countries over the years 2001 to 2013. Clustered-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Model I	**Model II**	**Model III**	**Model IV**	**Model V**
STOCK ER	0.153***	0.057**	0.151***	0.142***	0.096***
	(0.015)	(0.025)	(0.016)	(0.019)	(0.015)
Δ CONSUMPTION	2.503***	1.650***	2.694***	2.304***	2.174***
	(0.184)	(0.181)	(0.221)	(0.249)	(0.184)
Δ CPI	1.068***	0.262	1.135***	1.342***	1.179***
	(0.308)	(0.344)	(0.301)	(0.414)	(0.295)
SPREAD	0.664***	0.365*	0.494*	0.573**	0.632***
	(0.209)	(0.209)	(0.253)	(0.264)	(0.241)
Δ REAL XR			-0.091**	-0.094***	-0.109**
			(0.038)	(0.035)	(0.035)
REIT ER				0.037***	
				(0.008)	
Δ HOUSING				0.013	
				(0.034)	
FDI INFLOW			-0.002		
			(0.117)		
FINANCIAL DEPTH			-0.001		
			(0.018)		
Δ MONEY SUPPLY			-0.063**		
			(0.031)		
Δ UNEMPLOYMENT			0.386***		
			(0.141)		
EURODOLLAR					1.005***
					(0.217)
TED SPREAD					-3.126***
					(0.381)
Observation	1980	1980	1972	1859	1980
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time-Fixed Effects	No	Yes	No	No	No
Pesaran CD	50.566***	1.753*	42.214***	29.030***	49.242***
Adj.-R^2	0.258	0.068	0.269	0.290	0.291

Table 4: Results on Common Global Systematic Risk

This table shows regression results of international direct property excess returns on global risk factors. The MSCI world index (Global Stock ER) is used as proxy for the global market portfolio. Global consumption growth (Δ GLOBAL CONS.) denotes the first factor from a Principal Component Analysis. TED SPREAD is measured as difference between long- and short-term interest rates. The three-month Eurodollar rate is denoted as EURODOLLAR. REIT US ER indicates excess returns on the US MSCI REIT index. INVESTMENTS covers regional property investments flows for the USA, Central Europe, Eastern Europe, as well as Asia-Pacific from 2006 to 2013. Estimates are based on the within-estimator including property-specific fixed effects. We apply the Pesaran (2004) CD test and show *t*-statistics of the null hypothesis of cross-sectional residual independence. The unbalanced panel pools the three sectors logistic/industrial, office, and retail and all cities in 26 countries over the years 2001 to 2013. Clustered-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Model I	**Model II**	**Model III**	**Model IV**	**Model V**
GLOBAL STOCK ER	0.155***				
	(0.012)				
Δ GLOBAL CONS.		0.038***			
		(0.004)			
TED SPREAD			-5.797***		
			(0.397)		
EURODOLLAR			1.953***	1.336***	
			(0.196)	(0.180)	
REIT US ER				0.280***	0.064***
				(0.015)	(0.144)
INVESTMENTS					0.144***
					(0.013)
Δ REAL XR	-0.001	-0.054	-0.022	-0.035	-0.095**
	(0.041)	(0.042)	(0.038)	(0.038)	(0.039)
Observation	1980	1980	1980	1980	1852
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Pesaran CD	125.15***	140.67***	96.51***	57.14***	17.86***
Adj.-R^2	0.085	0.064	0.170	0.239	0.314

Table 5: Spatial Lag Model with Country-Specific Fundamentals

This table shows the results of the spatial lag model. In Panel A we regress property excess returns on its spatial lag and country-specific fundamentals using the JLL Transparency Index to compute the weight matrix. The spatial lag indicates the degree of spatial dependence. Estimations are based on the Mundlak (1978) fixed effects model. We conduct the Pesaran (2004) CD test and show *t*-statistics of the null hypothesis of residual independence. The panel consists of three sectors logistic/industrial, office, retail and cities in 26 countries from 2001 to 2013. HAC-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively. Panel B shows average direct and total impacts of changes in fundamentals derived from the reduced-form specification of the spatial model to account for spillover and feedback loop effects.

Panel A: Estimation Results

	GMM	2SLS	NLS
CONSTANT	0.031**	0.031**	0.027**
	(0.012)	(0.012)	(0.012)
SPATIAL LAG	0.539***	0.517***	0.603***
	(0.137)	(0.142)	(0.144)
STOCK ER	0.076***	0.078***	0.067***
	(0.024)	(0.024)	(0.025)
Δ CONSUMPTION	1.237***	1.251***	1.092***
	(0.353)	(0.356)	(0.370)
Δ CPI	0.590**	0.582**	0.548**
	(0.252)	(0.253)	(0.252)
SPREAD	0.306*	0.307*	0.287*
	(0.157)	(0.158)	(0.157)
Observation	2041	2041	2041
Fixed Effects	Yes	Yes	Yes
Pesaran CD	9.52***	11.27***	5.94***

Panel B: Direct and Total Impact

	GMM	2SLS	NLS
Average Direct Impact			
STOCK ER	0.081	0.082	0.073
Δ CONSUMPTION	1.319	1.325	1.193
Δ CPI	0.629	0.617	0.599
SPREAD	0.326	0.325	0.314
Average Total Impact			
STOCK ER	0.165	0.160	0.168
Δ CONSUMPTION	2.682	2.588	2.749
Δ CPI	1.278	1.204	1.380
SPREAD	0.663	0.634	0.723

Table 6: Spatial Lag Model Conditional on Global Funding Liquidity

This table extends the results of Table 5. In Panel A we estimate the spatial model of Table 5 controlling for global funding liquidity. The panel pools the three sectors (retail, office, and logistic) and all cities in 26 countries from 2001 to 2013. HAC-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively. Panel B shows average direct and total impacts of changes in fundamentals.

Panel A: Estimation Results

	GMM	2SLS	NLS
CONSTANT	0.047***	0.047***	0.032*
	(0.016)	(0.016)	(0.017)
SPATIAL LAG	0.416**	0.393**	0.613***
	(0.173)	(0.179)	(0.215)
STOCK ER	0.070***	0.070***	0.050*
	(0.022)	(0.022)	(0.027)
Δ CONSUMPTION	1.386***	1.406***	0.973**
	(0.390)	(0.394)	(0.488)
Δ CPI	0.768***	0.746***	0.582**
	(0.284)	(0.285)	(0.308)
SPREAD	0.133	0.132	0.111
	(0.159)	(0.160)	(0.154)
TED SPREAD	-1.238**	-1.270**	-0.763
	(0.541)	(0.547)	(0.592)
Observations	2041	2041	2041
Fixed Effects	Yes	Yes	Yes
Pesaran CD	17.24***	19.19***	5.68***

Panel B: Direct and Total Impact

	GMM	2SLS	NLS
Average Direct Impact			
STOCK ER	0.073	0.072	0.054
Δ CONSUMPTION	1.433	1.447	1.068
Δ CPI	0.794	0.767	0.638
SPREAD	0.138	0.136	0.122
TED SPREAD	-1.280	-1.307	-0.837
Average Total Impact			
STOCK ER	0.121	0.116	0.128
Δ CONSUMPTION	2.375	2.318	2.514
Δ CPI	1.316	1.229	1.503
SPREAD	0.228	0.217	0.287
TED SPREAD	-2.121	-2.093	-1.972

Table 7: Spatial Lag Model Conditional on Construction

This table extends the results of Table 5. Panel A shows estimates of the spatial model controlling for additional construction. The panel pools the three sectors (retail, office, and logistic) and all cities in 26 countries from 2006 to 2013. HAC-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively. Panel B shows average direct and total impacts of changes in fundamentals.

Panel A: Estimation Results

	GMM	2SLS	NLS
CONSTANT	0.011	0.011	0.008
	(0.012)	(0.012)	(0.011)
SPATIAL LAG	0.593***	0.593***	0.651***
	(0.118)	(0.118)	(0.118)
STOCK ER	0.079***	0.079***	0.084***
	(0.025)	(0.025)	(0.027)
Δ CONSUMPTION	1.530***	1.530***	1.125**
	(0.479)	(0.479)	(0.547)
Δ CPI	0.629*	0.629*	0.942*
	(0.346)	(0.346)	(0.482)
SPREAD	0.370	0.370	0.216
	(0.292)	(0.292)	(0.310)
Δ CONSTRUCTION	-0.426***	-0.426***	-0.436***
	(0.145)	(0.145)	(0.143)
Observation	880	880	880
Fixed Effects	Yes	Yes	Yes
Pesaran CD	0.29	0.29	-0.11

Panel B: Direct and Total Impact

	GMM	2SLS	NLS
Average Direct Impact			
STOCK ER	0.088	0.088	0.097
Δ CONSUMPTION	1.714	1.714	1.306
Δ CPI	0.704	0.704	1.093
SPREAD	0.415	0.415	0.251
Δ CONSTRUCTION	-0.477	-0.477	-0.507
Average Total Impact			
STOCK ER	0.194	0.194	0.241
Δ CONSUMPTION	3.764	3.764	3.229
Δ CPI	1.546	1.546	2.702
SPREAD	0.910	0.910	0.620
Δ CONSTRUCTION	-1.048	-1.048	-1.252

Table 8: Spatial Lag Model based on Sector Heterogeneity

This table extends the results of Table 5. In Panel A we estimate the spatial model for each sector (logistic/industrial, office, retail) separately. Estimates are based on GMM. Each sector consists of all cities pooled over all 26 countries from 2001 to 2013. HAC-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively. Panel B shows average direct and total impacts of changes in fundamentals.

Panel A: Estimation Results

	Logistic	Office	Retail
CONSTANT	0.081***	0.020	0.069***
	(0.018)	(0.014)	(0.022)
SPATIAL LAG	0.321**	0.611***	0.570***
	(0.156)	(0.157)	(0.141)
STOCK ER	0.093***	0.076**	0.072**
	(0.024)	(0.033)	(0.031)
Δ CONSUMPTION	1.829***	1.426***	1.260***
	(0.349)	(0.466)	(0.420)
Δ CPI	1.039***	0.256	0.520
	(0.349)	(0.395)	(0.477)
SPREAD	0.679***	-0.055	0.600**
	(0.212)	(0.269)	(0.283)
Observation	611	767	663
Fixed Effects	Yes	Yes	Yes
Pesaran CD	8.38***	2.59***	1.61

Panel B: Direct and Total Impact

	Logistic	Office	Retail
Average Direct Impact			
STOCK ER	0.096	0.087	0.081
Δ CONSUMPTION	1.899	1.643	1.428
Δ CPI	1.079	0.295	0.589
SPREAD	0.706	-0.063	0.680
Average Total Impact			
STOCK ER	0.136	0.195	0.166
Δ CONSUMPTION	2.694	3.668	2.932
Δ CPI	1.530	0.658	1.208
SPREAD	1.001	-0.141	1.396

Table 10: Spatial Lag Model with Country-Specific Fundamentals based on IPD

This table shows the results of the spatial lag model using the IPD data. In Panel A we regress property excess returns on its spatial lag and country-specific fundamentals using the JLL Transparency Index to compute the weight matrix. The spatial lag indicates the degree of spatial dependence. Estimators are based on the Mundlak (1978) fixed effects model. We conduct the Pesaran (2004) CD test and show *t*-statistics of the null hypothesis of residual independence. The panel pools three sectors (industrial/logistic, office, retail) and cities in 26 countries from 2001 to 2013. HAC-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively. Panel B shows average direct and total impacts of changes in fundamentals derived from the reduced-form specification to account for spillover and feedback loop effects.

Panel A: Estimation Results

	GMM	2SLS	NLS
CONSTANT	0.020**	0.018**	0.019**
	(0.008)	(0.008)	(0.008)
SPATIAL LAG	0.403**	0.456***	0.417**
	(0.186)	(0.177)	(0.182)
STOCK ER	0.032**	0.029**	0.031**
	(0.013)	(0.012)	(0.013)
Δ CONSUMPTION	1.144***	1.055***	1.120***
	(0.328)	(0.313)	(0.320)
Δ CPI	0.641***	0.596***	0.629***
	(0.230)	(0.222)	(0.226)
SPREAD	0.183	0.170	0.179
	(0.131)	(0.125)	(0.128)
Observation	1184	1184	1184
Fixed Effects	yes	yes	yes
Pesaran CD	8.53***	7.30***	8.22***

Panel B: Direct and Total Impact

	GMM	2SLS	NLS
Average Direct Impact			
STOCK ER	0.034	0.032	0.033
Δ CONSUMPTION	1.229	1.162	1.210
Δ CPI	0.688	0.656	0.680
SPREAD	0.197	0.188	0.193
Average Total Impact			
STOCK ER	0.053	0.053	0.053
Δ CONSUMPTION	1.915	1.941	1.920
Δ CPI	1.072	1.095	1.079
SPREAD	0.307	0.313	0.306

Table 11: Different Weighting Matrices

This table provides regression results of the spatial lag model using different weighting matrices. Inverse distance measures are based on the Index of Economic Freedom, the Corruption Perception Index and the EIU Political as well as Country Risk Index in Models I to IV. All weighting matrices are row-normalized. We regress property market excess returns on its spatial lag and country-specific risk factors. The spatial lag measures the degree of cross-sectional dependence as indicated by the weighting matrix. Estimates are based on 2SLS. We conduct the Pesaran (2004) CD test and show *t*-statistics of the null hypothesis of residual independence. The panel pools all three sectors (logistic/industrial, office, retail) and cities in 26 countries from 2001 to 2013. HAC-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Model I	**Model II**	**Model III**	**Model IV**
CONSTANT	0.040***	0.029**	0.028**	0.030***
	(0.012)	(0.012)	(0.012)	(0.012)
SPATIAL LAG	0.460***	0.625***	0.649***	0.625***
	(0.060)	(0.060)	(0.057)	(0.065)
STOCK ER	0.098***	0.064***	0.066***	0.065***
	(0.014)	(0.014)	(0.014)	(0.014)
Δ CONSUMPTION	1.551***	1.447***	1.331***	1.419***
	(0.221)	(0.189)	(0.248)	(0.261)
Δ CPI	0.721***	0.511**	0.596**	0.442*
	(0.254)	(0.246)	(0.395)	(0.246)
SPREAD	0.454***	0.406***	0.275*	0.303*
	(0.160)	(0.154)	(0.163)	(0.158)
Observation	2041	2041	2041	2041
Pesaran CD	21.00***	4.56***	4.30***	4.97***
Fixed Effects	Yes	Yes	Yes	Yes
W-Matrix	Economic Freedom	Corruption Perception	Political Risk	Country Risk