Learning Externalities in Opaque Asset Markets: Evidence from International Commercial Real Estate*

Roland Füss[†] Daniel Ruf[‡]

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Abstract

This paper uses a unique dataset to empirically test the implications of limited transparency in opaque, decentralized asset markets. We utilize the specific microstructure of international commercial real estate markets and capture differences in their level of transparency as a linkage mechanism. This market connectivity arises from the strategic interaction of informed and uninformed investors. Our identification strategy exploits the unique feature of spatial econometrics to analyze the transmission of learning externalities across segmented opaque markets. We find empirical evidence of cross-sectional dependence and implied co-movements among them. Furthermore, we show that local shocks are amplified via spillover effects and feedback loops, which provide a potential source of instability of the international commercial property sector.

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Key words: Commercial real estate; cross-sectional dependence; learning externalities; opaque markets; spatial econometrics; transparency risk.

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[†]Swiss Institute of Banking and Finance (s/bf), University of St.Gallen, Rosenbergstrasse 52, 9000 St. Gallen, Switzerland and Research Associate at the Centre for European Economic Research (ZEW), Mannheim, Germany; Phone: +41 (0)71 224-7055, Fax: +41 (0)71 224-7088; Email: roland.fuess@unisg.ch

[‡]Swiss Institute of Banking and Finance (s/bf), University of St.Gallen, Rosenbergstrasse 52, 9000 St. Gallen, Switzerland, Phone: +41 (0)71 224-7059, Fax: +41 (0)71 224-7088, Email: daniel.ruf@unisg.ch.

1 Introduction

Commercial real estate has become an important asset class in the portfolio of large international investors over the last decades. With 13.6 trillion U.S. dollars invested stock worldwide and total transaction volume of 633 billion U.S. dollars in 2014, trading in commercial properties has already surpassed its 2006 pre-financial crisis value (DTZ (2015)). However, capital growth in real estate investments is unequally distributed across the globe. Increasing risk appetite, excessive demand of investors, as well as economic growth prospects drive up property prices in emerging markets, particularly in China and Asia, while mature but more liquid markets in Europe and the U.S. offer lower expected returns.[1] Furthermore, the business and banking sector is linked to international commercial real estate through the credit and collateral channel. For instance, there is ample evidence of co-movements of property values and the investment behavior of firms (see, e.g., Chaney, Sraer, and Thesmar (2012); Liu, Wang, and Zha (2013)). Hence, the performance of property markets significantly impacts the real economy as well as global financial stability.

We focus on international commercial real estate as a natural laboratory to analyze spillover effects across segmented opaque, decentralized asset markets. To the best of our knowledge, this is the first paper which empirically studies the cross-sectional dependence and connectivity of these markets which arises from limited transparency. Compared to other assets, for instance, bonds, currency, and equity, direct investments in commercial properties are hindered by their specific market microstructure. First, property markets are geographically segmented due to the immobility of their assets and because of trading frictions, which impede the entry of foreign investors. Second, heterogeneous proper-

[1]DTZ (2015) reports growth of invested stock in commercial real estate of 10% to 5.1 trillion U.S. dollars in Asia-Pacific in 2014 compared to 5% from 4 trillion U.S. dollars to 4.2 trillion U.S. dollars in North America. Europe remains at 4.4 trillion U.S. dollars from 2013, which is slightly below its pre-financial crisis value. Investment volumes increased to a record o 107 billion U.S. dollars in Asia compared to a 30%-increase to 263 billion U.S. dollars in Europe and 12% to 291 billion U.S. dollars in North America in 2014. Global investment volumes remain particularly high in liquid property markets such as London, New York, San Francisco, Tokyo, Los Angeles, and Paris.

ties are privately negotiated and traded over-the-counter (OTC) in illiquid markets with limited transparency. Hence, transaction prices depend on search costs, asymmetric information, and the bargaining power of buyers and sellers. Third, the price incorporation of information in private markets and disclosure to other market participants is more sluggish compared to centralized trading platforms. Efficient prices are unobservable because of infrequent trading, while lack of transparency limits the amount of publicly available information. All these factors contribute to the segmentation and opacity of international commercial real estate markets.

We use market-specific transparency differentials to model the connectivity between opaque asset markets. These pairwise defined differences in the level of market transparency reflect trading frictions and explicitly capture the transmission channel in our empirical model. This identification strategy allows us to test the implications of limited market transparency and to estimate spillover effects which are transmitted through this linkage mechanism. We interpret this connectivity as a consequence of the strategic interaction of informed and uninformed investors under limited transparency. In general, risk-averse traders prefer to invest in more transparent, but mainly mature private markets for which information is easily accessible. However, property investments in these markets provide lower expected returns. Alternatively, investments in less transparent markets are associated with higher market entry costs, but offer potential benefits of higher expected returns and additional risk diversification. We argue that a subset of traders, such as return-seeking large institutional investors with higher risk appetite, who are domiciled in markets with higher opacity, have an comparative advantage to enter less transparent markets due to informational economies of scale, higher perceived familiarity, and consequently less information acquisition costs. While these informed investors bear the market entry costs, uninformed traders can avoid them by following the first-mover.

In order to underpin our economic intuition, we illustrate this mechanism in Figure 1. The market entry of large institutional investors leads to the herding behavior of uninformed traders, which allows the first-mover to realize higher expected returns by buying from local dealers in one period and selling at a higher price to uninformed traders in the subsequent one. Uninformed investors benefit from learning externalities as better informed investors reveal their knowledge by privately trading to their uninformed counterparties (see, e.g., Zhu (2012), Duffie, Malamud, and Manso (2014)). Using observed transaction prices allows assessing the friction-based markup on property prices, reducing the uncertainty about possible price ranges of comparable properties in opaque markets with similar level of transparency, and thereby improving the bargaining power of uninformed investors without paying information acquisition costs. Following the trading strategy of the first-mover, i.e., buying from local brokers and selling to uninformed investors whose demand is attracted by the market entry, enables them to reap higher expected returns. Consequently, this herding behavior can trigger a cascade of excessive demand driving up prices in multiple private markets. This is reflected in return co-movements as provoked by the linkage mechanism which serves as a breeding ground for potential instability of international private property markets.

[INSERT FIGURE 1 HERE]

Our empirical analysis is based on an extensive and exclusive dataset of property market indices for the sectors industrial, office, and retail, disaggregated at city-level in 26 countries from 2001 to 2013. In our identification strategy, we exploit the cross-sectional variation in a property-specific international transparency index to specify the connectivity between private commercial real estate markets. This index reflects international investors' perceived uncertainty due to legal restrictions, policy regulations, and trading barriers, but also covers broader components such as political stability and the ease of access to property market-specific information. Based on our economic intuition, we use transparency differentials as proxy for information acquisition and market entry costs between property markets. This paper finds empirical evidence of cross-sectional dependence and implied co-movements in segmented property market excess returns. A large variation in excess returns over time is explained by spillover effects from private markets with similar degree of transparency. We disentangle country-specific macroeconomic fundamentals from global systematic risk to show that spatial dependence prevails, even when we control for common factors. Based on our identifying economic assumptions we interpret these effects as learning externalities. Furthermore, we derive a spatial multiplier from the reduced-form specification of our model, through which local shocks are transmitted across private markets and are amplified via feedback loop effects.

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 on asset pricing (e.g., Duffie, Gârleanu, and Pedersen (2005, 2007); Zhu (2012)) and market illiquidity (e.g., Weill (2008); Lagos and Rocheteau (2009)). This paper sheds light on the effect of limited transparency and the connectivity between illiquid, segmented OTC markets implied by this trading friction.

Second, we relate learning externalities in opaque markets to ambiguity. Ambiguity, or incalculable uncertainty in contrast to calculable risk, occurs when individuals are incapable of assigning subjective probabilities from a unique prior belief to specific events or when information signals cannot be assessed with precision, see, e.g., Epstein and Schneider (2007, 2008). Ambiguity-aversion provides a rationale for investors to focus on assets they are more familiar with (Cao, Han, Hirshleifer, and Zhang (2011)). They reduce the level of uncertainty at the expense of potential mispricing and losses from trading with better informed counterparties (see, e.g., Caskey (2009)). This behavior is in line with our economic intuition. Learning externalities allow a reduction of ambiguity in opaque OTC markets, such as for international commercial real estate, by observing transaction prices in similarly transparent markets, thereby providing an explanation of the herding behavior in multiple private markets as well as the emergence of potentially mispriced and correlated price bubbles.

Third, we also contribute to the literature of panel data under cross-sectional dependence, which distinguishes between multi-factor models and spatial econometric methods. The first approach as proposed by, e.g., Pesaran and Tosetti (2011) as well as Chudik, Pesaran, and Tosetti (2011), is applied when the correlation structure is caused by common systematic risk. However, this method does not identify the source of spatial dependence. In contrast, our identification strategy is based on a pre-specified time-varying weighting matrix which is explicitly linked to an underlying economic transmission channel (see, e.g., Gibbons and Overman (2012); Corrado and Fingleton (2012)).

This paper also provides implications for institutional investors. If local risk factors dominate, investors would benefit from optimal diversification of risk in international commercial real estate. However, we show that limited transparency implies concentrated capital allocation and causes co-movements in excess returns which dilute potential diversification benefits. Our results are also important for financial market regulation. The concentrated trading of investors might enhance the emergence of demand-driven property price bubbles which cannot be adjusted immediately by additional property supply from the sluggish construction sector. Unlike the turmoil in the U.S. residential housing sector from which the financial crisis originated in 2007, the following emerging commercial real estate bubble and its burst have not been the focus of regulators and policymakers (Levitin and Wachter (2013)). To prevent the instability of property markets and the inherent systemic risk for the whole commercial real estate system in case of a bubble burst, policy regulation is required. International transparency standards in commercial property markets must be established and enforced by policy makers, thereby reducing the amount of ambiguity in thinly traded and opaque property markets (see, e.g., Easley and O'Hara (2010)).

The remainder of the paper is structured as follows. Section 2 provides the general theoretical background and explains how learning externalities lead to price co-movements in segmented markets. Section 3 presents our econometric methodology. In Section 4, we discuss our data and define the spatial weighting matrix. Section 5 shows the empirical results. Section 6 concludes.

2 Strategic Interaction in Opaque Markets

Investments in actively traded and mature property markets offer lower expected return opportunities, little growth, and limited diversification potential compared to investments in emerging, but less transparent, private markets. Information is easily accessible in transparent, mature property markets as brokers and data providers enhance costly local knowledge to foreign investors. Hence, these markets are generally attractive for risk-averse investors, e.g., pension funds and insurance companies. On the other hand, more return-seeking large institutional investors, such as investment banks and hedge funds, have an incentive to shift their investment focus to less transparent but also more risk-rewarding foreign private markets. This investment potential is related to the growth prospects in economically booming emerging markets which are also reflected in rapid urbanization and increasing demand for commercial real estate.

However, foreign investors are confronted with locally better informed dealers who have a local monopoly power because of the market segmentation. This better bargaining power of domestic dealers compels less informed investors to accept a higher opacity-based markup (see, e.g., Duffie, Gârleanu, and Pedersen (2005), Green, Hollifield, and Schürhoff (2007), Sato (2014)). Eichholtz, Koedijk, and Schweitzer (2001) show empirically that the underperformance of foreign investors compared to domestic dealers is related to asymmetric information.[2] Hence, large institutional investors strategically invest in information acquisition before they enter less opaque private markets to improve their bargaining power. Particularly, we expect a positive association between market entry costs and the transparency differential between the home market of an investor and

[2] Local dealers have superior information about the market structure (Garmaise and Moskowitz (2004)). For instance, they are more familiar with regulations, such as the enforcement of property rights, infrastructure, and geographic amenities. However, information disadvantages can also emerge because of agency and monitoring costs foreign investors are exposed to when they trade through financial intermediaries (Lewitt and Syverson (2008)).

a less transparent market. This link might be explained by informational economies of scale or higher perceived familiarity which allow investors from less transparent markets to access information in opaque markets with similar level of transparency at lower costs (see, e.g., Massa and Simonov (2006)). Therefore, we argue that investors who are located in markets with higher opacity have a comparative advantage to invest and obtain higher returns in less transparent markets.

For instance, consider an institutional investor who is located in an opaque market, such as Greece. Relative to his emerging home market for which he has superior information, this investor would be rewarded with lower expected returns in more transparent but mature markets, e.g., the U.S., and therefore abstains from investing in these markets. However, benchmark returns which are obtained in the home market can also be realized or even surpassed in similarly transparent or even more opaque markets since the implied information acquisition costs are smaller for the Greek investor than, for instance, for the U.S. investor. In contrast, the U.S. investor is only willing to invest in foreign private markets as long as the corresponding entry costs are smaller than the adverse selection costs arising from trading with locally better informed dealers.

Furthermore, large institutional investors have an incentive of diversification in information acquisition. Following the argumentation of Pasquariello (2007), we expect institutional investors to enter multiple markets which enables them to strategically hide their obtained private information from the construction sector, thereby preventing additional supply of commercial real estate. While market entry elicits higher prices driven by the herding behavior of uninformed traders, a reaction of the supply sector would reduce the information advantage by lowering the price level and consequently should be offset by multiple market entry.

Morris (2000) provides the theoretical foundation for our empirical analysis. Since we are interested in the cross-sectional dependence in segmented markets arising from transparency differentials we use his concept of local interaction games to illustrate how successive learning externalities arising from local private markets serve as a trigger mechanism for return co-movements in the commercial real estate sector. We argue that the strategic interaction of informed and uninformed investors leads to learning externalities in opaque markets. In a first step, we outline the local interaction game. We assume an infinite population of traders of two different types, i.e., being informed if invested in information acquisition and else being uninformed. All traders are located along a linear transparency line with property markets ordered according to their transparency level. Each type of trader locally interacts with an agent of the other type located in a subset of similarly transparent markets. Both players have two possible strategies: market entry indicated as 1 and no market entry denoted as 0, i.e., $\alpha = \alpha' = \{0, 1\}$. A trader playing strategy α in interaction with a counterparty who chooses strategy α' receives a utility level of $u(\alpha, \alpha')$. The normal-form representation of the game is represented in Table 1.

[INSERT TABLE 1 HERE]

We assume *(i)* $u(0,0) > u(1,0)$ and *(ii)* $u(1,1) > u(0,1)$. Condition *(i)* states that the utility from market entry is lower compared to the utility which can be obtained from deviating from this strategy if the trading counterparty does not enter the market. Similarly, condition *(ii)* indicates that, given the market entry of the counterparty, also investing in the market is the optimal response of each type of player. If both conditions are fulfilled, the game has two possible Nash-equilibria, with both players choosing the same strategy, which reflects the outcome of the strategic interaction of informed and uninformed agents in private markets. Intuitively, the anticipated herding behavior of uninformed investors enables the first-mover to buy from local dealers in one period and to sell at a higher price to the uninformed traders in the subsequent one. Hence, the informed trader cannot realize positive returns if uninformed investors do not follow the first-mover to drive up the price level in the private market by additional demand. Similarly, uninformed investors who follow the trading strategy of the first-mover benefit from the market entry. First, trading with the first-mover enables foreign investors to circumvent the local monopoly power of the domestic dealer.[3] Second, an even more important, uninformed investors benefit from learning externalities through privately trading with the first-mover, which allow them to enter similarly transparent and even more opaque markets without investing in information acquisition costs. More precisely, the externality effect helps to assess the transparency-specific markup in property markets, improves the bargaining power against domestic dealers, and allows them to apply the same trading strategy as the first-mover.

Our economic intuition of learning externalities is in line with the related literature. Studies such as Pasquariello (2007), Cespa and Foucault (2014), and Duffie, Malamud, and Manso (2014) argue that markets are connected via investors' cross-market learning. For instance, Duffie, Malamud, and Manso (2014) show that learning externalities occur in segmented OTC markets as individuals learn from observed bid and offer prices of their trading counterparties. However, this literature assumes that investors have a unique prior belief from which they assign probabilities to revealed information signals. In contrast, we interpret the lack of information in private markets in terms of ambiguity. As the first-mover reveals his private knowledge of transparency-based trading frictions during the negotiation process to his counterparty, less informed followers use this source of information to reduce the set of prior beliefs about possible price ranges of comparable properties in opaque markets with similar transparency levels, thereby mitigating the uncertainty in these markets. This interpretation is also in line with the standard hedonic pricing approach of heterogeneous properties which refers to Rosen (1974). While we allow investors to assess the individual property value based on a set of location-specific characteristics and observable state variables, the ambiguity is induced by the lack of transparency which veils the true mapping of the state variables to the unique price, i.e., the exact functional form of the property-specific pricing kernel.

[3]Generally, the higher market activity arising from the strategic interaction of informed and uninformed investors in the subsequent trading period reduces search costs and restricts the bargaining power of local intermediaries. This implication is one of the key contributions of Duffie, Gârleanu, and Pedersen (2005)

In a second step, we follow the logic of Morris (2000) to describe how market entry in a finite set of private markets can lead to potential price bubbles, which contagiously spill over through learning externalities to similarly transparent or even more opaque commercial real estate markets. Particularly, a player adapts market entry as the best response in one local interaction game if this best response strategy is also chosen by a critical amount of potential trading counterparties who are located in neighboring private markets. Applied to the strategic interaction of traders in private markets, a threshold of uninformed investors must be reached, following the first-mover, to increase the overall price level. Similarly, a critical number of first-movers, investing in information acquisition and, consequently, entering private markets, is required to serve as a signal strong enough to provoke the herding behavior of uninformed market participants. As the first-mover strategically invests in multiple markets, we conceptually allow for the possibility that multiple informed investors from different home markets simultaneously enter an opaque market, thereby providing the trigger mechanism for learning externalities to similarly transparent and opaque markets. In that case, the best response can contagiously spill over from one local private market interaction to another interaction in a less transparent private market, which eventually reaches the whole commercial real estate sector.[4]

Economically, the implied cascade effect can be explained by the behavior of uninformed, ambiguity-averse individuals. They base their investment decision on aggregated information signals, i.e., information of better informed agents revealed by privately observable transaction prices, which allows them to reduce the level of ambiguity even though this cause mispricing and losses from trading with better informed counterparties (Caskey (2009)). In our setup, uninformed investors accept paying a premium to the informed trading counterparty. In anticipation of the herding effect, they speculate to sell the property at a higher price in the future, thereby passing the trading loss to

[4]Note that our concept of neighbors is defined along a transparency line between the spectrum of transparent and opaque markets. Morris (2000) shows that for local interaction games on a line, the threshold value must be smaller than a specific contagion parameter, which is equal to $\frac{1}{2}$. In that case, the best response can contagiously spill over from one local interaction game to the whole population, when at least one neighbor decides to adapt market entry as best response strategy.

other uninformed investors. Intuitively, a reduction in ambiguity should contribute to the disclosure of the efficient price. For instance, Mele and Sangiorgi (2015) argue that ambiguity-averse traders have an incentive to invest in information acquisition if a large share of other investors is informed. This effect might dominate the free-riding behavior of uninformed investors on the learning of other market participants. However, in our framework, investors attempt to exploit a potential property price bubble by strategically delaying its inevitable burst (see, e.g., Abreu and Brunnermeier (2003)). Hence, prices gradually increase in multiple markets, which lower each investors expected returns until the marginal investor cannot realize positive gains from market entry. Hence, the cascade effect contagiously drives up market-wide property price level beyond their fundamental value, leading to co-movements and cross-sectional dependence in commercial real estate markets with similar level of transparency.

3 Empirical Framework

In this section, we discuss our methodology. Our empirical framework is based on a spatial econometric model in which we use economic restrictions to explicitly model the connectivity of segmented asset market in a pre-specified weighting matrix. Exploiting the merits of such a specification enables us to empirically test and analyze the transmission of learning externalities across opaque markets. Based on this empirical model, we discuss our identification and estimation strategy.

3.1 Spillover Effects and Feedback Loops

The econometric literature on panel data proposes two different alternatives to account for cross-sectional dependence in observational data. The need for specific estimation strategies has emerged because of the violation of the residual independence assumption and potential inconsistency of standard estimators. One approach attempts to approximate common latent factors by a multi-factor structure.[5] This common factor approach is sufficient, if the interest is aimed at robust inference against any form of cross-sectional dependence. However, the estimation strategy is inappropriate if the focus lies on explicitly modeling the linkage mechanism between observations. The literature on spatial econometrics accounts for the cross-sectional dependence in a pre-specified weighting matrix. In a first step, we build our weighting matrix to specify the linkage mechanism. We exploit transparency differentials between observations of the endogenous variable as spatial weights and use its weighted average as additional regressor in our econometric model

$$Y_t = \lambda W Y_t + X_t \beta + \epsilon_t, \tag{1}$$

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 pre-specified spatial weights w_{kl} between observations k and l, and the error term vector ϵ_t for period $t = 1 \ldots T$. Parameter λ measures the degree of cross-sectional dependence. In a second step, we rewrite the model in its reduced-form

$$Y_t = (I_n - \lambda W)^{-1} (X_t \beta + \epsilon_t), \tag{2}$$

which represents the equilibrium specification, after local shocks have been simultaneously propagated through the transmission channel. This specification allows us to quantify the spillover effects across property markets. As implied by our theoretical background in Section 2, we interpret these information spillovers as learning externalities between neighboring property markets which are defined along a transparency line. In Figure 2, we illustrate these spillovers arising from the local interaction game between informed

[5] We refer to Chudik, Pesaran, and Tosetti (2011) as well as Pesaran and Tosetti (2011) for a brief review. In its simplest form, however, the latent common factor structure can be represented by a two-way fixed-effects model, where a combination of time-invariant fixed-effects and time dummies approximate the factor structure (Sarafidis and Wansbeek, 2012).

and uninformed investors due to fundamental changes in property markets, which lead to co-movements in property markets.

[INSERT FIGURE 2 HERE]

Spillover and feedback loops are transmitted through the spatial multiplier, i.e.

$$S(\lambda)^{-1} = (I_n - \lambda W)^{-1} \approx I_n + \lambda W + \lambda^2 W^2 + \lambda^3 W^3 + \ldots + \lambda^q W^q, \tag{3}$$

Given the connectivity by the weighting matrix, shocks originating in one location spill over to direct neighbors (first-order W), then they are transmitted to neighbors' neighbors (second-order $W-2$), including feedback loops, and so forth. Depending on the estimated spatial lag λ as well as the strength of the spatial weights, spillovers are decreasing in magnitude until the new steady-state equilibrium is reached. Hence, we expect a pattern of declining impact on segmented private markets as local shocks propagate from neighboring markets of low-order with similar transparency level to private markets of higher-order, which are located further away in terms of transparency differentials.

3.2 Methodology

In this subsection, we present our econometric model. We discuss the underlying identifying economic assumptions, the specification, as well as the estimation strategy.

Identification. Our baseline regression model is specified as

$$Y_{nt} = \lambda_0 W_{nt} Y_{nt} + X_{nt}\beta_0 + \eta_n + e_{nt}, \tag{4}$$

where Y_{nt} is a $n \times 1$ vector of endogenous variable, pooled over the cross-section of all $j = 1, \ldots J$ property sectors, i.e., industrial, office, and retail, as well as $i = 1, \ldots, M$ cities in all $k = 1, \ldots, K$ countries. Matrix X_{nt} contains a set of country-specific and global regressors. We impose parameter homogeneity, i.e., $\beta_{ij} = \beta$, $\forall\, i, j$, because of the limited data availability in international private commercial real estate markets. However, estimates of the parameter vector β can be interpreted as population average effects.[6] We model the dependence structure in terms of the weighting matrix W_{nt} with distance-decaying weights $\omega_{kl,t}$ between property markets k and l for each time period t and we allow for a time-varying weighting matrix $W_{nT} = \begin{pmatrix} W_{n1} & & \\ & \ddots & \\ & & W_{nT} \end{pmatrix}$.

This specification leads to the potential reflection problem, as proposed by Manski (1993). The reflection problem arises from the difficulty to disentangle the spatial interaction in the endogenous variable Y_{nt} from cross-sectionally correlated, observed or unobserved, common factors or spatial dependence in exogenous variables of matrix X_{nt}. We resolve the identification problem by two identifying economic assumptions: First, we impose the exclusion restriction of the exogenous spatial lag WX which is based on a theoretical rationale. Learning externalities propagate through revealed transaction prices and not via country-specific fundamentals. This model restriction serves as a justification for an endogenous spatial lag WX.[7] Second, we follow Blume, Brock, Durlauf, and Jayaraman (2015) and impose an *a priori* knowledge about the structure of the spatial transmission process which is reflected in our weighting matrix. Particularly, we use pair-specific, distance-decaying transparency differentials as spatial weights which are linked to the transmission channel under study. However, as we derive the weighting matrix from transparency index values, we postpone the discussion to Sub-section 4.3. Furthermore, we attempt to disentangle the spatial dependence from common factors. We control for common state variables to isolate the endogenous interaction effect from co-movements in systematic risk factors.

Fixed-Effects. The fixed-effects specification (η_{ij}) arises from the need to control

[6] We assume an underlying unit-specific coefficient $b_{ij} = \beta + d_{ij}$. Parameter d_{ij} is defined as zero-mean deviation of β_{ij} from its mean, $E(\beta_{ij}) = \beta$. The average effect is identified under the sufficient condition $E\left(\beta_{ij} \mid \left(x_{ij} - T^{-1}\sum_t x_{ij}\right)\right) = E(\beta_{ij}) = \beta$ as shown by Wooldridge (2010) and is consistently estimated by the within-estimator under standard regularity conditions.

[7] This assumption is crucial as the exclusion restriction allows us to use WX as instrument for WY.

for time-invariant, individual-specific effects that are correlated with explanatory variables and cause a potential omitted variable bias. Following Mundlak (1978), we specify an auxiliary regression term denoted as

$$\eta_{ij} = \bar{x}_{ij}\xi + \alpha_{ij}, \tag{5}$$

with time-averages of explanatory variables, i.e. $\bar{x}_{ij} = T^{-1}\sum_{t=1}^{T} x_{ijt}$, to account for this potential source of endogeneity. By construction of the conditional expectation, i.e., $E\left(\epsilon_{ij} = \alpha_{ij} + e_{ij} \mid x_i\right) = 0$, the new random effect α_{ij} is uncorrelated with exogenous regressors. The estimates of this correlated random effects model, as shown by Mundlak (1978), are identical to the results of the within-estimator. The structural equation of our model is therefore specified as

$$Y_{nT} = \lambda_0 W_{nT} Y_{nT} + X_{nT}\beta_0 + K_{nT} X_{nT}\pi_0 + \epsilon_{nT}, \tag{6}$$

with a vector of cross-sectional endogenous variables $Y_{nT} = \left(Y_{n1}^{'}, \ldots, Y_{nT}^{'}\right)^{'}$, a vector of covariates $X_{nT} = \left(X_{n1}^{'}, \ldots, X_{nT}^{'}\right)^{'}$, and a residual vector $\epsilon_{nT} = \left(\epsilon_{n1}^{'}, \ldots, \epsilon_{nT}^{'}\right)^{'}$ for $t = 1, \ldots, T$. 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.

Estimation. Wang and Lee (2013a,b) derive an estimation strategy for spatial models with randomly missing endogenous data. Latent observations of the dependent variable are replaced by predicted values using its own and spatially correlated covariates. A selection matrix D_{nt} captures all $n_t^{(o)}$ observable endogenous variables from the cross-sectional vector Y_{nt} in period t and the $n_t^u = n_t - n_t^{(o)}$ missing dependent variables $(I_n - D_{nt})\, Y_{nt}$ are replaced by predicted values obtained from the implied reduced-form $(I_n - D_{nt})\, S_{nt}^{-1}(\hat{\lambda}) \left[X_{nt}\hat{\beta} + K_{nt} X_{nt}\hat{\pi}\right]$, taking into account the spatial lag multiplier. This imputation strategy is empirically valid since we assume that unobserved variables in vector Y_{nt} are missing at random (MAR) as discussed in Rubin (1976). In our context, returns are systematically more missing for opaque markets. To satisfy the MAR condition, we assume that conditional on explanatory variables, particularly on the level of market-specific transparency, the probability of observing a missing observation is unrelated to the unobserved endogenous variable itself.

Following Wang and Lee (2013b), we base our estimation on Generalized Methods of Moments (GMM) and refer the reader to their paper for a detailed discussion of the standard regularity conditions. Compared to other estimation strategies, such as maximum likelihood, GMM requires less restrictive assumptions about the functional form, which allows us to avoid potential misspecification, e.g., arising from measurement errors in the economic distance measure. The parameter vector $\theta_0 = \left(\lambda_0, \beta_0^{'}, \pi_0^{'}\right)^{'}$ is estimated by minimizing $\hat{g}^{*}_{nT}(\theta)\hat{\Omega}^{-1}_{nT}\hat{g}^{*}_{nT}(\theta)$.[8] The moment function $\hat{g}_{nT}(\theta) = Q^{'}_{nT}U_{nT}$ is defined as standard orthogonality condition of the $nT \times k$ instrumental matrix Q_{nT} and the disturbance vector of the structural equation, which is defined as

$$U_{nT} = S_{nT}\left[D_{nT}Y_{nT} + (I_n - D_{nT})\, S_{nt}^{-1}\left(X_{nt}\beta_0 + K_{nt}X_{nt}\pi_0\right)\right] - X_{nt}\beta_0 - K_{nt}X_{nt}\pi_0. \quad (7)$$

We apply a heteroscedasticity and autocorrelation consistent (HAC) estimator of the variance-covariance matrix $\Omega = Var(g_{nT}(\theta_0))$. The elements of the matrix $n^{-1}\hat{\Omega}_{nT} = \left(\hat{\Psi}_{rs,nT}\right)$ are computed as $\hat{\Psi}_{rs,nT} = n^{-1}\sum_{t=1}^{nT}\sum_{j=1}^{nT} Q_{nT,ir}Q_{nT,js}\hat{u}_{i,nT}\hat{u}_{j,nT}K\left(d_{ij,nT}/d_{nT}\right)$, with residuals $\hat{u}$ from our model as proposed by Kelejian and Prucha (2007).[9] Required

[8]Without knowing the true structure of the variance-covariance matrix $Var(U_{nT}) = T_{nT}Var(\epsilon_{nT})T^{'}_{nT}$, the optimal weighting matrix, i.e., the inverse of $\Omega_{nT} = Var(g_{nT}(\theta_0)) = Q^{'}_{nT}Var(U_{nT})Q_{nT}$, 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 $Q^{*}_{nT} = T^{'+}_{nT}C^{m}_{nT} = \left[W_{nT}S^{-1}_{nT}\left(X_{nT}\beta_0 + K_{nT}X_{nT}\pi_0\right), X_{nT}, K_{nT}X_{nT}\right]$, where $T_{nT} = S_{nT}D_{nT}S^{-1}_{nT}$ arises from the missing data structure, and $T^{'+}_{nT}$ is defined as the Moore-Penrose inverse of $T^{'}_{nT}$.

[9]We use the Bartlett kernel for $K_{\nu}\left(d_{ij}/d_{nT}\right)$ to ensure that the estimated variance-covariance matrix is positive semi-definite in small samples. The bandwidth parameter is specified as $d_{nT} = (n \times T)^{1/4}$ and we assume that the distance between observations is non-zero within the same time period. Standard errors as proposed by Driscoll and Kraay (1998) are based on less restrictive assumptions and would be more appropriate to be fully robust against cross-sectional dependence. However, the limited time dimension of our panel and the resulting poor finite sample properties of the variance-covariance matrix prevent us from applying their approach.

regularity assumptions are discussed in Wang and Lee (2013b) and Kelejian and Prucha (2007). For reasons of comparison, we also estimate the structural parameter vector by applying the 2SLS- and the NLS-estimator, as proposed by Wang and Lee (2013b).[10]

4 Panel Data

This section presents our panel data. First, we discuss the return proxy for private commercial real estate markets and inherent potential measurement errors. Second, we describe country-specific fundamentals, global systematic risk factors, as well as control variables. We identify different economic channels through which the real and financial sector impact private property markets. Subsequently, we focus on the specification of the weighting matrix.

4.1 Property Market-Specific Returns

We use annual total market returns on commercial real estate from 2001 to 2013 disaggregated at city-level and for the three sectors industrial, office, and retail in 26 countries.[11] The data is provided by Property Market Analysis (PMA). To our knowledge this exclusive dataset contains the most comprehensive cross-section of international property markets including cities in the largest global markets for institutional-grade commercial real estate such as the U.S., Japan, China, Germany, and the U.K.[12] Our sample also

[10]Similar to GMM, the 2SLS-estimator is based on imputation of predicted estimates from the reduced-form specification $(I_{nT} - D_{nT}) S_{nT}^{-1} \left(\tilde{\lambda}\right) \left[X_{nT}\tilde{\beta} + K_{nT}X_{nT}\tilde{\pi}\right]$, however plug-in values, $\tilde{\theta} = \left(\tilde{\lambda}, \tilde{\beta}', \tilde{\pi}'\right)'$, are based on NLS. The NLS-estimator uses only observable dependent variables to estimate the parameter vector. All three estimators are consistent, asymptotically normal, and asymptotically equivalent even in case of an unknown heteroskedasticity and correlation structure (Wang and Lee (2013b). In Part B of the Internet Appendix, we provide a more detailed discussion of HAC-robust versions of the NLS- and 2SLS-estimator.

[11]Table C.2 in the Internet Appendix provides an overview of the market coverage of all cities in our sample.

[12]As reported by PREI (2012) market activity is mostly concentrated in the U.S. with a transaction volume of 6.8 trillion U.S. dollars for institutional-grade commercial real estate and estimated global market size of 25.4% in 2011. The U.S. is followed by Japan with 2.7 trillion U.S. dollars (10.1%), China with 1.9 trillion U.S. dollars (7%), Germany with 1.6 trillion U.S. dollars (6.1%), as well as the

includes global financial centers in Asia-Pacific, such as Hong Kong and Singapore, as well as emerging property markets in China and Eastern Europe.

Periodic nominal total returns reflect net cash flows and capital appreciation earned by international investors and are derived from prime yield and rent data. We measure total returns in local currency to isolate the dependence between segmented property markets from the potential impact of common exchange rate movements. Excess returns are calculated relative to the risk-free rate, for which we use the annualized three-month U.S. Treasury Bill rate.[13] Table 2 provides a descriptive summary of country-specific private market excess returns, 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 a standard deviation of 23.6%, followed by Hong Kong (21.4%), Singapore (20.7%), Japan (18.7%), and Finland (17.6%).[14] The overall low standard deviations are in line with the observed sustained growth in property prices over the sample period, except during the crisis years, and might indicate the emergence of a potential commercial real estate bubble (see, e.g., Brunnermeier and Oehmke (2013)).

The current transparency level as published by Jones Lang LaSalle (JLL) in 2012 is provided in the seventh column of Table 2. We follow their classification and differentiate between "highly transparent", "transparent", and "semi-transparent" property markets. Index values have been stable in most countries, although transparency has gradually increased in private markets of Eastern European countries, such as Czech Republic, Hungary, and Poland. Our sample is equally distributed between highly transparent and transparent markets, with exceptions of semi-transparent markets in China, Greece, and

U.K. with 1.4 trillion U.S. dollars (5.2%).

[13]We abstain from using a long-term government bond as proxy for the risk-free rate, which would correspond to the investment horizon of properties because the obtained yield is not completely risk-adjusted.

[14]The Internet Appendix (see Figure C.1 therein) provides an overview of the variation of the average commercial real estate market performance over time. Unsurprisingly, all private markets follow a systematic downward trend in the aftermath of the recent financial crisis. We also observe a recovery afterwards, which is only slightly below the mean excess return of the pre-financial crisis period.

South Korea. Data availability for fully opaque private markets is limited and cannot *per se* be included in our analysis, since these markets provide only insufficient information on, e.g., performance measures such as price indices.

Commercial real estate is privately traded between two counterparties in illiquid OTC markets in which the true underlying market value is unobservable. Because of the infrequent trading of heterogeneous properties, estimated market values are based on observed transaction prices. Using return proxies for the unknown efficient value, this might lead to potential measurement problems. Therefore, we allow for a measurement error ν_{ijt} of sector $j = 1, \ldots, J$ for city $i = 1, \ldots, M$ at time t defined as the difference between the true latent return y'_{ijt} and its observed market proxy $y_{ijt} = y'_{ijt} + \nu_{ijt}$. We assume that the measurement error is uncorrelated with explanatory variables in our sample to capture the potential measurement error in the disturbance term of the regression model without causing inconsistency in our parameter estimates.

[INSERT TABLE 2 HERE]

4.2 Explanatory Variables

We use country-specific and global systematic risk factors as main drivers of property markets. These variables are obtained from different providers. We refer the reader to Table C.1 in the Internet Appendix, where we list all regressors and provide a detailed discussion of their construction and their sources. All variables are determined in nominal values and are denominated in local currencies. To ensure stationarity we apply the Im, Pesaran, and Shin (2003) panel unit root test, which accounts for cross-sectional dependence and can be applied to unbalanced panels. Furthermore, country-specific factors are only moderately correlated such that there is no evidence of potential multicollinearity, however, some common global risk factors are highly correlated.[15]

[15] In particular, we find correlation coefficients larger than 0.5 between global stock excess returns and national stock market excess returns, global consumption growth and the Eurodollar rate, as well as

Country-Specific Fundamentals. Country-specific financial and macroeconomic state variables systematically affect the performance of commercial real estate markets. We mainly borrow them from the previous literature, see e.g., Chen, Roll, and Ross (1986). Investors who hold income-producing properties in their portfolio demand future cash flows as opportunity costs of capital and require compensation for sacrificed stock returns. Hence, we expect a positive correlation of property market excess returns and the market portfolio, reflecting the local market price of risk. To capture the financial performance of the capital market, we compute excess returns on each *national market portfolio (STOCK ER)* based on the MSCI equity index relative to the annualized three-month U.S. Treasury Bill rate. Expected discounted cash flows from property investments are also driven by macroeconomic conditions. We also use log changes in *personal consumption expenditures* (Δ*CONSUMPTION)* per capita to account for demand factors. Economic growth and rising households' consumption spur property demand in all sectors. The level effect of the *term spread (TERM SPREAD)*, measured as difference between long-term government bond yields and short-term interbank rates, captures macroeconomic supply conditions. The spread reflects investors' expectation of future interest rates. They demand a higher risk premium as compensation for expected higher refinancing costs and lower payoffs from discounted future property cash flows. We also calculate log changes in the consumer price index to proxy *expected inflation* (Δ*CPI).* Commercial real estate is considered as a hedge against inflation. Hence, we expect a positive association with the inflation rate.

Common Global Systematic Risk. We also compute excess returns on a *world market portfolio (GLOBAL STOCK ER)*, using Morgan Stanley Capital International (MSCI) world equity index returns to test a global CAPM specification for segmented property markets. Additionally, we measure *growth in global consumption expenditures* (Δ*GLOBAL CONSUMPTION)* as first latent factor of a Principal Component Analysis

private market investment inflows and excess returns on publicly traded REIT shares. The correlation matrix among all explanatory variables is shown in Table C.3 in the Internet Appendix.

(PCA) applied to national consumption expenditure values. The *three-month Eurodollar rate (EURODOLLAR)* captures investors' expectation about the global economy (see, e.g., Bekaert and Harvey (1995)). We use the *TED spread (TED SPREAD)* to reflect global funding liquidity and credit risk, which was particularly high during the recent financial crisis (e.g., Brunnermeier (2009)). For the U.S. and Asia-Pacific, we compute the difference between the three-month LIBOR rate and the risk-free three-month U.S. Treasury Bill rate as TED spread. For the European area, we use the difference between the three-month EURIBOR and three-month EONIA rate.

Controls. Additionally, we specify a set of control variables. We control for the country-specific *unemployment rate (*Δ*UNEMPLOYMENT)* and *changes in real exchange rates (*Δ*REAL XR)*. Currency risk is also a priced factor in international segmented markets. Deviations from the purchasing power parity (PPP) cause a home bias in the portfolio choice of investors to hedge country-specific inflation risk (Adler and Dumas (1983); Lewis (1999)). We follow the definition of the PPP and compute log changes in the nominal exchange rate, measured as U.S. dollar per unit of foreign currency, and adjust for differences in the inflation rate. This corresponds to the perspective of an U.S. investor who translates nominal returns earned in foreign currency into real returns denominated in U.S. dollars (Adler and Dumas (1983)). We also control for market-specific characteristics, such as funding liquidity. Investors issue bonds sell publicly traded equity shares of securitized real estate vehicles, such as real estate investment trusts (REITs) to finance investments in income-producing properties. Particularly, the boom in commercial real estate has been accompanied by the emerging securitization process, providing funding liquidity through pooled mortgage loans which are sold as commercial mortgage-backed securities (CMBS) in the credit market (Levitin and Wachter (2013)). Hence, we use *U.S. CMBS yield spreads relative to the long-term government bond (U.S. CMBS SPREAD)* as leading indicator for commonality in funding liquidity risk. For instance, a widened spread due to flight to quality, moving capital to less risky bonds, reduces the amount of debt-financed capital flows to the commercial real estate sector and leads to a decrease in funding liquidity. To account for equity-based funding liquidity, we use *excess returns on publicly traded REITs (REIT ER)*. This control variable also reflects the information adjustment, arbitrage opportunities and market duality between private asset markets and publicly traded REIT shares. We include appreciation in *residential housing market prices* (Δ*HOUSING)*. In equilibrium, both sectors are exposed to similar construction costs and compete for production factors such as capital, labor, and available land. To avoid a potential simultaneity bias, we use lagged values as instruments. Furthermore, we add *total investment inflows in commercial real estate markets (INVESTMENT)* for the U.S., Asia-Pacific, as well as Western, Central, and Eastern Europe. Data limitation prevents us from using disaggregated investment flows in commercial real estate. Similarly, we control for market-specific *changes in property stocks* (Δ*CONSTRUCTION)*, however, construction data is only available for the sectors office and retail.

4.3 Economic Distance Measure

We use the distance in the JLL global commercial real estate transparency index between two property markets to specify the elements of the weighting matrix. This index reflects potential information acquisition and market entry costs of a hypothetical trader who is located in one market and invests in another.[16] A small transparency differential between two markets implies a higher perceived familiarity and consequently less information acquisition costs. In order to identify and estimate learning externalities, we base our second identifying restriction on Blume, Brock, Durlauf, and Jayaraman (2015) and assume that the spatial linkage mechanism between private markets is known and can

[16]The 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. Hence, 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 Section A of the Internet Appendix. Note that despite the small numerical differences in the JLL index scores among the private markets, the differences are economically significant.

be specified. We impose symmetric, distance-decaying weights, i.e., we do not differentiate between economic distances to more or less transparent markets. As previously discussed, the symmetry assumption of the weighting matrix can be justified by the fact that a subset of risk-averse traders from less transparent markets prefer investments in transparent markets, while similarly more risk-seeking informed investors, namely first-movers, benefit from an information advantage to allocate their capital into more opaque markets. While the transparency differential is associated with information acquisition costs along less transparent markets, we furthermore assume that expected returns are negatively related to the transparency level along more transparent markets. Because of the accessibility of available information, and thus, less risk perceived by investors and reduced risk premiums but also lower growth prospects, expected returns should be lowest in most transparent and liquid markets. Consequently, rational, risk-averse investors should prefer investments in *less distant transparent* markets.

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

$$w_{kl,t} = d_{kl,t}^{-1} \; for \; k, l = 1, \ldots, N, \tag{8}$$

where $d_{kl,t}$ measures the distance between the index values of cross-sectional units k and l.[17] A smaller distance implies a larger weight. Spatial units are all property markets pooled across all sectors and cities in our sample. Diagonals of the time-varying weighting matrices are restricted to zero to rule out that spatial units can influence themselves. Spatial weights which are smaller than the median are restricted to zero.[18] We row-

[17]The JLL index is aggregated at country level, but we use disaggregated city-level data. We therefore normalize the distance between two cities or sectors within the same country to the smallest distance in period t of the sample, such that $d_{k',l',t} < min(d_{kl,t})$ for k', l' being different sectors and/or cities in the same country. This is economically justified as real estate investments across sectors or cities within the same country can be realized without significant additional information acquisition costs.

[18]We also use the 25%-percentile as threshold value and compare the results to a weighting matrix specification without any threshold. The results are robust and do not change for different threshold values.

normalize the W_t matrices to unit sum, such that each elements of the weighting matrix are defined as

$$w^*_{kl,t} = \frac{w_{kl,t}}{\sum_l^N w_{kl,t}}. \tag{9}$$

Our proximity measure fulfills several properties. First, the weighting matrix is exogenous from investors' perspective and independent from the covariates as suggested by Manski (1993). This exogeneity assumption enables us to disentangle the effect of transparency-based trading frictions on the international investment behavior from changes in the main fundamental determinants. We abstain from including market-specific transparency as additional regressor variable. As the index value does not show much variation over time and is only updated every two years, the effect on market excess returns is likely to be swept away by fixed-effects. However, the time-variation of the weighting matrix allows us to explicitly take into account the evolution of the market-wide transparency in commercial real estate markets. Second, we use an economic distance measure to capture the underlying linkage mechanism rather than following the concept of a geographic distance as a proxy for private information as suggested by the empirical home bias literature, such as Coval and Moskowitz (2001), Van Nieuwerburgh and Veldkamp (2009), as well as Seasholes and Zhu (2010). As a placebo test, we specify the weighting matrix based on the Haversine distance *(GEOGRAPHIC DISTANCE)*. If trading frictions matter, we expect a lower effect of the cross-sectional dependence captured by the geographic proximity.

Furthermore, we control for a broader set of economic distances measures. For instance, Pastor and Veronesi (2013) find empirical evidence of a risk premium which is demanded for investments in countries with higher political uncertainty. Hence, we compute risk differentials reflected by the Heritage Foundation Index *(ECONOMIC FREEDOM)*, the Transparency International Corruption Perception Index *(CORRUPTION PERCEPTION)*, and based on the Economist Intelligence Unit (EIU) released Political Risk Index

(POLITICAL RISK). Similarly, we control or the overall country risk *(COUNTRY RISK)*, including national sovereign risk, currency risk, and systemic risk in the banking sector. These distance measures serve as a robustness check since they are interpreted as broader indicators of uncertainty affecting the investment behavior in international commercial real estate. Hence, we expect similar effects compared to the JLL transparency index. We also compare the cross-sectional dependence arising from cultural distances in the Hofstede Index. Particularly, we capture country-specific differences in how individuals perceive uncertainty *(AMBIGUITY AVERSION)*, the extend to which society accepts unequally distributed power *(POWER DISTANCE)* and individual responsibility in contrast to collectivism *(INDIVIDUALISM)*, as well as it is oriented towards ideals, such as competition, achievement, or reward for success *(MASCULINITY)*. These cultural distances also capture aspects such as closer familiarity with foreign markets due to a common legal system (La Porta, de Silanes, Shleifer, and Vishny (1998)) or a common language (see, e.g., Grinblatt and Keloharju (2001), Chan, Covrig, and Ng (2005)).[19]

5 Estimation Results

In this section, we present our results. We find empirical evidence that segmented property markets are interlinked via the identified transparency channel. We also determine the main driving fundamentals of private markets. In a second step, we estimate the transmission process of spillover and feedback loops of local shocks and analyze the adjustment of international commercial real estate markets to the new steady-state. We also test for market integration and show that the cross-sectional dependence is not explained by common systematic risk factors. Finally, we conduct several robustness tests to confirm and extend our main results.

[19] See Tang and Koveos (2008) for an overview. For instance, countries with higher degree of uncertainty avoidance share a more complex and developed legal system, while similarities in the Arabic, Spanish, and Asian language are reflected in a lower degree of individualism and higher power distance. The rank correlations between all index variables can be found in Table C.4 in the Internet Appendix. We also provide a more detailed description of all applied distance measures in Table C.1 therein.

5.1 Cross-Sectional Dependence and Spillover Effects

In this section, we show and interpret the results of our spatial lag models. Transparency differentials reflect the connectivity among spatially correlated private markets as implied by trading frictions under market opacity. Panel A of Table 3 provides the estimates of our three spatial models: the baseline model on country-specific fundamentals (Model I) and two extended specifications conditional on market-specific funding liquidity (Model II), construction (Model III), and international investment flows in commercial real estate (Model IV). We include fixed-effects in all models to control for heterogeneous, time-invariant market frictions arising from capital controls, policy restrictions, land use regulations (Glaeser, Gyourko, and Saks (2005)), and inelastic supply factors, e.g., land scarcity (Saiz (2010)).[20] The results are similar for all three estimators (GMM, 2SLS, and NLS), although each estimator proposes a different strategy to account for missing endogenous variables. From this, we conclude that our estimates are not contaminated by missing data. The spatial lag coefficient is statistically significant and ranges from 0.490 for NLS to 0.557 based on GMM. A positive spatial lag coefficient suggests that investors consider property markets as strategic complements. As implied by our economic intuition, we interpret trading frictions which arise from opacity to be responsible for distorted capital allocations of international investors, which cause excess return to co-move in markets with similar level of transparency. Hence, we conclude that the cross-sectional dependence of segmented markets counteracts and limits the potential diversification benefits to investors.

[INSERT TABLE 3 HERE]

We also identify excess returns on the local market portfolio, the change in consumption per capita, inflation rate, and the term spread as main economic fundamentals

[20] We do not include time fixed-effects in our model for two reasons. First, a two-way fixed-effects specification approximates a common factor model which, by construction, sweeps away the spatial dependence. Second, we are interested in estimating the effect of spillovers from economically nearby-related markets on the variation over time within property markets, which would be similarly wiped out by cross-sectional and time-demeaning of the within-estimator.

in Model I. However, a large portion of the variation of private market excess returns over time can be explained by spillover effects from internationally segmented markets. For instance, we observe an adjusted R^2 of 37.3% compared to an explanatory power of 25.8%, when we regress on the same country-specific state variables but exclude the spatial lag term. We report this regression result in the Internet Appendix.[21] However, we still find evidence of dependence left in the error term, which cannot fully be captured by the weighting matrix. For instance, applying the Pesaran (2004) CD test, we reject the null hypothesis of residual independence. However, explicitly taking into account the cross-sectional dependence significantly reduces the value of the test statistic and increases the explanatory power.

The signs of the estimated coefficients are in line with our economic intuition. Private market excess returns are positively correlated with excess returns on the country-specific market portfolio. Higher opportunity costs of capital are reflected in a higher risk premium required for investments in income-producing properties. At the same time, a well-performing public asset market provides institutional investors with easy access to financing direct property investments. Growth in households consumption increases the demand for retail space and spurs investments in the office and industrial property sector. A 1%-increase in consumption expenditures instantaneously rises local property market excess returns by 1.209%. We also estimate a positive effect of expected inflation, which provides evidence that direct real estate serves as a hedge against inflation. The positive effect of the term spread on private market excess returns can be explained by different channels: First, higher refinancing costs, i.e. an increasing long-term interest rate relative to the short-term rate, fosters a higher required risk premium on commercial real estate. Second, higher expected returns are driven by investors increasing risk-aversion regarding future economic prospects as indicated by a higher term spread.

[21] Table C.5 in the Internet Appendix provides a more detailed discussion of the standard fixed-effect model. We also include time dummies to control for time-varying common latent factors. The two-way fixed-effects specification approximates a multi-factor structure and absorbs the cross-sectional dependence. As a robustness check, we also include additional controls.

The results are similar when we control for market-specific characteristics and confounding common factors which systematically affect the endogenous variable as well as its weighted average.[22] In Model II, we account for funding liquidity risk. A more restrictive and tightening global funding liquidity negatively impacts private commercial real estate markets, which has been observed particularly in the aftermath of the recent financial crisis (Brunnermeier (2009)). Excess returns on publicly traded REIT shares as well as the funding liquidity risk implied by a higher CMBS yield spread are positively correlated with private market excess returns. For instance, REITs invest in income-producing properties, thereby providing capital inflows to illiquid private property markets, which ensures additional market liquidity in the real estate sector (see, e.g., Bond and Chang (2012)). The degree of spatial dependence, as indicated by an estimated spatial lag of 0.414 (based on GMM), is slightly smaller compared to the result in Model I, since a degree of spatial dependence is absorbed by the common factor. However, our results indicate that, even conditional on global funding liquidity, private market co-movements prevail. Hence, we argue that the underlying source of spatial interaction is not driven by systemic risk of commonality in liquidity (Karolyi, Lee, and van Dijk (2012)) or liquidity dry-ups arising from the reinforcement between funding and market liquidity (see, e.g., Brunnermeier and Pedersen (2008); Cespa and Foucault (2014)).

Furthermore, we add new construction as well as international investment flows in Models III and IV. The specification in Model III allows us to disentangle the rise in capital value of invested stock due to exaggerated investors' demand from the effect of additional value of invested stock provided by the construction sector. Based on GMM, we estimate a spatial lag of 0.620, which is marginally larger in magnitude compared to the estimate of 0.575 in the baseline model. Additional construction increases the supply and capital value of invested stock and drives down long-term return expectations which is reflected in an estimate of -0.420. We re-estimate the baseline model conditional on international

[22]For instance, the estimated spatial lag coefficients are similar, e.g., 0.575 based on GMM, if we additionally control for the unemployment rate as well as the real exchange rate. To conserve space we do not show the results here. However, they are available from the authors upon request.

investment flows (Model IV). A rise of investment inflows in a property market implies higher expected returns. The estimated spatial lag (from 0.365 for GMM to 0.391 based on NLS) decreases in magnitude compared to Model I if we condition on property-specific investment inflows at a regional level. This results from the fact that the control variable partly absorbs the source of cross-sectional dependence which is transmitted through transparency differentials. We interpret the reduction of the magnitude as empirical evidence that the strategic interaction between opaque asset markets is linked to the behavior of international investors and their capital movements under trading frictions as proposed by our weighting matrix. Both model specifications are based on a subsample from 2006 to 2013 for which all data is available and thus results in identical estimates based on GMM ans 2SLS. Both approaches use the same vector of instrumental variables but differ in the strategy to replace missing endogenous variables in the sample.

However, the impact of the explanatory variables described above can only be interpreted as immediate or first-round effect on private asset markets. To take into account the complex dependence structure, we compute average direct, average total, as well as average indirect impact measures in Panel B of Table 3. All measures are derived from the reduced-form specification of the model. The *average direct impact*, computed as $(nT)^{-1} trace\,(S_r(\lambda)^{-1} I_{nT} \beta_r)$, measures the effect of parameter β_r for $r = 1, \ldots, k$, on its own local property market taking into account spillover and feedback loop effects. Local shocks and changes in fundamentals are amplified because of the spatial multiplier effect through which simultaneous equilibrium price adjustments are mediated to a new steady-state of the market system. The *average total impact* measures the average effect of a unit change of the explanatory variable in one local market on all other markets. We calculate this total effect as average of the row sums of the reduced-form, $(nT)^{-1} \iota_{nT}' S_r(\lambda)^{-1} I_{nT} \beta r \iota_{nT}$, where we denote the unit vector of ones as ι_{nT}. This summary measure can also be interpreted as a local market change caused by a hypothetical unit change in all private markets. The *average indirect effect*, or pure spillover effect, from other markets is measured as the difference between the average total and direct impact.

The direct impact is larger in magnitude than the immediate impact of a change in explanatory variables because of the spatial multiplier and amplified feedback effects from similarly transparent markets. For instance, compared to the immediate impact of 1.209%, we estimate an elasticity of 1.295% of direct impact in local market excess returns for a 1%-increase in consumption expenditures (based on GMM). Similarly, a hypothetical 1%-change of consumption expenditures in one market increases market excess returns in all other markets on average by up to 2.627% (for 2SLS), while we estimate an average pure spillover effect arising from a change in all property markets to one market ranging from 1.109% (NLS) to 1.443% (GMM). As implied by our economic intuition, we interpret these empirically observed spillover and feedback loops to be driven by learning externalities. While country-specific changes in fundamentals are incorporated into local property prices through private trading, investors use this information revealed in privately observed transaction prices to reduce the ambiguity of potential price ranges in similarly transparent or even more opaque private markets. Local property price changes are mediated across international commercial real estate markets through this externality effect. We interpret the distorted trading behavior of investors, who are confronted with informational frictions as implied by transparency differentials, as driving factor of co-movements in property markets with similar level of transparency. The strength of how local price adjustments are cross-sectionally transmitted to other opaque markets thereby depends on the magnitude of the spatial lag as well as the connectivity of private markets induced by the spatial weights. This adjustment process lasts several rounds until a new steady-state is reached.

To analyze the economic significance of the dynamic adjustment process, we decompose the three impact effects by the order of neighbors in Table 4. The multiplier effect should be decaying with economic distance and spillover effects are larger in neighboring markets of low orders, which have a similar transparency level compared to the shock-originating local market. We illustrate this effect for a change in consumption expenditures and show the decaying pattern for the direct, the indirect, and the total impact. The indirect impact can be interpreted as a pure spillover effect from a local shock to all other markets. For $W-0$, the direct impact reflects the immediate or first-round effect, while there is no direct, but only spillover effect to the adjacent private markets ($W-1$). We show that the indirect and total impact is smaller for higher-order neighbors. When the fundamental shock reaches neighbors of order 4 from the originating market, 90% of the total spillover or indirect effect, i.e., an accumulated magnitude of 1.295 out of 1.443, is explained. We interpret this as support for our economic intuition that the opacity of property markets renders learning externalities, i.e., the identified information spillovers are predominantly concentrated in markets with similar level of transparency. We also show empirically that only a little portion of the direct impact effect is explained by feedback loops from neighboring markets.

[INSERT TABLE 4 HERE]

5.2 Common Systematic Risk Factors

In Table 5 we show that spatial correlation among global commercial real estate markets is not caused by common systematic risk factors. The Pesaran (2004) CD t-statistics are higher than in Table 3 and remain significantly different from zero. In all model specifications, we control for potential exchange rate effects, since common explanatory variables are denominated in U.S. dollars. We calculate clustered-robust standard errors to ensure robust inferences (Petersen (2009)). Conditional on fixed-effects, excess returns on income-producing properties are positively correlated with the global market portfolio (Model I). 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 and locally segmented commercial real estate markets. If market integration rather than learning externalities would be the source of the cross-sectional dependence, we would observe a higher explanatory power of global systematic risk in the common factor model.

Regressing on global consumption growth, which is computed as the first latent factor from a principal component analysis of international consumption growth data (Model II), we find a low explanatory power of 6.4%. Similar results are obtained testing for the impact of global funding liquidity and expectations of global economic prospects on expected property returns (Models III and IV). For instance, a higher credit risk, as indicated by the TED spread, negatively affects commercial real estate markets. 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. Because residual cross-dependency is left and cannot be explained by multi-factor models, we conclude that international property markets are not integrated. However, a variation in private market excess returns can be explained by funding liquidity, proxied by excess returns on U.S. REITs as leading indicator and by the spread in CMBS yields (Model IV), which is indicated by an adjusted R^2 of 25.2%. Additionally accounting for global investment inflows in international commercial real estate (Model V) increases the adjusted R^2 to 31.6%.

[INSERT TABLE 5 HERE]

5.3 Robustness Tests

This section provides several robustness checks. First, we compare the results of our baseline model of Table 3 with specifications using alternative weighting matrices. We detect transparency differentials as the main source of cross-sectional dependence and co-movements in excess returns. Second, we re-estimate our model separately for each sector to test for potential sector-specific heterogeneity. Finally, we compare our results with spatial lag models using a different dataset of global commercial real estate markets, which is provided by the Investment Property Databank (IPD).

Model Specifications with Alternative Weighting Matrices. As a robustness check, we re-estimate our baseline model and use different specifications of the weighting matrix. We replace the JLL transparency index by indices which reflect similar aspects of the JLL index. All indices can be used as broad proxies for potential trading frictions and related information acquisition costs for foreign investors. Hence, we expect a magnitude of the spatial lag very much in line to the baseline model using transparency differentials. The construction of the spatial weights is analogous to the approach described in Sub-section 4.2.

Model I of Table 6 is based on a country-specific index of economic freedom, reflecting investors overall market entry risk in terms of property rights, economic and political stability, as well as investment freedom. The magnitude of the estimated spatial lag (0.694 based on GMM) is slightly higher compared to the baseline model in Table 3. Using differentials based on the perceived corruption in a country (Model II), we estimate a spatial lag of 0.641. Similar results are observed using political risk (Model III) and a broader indicator of country risk (Model IV), which is based on different aspects, such as the banking sector risk, political, structural, as well as economic risk. We do not test for potential linkage mechanisms 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, as these weights might endogenously depend on our covariates. However, we test for geographic distance in Model V of Table 6 as a placebo test. The estimated coefficient of the spatial lag is insignificant and serves as empirical evidence that the source of cross-sectional dependence is unrelated to the neighborhood relationship of segmented asset markets but underlies a more sophisticated linkage mechanism. Based on the country-specific ambiguity-aversion which is reflected in the cultural difference (Model VI) we find a degree of cross-sectional dependence which is similar to the estimated spatial lag using the JLL index. We interpret this result in favor of our economic intuition. Ambiguity-averse investors seem to prefer property investment in more regulated, i.e., more transparent, markets because of their aversion to the level of ambiguity in more opaque private markets. Similarly, we also find evidence of cross-sectional dependence an implied co-movements arising from the alternative cultural differences such as power distance, individualism, and masculinity (Models VII to IX). Similar to the political risk indices these differentials cover a broader range of property market-affecting characteristics, such as common language or the same legal law system which are reflected in cultural differences (see, e.g., Tang and Koveos (2008)).

[INSERT TABLE 6 HERE]

Sector-Specific Heterogeneity. We also find some weak evidence of sector-specific heterogeneity. For each sector industrial, office, and retail, we separately re-estimate the baseline model. All three model specifications are based on GMM. The results can be found in Table C.6 in the Internet Appendix. Our outcomes for the sector-specific models indicate similar estimates of the spatial lag for office (0.645) and retail (0.466), which slightly deviate from the estimate of 0.557 in the baseline model. However, we find a significantly smaller degree of cross-sectional dependence, i.e., a spatial lag coefficient of 0.301, for the industrial sector. This is in line with our intuition. The smaller industrial sector is more heterogeneous, more local, and owner-occupied, while the commercial real estate markets for the office and retail sector is more attractive for large international investors. We identify growth in consumption expenditures as main fundamental driver in all three sectors. However, we find no significant impact of the term spread on excess returns in the office market, while the expected inflation rate has only a significant impact on property market excess returns in the industrial sector.

IPD Commercial Real Estate Indices. Empirical results might also be contaminated by measurement errors in the return proxy for thinly traded private markets. For robustness, we re-estimate the spatial lag model using a different dataset of annual property market returns provided by IPD. The IPD sample ranges from 1998 to 2013 and includes three sectors industrial, office, and retail in 25 countries, with the exception of

South Korea, for which no data is available for the industrial property sector. In contrast to the PMA sample which is based on city-level data, IPD returns are only aggregated at sector level. The coverage also includes additional private markets in Canada, New Zealand, and South Africa, but data is unavailable for China, Hong Kong, and Singapore. Data availability is also limited for emerging markets, particularly for Eastern European countries, such as Hungary, Poland, and the Czech Republic, which results in a more unbalanced panel structure compared to the PMA dataset. We provide the results of the spatial lag model for all three estimators in Table C.10 in the Internet Appendix. The spatial lag is smaller in magnitude compared to the estimates in Table 3 which are based on disaggregated city-level data from PMA. The degree of spatial dependence varies from 0.378 based on NLS and 2SLS to 0.456 using the GMM-estimator. The estimated signs of the explanatory variables are in line with our economic intuition. The coefficients of the country-specific fundamentals are comparable to the results in Table 3 in all three specifications, with the exception of the estimated effect of the term spread, which is insignificant.

6 Conclusion

This paper provides the first empirical analysis of the economic implication of limited transparency and market opacity, which serve as an entry barrier for international investors and results in segmented asset markets. However, we find evidence of cross-sectional dependence and implied co-movements across international, opaque OTC markets. We explain this dependence by a local interaction game which models the strategic decision-making of informed and uninformed investors who are confronted with limited transparency. Large institutional traders can invest in information acquisition before they strategically enter opaque markets. We argue that these entry costs are positively related to the transparency differential between an investors home market and a less transparent market. This implies lower information acquisition costs due to a higher perceived familiarity. Informed investors bear these costs, while uninformed investors can follow the first-mover, which leads to learning externalities. Informed investors reveal their information by privately trading with uninformed counterparties who use transaction prices as cheap source of information to learn about unobserved prices in less transparent markets, thereby reducing the perceived ambiguity in these markets.

In our empirical study, we utilize an extensive dataset of international private property markets. International commercial real estate provides an ideal laboratory to analyze the economic implications of market opacity. We identify transparency differentials as a linkage mechanism through which private markets are connected. Our identification strategy enables us to use this source of connectivity in a pre-specified weighting matrix to empirically test and estimate the transmission of learning externalities across opaque asset markets. As implied by our theoretical framework, we find empirical evidence of spatial dependence and co-movements across property market excess returns, which cannot be explained by common global systematic risk factors. The estimated spatial lag is positive, statistically significant, and indicates that investors consider property markets as strategic complements. For instance, higher expected returns in one private market imply also higher expected returns in another. This effect prevails even conditional on common systematic risk factors. Furthermore, local shocks have a strong tendency to propagate internationally across segmented markets. We show empirical evidence of spillover and feedback loop effects between private markets. We interpret this transmission channel in terms of learning externalities, which allow investors to reduce the level of ambiguity about foreign property markets, thereby reducing their market entry costs.

Our results provide general economic insights and important implications for institutional investors as well as policy makers. First, limited transparency causes a distorted capital allocation of investors, higher return co-movements, and hence, renders risk diversification strategies obsolete. Second, we identify market opacity as source of potential instability in private asset markets. This trading friction serves as an intuitive explanation for the emergence of multiple price bubbles, which might, in case of a burst, culminate in a transmission across international commercial real estate markets. To prevent either these bubbles or the transmission of locally originating but systemically spreading shocks, the establishment of international transparency standards is required. The enforcement of such standards helps to prevent concentrated investment behavior, the emergence of potential property price bubbles, and reduces trading frictions, market entry costs, as well as the level of ambiguity in opaque asset markets (Easley and O'Hara (2010)).

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Table 1: Normal-Form Representation of the Game

This table shows the normal-form representation of the local interaction game between an informed (i) and an uninformed investor (u). Each trader can choose between two different trading strategies: no market entry indicated as 0, or market entry denoted as 1. This game has two Nash-equilibria: both players enter the market or both players do not enter the market.

		Uniformed Investor	
		No Market Entry (0)	Market Entry (1)
Informed Investor	No Market Entry (0)	$u^i(0,0)$,$u^u(0,0)$	$u^i(0,1)$,$u^u(1,0)$
	Market Entry (1)	$u^i(1,0)$,$u^u(0,1)$	$u^i(1,1)$,$u^u(1,1)$

Table 2: 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 3: Spatial Lag Models

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 a weighting matrix based on the JLL Transparency Index (Model I). Models II, III, and IV control for funding liquidity, construction, and investment flows, respectively. The spatial lag indicates the degree of spatial dependence. STOCK ER reflects excess returns on the national market portfolio. Personal consumption expenditures (ΔCONSUMPTION) is measured per capita. Changes in the consumer price index (ΔCPI) proxy expected inflation. The term spread (TERM SPREAD) measures the difference between long-term government bond yields and short-term interbank rates. REIT ER denote excess returns on publicly traded REIT shares and U.S. CMBS SPREAD is defined as the difference between the U.S. CMBS bond index and the U.S. long-term government bond yield. Changes in property stocks (ΔCONSTRUCTION) and INVESTMENTS are used to control for market-specific characteristics. Estimations are based on the Mundlak (1978) fixed-effects model. We show the Pesaran (2004) CD t-statistics of the null hypothesis of residual independence. The panel pools the three sectors (industrial, office, and retail) 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, total, and indirect impacts of shocks in explanatory variables to measure spillover and feedback loop effects. The corresponding standard errors are based on simulations.

Panel A: Estimation Results

	Model I			**Model II**			**Model III**			**Model IV**		
	GMM	**2SLS**	**NLS**	**GMM**	**2SLS**	**NLS**	**GMM**	**2SLS**	**NLS**	**GMM**	**2SLS**	**NLS**
SPATIAL LAG	0.557***	0.548***	0.490***	0.414**	0.396**	0.275	0.620***	0.620***	0.575***	0.365**	0.365**	0.391**
	(0.137)	(0.138)	(0.144)	(0.173)	(0.173)	(0.236)	(0.118)	(0.118)	(0.120)	(0.172)	(0.172)	(0.188)
STOCK ER	0.073***	0.075***	0.087***	0.090***	0.091***	0.106***	0.075***	0.075***	0.078***	0.058**	0.058**	0.053**
	(0.024)	(0.024)	(0.026)	(0.028)	(0.028)	(0.034)	(0.025)	(0.025)	(0.025)	(0.023)	(0.023)	(0.027)
ΔCONSUMPTION	1.209***	1.174***	1.206***	1.296***	1.228***	1.481***	1.451***	1.451***	1.556***	1.305***	1.305***	1.241***
	(0.354)	(0.357)	(0.355)	(0.367)	(0.369)	(0.423)	(0.480)	(0.480)	(0.475)	(0.423)	(0.423)	(0.453)
ΔCPI	0.566**	0.609**	0.870**	0.423*	0.454*	0.206	0.598*	0.598*	0.547	0.308	0.308	0.243
	(0.252)	(0.254)	(0.379)	(0.252)	(0.256)	(0.351)	(0.346)	(0.346)	(0.357)	(0.341)	(0.341)	(0.347)
TERM SPREAD	0.298*	0.283*	0.201	0.136	0.112	-0.009	0.346	0.346	0.452	0.106	0.106	0.108
	(0.157)	(0.158)	(0.199)	(0.154)	(0.157)	(0.241)	(0.292)	(0.292)	(0.303)	(0.285)	(0.285)	(0.285)
REIT ER				0.019***	0.021***	0.027**						
				(0.007)	(0.008)	(0.011)						
U.S. CMBS SPREAD				0.033***	0.034***	0.043***						
				(0.012)	(0.012)	(0.017)						
ΔCONSTRUCTION							-0.420***	-0.420***	-0.434***			
							(0.143)	(0.143)	(0.145)			
INVESTMENT										0.085***	0.085***	0.084***
										(0.026)	(0.026)	(0.027)
Observations	2041	2041	2041	2041	2041	2041	880	880	880	880	880	880
Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pesaran CD	8.37***	9.17***	12.86***	6.73***	7.35***	11.58***	-0.14	-0.14	1.10	0.08	0.08	0.16
Adj.-R^2	0.373	0.368	0.366	0.380	0.372	0.356	0.451	0.451	0.447	0.494	0.491	0.498

Table 3 continued

Panel B: Direct, Total, and Indirect Impact												
	Model I			**Model II**			**Model III**			**Model IV**		
	GMM	2SLS	NLS	GMM	2SLS	NLS	GMM	2SLS	NLS	GMM	2SLS	NLS
Average Direct Impact												
STOCK ER	0.074	0.086	0.078	0.099	0.099	0.112	0.863	0.073	0.078	0.053	0.083	0.064
ΔCONSUMPTION	1.295***	1.269***	1.279***	1.337***	1.265***	1.491***	1.648***	1.664***	1.723***	1.366***	1.350***	1.303***
ΔCPI	0.609***	0.653*	0.945	0.435**	0.463***	0.201	0.682	0.661	0.613*	0.297	0.324	0.244
TERM SPREAD	0.319	0.293*	0.202	0.139*	0.117	-0.012	0.385	0.390	0.488	0.109	0.108	0.118
REIT ER				0.017	0.021	0.030						
U.S. CMBS SPREAD				0.041	0.031	0.063						
ΔCONSTRUCTION							-0.471	-0.471	-0.466			
INVESTMENT										0.107	0.088	0.094
Average Total Impact												
STOCK ER	0.152	0.179	0.146	0.119	0.159	0.153	0.200	0.168	0.166	0.081	0.126	0.101
ΔCONSUMPTION	2.738***	2.627***	2.388***	2.213***	2.034***	2.031***	3.813***	3.850***	3.657***	2.081***	2.055***	2.055***
ΔCPI	1.285***	1.351*	1.764	0.743**	0.745***	0.274	1.577	1.530	1.300*	0.452	0.493	0.385
TERM SPREAD	0.680	0.607*	0.377	0.228*	0.189	-0.016	0.891	0.902	1.034	0.167	0.165	0.186
REIT ER				0.058	0.034	0.041						
U.S. CMBS SPREAD				0.003	0.049	0.085						
ΔCONSTRUCTION							-1.089	-1.089	-0.989			
INVESTMENT										0.163	0.134	0.149
Average Indirect Impact												
STOCK ER	0.078	0.093	0.068	0.021	0.060	0.041	0.113	0.095	0.088	0.028	0.043	0.037
ΔCONSUMPTION	1.443**	1.358***	1.109***	0.875***	0.769***	0.054***	2.165***	2.186***	1.933***	0.714***	0.706***	0.753***
ΔCPI	0.676*	0.698*	0.819	0.309	0.282***	0.073	0.895	0.868	0.687	0.155	0.169	0.141
TERM SPREAD	0.361	0.314*	0175	0.088	0.071	-0.004	0.506	0.512	0.547	0.057	0.057	0.068
REIT ER				-0.014	0.013	0.011						
U.S. CMBS SPREAD				0.017	0.019	0.023						
ΔCONSTRUCTION							-0.618	-0.618	-0.523			
INVESTMENT										0.056	0.046	0.054

Table 4: Spatial Partitioning

This table shows the spatial partitioning of direct, indirect, and total effects for different neighbor orders up to order 8. The indirect effect is computed as difference between the total and the direct effect. The effects are illustrated for a 1%-change in consumption expenditures (ΔCONSUMPTION). The estimates refer to the baseline regression using GMM. For comparison we indicate the mean direct, indirect, and total impact effects.

W-Order	**DIRECT**	**INDIRECT**	**TOTAL**
W-0	1.208	0.000	1.208
W-1	0.000	0.673	0.673
W-2	0.052	0.323	0.375
W-3	0.015	0.194	0.209
W-4	0.011	0.105	0.116
W-5	0.004	0.060	0.065
W-6	0.003	0.033	0.036
W-7	0.001	0.019	0.020
W-8	0.001	0.010	0.011
$\sum_{q=0}^{8} W^q$	1.295	1.417	2.713
AVERAGE IMPACT EFFECTS	**DIRECT EFFECT**	**INDIRECT EFFECT**	**TOTAL EFFECT**
ΔCONSUMPTION	1.295	1.443	2.738

Table 5: 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 (ΔGLOBAL CONSUMPTION) denotes the first factor from a Principal Component Analysis. TED SPREAD is measured as the difference between the annualized three-month LIBOR rate and the corresponding three-month U.S. Treasury Bill rate. The three-month Eurodollar rate is denoted as EURODOLLAR. U.S. REIT ER indicates excess returns on the U.S. MSCI REIT index. The U.S. CMBS SPREAD is defined as the difference between the U.S. CMBS bond index and the U.S. long-term government bond yield. INVESTMENT covers regional property investments flows for the USA, Central Europe, Eastern Europe, as well as Asia-Pacific from 2006 to 2013. ΔREAL XR reflects changes in the real exchange rate relative to the U.S. dollar. 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 industrial, office, and retail as well as 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.

Systematic Factors	**Model I**	**Model II**	**Model III**	**Model IV**	**Model V**
GLOBAL STOCK ER	0.155***				
	(0.012)				
ΔGOBAL CONS.		0.038***			
		(0.004)			
TED SPREAD			-5.359***		
			(0.514)		
EURODOLLAR			1.099***	1.607***	
			(0.188)	(0.195)	
U.S. REIT ER				0.273***	0.060***
				(0.016)	(0.021)
U.S. CMBS SPREAD				0.053***	0.021***
				(0.008)	(0.007)
INVESTMENT					0.143***
					(0.012)
ΔREAL XR	-0.001	-0.054	-0.015	-0.031	-0.092**
	(0.041)	(0.042)	(0.038)	(0.038)	(0.039)
Observations	1980	1980	1980	1980	1852
Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Pesaran CD	125.15***	140.67***	127.09***	49.12***	16.81***
Adj.-R^2	0.085	0.064	0.077	0.252	0.316

Table 6: 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. We use the geographic Haversine distance in Model V as placebo test. Models VI to IX are based on the Hofstede sub-indices and measure cultural differences. Excess returns are regressed on a spatial lag and fundamentals. The spatial lag measures the degree of cross-sectional dependence. STOCK ER indicates excess returns on the national market portfolio based on the MSCI equity index. Personal consumption expenditures (ΔCONSUMPTION) is measured per capita. Changes in the consumer price index (ΔCPI) proxy expected inflation. The term spread (TERM SPREAD) measures the difference between long-term government bond yields and short-term interbank rates. Estimates are based on GMM. We show the Pesaran (2004) CD t-statistics of the null hypothesis under residual independence. We pool all sectors (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**	**Model V**	**Model VI**	**Model VII**	**Model VIII**	**Model IX**
W-Matrix	Economic Freedom	Corruption Perception	Political Risk	Country Risk	Geographic Distance	Ambiguity Aversion	Power Distance	Individualism	Masculinity
SPATIAL LAG	0.694***	0.641***	0.630***	0.612***	-0.031	0.514***	0.559***	0.605***	0.683***
	(0.108)	(0.083)	(0.066)	(0.080)	(0.367)	(0.072)	(0.034)	(0.055)	(0.053)
STOCK ER	0.054***	0.065***	0.064***	0.067***	0.157***	0.088***	0.070***	0.077***	0.043***
	(0.028)	(0.017)	(0.015)	(0.017)	(0.056)	(0.013)	(0.012)	(0.014)	(0.014)
ΔCONSUMPTION	0.994***	1.306***	1.337***	1.291***	2.554***	1.653***	1.599***	1.394***	1.512***
	(0.274)	(0.222)	(0.188)	(0.209)	(0.909)	(0.211)	(0.167)	(0.176)	(0.171)
ΔCPI	0.382	0.660***	0.697***	0.677***	1.114**	0.708***	0.549**	0.373	0.388
	(0.233)	(0.245)	(0.242)	(0.245)	(0.472)	(0.247)	(0.239)	(0.243)	(0.245)
TERM SPREAD	0.261*	0.482***	0.484***	0.287	0.678**	0.801***	0.435***	0.200	0.454***
	(0.157)	(0.155)	(0.153)	(0.155)	(0.288)	(0.170)	(0.158)	(0.156)	(0.152)
Observations	2041	2041	2041	2041	2041	2041	2041	2041	2041
Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pesaran CD	2.27**	4.02***	2.85***	4.03***	53.70***	16.83***	17.74***	4.86***	9.06
Adj.-R^2	0.405	0.368	0.371	0.343	0.284	0.346	0.353	0.359	0.333

Figure 1: Learning Externalities in Opaque Markets

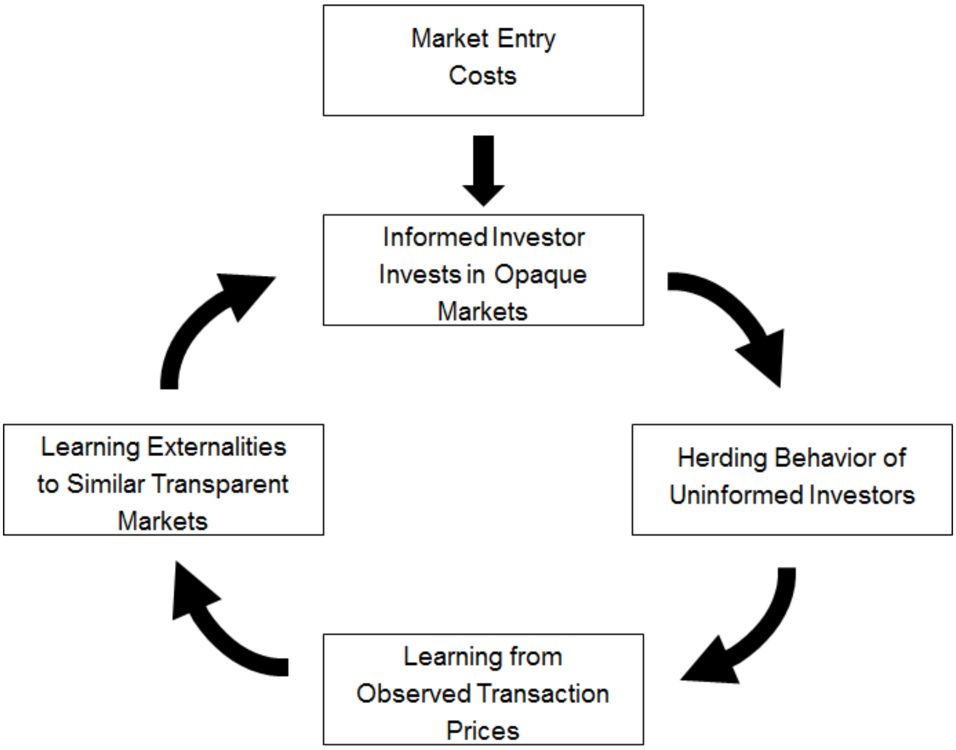
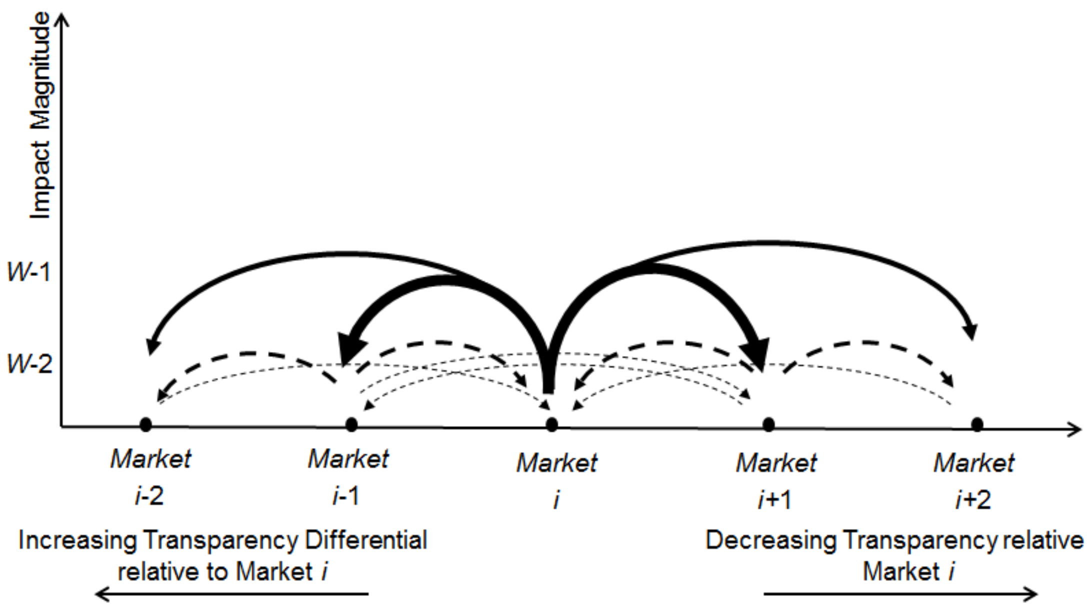


Figure 2: Spillover Effects and Feedback Loops

This figure illustrates the cascade effect of local interaction games as learning externalities are transmitted to neighboring private markets. Our concept of neighbors is defined along a linear transparency line between the spectrum of transparent and opaque property markets on the horizontal ray. The vertical axis reflects the magnitude of spillover effects, which depends on the transparency differential between property markets. We assume that a change in fundamental risk is incorporated in the property price of market i due to the bargaining process between the informed first-mover and uninformed traders, which culminates in learning externalities. We expect a declining pattern of the impact of spillovers and feedback loops as the externality effect propagate through international property markets. Spillovers are higher in neighboring markets of low-order, e.g., $W-1$ and smaller in magnitude in private markets of higher-order n, e.g., $W-n$, which are located further away. For simplicity, we only illustrate the transmission up to order 2.



Internet Appendix for "Learning Externalities in Opaque Asset Markets: Evidence from International Commercial Real Estate"

Roland Füss*   Daniel Ruf †

September 9, 2015

Abstract

This supplementary appendix contains additional material related to the main text. Appendix A discusses the composition of the Jones Lang LaSalle (JLL) Transparency Index. Appendix B provides a more detailed discussion about the estimators used for the spatial model. Particularly, it outlines the estimation strategies based on nonlinear least squares (NLS) and two-stage least squares (2SLS), which are compared to the Generalized Method of Moment (GMM) approach in terms of asymptotic efficiency. Furthermore, Appendix C presents additional figures and tables that describe our dataset in more detail and extend our analysis.

*Swiss Institute of Banking and Finance (s/bf), University of St.Gallen, Rosenbergstrasse 52, CH-9000 St. Gallen, Switzerland and Research Associate at the Centre for European Economic Research (ZEW), Phone: +41 (0)71 224 7055, Fax: +41 (0)71 224 7088, E-mail: roland.fuess@unisg.ch.

†Swiss Institute of Banking and Finance (s/bf), University of St.Gallen, Rosenbergstrasse 52, CH-9000 St. Gallen, Switzerland, Phone: +41 (0)71 224 7059, Fax: +41 (0)71 224 7088, E-mail: daniel.ruf@unisg.ch.

Appendix A: The Jones Lang LaSalle Transparency Index

Table A1: Jones Lang LaSalle Subindices

This table provides an overview of the subindices of the Jones Lang LaSalle Index (JLL). For each subindex we provide an overview of the different components to determine the value.

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 return 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 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 - take-up/absorption (office, retail, industrial, and residential) - property rents (office, retail, industrial, and residential) - vacancy (office, retail, industrial, and residential) - yields/cap rates (office, retail, industrial, residential, hotels) - capital values (office, retail, industrial, residential, and hotels) - investment volume (office, retail, industrial, residential, hotels) - revenue per available room for hotels - Existence of a comprehensive database of - buildings (office, retail, industrial, residential, and hotels) - leases (office, retail, industrial, residential, and hotels) - transactions (office, retail, industrial, residential, and hotels)

Table A1 continued

Governance and Listed Vehicles (10%)	Financial Disclosure	- Stringency of accounting standards - Reliability of the index and extent to which it is used as a benchmark of performance - 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 - 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 and 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
		  - public records on transaction prices
		  - 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, maturities, and origination 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

Table A1 continued

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-notesthash.zzAn241k.dpuf; (13 Topics and 115 Factors).

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

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 apply both estimators as alternative strategies to the GMM approach to estimate our spatial model under missing data. First, we briefly introduce each estimator and then show that all three of them 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 $\tilde{\theta} = \left(\tilde{\lambda}, \tilde{\beta}', \tilde{\pi}'\right)'$ 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 by using the vector of dependent variables $\tilde{Y}_{nt} = D_{nt}Y_{nt} + (I_n - D_{nt})\, S_{nt}^{-1}(\tilde{\lambda}) \left[X_{nt}\tilde{\beta} + K_{nt}X_{nt}\tilde{\pi}\right]$. By using $\tilde{Z}_{nT} = [W_{nT}\tilde{Y}_{nT}, X_{nT}, K_{nT}X_{nT}]$ and $Q_{nT}^{*} = [W_{nT}S_{nT}^{-1}(X_{nT}\beta_0 + K_{nT}X_{nT}\pi_0), X_{nT}, K_{nT}X_{nT}]$ as best instrumental variable matrix of dimension $nT \times k_x$, the 2SLS-estimator is computed as

$$\begin{aligned}\hat{\theta}_{2SLS} = {} & [\tilde{Z}_{nT}'(H_{nT}\Sigma_{\epsilon,nT}H_{nT}')^{+}Q_{nT}(Q_{nT}'(H_{nT}\Sigma_{\epsilon,nT}H_{nT}')^{+}Q_{nT})^{-1}Q_{nT}'(H_{nT}\Sigma_{\epsilon,nT}H_{nT}')^{+}\tilde{Z}_{nT}]^{-1} \\ & \times \tilde{Z}_{nT}'(H_{nT}\Sigma_{\epsilon,nT}H_{nT}')^{+}Q_{nT}(Q_{nT}'(H_{nT}\Sigma_{\epsilon,nT}H_{nT}')^{+}Q_{nT})^{-1}Q_{nT}'(H_{nT}\Sigma_{\epsilon,nT}H_{nT}')^{+}\tilde{Y}_{nT},\end{aligned}$$

where $\Sigma_{\epsilon,nT} = Var(\epsilon_{nT})$, $(H_{nT}\Sigma_{\epsilon,nT}H_{nT}')^{+}$ is denoted as Moore-Penrose generalized inverse of $(H_{nT}\Sigma_{\epsilon,nT}H_{nT}')^{+}$ with $H_{nT} = T_{nT} + (I_{nT} - T_{nT})C_{nT}[C_{nT}'R_{nT}'R_{nT}C_{nT}]^{-1}C_{nT}'R_{nT}'R_{nT}$ and $T_{nT} = S_{nT}D_{nT}S_{nT}^{-1}$. As the true specification of $\Sigma_{\epsilon,nT} = Var(\epsilon_{nT})$ is unknown, we follow Wang and Lee (2013b) and choose $(H_{nT}H_{nT}')^{+}$ instead of the generalized inverse of $H_{nT}\Sigma_{\epsilon,nT}H_{nT}'$ in order to weight the IV matrix.

NLS-Estimator. The NLS-estimator ignores missing dependent variables in the parameter estimation of the structural model $Y_{nT}^{(o)} = h_{nT}(X_{nT}, K_{nT}X_{nT}, \theta_0) + U_{nT}$, with defined vector of error terms $U_{nT} = J_{nT}^{(o)}S_{nT}^{-1}\epsilon_{nT}$. The parameter vector $\theta_0 = (\lambda_0, \beta_0', \pi_0')'$ is estimated by minimizing the following object function:

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

where the time-varying selection matrix $J_{nt}^{(o)}$ captures observable data from the vector of endogenous variables $Y_{nT}^{(o)} = [(J_{n1}^{(o)}Y_{n1})', ..., (J_{nT}^{(o)}Y_{nT})']'$. In order to estimate the Mundlak (1978) fixed effects specification, we derive the moment condition from the reduced-form specification $h_{nT}(X_{nT}, K_{nT}X_{nT}, \varsigma_0) = R_{nT}(\lambda_0)[X_{nT}\beta_0 + K_{nT}X_{nT}\pi_0]$, with

$$R_{nT}(\lambda_0) = \begin{pmatrix} J_{n1}^0 S_{n1}^{-1}(\lambda_0) & & \\ & \ddots & \\ & & J_{nT}^0 S_{nT}^{-1}(\lambda_0) \end{pmatrix} \text{ and } S_{nt} = (I_n - \lambda_0 W_{nt}) \text{ for } t = 1, ..., T.$$

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

Asymptotic Equivalence of GMM, 2SLS, and NLS. Based on the instrumental matrix $Q_{nT}^* = T_{nT}^{'+}[W_{nT}S_{nT}^{-1}(X_{nT}\beta_0 + K_{nT}X_{nT}\pi_0), X_{nT}, K_{nT}X_{nT}]$, the optimal GMM-estimator $\hat{\theta}_{gmm} = (\hat{\lambda}, \hat{\beta}', \hat{\pi}\prime)'$ has the asymptotic distribution $\sqrt{n}(\hat{\theta}_{gmm} - \theta_0) \to \mathcal{N}(0, \Sigma_{bgmm})$, where the asymptotic variance-covariance matrix is denoted as

$$\Sigma_{bgmm} = lim_{n\to\infty} n(C_{nT}'T_{nT}'T_{nT}^{'+}C_{nT})^{-1}C_{nT}'T_{nT}^{+}T_{nT}\Sigma_{\epsilon,nT}T_{nT}'T_{nT}^{'+}C_{nT}(C_{nT}'T_{nT}^{'+}T_{nT}'C_{nT})^{-1},$$

with $C_{nT} = [W_{nT}S_{nT}^{-1}(X_{nT}\beta_0 + K_{nT}X_{nT}\pi_0), X_{nT}, K_{nT}X_{nT}]$.

Similarly, Wang and Lee (2013b) show that the 2SLS-estimator is consistent with asymptotic variance-covariance matrix

$$\begin{aligned}\Sigma_{2SLS} = lim_{n\to\infty} n(C_{nT}'H_{nT}'H_{nT}^{'+}C_{nT})^{-1}C_{nT}'H_{nT}^{+}H_{nT}\Sigma_{\epsilon,nT}H_{nT}'H_{nT}^{'+} \\ \times C_{nT}(C_{nT}'H_{nT}^{'+}H_{nT}^{+'}C_{nT})^{-1}.\end{aligned}$$

The practical weighted NLS estimator is consistent, i.e., $\sqrt{n}(\hat{\theta_{nls}} - \theta_0) \to \mathcal{N}(0, \Sigma_{nls})$, with the asymptotic distribution being determined as

$$\begin{aligned}lim_{n\to\infty} n(C_{nT}'R_{nT}'(R_{nT}R_{nT}')^{-1}R_{nT}C_{nT})^{-1}C_{nT}'R_{nT}'(R_{nT}R_{nT}')^{-1}R_{nT}\Sigma_{\epsilon,nT}R_{nT}'(R_{nT}R_{nT}')^{-1} \\ \times R_{nT}C_{nT}(C_{nT}'R_{nT}'(R_{nT}R_{nT}')^{-1}R_{nT}C_{nT})^{-1}.\end{aligned}$$

Wang and Lee (2013b) show that the HAC-robust versions of all three estimators do not have the smallest variance. However, they prove that based on a simple NLS estimator as plug-in estimator in the first step, all three estimators are consistent and asymptotically equivalent even under unknown heteroscedasticity.[1]

[1] For further technical details we refer to Wang and Lee (2013a,b).

Appendix C: Additional Tables and Figures

In this part of the appendix we show additional figures and tables to extend the empirical analysis in Section 5 and to provide a more in-depth discussion of the data.

- Figure C.1 illustrates the time-varying systematic performance of commercial real estate market excess returns from 2001 to 2013. We pool over all cities and all three sectors industrial, office, and retail. The coverage is based on the Property Market Analysis (PMA) market coverage.
- Figure C.2 shows averaged property market excess returns pooled across all sectors and countries based on the International Property Databank (IPD) market coverage over the period from 1998 to 2013 to illustrate a time-varying common factor effect.
- Table C.1 contains a detailed description of the data which are used in our sample as well as their sources.
- Table C.2 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 industrial, office, and retail separately.
- Table C.3 provides the correlation matrix of all explanatory variables in our sample.
- Table C.4 shows the cross-sectional rank correlation between all index values which are used to compute the alternative weighting matrices.
- Table C.5 shows the results of a standard fixed-effects model using country-specific fundamentals as well as a set of different control variables.
- Table C.6 provides the results of our spatial lag model estimated separately for each sector as a robustness check in order to test for potential sector-specific heterogeneity.
- Tables C.7 to C.10 extend our empirical analysis to a different dataset. Instead of the disaggregated city-level PMA coverage we apply the same estimation strategy to an aggregated, sector-specific database provided by IPD. Table C.7 depicts a descriptive summary statistic of the IPD market coverage where we average over all sectors of each country. We

provide mean, standard deviation, maximum, and minimum values. Tables C.8 and C.9 illustrate the fixed-effects regression results based on country-specific and global multi-factor models using IPD data. Table C.10 shows the spatial lag models based on the IPD data.

Figure C1: Illustration of Time-Varying Effects based on PMA Coverage

This figure illustrates the common systematic variation of property market excess returns over time, pooled across all sectors and cities over the years from 2001 to 2013. The data are based on the PMA market coverage. Particularly, we find evidence of a systematic downward trend in all private markets in the aftermath of the recent financial crisis 2007/2008. Similarly, we also observe a recovery afterwards, which is only slightly below the average excess return of the pre-financial crisis period.

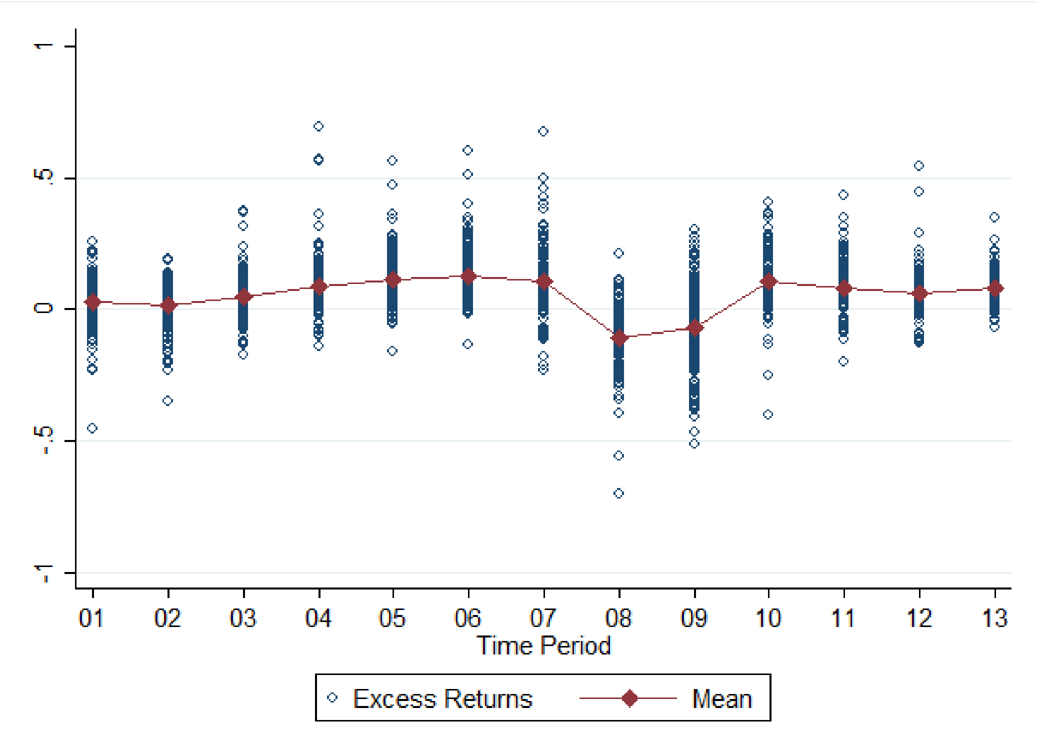


Figure C2: Illustration of Time-Varying Effects based on IPD Coverage

This figure shows the average of property market excess returns based on the IPD dataset pooled across country and sector over the time period from 1998 to 2013. We find evidence of a systematic downward trend in all private markets in the aftermath of the recent financial crisis 2007/2008. A recovery in the year 2010 leads to an average return which is below the average excess return of the pre-crisis period 1998 to 2007.

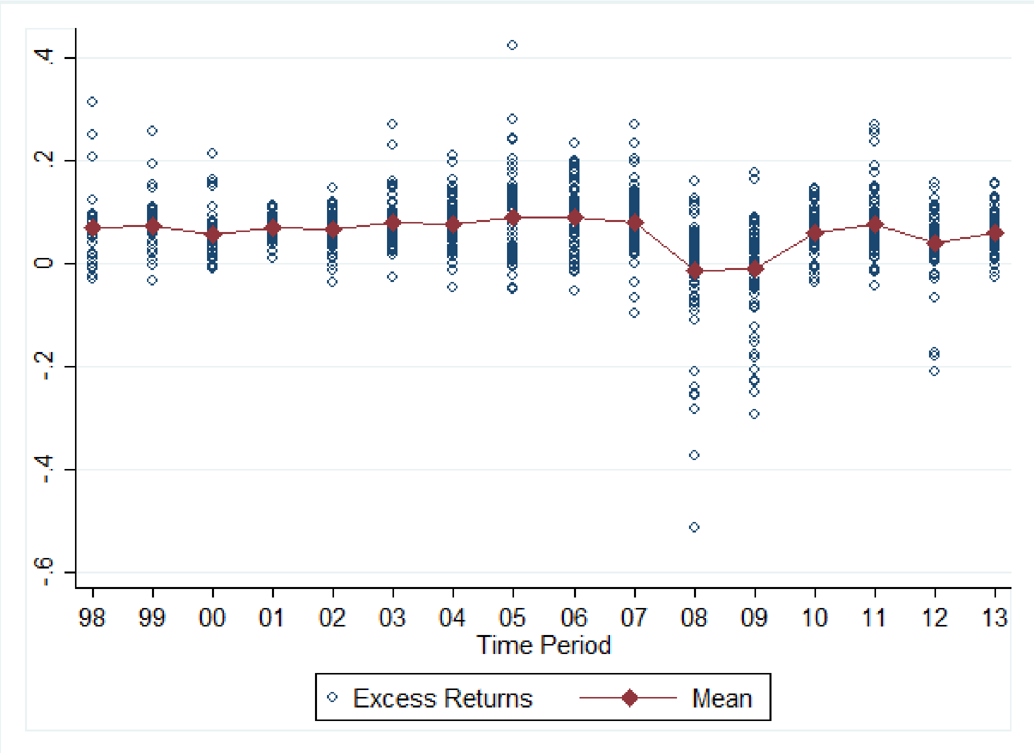


Table C1: Definition of Global and Country-Specific Data

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 (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. We have an unbalanced sample of country indices. Returns are computed in excess to the annualized U.S. three-month Treasury Bill.	Property Market Analysis (PMA) and Investment Property Databank (IPD)
Indices used to compute Weighting Matrices (Market-Specific)		
Global Commercial Real Estate Index (JLL)	The global commercial real estate index consists of five indicators to proxy the degree of information on performance measurement, market fundamentals, governance and public vehicles, such as REITs, the legal framework, as well as fairness and efficiency of the transaction process in international property markets. Section A of the Internet Appendix provides a more detailed discussion. We use this index as ideal proxy for the level of market transparency and potential information acquisition and market entry costs. We use index values released in 2004, 2006, 2008, 2010, and 2012 and compute a time-varying weighting matrix based on inverse distance.	Jones Lang LaSalle
Economic Freedom Index (ECONOMIC FREEDOM)	The index of economic freedom reflects the degree to which institutions ensure the freedom of individual decision-making. We use this measure as proxy for political risk. This index is released annually and we compute a time-varying weighting matrix based on cross-sectional inverse distance measures.	Heritage Foundation
Corruption Perception Index (CORRUPTION PERCEPTION)	The corruption perception index measures the perceived level of corruption of the public sector as indicated by a survey among analysts, businessmen and experts. The index is annually released. We construct a time-varying weighting matrix based on cross-sectional inverse distance measures.	Transparency International
Political Risk Index (POLITICAL RISK)	Political risk includes factors such as political stability, the commitment of government to service debt obligations, and its effect on foreign exchange market stability. The index is released at an annual basis. We compute a time-varying weighting matrix based on inverse distance. Our data ranges from 2001 to 2011 with missing values in 2012 and 2013.	Economist Intelligence Unit (EIU)

Table C1 continued

Country Risk Index (COUNTRY RISK)	The overall country risk index is released each year and includes the assessment of the three indicators sovereign risk, currency risk (devaluation against reference currency), and banking sector risk (systemic crisis risk of bank defaults). We use country-specific index values from 2001 to 2011. Missing data in 2012 and 2013 are replaced by lagged values.	Economist Intelligence Unit (EIU)
Haversine Distance (GEOGRAPHIC DISTANCE)	We use the geographic distances between the capital cities of all countries in our sample. In order to calculate the geographic distance, we use the Haversine method which calculates the shortest distance between two capital cities based on the longitude and latitude coordinates taking into account the spherical shape of the earth.	Own Calculation
Uncertainty Avoidance (AMBIGUITY AVERSION)	The uncertainty avoidance index compares country-specific differences of how individuals perceive ambiguity, i.e., incalculable risk, as a potential thread. The index proxies the degree to which society has established institutions to approach uncertain events. We compute a weighting matrix based on time-invariant country-specific inverse distance measures.	Hofstede Cultural Index
Power Distance (POWER DISTANCE)	This cross-sectional cultural index captures country-specific differences in how members in the society, particularly the less powerful individuals in organizations and the country, are willing to accept unequally distributed power. We compute a weighting matrix based on time-invariant country-specific inverse distance measures.	Hofstede Cultural Index
Individualism (INDIVIDUALISM)	This cross-sectional cultural index measures country-specific differences in how individuals in the society are integrated and connected in society. Particularly, this measure accounts for the extend to which members value their individual responsibility and freedom in contrast to collectivism. We compute a weighting matrix based on time-invariant country-specific inverse distance measures.	Hofstede Cultural Index
Masculinity (MASCULINITY)	This cross-sectional cultural index takes into account country-specific differences in how society is oriented towards ideals such as competition, achievement, and reward for success. These attributes are usually linked to the male gender. We compute a weighting matrix based on time-invariant country-specific inverse distance measures.	Hofstede Cultural Index
Explanatory Variables (Common Global Factors)		
Global Market Portfolio (GLOBAL STOCK ER)	This variable is based on the MSCI (Morgan Stanley Capital International) world index and serves as a proxy for the global market portfolio. We compute excess returns relative to the annualized thee-year U.S. Treasury Bill rate which is used as proxy for the risk-free rate. The sample ranges from 1998 to 2013.	Datastream

Table C1 continued

Eurodollar Rate (EURODOLLAR)	The annualized London three-month Eurodollar deposit rate reflects changes in the risk aversion of international investors with respect to their perception of the global economy, integrated financial market, and changes in exchange rates. The sample ranges from 1998 to 2013.	Datastream
TED Spread (TED SPREAD)	The TED spread serves as a proxy for global funding liquidity and credit risk. For the U.S. and Asia-Pacific we compute the TED spread as difference between the three-month LIBOR and three-month U.S. Treasury Bill rate. For the European area we base our proxy on the difference between the three-month EURIBOR rate and the three-month EONIA rate. All variables are annualized.	Datastream
Growth in Global Consumption (ΔGLOBAL CONSUMPTION)	Growth in global consumption is based on the first latent factor of a Principal Component Analysis (PCA). In order to extract this latent factor we use the country-specific cross-sectional variation in household consumption expenditures over time of all 29 countries in our sample.	Own Calculation
Excess Returns on U.S. Publicly Traded Securitized Real Estate (REIT US ER)	Excess returns on the publicly traded U.S. REIT (Real Estate Investment Trust) index serves as a global leading indicator for private commercial real estate. We use the NAREIT/MSCI U.S. REIT index to construct returns relative to the risk-free rate. The variable ranges from 1998 to 2013.	Own Calculation
Explanatory Variables (Country-Specific Factors)		
Term Spread (SPREAD)	The term spread is computed as difference between long-term government bond yields (10 years) and the three- month short-term interbank rate for each country from 1998 to 2013. Because of data limitations we use six-month interest rates as proxy for long-term interest rates for the following countries: China, Czech Republic, Greece, Hungary, and Poland.	Own Calculation
Expected Inflation Rate (ΔCPI)	We use a proxy for the expected inflation which is based on the annual Consumer Price Index (CPI). We compute log-differences based on the index level for all countries. The sample ranges over a time period from 1998 to 2013.	Datastream
Stock Market Excess Returns (STOCK ER)	Analogous to a CAPM model, country-specific stock market indices proxy national market portfolios. The performance of the financial market indicates also opportunity cost of capital of real estate investments. We use stock market indices provided by MSCI from 1997 to 2013. Excess returns are computed relative to the annualized thee-year U.S. Treasury Bill rate.	Datastream

Table C1 continued

Growth in Consumption Expenditures (ΔCONSUMPTION)	For each of the 29 countries in our sample, we collect data on consumption expenditures over a time period from 1997 to 2013. This data is based on individual household consumption expenditures, for which we compute log changes from the level. Changes in consumption expenditure are measured per capita.	Datastream
GDP Growth (ΔGDP)	We 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, with the exception of China, for which GDP is measured in current prices.	Datastream
Country-Specific Control Variables		
Changes in Real Exchange Rate (ΔXR REAL)	We compute log changes of the real exchange rate as a linear approximation of changes in nominal exchange measured as U.S. dollar per unit of foreign currency (direct quotation) and adjust for differences in log changes of the price levels (CPI) between both countries. The values range from 1998 to 2013.	Own Calculation
Unemployment Rate (ΔUNEMPLOYMENT)	We collect the annualized unemployment rate for each of the 29 countries in our sample to cover the cross-sectional variation in the macroeconomic supply condition. The sample covers a time period which ranges over the years from 1998 to 2013.	Datastream
U.S. CMBS Yield Spread (CMBS SPREAD)	We compute the CMBS yield spread relative to the U.S. 10-year government bond. We use this variable as leading indicator for commonality in funding liquidity risk. A higher yield spread causes a debt-financed funding liquidity dry-up in the commercial real estate sector.	Datastream
Excess Returns on REITs (REIT ER)	This variable serves as proxy for equity-based funding liquidity. We compute excess returns on securitized real estate based on NAREIT/MSCI REIT. For Finland and Ireland we use data from FTSE EPRA REIT. Missing values in the sample for Hungary, South Korea, and Poland are replaced by forecasts. Excess returns are relative to the annualized three-month U.S. Treasury Bill rate.	Datastream
Residential Housing Appreciation (ΔHOUSING)	We use log changes in residential property price indices for all 29 countries in our sample. The data covers a time period from 1998 to 2013. As main source we use residential house prices from the Bank for Intenrational Settlements. House prices for China are based on the Oxford Economics Database.	Bank for International Settlement (BIS) and Oxford Economics Database
Additional Commercial Real Estate Construction (ΔCONSTRUCTION)	Construction in the property sector reflects changes in the supply of additional stock. The variable is computed as log difference in the property stock for all countries covered by the PMA databank. Construction data is not available for the industrial sector.	Property Market Analysis (PMA)

Table C1 continued

Investment (INVESTMENT)	This variable measures total investment flows of international investors in global commercial real estate markets. We compute regional investment inflows for Western Europe, Eastern Europe, Asia-Pacific, as well as the U.S. at an annual basis from 2005 to 2013.	Property Market Analysis (PMA)
Additional Variables		
Long-Term Interest Rate	Country-specific 10-year government bonds yields are used as proxy for the long-term interest rate. Our data sample ranges from 1998 to 2013. Alternatively, we use six-month interest rates as long-term interest rate proxies for China, Czech Republic, Greece, Hungary, and Poland because of limited data availability of 10-year bond yields.	Datastream
Short-Term Interest	This variable is based on country-specific three-month interbank rates which are used as proxy variable for the short-term interest rate. We use interbank rates as alternative for the three-month Treasury Bill rate which is not available over the whole time period from 1998 to 2013 for all 29 countries in our sample.	Datastream
Risk-Free Rate	The three-month U.S. Treasury Bill rate is used as proxy for the risk-free rate.	Datastream
Changes in Nominal Exchange Rate (ΔXR)	Log changes of nominal exchange rates are computed for all countries in our sample relative to the U.S. dollar. The sample period ranges from 1998 to 2013.	Datastream
Change in Total Population (ΔPOPULATION)	We compute log changes of the 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 EURIBOR Rate	The EURIBOR (Euro Interbank Offered Rate) reflects the average lending rate between prime banks in the Euro-zone interbank market.	Datastream
Three-Month EONIA Rate	The EONIA (Euro OverNight Index Average) reflects the effective overnight interest rate for unsecured lending in the Euro-zone interbank market.	Datastream
Three-Month LIBOR Rate	The LIBOR (London Interbank Offered Rate) ranges from 1998 to 2013 and is used to construct the TED spread for the U.S. and Asia-Pacific regions.	Datastream
Barclays Capital U.S. Commercial Mortgage-Backed Security (CMBS) Bond Index	This bond index reflects the performance of investment-grade CMBSs in the U.S.	Datastream

Table C2: PMA Market Coverage

This table depicts 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**	**Industrial**	**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**	**Industrial**	**Office**	**Retail**
Australia	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 C2 continued

Panel C: Europe				
Country	**City**	**Industrial**	**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 C3: 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**	**TERM SPREAD**	**ΔCPI**	**GLOBAL STOCK ER**	**GLOBAL CONS.**	**EURODOLLAR**	**TED SPREAD**	**ΔUNEMPLOYMENT**	**ΔXR REAL**	**U.S. CMBS SPREAD**	**REIT ER**	**ΔHOUSING**	**INVESTMENTS**	**ΔCONSTRUCTION**
STOCK ER	1.000														
ΔCONSUMPTION	0.119	1.000													
TERM SPREAD	0.034	-0.328	1.000												
ΔCPI	-0.371	0.0002	-0.183	1.000											
GLOBAL STOCK ER	0.779	-0.020	0.180	-0.463	1.000										
GLOBAL CONS.	0.016	0.312	-0.230	0.136	-0.161	1.000									
EURODOLLAR	-0.101	0.238	-0.362	0.149	-0.272	0.772	1.000								
TED SPREAD	-0.191	0.096	-0.157	0.131	-0.272	0.113	0.254	1.000							
ΔUNEMPLOYMENT	-0.006	-0.340	0.443	-0.049	0.148	-0.157	-0.222	-0.166	1.000						
ΔXR REAL	0.006	0.144	-0.040	0.046	0.077	0.131	0.037	-0.110	-0.072	1.000					
U.S. CMBS SPREAD	-0.082	-0.021	0.164	0.143	0.017	-0.298	-0.363	0.075	0.082	-0.028	1.000				
REIT ER	0.146	0.329	-0.151	0.0001	0.057	0.486	0.239	0.002	-0.095	0.068	0.327	1.000			
ΔHOUSING	0.217	0.316	-0.138	0.076	0.142	0.227	0.128	-0.101	-0.042	0.153	-0.079	0.156	1.000		
INVESTMENTS	0.379	0.276	0.061	-0.081	0.395	0.425	0.070	-0.200	0.063	0.131	0.136	0.557	0.265	1.000	
ΔCONSTRUCTION	0.037	0.471	-0.147	-0.043	-0.035	0.101	0.115	0.113	-0.115	0.097	-0.078	0.039	0.111	-0.002	1.000

Table C4: Correlation Matrix of Alternative Transparency Indices

This table shows the correlation of alternative indices which are used to construct the weighting matrix. The upper and lower off-diagonals show the Spearman Rank correlation and the correlation based on Pravais Pearson, respectively.

	JLL	ECONOMIC FREEDOM	CORRUPTION PERC.	POLITICAL RISK	COUNTRY RISK	AMBIGUITY AVERSION	INDIVIDUALISM	POWER DISTANCE	MASCULINITY
JLL	**1.000**	-0.700	-0.687	0.655	0.555	0.478	-0.618	0.409	0.185
ECONOMIC FREEDOM	-0.697	**1.000**	0.777	-0.497	-0.483	-0.575	0.184	-0.351	-0.041
CORRUPTION PERCEPTION	-0.814	0.756	**1.000**	-0.825	-0.748	-0.507	0.357	-0.591	-0.382
POLITICAL RISK	-0.813	-0.565	-0.872	**1.000**	0.881	0.281	-0.556	0.679	0.328
COUNTRY RISK	0.660	-0.487	-0.802	0.806	**1.000**	0.358	-0.223	0.442	0.480
AMBIGUITY AVERSION	0.446	-0.609	-0.546	0.396	0.386	**1.000**	-0.096	0.334	0.236
INDIVIDUALISM	-0.631	0.289	0.332	-0.450	-0.223	-0.200	**1.000**	-0.493	0.063
POWER DISTANCE	0.524	-0.351	-0.591	0.679	0.442	0.286	-0.621	**1.000**	0.129
MASCULINITY	0.211	-0.023	-0.341	0.326	0.360	0.116	0.007	-0.016	**1.000**

Table C5: Results on Country-Specific Fundamentals

This table provides regression results of private market excess return on country-specific fundamentals. Estimations are based on the within-estimator. STOCK ER reflects excess returns on the national market portfolio. Personal consumption expenditures (ΔCONSUMPTION) is measured per capita. Changes in the consumer price index (ΔCPI) proxy expected inflation. The term spread (TERM SPREAD) measures the difference between long-term government bond yields and short-term interbank rates. ΔXR REAL reflects changes in the real exchange rate relative to the U.S. dollar. REIT ER denote excess returns on publicly traded REIT shares and U.S. CMBS SPREAD is defined as the difference between the U.S. CMBS bond index and the U.S. long-term government bond yield. ΔUNEMPLOYMENT captures the country-specific unemployment rate and ΔHOUSING indicates the appreciation in the residential housing sector. TED SPREAD is measured as the difference between the three-month LIBOR rate and the risk-free three-month U.S. Treasury Bill rate. Changes in property stocks (ΔCONSTRUCTION) and INVESTMENTS are used to control for market-specific characteristics. We show the Pesaran (2004) CD t-statistics of the null hypothesis of cross-sectional residual independence. The unbalanced panel pools the three sectors 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.

Systematic Factors	**Model I**	**Model II**	**Model III**	**Model IV**	**Model V**
STOCK ER	0.153***	0.057**	0.143***	0.127***	0.096***
	(0.015)	(0.025)	(0.016)	(0.017)	(0.025)
ΔCONSUMPTION	2.503***	1.650***	2.164***	2.235***	1.597***
	(0.184)	(0.181)	(0.176)	(0.259)	(0.280)
ΔCPI	1.068***	0.262	0.592***	1.089***	0.951**
	(0.308)	(0.344)	(0.310)	(0.316)	(0.461)
TERM SPREAD	0.664***	0.365*	0.198	0.162	-0.158
	(0.209)	(0.209)	(0.231)	(0.326)	(0.363)
ΔXR REAL			-0.092**	-0.105***	-0.185***
			(0.036)	(0.034)	(0.054)
REIT ER			0.034***	0.034**	
			(0.007)	(0.172)	
U.S. CMBS SPREAD			0.058***		
			(0.007)		
ΔUNEMPLOYMENT				0.345**	
				(0.172)	
ΔHOUSING				0.023	
				(0.029)	
TED SPREAD				-1.683***	
				(0.505)	
ΔCONSTRUCTION					-0.453**
					(0.182)
INVESTMENT					0.123***
					(0.015)
Observations	1980	1980	1980	1927	1288
Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Time-Fixed Effects	No	Yes	No	No	No
Pesaran CD	50.566***	1.753*	20.375***	27.186***	11.302***
Adj.-R^2	0.258	0.068	0.296	0.289	0.366

Table C6: Spatial Lag Model based on Sector Heterogeneity

This table extends the results of the baseline model. In Panel A, we estimate the spatial model for each sector (industrial, office, retail) separately. Estimates are based on GMM. The spatial lag indicates the degree of spatial dependence. Each sector consists of all cities pooled over all 26 countries from 2001 to 2013. STOCK ER reflects excess returns on the national market portfolio. Personal consumption expenditures (ΔCONSUMPTION) is measured per capita. Changes in the consumer price index (ΔCPI) proxy expected inflation. The term spread (TERM SPREAD) measures the difference between long-term government bond yields and short-term interbank rates. HAC-robust standard errors are given in parenthesis. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively. Panel B shows average direct, total, and indirect impacts of shocks in explanatory variables to measure spillover and feedback loop effects. The corresponding standard errors are based on simulations.

Panel A: Estimation Results			
	Industrial	**Office**	**Retail**
SPATIAL LAG	0.301**	0.645***	0.466***
	(0.145)	(0.115)	(0.131)
STOCK ER	0.096***	0.076**	0.091***
	(0.023)	(0.028)	(0.030)
ΔCONSUMPTION	1.837***	1.376***	1.513***
	(0.317)	(0.397)	(0.395)
ΔCPI	1.078***	0.227	0.461
	(0.337)	(0.387)	(0.455)
TERM SPREAD	0.714***	-0.054	0.626**
	(0.214)	(0.264)	(0.276)
Observations	611	767	663
Fixed-Effects	Yes	Yes	Yes
Pesaran CD	8.73***	2.32**	3.55***
Adj.-R^2	0.447	0.434	0.392
Panel B: Direct, Total, and Indirect Impact			
	Industrial	**Office**	**Retail**
Average Direct Impact			
STOCK ER	0.101	0.084	0.088
ΔCONSUMPTION	1.890***	1.611***	1.630***
ΔCPI	1.120***	0.271	0.494
TERM SPREAD	0.734	-0.075	0.676**
Average Total Impact			
STOCK ER	0.131	0.211	0.186
ΔCONSUMPTION	2.599***	3.887***	2.859***
ΔCPI	1.535***	0.657	0.829
TERM SPREAD	1.022***	-0.175	1.155**
Average Indirect Impact			
STOCK ER	0.030	0.128	0.097
ΔCONSUMPTION	0.709	2.276**	1.229
ΔCPI	0.425	0.386	0.335
TERM SPREAD	0.288	-0.100	0.479

Table C7: Summary Statistics 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	0.05	0.317	0.003	0.117	27	Transparent
Canada	0.089	0.048	-0.046	0.154	41	Highly Transparent
Czech Republic	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	0.08	0.053	-0.04	0.181	48	Highly Transparent
Norway	0.074	0.055	-0.078	0.27	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	0.07	-0.031	0.27	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	0.17	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 C8: Results on Country-Specific Fundamentals (based on IPD)

This table shows regression results of international direct property excess return on country-specific risk factors. Estimations are based on the within-estimator. STOCK ER reflects excess returns on the national market portfolio. Personal consumption expenditures (ΔCONSUMPTION) is measured per capita. Changes in the consumer price index (ΔCPI) proxy expected inflation. The term spread (TERM SPREAD) measures the difference between long-term government bond yields and short-term interbank rates. ΔXR REAL reflects changes in the real exchange rate relative to the U.S. dollar. REIT ER denote excess returns on publicly traded REIT shares and U.S. CMBS SPREAD is defined as the difference between the U.S. CMBS bond index and the U.S. long-term government bond yield. ΔUNEMPLOYMENT captures the country-specific unemployment rate and ΔHOUSING indicates the appreciation in the residential housing sector. The TED SPREAD and EURODOLLAR are proxies for common global systematic risk. 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 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.

Systematic Factors	**Model I**	**Model II**	**Model III**	**Model IV**	**Model V**
STOCK ER	0.048***	0.009	0.048***	0.052***	0.050***
	(0.018)	(0.019)	(0.018)	(0.019)	(0.008)
ΔCONSUMPTION	1.816***	1.801***	1.750***	1.651***	1.851***
	(0.207)	(0.263)	(0.228)	(0.240)	(0.131)
ΔCPI	0.942***	0.972***	0.724***	0.854***	0.816**
	(0.236)	(0.260)	(0.243)	(0.247)	(0.203)
TERM SPREAD	0.478***	0.073	0.205	0.723***	0.099
	(0.184)	(0.158)	(0.176)	(0.222)	(0.173)
ΔXR REAL			0.004	0.018	-0.023
			(0.028)	(0.022)	(0.021)
REIT ER			0.009	0.013	
			(0.008)	(0.008)	
U.S. CMBS SPREAD			0.038***		0.039***
			(0.007)		(0.008)
ΔUNEMPLOYMENT				-0.391***	
				(0.113)	
ΔHOUSING				-0.041	
				(0.030)	
TED SPREAD					-0.844**
					(0.410)
EURODOLLAR					-0.109
					(0.144)
Observations	969	969	969	957	902
Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Time-Fixed Effects	No	Yes	No	No	No
Pesaran CD	17.063***	1.929*	11.543***	16.111***	9.424***
Adj.-R^2	0.271	0.176	0.293	0.292	0.277

Table C9: Results on Common Global Systematic Risk (based on IPD)

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. U.S. REIT ER indicates excess returns on U.S. MSCI REIT index. The U.S. CMBS SPREAD measures the spread of U.S. CMBS yield relative to the 10-year U.S. government bond yield and REAL XR reflects changes in the real exchange rate relative to the U.S. dollar. 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.

Systematic Factors	**Model I**	**Model II**	**Model III**	**Model IV**
GLOBAL STOCK ER	0.054***			
	(0.014)			
ΔGOBAL CONS.		0.021***		
		(0.003)		
TED SPREAD			-2.090***	-0.047
			(0.344)	(0.395)
EURODOLLAR			0.389***	
			(0.121)	
U.S. REIT ER				0.105***
				(0.021)
U.S. CMBS SPREAD				0.013
				(0.008)
ΔXR REAL	-0.007	-0.018	0.022	-0.003
	(0.026)	(0.034)	(0.027)	(0.028)
Observations	969	866	902	902
Fixed-Effects	Yes	Yes	Yes	Yes
Pesaran CD	44.53***	41.62***	43.20***	36.35***
Adj.-R^2	0.028	0.062	0.029	0.118

Table C10: Spatial Lag Model (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. The weighting matrix is based on time-aggregated JLL index differentials. The spatial lag indicates the degree of spatial dependence. Estimators are based on the Mundlak (1978) fixed-effects model. STOCK ER reflects excess returns on the national market portfolio. Personal consumption expenditures (ΔCONSUMPTION) is measured per capita. Changes in the consumer price index (ΔCPI) proxy expected inflation. The term spread (TERM SPREAD) measures the difference between long-term government bond yields and short-term interbank rates. The Pesaran (2004) CD test shows t-statistics of the null hypothesis of residual independence. The panel pools three sectors (industrial, office, retail) in 25 countries from 1998 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, total, and indirect impacts of shocks in explanatory variables to measure spillover and feedback loop effects. The corresponding standard errors are based on simulations.

Panel A: Estimation Results			
	GMM	**2SLS**	**NLS**
SPATIAL LAG	0.456**	0.377*	0.378**
	(0.179)	(0.195)	(0.018)
STOCK ER	0.030**	0.033**	0.033**
	(0.012)	(0.013)	(0.013)
ΔCONSUMPTION	1.051***	1.122***	1.159***
	(0.316)	(0.341)	(0.331)
ΔCPI	0.590***	0.609**	0.645***
	(0.222)	(0.240)	(0.232)
TERM SPREAD	0.161	0.042	0.152
	(0.125)	(0.197)	(0.135)
Observations	1184	1184	1184
Fixed-Effects	Yes	Yes	Yes
Pesaran CD	7.31***	9.98***	9.31***
Adj.-R^2	0.568	0.553	0.547
Panel B: Direct, Total, and Indirect Impact			
	GMM	**2SLS**	**NLS**
Average Direct Impact			
STOCK ER	0.029	0.028	0.053
Δ CONSUMPTION	1.162***	1.205***	1.236***
Δ CPI	0.653***	0.647**	0.698***
TERM SPREAD	0.177	0.034	0.167
Average Total Impact			
STOCK ER	0.048	0.042	0.081
Δ CONSUMPTION	1.941***	1.820***	1.867***
Δ CPI	1.090***	0.978**	1.054***
TERM SPREAD	0.296	0.052	0.253
Average Indirect Impact			
STOCK ER	0.019	0.014	0.027
Δ CONSUMPTION	0.780***	0.615***	0.631***
Δ CPI	0.438***	0.330**	0.356***
TERM SPREAD	0.119	0.018	0.085