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

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Abstract

This paper uses a unique dataset to empirically test the implications of limited transparency in decentralized markets. We capture differences in the transparency level as a linkage mechanism among international commercial real estate markets. This connectivity arises from learning externalities of international investors. Our identification strategy exploits the specific feature of spatial econometrics to analyze the transmission of these externalities across opaque markets. We find empirical evidence of cross-sectional dependence and co-movements among global property market excess returns. Furthermore, local shocks are amplified via spillovers and feedback loops, which provide a source of instability in international property markets.

JEL Classification: $C33$, $D82$, $D83$, $G15$, $R30$
Key words: Commercial real estate; cross-sectional dependence; learning externalities; opaque markets; spatial econometrics; transparency.

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1 Introduction

Commercial real estate has become an important asset class in the portfolio of large institutional investors over the last decades. With 13.6 trillion U.S. dollars invested in international stock and total transaction volume of 633 billion U.S. dollars in 2014, trading in commercial properties has already surpassed its 2006 pre-financial crisis level (DTZ (2015)). However, capital growth in real estate investments is unequally distributed across the globe. Low interest rates worldwide, increasing risk appetite, excessive demand from investors, as well as economic growth perspectives drive up property prices in emerging markets, particularly in Asia-Pacific. While mature, liquid markets in Europe and the U.S. offer on average lower expected returns than emerging markets, global investment volume remains particularly high in major gateway cities and financial centers, such as London, New York, Tokyo, Hong Kong, and Singapore.[1] Furthermore, the business and banking sector is linked to commercial real estate through the credit and collateral channel. There is also ample evidence of co-movements of property values and the investment behavior of firms (see, e.g., Chaney, Sraer, and Thesmar (2012)). Hence, the performance of property markets significantly impacts the real economy as well as global financial stability (Crowe, Dell'Ariccia, Igan, and Rabanal (2013)).

We focus on international commercial real estate as a natural laboratory to analyze spillover effects across segmented opaque asset markets. To the best of our knowledge, this is the first paper which empirically studies the 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

[1] DTZ (2015) reports growth of invested stock in commercial properties of 10% in Asia-Pacific and 5% in North America in 2014, while no growth is recorded in Europe. Investment volumes increased to a record of 107 billion U.S. dollars in Asia compared to a 30% increase to 263 billion U.S. dollars in Europe and a 12% increase to 291 billion U.S. dollars in North America in 2014.

investors. Second, heterogeneous properties 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 the trading counterparties. 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 transparency between international property markets reflect trading frictions and explicitly capture the linkage mechanism in a pre-specified weighting matrix of our spatial model. Our identification strategy allows us to clearly disentangle the transmission channel of local shocks in commercial real estate markets from their potential driving factors. We empirically test the implications of market opacity and estimate spillovers as well as feedback loops which are transmitted through this linkage mechanism. Furthermore, we interpret this cross-sectional dependence as a consequence of transparency-based trading frictions which serve as a trigger mechanism for return co-movements in commercial real estate markets.

Investments in mature, transparent property markets offer little growth perspectives and limited diversification potentials. As information is accessible and brokers enhance costly local knowledge, these markets are attractive for risk-averse investors, such as pension funds and insurance companies. On the other hand, institutional investors with more risk-appetite, e.g., investment funds, attempt to shift their investment focus to less transparent, but also more risk-rewarding emerging markets. To underpin our intuition, we illustrate in Figure 1 the positive relationship between property market excess returns and growth in consumption expenditure of countries where these markets are located. This illustration also suggests, conditional on economic growth rates, a connectivity of segmented markets via the proximity in their transparency level.[2] On average, higher expected returns are obtained in booming, but less transparent emerging markets which also feature higher market entry costs. However, conditional on negative growth rates, more opaque markets also bear the risk of on average lower expected returns.

[INSERT FIGURE 1 HERE]

Because of the market segmentation foreign investors are confronted with locally better informed brokers who have a local monopoly power which causes less informed investors to accept an opacity-based markup at lower expected returns. We propose a theoretical model in which a subset of institutional investors, who are domiciled in markets with higher opacity, have a comparative advantage to enter similarly transparent or even more opaque markets. For instance, consider an investor who is located in an opaque market, such as Greece. Relative to his home market for which he has superior information, this investor would be rewarded with lower expected returns in more transparent markets, e.g., the U.S., and therefore abstains from investing in these markets. However, home market benchmark returns can be realized or surpassed in similarly transparent or even more opaque markets. As the implied market entry costs are smaller for the Greek investor than for the U.S. investor, he has a comparative advantage in the assessment of the potential price range in less transparent markets. In contrast, the U.S. investor enters only markets as long as the corresponding information acquisition costs are smaller than the adverse selection costs from trading with better informed brokers. Consequently, he prefers investments in property markets with a higher transparency level.

Particularly, we suggest a positive association between entry costs and the transparency differential between the home market of a hypothetical investor and a less transparent market. This link might be explained by informational economies of scale or higher

[2] We follow the classification of the Jones Lang LaSalle (JLL) global real estate transparency index to differentiate between between "highly transparent", "transparent", and "semi-transparent" property markets. Section 4 discusses the index as well as its classification in more detail.

perceived familiarity, allowing investors from less transparent markets to access information in opaque markets with a similar level of transparency at lower acquisition costs (see, e.g., Massa and Simonov (2006)). Similarly, investors benefit from learning externalities as local brokers reveal their knowledge by privately trading to their counterparties (see, e.g., Zhu (2012), Duffie, Malamud, and Manso (2014)). Hence, the bilateral negotiation mitigates the uncertainty about possible price ranges in markets with a similar opacity. Our model provides an explanation of excessive demand and momentum trading which drive up prices in multiple private markets. We propose a linkage mechanism which serves as a breeding ground for the emergence of co-movements, potential instability as well as correlated price bubbles in international segmented property markets.

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 excess returns on segmented property markets. A large variation in excess returns over time is explained by spillover effects from private markets with similar degree of transparency. Based on our identifying economic assumptions we interpret these effects as learning externalities. We disentangle country-specific macroeconomic fundamentals from global systematic risk to show that spatial dependence prevails, even when we control for common factors. Furthermore, we show that our distance measure does not merely echo geographic proximity. In a second step, we derive a spatial multiplier from the reduced-form specification of our model, through which local shocks, particularly associated with consumption patterns, 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 and market liquidity (e.g., Duffie, Gârleanu, and Pedersen (2005, 2007); 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 to ambiguity. Ambiguity, or incalculable uncertainty in contrast to calculable risk, occurs when individuals are incapable of assigning probabilities from a unique prior belief to events or when information signals cannot be assessed with precision, see, e.g., Epstein and Schneider (2007, 2008). For instance, ambiguity-aversion provides a rationale for investors' preference in reducing the uncertainty at the expense of losses from trading with better informed counterparties (Caskey (2009)) or to focus on more familiar assets (Cao, Han, Hirshleifer, and Zhang (2011)). Following Mele and Sangiorgi (2015), we argue that traders invest in information acquisition to learn about the revealed price information, which allows them to reduce the level of ambiguity.

Third, we also contribute to the literature on 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 the underlying economic transmission channel (see, e.g., Gibbons and Overman (2012); Corrado and Fingleton (2012)). Particularly, our spatial econometric approach enables us to use transparency differentials as the transmission channel through which priced risk factors are propagated across private markets.

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 immediately adjusted by additional property supply from the inelastic construction sector. Unlike the turmoil in the U.S. residential housing sector from which the financial crisis originated in 2007, the subsequently 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 private 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 policymakers, 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 Theoretical Framework

In this section, we present a simple bargaining model for private property markets. To purchase commercial real estate at such an OTC market an institutional investor has to contact a local broker. Brokers share costly information about the local market structure with their clients and act as an intermediary. They are more familiar with the regulatory and legal framework, such as the enforcement of property rights and provide the connectivity to local networks of lenders and enhance the access to finance property investments (see e.g.,Garmaise and Moskowitz (2003, 2004)). Our model is an adaption of the Green, Hollifield, and Schürhoff (2007) bargaining game in decentralized OTC markets, in which a foreign investor faces a markup when he trades with a better informed local broker. We link the bargaining power of the potential buyer to the transparency differential between the opaque market and his home market. Furthermore, we extend the model by introducing an ambiguity-based component which relates the information acquisition costs of the foreign investor to the uncertainty in opaque markets.

Market Structure and Agents. Consider a continuum of markets arranged along a linear transparency line with increasing transparency differential d, i.e., increasing in opacity relative to the home market of an investor. For two opaque markets located at d' and d with $d' \leq d$, fundamental property prices in period t are determined by $p_t(d') = m_t x_{t,d'} + \theta_{d'}$ and $p_t(d) = m_t x_{t,d} + \theta_d$, respectively. The fundamental value depends on a set of specific observable state variables $x_{t,d'}$, $x_{t,d}$, and a common stochastic discount factor m_t, i.e., the functional form of the implied pricing kernel, as well as market-specific parameters $\theta_{d'}$ and θ_d, which capture the market opacity.[3]

Each market is occupied by a domestic broker with a local monopoly power due to his superior information about the market structure. A broker in market d has a reservation value v and bargains for the transaction price $p_t(d)$. His trading gain in t,

[3]The opacity-based parameter can be interpreted as a catch-up variable which reflects all potential factors which arise from the market-specific level of transparency and affect the potential property price.

W_t^b, results from the difference between the transaction price and the reservation value, i.e., $W_t^b = p_t(d) - v \geq 0$, which also represents the markup, $\tau = W_t^b \geq 0$, the investor has to pay due to the market opacity. The markup or opacity-based premium arises from the local monopoly power of the broker and can partially be offset by the bargaining power of the trading counterparty. We assume that the markup is smaller or equal to the potential adverse selection costs, τ^*, an uninformed investor faces when trading with the broker, i.e., $\tau \leq \tau^*$.

A representative institutional investor successively enters multiple property markets, all of them are on a lower transparency level compared to his home market for which he has superior information.[4] He first invests in less distant markets and gradually shifts his investment focus to more opaque markets along the line, i.e., moving from d' to d. To enter the market with transparency differential d relative to his home market, he has to invest in information acquisition costs $C(d)$.[5] For the information acquisition cost, we assume a convex function with $\frac{\partial C(d)}{\partial d} > 0$ and $\frac{\partial^2 C(d)}{\partial d^2} > 0$. Intuitively, the investor faces increasing marginal entry costs when he shifts his investment focus to private markets which are more distant to his home market in terms of the transparency level.[6] The investor enters a less transparent market as long as the entry costs are smaller than the potential adverse selection costs, i.e., $C(d) \leq \tau^*$. For the sake of simplicity, we normalize the continuum of transparency differentials of markets the investor enters between zero and one, $d \in [0, 1]$. This framework is given in Figure 2.

[INSERT FIGURE 2 HERE]

The trading gain for the institutional investor i in the next period $t + 1$ is defined

[4] Our setup is flexible enough to generalize the home market of an investor as a global market which includes all segmented markets with a higher transparency level compared to the home market. For these markets the investor can *per se* easily access information, while for markets which are less transparent than his home market, the investor has to invest in additional information acquisition.

[5] If $d = 0$, the institutional investors invests in his home market, for which he has superior information and faces no information acquisition costs. Hence, we assume $C(d = 0) = 0$.

[6] The convexity assumption of the implied information acquisition costs follows the standard literature. We refer the reader to Vives (2008) for an overview.

as $W^i_{t+1} = p_{t+1}(d) - C(d) - p_t(d)$ and reflects the increase in net wealth of the property between period t and $t+1$ less the invested information acquisition costs. Both trading counterparties have a mean-variance utility function $U(W) = E[W] - \frac{\delta}{2}Var[W]$, with risk-tolerance parameter δ and individual wealth W. Conditional on the information set G_t available up to period t, the indirect utility functions for the investor i and the broker b are then defined as

$$U(W^i_t|G_t) = E[p_{t+1}(d)|G_t] - C(d) - p^*_t(d) - \frac{\delta}{2}Var[p_{t+1}(d)|G_t] \tag{1}$$

and

$$U(W^b_t|G_t) = E[p^*_t(d) - v|G_t] = p^*_t(d) - v, \tag{2}$$

respectively. The transaction price $p^*_t(d)$ is maximized in the bargaining process.

Ambiguity Aversion. The investor forms expectations of the future price in period $t+1$, $E[p_{t+1}(d)|G_t] = E[m_{t+1}x_{t+1,d} + \theta_d|G_t]$, conditional on his information set up to period t. Mele and Sangiorgi (2015) model ambiguity as parameter uncertainty of the underlying fundamental asset value. In our setup, we assume that $\theta_d \sim \mathcal{N}(\mu, \sigma^2_\theta)$, with its expected value being unknown to the institutional investor. However, the investor can assess an interval, i.e., $\theta_d \in [\underline{\theta}_d, \overline{\theta}_d]$, in which the parameter lies. Using the opacity-based parameter $\theta_{d'}$ from the previous bargaining process in market d' as a source of information, the investor specifies the lower and upper bounds $\underline{\theta}_d = \theta_{d'} - \frac{\partial C(d)}{\partial d}$ and $\overline{\theta}_d = \theta_{d'} + \frac{\partial C(d)}{\partial d}$, respectively. Particularly, for markets d and d', we assume that $\theta_d \approx \theta_{d'} \pm \frac{\partial C(d)}{\partial d}$. Consequently, the market entry costs can be decomposed into learning externalities from the previous bargaining process in a marginally more transparent market d' and the additional information acquisition cost arising from entry in market d. Because of the externality effect, the investor can assess the price range of the expected future property value, i.e., we define the lower and upper price range as

$$E[\underline{p}_{t+1}(d)|G_t] = E[m_{t+1}x_{t+1,d}|G_t] + \theta_{d'} - \frac{\partial C(d)}{\partial d} \tag{3}$$

and

$$E[\overline{p}_{t+1}(d)|G_t] = E[m_{t+1}x_{t+1,d}|G_t] + \theta_{d'} + \frac{\partial C(d)}{\partial d}. \tag{4}$$

As implied by its convex functional form, the information acquisition cost marginally increases with the transparency differential.

Our economic intuition is in line with related studies, such as Pasquariello (2007), Cespa and Foucault (2014), and Duffie, Malamud, and Manso (2014), who argue that markets are connected via investors' cross-market learning 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 local broker reveals his private knowledge of transparency-based trading frictions during the negotiation to his counterparty, the institutional investor uses this information to limit the set of prior beliefs about possible price ranges in opaque markets with similar transparency levels.[7] As implied by the ambiguity-averse behavior of the investor, a higher level of opacity leads to a surge in the anticipated price range in less transparent market.

Bargaining Process. The bargained price between the institutional investor and the broker is the solution of the generalized Nash bargaining product

$$p_t^*(d) \in argmax(E[p_{t+1}(d)|G_t] - C(d) - p_t^*(d) - \frac{\delta}{2}Var[p_{t+1}(d)|G_t])^{(1-d)}(p_t^*(d) - v)^d \tag{5}$$

[7] For instance, based on a sales comparison approach, the institutional investor can assess the opacity-based markup from privately negotiated transaction prices of comparable properties in markets with similar transparency level. Our model implies that for the home market, when $d = 0$, the investor has superior information about the local market structure, which enables him to assess the underlying transparency-based parameter value $\theta_{d=0}$.

subject to the following participation constraints:

$$E[p_{t+1}(d)|G_t] - C(d) - p_t^*(d) - \frac{\delta}{2}Var[p_{t+1}(d)|G_t] \geq 0$$

$$p_t^*(d) - v = \tau \geq 0$$

$$E[p_{t+1}(d)|G_t] - C(d) - v - \frac{\delta}{2}Var[p_{t+1}(d)|G_t] \geq 0.$$

The first two conditions ensure that the obtained indirect utility functions of both trading counterparties are non-negative. The third participation constraint assumes positive gains from trade of the bargaining game. The bargaining power of the investor depends on transparency differential relative to his home market. When the institutional investor remains in his home market, i.e., $d = 0$, he has the bargaining power. Similarly, for $d = 1$, the investor is indifferent between investing in information acquisition and accepting adverse selection costs from trading with the locally better informed broker who has the bargaining power. The equilibrium transaction price that maximizes the bargaining Nash product is denoted as

$$p_t^*(d) = (E[p_{t+1}(d)|G_t] - C(d) - \frac{\delta}{2}Var[p_{t+1}(d)|G_t])d + v(1-d). \tag{6}$$

The transaction price is the weighted average of the indirect utility of the institutional investor and the reservation value of the local broker. For $d = 0$, the transaction price $p_t^*(d)$ equals the reservation value of the broker and the investor does not pay an opacity-specific markup. For $d = 1$, the trading gains of the institutional investor are equal to zero as he faces adverse selection costs from trading with the better informed broker.

Cross-Sectional Dependence. From the optimized bargaining Nash product it can be seen that transaction prices of similarly transparent markets are cross-sectionally dependent. The institutional investor uses the observable realized transaction price in market d' as proxy for the unobservable opacity-based parameter $\theta_{d'}$ to assess the price interval.[8] Hence, we can rewrite the optimal bargaining price as

$$p_t^*(d) = (E[m_{t+1}x_{t+1,d} - m_t x_{t,d'}|G_t] + p_t(d') \pm \frac{\partial C(d)}{\partial d} - C(d) - \frac{\delta}{2} Var[p_{t+1}(d)|G_t])d + v(1-d). \tag{7}$$

We derive several implications from this equation. First, our model is in line with related studies such as Barberis and Shleifer (2003) and Barberis, Shleifer, and Wurgler (2005) who show how co-movements can emerge when assets share specific characteristics, e.g., arising from a close proximity in the level of transparency, or common fundamentals, such as a surge in emerging market growth rates. As captured by the differential in growth perspectives, our model is flexible enough to explain market co-movements because of investors who systematically shift their investment focus to emerging markets with better growth perspectives compared to their home market. Second, we provide an intuitive explanation of how the market entry in private markets can lead to a cascade which contagiously spills over to similarly transparent or even more opaque markets. Economically, the cascade effect can be explained by the herding behavior of investors following the market entry of a first-mover, which drives up property prices in multiple markets and serves as a trigger mechanism for co-movements and price bubbles in property markets. For instance, Abreu and Brunnermeier (2003) provide a model where investors exploit the emergence of a price bubble by strategically delaying its inevitable burst. In the next section, we specify our identification strategy in order to test the cross-sectional dependence as implied by our theoretical model specification.

[8] From rearranging the fundamental price equation for market d', i.e., $\theta_{d'} = p_t(d') - m_t x_{t,d'}$, and plugging in the term for $\theta_{d'}$ in equations (3) and (4), it can be seen that learning externalities from the negotiated transaction price in an opaque market enables investors to assess the potential price range in similarly opaque markets.

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 markets 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 our theoretical framework, 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.[9] 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 exogenous 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

$$Y_{nt} = \lambda W_{nt} Y_{nt} + X_{nt}\beta + \epsilon_{nt}, \tag{8}$$

[9]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).

with vector Y_{nt} of n cross-sectional observations, $n \times k$ matrix X_{nt} of covariates, $1 \times k$ parameter vector β, a $n \times n$ weighting matrix W_{nt} with pre-specified spatial weights w_{kl} between observations k and l, and the error term vector ϵ_{nt} for period $t = 1 \ldots T$. The parameter λ measures the degree of cross-sectional dependence. In a second step, we rewrite the model in its reduced-form

$$Y_{nt} = (I_n - \lambda W_{nt})^{-1} (X_{nt}\beta + \epsilon_{nt}), \tag{9}$$

which represents the equilibrium specification, after local shocks, i.e., changes in the explanatory variables, 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 model in Section 2, we interpret these information spillovers as learning externalities between neighboring property markets which are defined along a transparency line. In Figure 3, we illustrate these spillovers arising from the portfolio rebalancing of institutional investors due to changes in local fundamentals, which lead to co-movements in property markets.

[INSERT FIGURE 3 HERE]

Spillover and feedback loops are transmitted through the spatial multiplier

$$S(\lambda)^{-1} = (I_n - \lambda W_{nt})^{-1} \approx I_n + \lambda W_{nt} + \lambda^2 W_{nt}^2 + \lambda^3 W_{nt}^3 + \ldots + \lambda^q W_{nt}^q. \tag{10}$$

Given the connectivity induced 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 geometrically 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 Sub-section, 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

$$Y_{nt} = \lambda_0 W_{nt} Y_{nt} + X_{nt}\beta_0 + \eta_n + e_{nt}, \tag{11}$$

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 common 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.[10] 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 $W = \begin{pmatrix} W_{n1} & & \\ & \ddots & \\ & & W_{nT} \end{pmatrix}$.

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

[10]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.

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 $W_{nt}X_{nt}$ which is based on a theoretical rationale. Learning externalities propagate through privately revealed transaction prices of the bargaining process and not via country-specific fundamentals. This model restriction serves as a justification for an endogenous spatial lag $W_{nt}Y_{nt}$.[11] 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} for city i and property sector j) arises from the need to control 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

$$\eta_{ij} = \bar{x}_{ij}\xi + \alpha_{ij}, \tag{12}$$

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., $E\left(\varepsilon_{ij} = \alpha_{ij} + e_{ij} \mid x_i\right) = 0$, 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

[11] This assumption is crucial as the exclusion restriction allows us to use $W_{nt}X_{nt}$ as instrument for $W_{nt}Y_{nt}$.

$$Y = \lambda_0 WY + X\beta_0 + KX\pi_0 + \varepsilon, \tag{13}$$

with a vector of cross-sectional endogenous variables $Y = \left(Y_{n1}', \ldots, Y_{nT}'\right)'$, a vector of covariates $X = \left(X_{n1}', \ldots, X_{nT}'\right)'$, and a residual vector $\varepsilon = \left(\varepsilon_{n1}', \ldots, \varepsilon_{nT}'\right)'$ for $t = 1, \ldots, T$. The Mundlak (1978) correction term $\left(\frac{l_T l_T'}{T} \otimes I_n\right) X = KX$ 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, taking into account the spatial lag multiplier. Hence, we define the vector of replaced missing endogenous variables as $(I_{nT} - D)\, S^{-1}\left(X\hat{\beta} + KX\hat{\pi}\right)$, with the matrices

$$D = \begin{pmatrix} D_{n1} & & \\ & \ddots & \\ & & D_{nT} \end{pmatrix} \text{ and } S^{-1} = \begin{pmatrix} S_{n1}^{-1}(\hat{\lambda}) & & \\ & \ddots & \\ & & S_{nT}^{-1}(\hat{\lambda}) \end{pmatrix}.$$

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 $\hat{g}^{'}(\theta)\hat{\Omega}^{-1}\hat{g}(\theta)$.[12] The moment function $\hat{g}(\theta) = Q^{'}U$ is defined as a standard orthogonality condition of the $nT \times k$ instrumental matrix Q and the disturbance vector of the structural equation $U = \left(U_{n1}^{'}, \ldots, U_{nT}^{'}\right)^{'}$, which is defined as

$$U = S\left[DY + (I_{nT} - D)\, S^{-1}\left(X\beta_0 + KX\pi_0\right)\right] - X\beta_0 - KX\pi_0, \tag{14}$$

with matrix $S = \begin{pmatrix} S_{n1} & & \\ & \ddots & \\ & & S_{nT} \end{pmatrix}$.

We apply a heteroscedasticity and autocorrelation consistent (HAC) estimator of the variance-covariance matrix $\Omega = Var(g(\theta_0))$. The elements of the matrix $n^{-1}\hat{\Omega} = \left(\hat{\Psi}_{rs}\right)$ are computed as $\hat{\Psi}_{rs} = n^{-1}\sum_{i=1}^{nT}\sum_{j=1}^{nT} Q_{ir}Q_{js}\hat{U}_i\hat{U}_j K(d_{ij}/d_{nT})$, with residuals $\hat{u}$ from our model as proposed by Kelejian and Prucha (2007).[13] Required 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).[14]

[12] Without knowing the structure of the variance-covariance matrix $Var(U) = (SDS^{-1})Var(\varepsilon)(SDS^{-1})^{'}$, the optimal weighting matrix, i.e., the inverse of $\Omega = Var(g(\theta_0)) = Q^{'}Var(U)Q$, 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 $Q^{*} = T^{'+}C = \left[WS^{-1}\left(X\beta_0 + KX\pi_0\right), X, KX\right]$, where $T = SDS^{-1}$ arises from the missing data structure, and $T^{'+}$ is defined as the Moore-Penrose inverse of $T^{'}$.

[13] 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.

[14] Similar to GMM, the 2SLS estimator is based on imputation of predicted estimates from the reduced-form specification $(I_{nT} - D)\, S^{-1}\left(\tilde{\lambda}\right)\left(X\tilde{\beta} + KX\tilde{\pi}\right)$, 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

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 impacts 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.[15] 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.[16] Our sample also 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

estimator.

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

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

U.S. Treasury Bill rate.[17] Table 1 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%).[18] 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 potential emergence of a 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 1. We follow its 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 the 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 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

[17] 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. Similarly, we use the U.S. Treasury Bill rate as risk-free benchmark for all markets to forgo the need of isolating risk premiums from country-specific short-term interest rates.

[18] 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 in 2010, which is only slightly below the mean excess return of the pre-crisis period.

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 1 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, while some common global risk factors are highly correlated.[19]

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

[19] 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 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.

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 (ΔCONSUMPTION)* 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 (ΔCPI)*. Commercial real estate is considered as a hedge against inflation (see, e.g., Fama and Schwert (1977)). 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 (ΔGLOBAL CONSUMPTION)* as first latent factor of a Principal Component Analysis (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 annualized three-month LIBOR rate and the annualized risk-free three-month U.S. Treasury Bill rate as TED spread. For the European area, we use the difference between the annualized three-month EURIBOR and annualized 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 or 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 the uncertainty reflected by the opacity of a private market and we interpret the transparency differentials as proxy for the potential market entry costs of a hypothetical trader who is located in one market and invests in another. A small transparency differential between two markets implies a higher perceived familiarity and consequently less information acquisition costs.[20] In order to identify and estimate learning externalities, we base our second identifying economic restriction on Blume, Brock, Durlauf, and Jayaraman (2015) and assume that the spatial linkage mechanism between private markets is known and can be specified in a weighting matrix. We impose symmetric, distance-decaying weights, i.e., we do not differentiate between the direction in the economic distance to a more opaque or a less transparent market. As previously discussed, the symmetry assumption of the weighting matrix can also be justified by the fact that a subset of risk-averse

[20]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 uncertainty. We provide a more detailed discussion of the components in Section A of the Internet Appendix. The score values range from 1.0 for highly transparent markets to 5.0, indicating opaque markets. For instance, our sample covers property markets which can be classified between "highly transparent" (scores from 1.00 to 1.70), "transparent" (ranging from 1.71 to 2.45), and "semi-transparent" (from 2.46 to 3.46). Note that despite the small numerical differences in the JLL index scores among the private markets, the differences are economically significant, even within each of these classifications.

traders from less transparent markets prefer investments in transparent markets, while 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 further assume that expected returns are lowest in most transparent markets. This can be explained by limited economic growth prospects as well as higher market liquidity, less perceived risk, and reduced risk premiums as implied by the accessibility of available information in these mature markets. Consequently, rational, risk-averse investors, who are located in opaque markets, should prefer investments in *less distant transparent* markets. Particularly, this symmetry assumption keeps the flexibility in our weighting matrix to account for institutional investors who rebalance their portfolio and reallocate funds from property investments in opaque markets to more transparent countries, which are interpreted as safe havens in crises and turmoil times.[21]

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

$$w_{kl,t} = d_{kl,t}^{-1} \; for \; k, l = 1, \dots, N, \tag{15}$$

where $d_{kl,t}$ measures the distance between the index score values of cross-sectional units k and l.[22] 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.[23] We row-

[21] For instance, Gelos and Wei (2005) find empirical evidence of this capital flight of investors from equity investments in opaque markets back to transparent markets during crisis periods.

[22] 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.

[23] 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

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

$$w^*_{kl,t} = \frac{w_{kl,t}}{\sum_l^N w_{kl,t}}. \tag{16}$$

Our proximity measure fulfills several properties. First, the weighting matrix is exogenous from the investors' perspective and independent from the explanatory driving fundamentals as suggested by Manski (1993). This assumption enables us to disentangle the effect of opacity-based trading frictions as the exogenous transmission channel from local changes in fundamental determinants, which serve as the underyling source of spillover effects. 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. As the changes in the transparency level might also affect the trading behavior of investors in the long term, the time-variation in the exogenous weighting matrix also circumvents potential endogeneity problems between transparency and the market performance. 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, the geographic proximity as a transmission channel should not capture any effect of the cross-sectional dependence.

Furthermore, we control for a broader set of economic distance measures. For in-

values.

stance, 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 for 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 the degree to which society is oriented towards ideals, such as competition, achievement, or reward for success *(MASCULINITY)*. These cultural distances also capture aspects such as higher 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)).[24]

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

[24]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 a 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.

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.

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 2 provides the estimates of our spatial models: the baseline model on country-specific fundamentals (Model I) and three 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)).[25] 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

[25] 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.

allocations of international investors, which cause excess returns 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 2 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 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.[26] However, we still find evidence of remaining dependence 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 sec-

[26]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.

tor. Particularly, a 1%-increase in consumption expenditures instantaneously rises local property market excess returns by 1.209% within one year. 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.

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.[27] 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 or real estate operating companies 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 the degree of spatial dependence is partly absorbed by the common factor. However, our results indicate that, even conditional on global funding liquidity, co-movements in private markets 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 rein-

[27] 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.

forcement 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 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 2.[28] The measures are derived

[28]We refer to LeSage and Pace (2009) for a more detailed discussion of the impact measures.

from the reduced-form specification of the model. The *average direct impact*, computed as $(nT)^{-1} trace\,(S(\lambda)^{-1} I_{nT} \beta_r)$, 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 price adjustments are mediated to a new equilibrium 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, $(nT)^{-1} \iota_{nT}' S(\lambda)^{-1} I_{nT} \beta r \iota_{nT}$, where we denote the unit vector 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 a long-term elasticity of 1.295% of direct impact in local market excess returns which results from a 1%-increase in consumption expenditures (based on GMM). Similarly, a hypothetical 1%-change of consumption expenditures in one market increases market excess returns over all other markets 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 bargaining process, investors use the revealed information during the negotiation to assess the ambiguity of potential price ranges in similarly transparent or even more opaque private markets. Hence, local property price changes are mediated across international commercial real estate markets through this externality effect. As implied by transparency differentials, we interpret the distorted trading behavior of investors, who are confronted with informational frictions, as underlying source of co-movements in property markets with similar transparency levels. The strength of how local price adjustments are cross-sectionally transmitted to other opaque markets thereby depends on the magnitude of the spatial lag, the connectivity of private markets induced by the spatial weights as well as the strength of local shocks. This simultaneous adjustment process due to the portfolio rebalancing of institutional investors lasts several rounds until a new equilibrium of the market system is reached.

To analyze the economic significance of the adjustment process, we decompose the three impact measures by the order of neighbors in Table 3. The multiplier effect should be geometrically 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 as we identify this fundamental variable as main driving factor of property market returns. We 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 a spillover effect to the adjacent private markets (W^1). Indirect and total impacts are 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 empirical support for our economic intuition that the increasing opacity level of property markets renders learning externalities, i.e., the identified information spillovers, to be predominantly transmitted across markets with a similar level of transparency. In accordance with Figure 1, positive changes in local consumption growth tend to imply positive cross-sectional dependence in clustered segmented markets and particularly intensified co-movements in opaque emerging markets with higher growth perspectives. Similarly, economic turmoil times and crisis periods, causing negative shocks on consumption growth, seem to foster negative co-movements of property markets with a similar transparency level, especially in opaque markets, which can be explained in terms of capital flight of institutional investors from these markets (see, e.g., Gelos and Wei (2005)).

[INSERT TABLE 3 HERE]

5.2 Common Systematic Risk Factors

In Table 4 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 2 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 inference (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 unique 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. These findings support our hypothesis that the cross-sectional dependence across segmented markets is not explained by global risk factors, but that the implied market co-movements are mainly driven by local shocks which are transmitted through learning externalities as proposed by our linkage mechanism. However, the 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 4 HERE]

5.3 Robustness Tests

This section provides several robustness checks. First, we compare the results of our baseline model of Table 2 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 5 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.[29] 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 and violate the identification of the spillover effects through the transmission channel (see Manski (1993)).

However, we test for geographic distance in Model V of Table 5 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 economic 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 ambi-

[29] As is evident from Table C.4 in the Internet Appendix these broader transparency measures also indicate a high correlation with the JLL transparency index.

guity in more opaque private markets. Similarly, we also find evidence of cross-sectional dependence and 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 characteristics, creating distortions in investors' capital allocation in private markets, 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 5 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. The 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 2 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 connectivity in terms of learning externalities of institutional investors who are confronted with limited transparency and strategically invest in information acquisition before their market entry. These entry costs are positively related to the transparency differential between an investors home market and a less transparent market. Local brokers reveal their knowledge by privately trading to less informed counterparties, who use the bargained transaction price as a cheap source of information to assess the perceived ambiguity, i.e., the potential price range, in similarly transparent or even more opaque 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 the exogenous 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 estimate the transmission of learning externalities across opaque asset markets. As implied by our theoretical framework, we find empirical evidence of cross-sectional 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 arising from local shocks imply also higher expected returns in another. This effect prevails even conditional on common systematic risk factors. Furthermore, local shocks, particularly growth in consumption expenditures, have a strong tendency to propagate internationally across segmented markets. We show empirical evidence of spillover effects and feedback loops between private markets.

Our results also provide general insights and important implications for institutional investors as well as policymakers. First, limited transparency causes a distorted capital allocation of investors, higher return co-movements, and might render 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. Particularly, our model suggests downward spirals in the performance of similarly opaque private markets during turmoil periods, which are mirrored in decreasing consumption patterns. 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: Summary Statistic of Property Market Excess Returns

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

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

Table 2: 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 2 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 3: 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 4: Results on Common Global Systematic Risk

This table shows regression results of international direct property excess returns on global risk factors. The MSCI world index (Global Stock ER) is used as proxy for the global market portfolio. Global consumption growth (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 investment 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 5: 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: International Property Markets Excess Returns

This figure shows the association between international property market excess returns and growth in consumption per capita of the countries where the property markets are located. We estimate a statistically significant positive linear OLS slope coefficient of 1.38 (with a standard error of 0.09). The sample is based on the Property Market Analysis (PMA) and ranges from 2001 to 2013. Following the classification of the Jones Lang LaSalle (JLL) global real estate transparency index we distinguish between "highly transparent", "transparent", and "semi-transparent" property markets. The figure suggests that positive consumption growth drives positive cross-sectional dependence in excess returns of similarly transparent private markets, while negative consumption growth implies negative cross-sectional dependence across segmented property markets with similar transparency level.

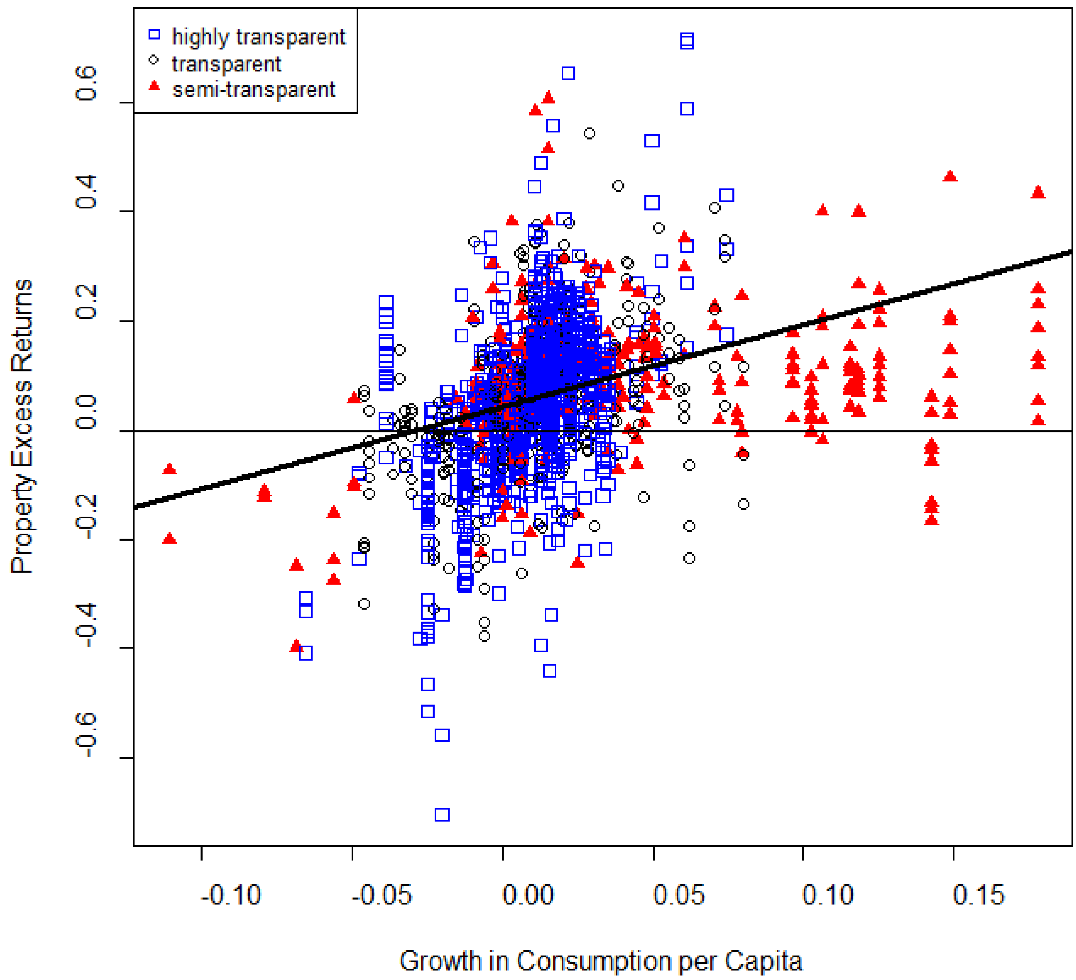

Figure 2: Transparency Differentials and Information Acquisition Costs

This figure illustrates the trade-off between market information acquisition or entry costs, $C(d)$, and adverse selection costs, τ^*. Investors enter a continuum of multiple property markets which are less transparent than their home market $d = 0$ along the transparency line of increasing transparency differnetial d. They enter these markets as long as information acquisition is less costly than adverse selection costs of trading with locally better informed brokers. Information acquisition costs $C(d)$ are positively associated with the transparency differential, d, between the home market of a hypothetical investor and a more opaque market. The continuum of entered property markets is normalized to $d \in [0, 1]$.

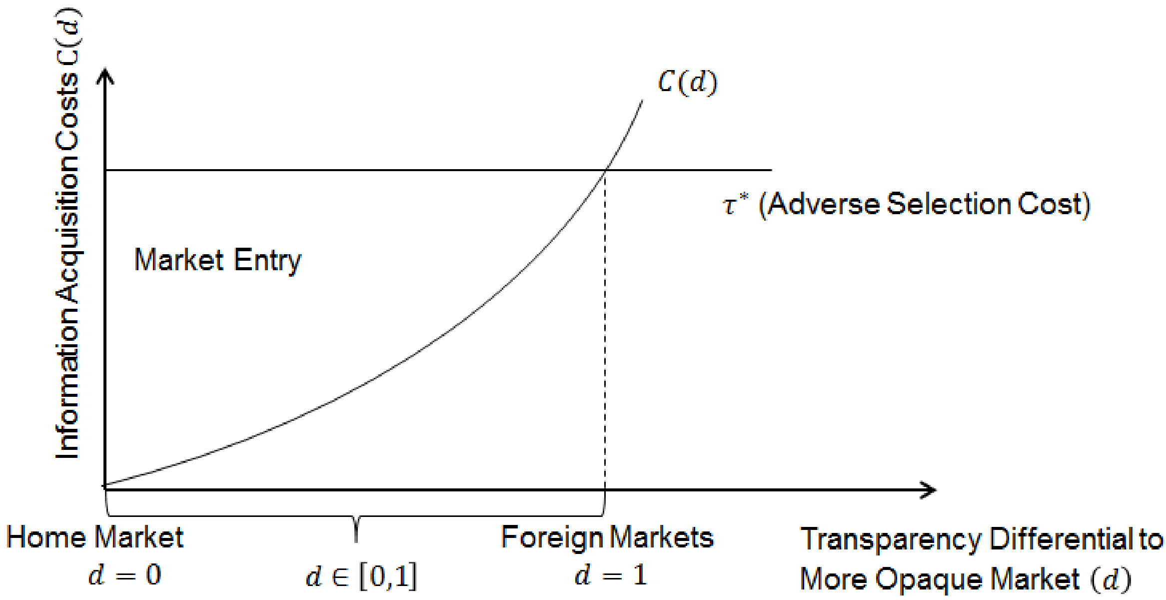

Figure 3: Spillover Effects and Feedback Loops

This figure illustrates the cascade effect of local shocks 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 local broker and the less informed foreign institutional investor, 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.