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PRE-TRADE TRANSPARENCY AND RETURN CO-MOVEMENTS IN COMMERCIAL REAL ESTATE MARKETS

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Abstract

This paper examines the effect of pre-trade transparency on return co-movements in international commercial real estate. We introduce a reference portfolio as a market's individual return benchmark. For each property market, the portfolio includes all markets with a higher pre-trade transparency. Their proximity in transparency levels imposes a learning-based linkage mechanism. A large variation in excess returns is explained by the risk exposure to the reference portfolio. Through the implied transmission channel, spillover and feedback effects arise from local shocks and lead to co-movements across real estate markets. Specifically, cultural familiarity allows investors to overcome the limited pre-trade transparency.

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

1 Introduction

In financial markets, pre-trade transparency is defined as publicly available information on price quotes and order volumes at the time a trade takes place. In commercial real estate markets, pre-trade transparency denotes the access to information on legal and regulatory restrictions, market entry and transaction costs, as well as market-specific performance measures. However, price quotes at which individual properties can be bought or sold are not observable in these over-the-counter (OTC) markets. In addition, the level of pre-trade transparency differs across international commercial real estate markets. Transparent property markets, such as London, New York, San Francisco, or Tokyo, attract international investments. In contrast, less transparent property markets involve higher information acquisition costs and therefore restrict the entry of foreign investors.[1] This limited information in property markets implies investment decisions are made under ambiguity.[2] For instance, lack of information about legal requirements, regulations, taxation, or property rights leads to ambiguity about potential rental cash flows and conceals the correct functional form of the pricing model for foreign investors. How does this limited pre-trade transparency affect the return performance of income-producing real estate markets? What are the implications of differences in pre-trade transparency levels across international commercial real estate markets?

This paper gives answers to these questions by empirically testing whether the limited pre-trade transparency and its cross-sectional differences provides a channel for return co-movements among segmented commercial real estate markets. We introduce a new concept of the global property market portfolio, which serves as the investor benchmark for expected returns in less transparent real estate markets. Each property market is ex-

[1]DTZ (2015) reports that between 2014 and 2015 global investment activity was concentrated in the major global cities of London (with an investment volume of 35 billion U.S. dollars), New York (26 billion U.S. dollars), San Francisco (23 billion U.S. dollars), and Tokyo (20 billion U.S. dollars).

[2]Ambiguity, or incalculable uncertainty in contrast to calculable risk, occurs when individuals assign probabilities from multiple prior beliefs to events or when information signals are imprecise (Epstein and Schneider (2007, 2008)).

posed to its individually perceived reference portfolio. From the perspective of a property market, which we define as the marginal market, this benchmark portfolio includes all markets with a higher pre-trade transparency. The portfolio weights are based on the transparency differentials between the less transparent marginal market and all markets included in the individual reference portfolio. Hence, transparency differentials capture the differences in the level of pre-trade transparency. Limited pre-trade information in the marginal market impedes the knowledge about the marginal market. However, investors have access to available pre-trade information in more transparent markets. Moreover, based on the reference portfolio, they assess the expected returns of comparable properties in the marginal market. Investors exploit this source of information to overcome the ambiguity that is implied by the lack of transparency.

Property markets are dominated by a small number of large market participants, such as pension funds, insurance companies, or real estate funds. Investments in transparent, global markets offer limited diversification potential and few growth perspectives. Institutional investors who search for more risk-rewarding investments enter less transparent markets as a first-mover.[3] Property markets are not anonymous because of the limited market participants. Commercial real estate transaction volumes are significant, and thus, trade and price signals can be observed by other investors. Revealed post-trade information of the first-mover investing in the marginal market attracts followers and triggers herding behavior. The higher demand increases prices and allows speculative investors to earn abnormal returns in the short term. We show empirically how the interaction between the limited pre-trade transparency and these revealed post-trade signals serves as a trigger mechanism for return co-movements and correlated price bubbles.

Investors can overcome the market entry costs that are implied by the opacity in the marginal market through several channels. First, large institutional investors benefit from economies of scale when entering the marginal market (see, e.g., Eichholtz, Koedijk, and

[3]The annual investment intention survey conducted by INREV (2016) confirms that "investors continue moving up the risk curve" rather than remain in core markets in their global real estate portfolios.

Schweitzer (2001)). Second, from anecdotal evidence we know that investors learn about the marginal market by investing indirectly in foreign real estate, using local investment vehicles, such as real estate investment trusts (REITs) or joint ventures with local partners (e.g., Colliers (2016)). We test for a third alternative: perceived familiarity, denoted as cultural and geographic proximity, serves as an additional learning-based channel between property markets. For instance, foreign investors with a similar cultural background access relevant business networks and regulatory information at lower costs. This comparative advantage improves their bargaining position against domestic market participants in less transparent markets compared to their international competitors.

To test our hypotheses, we use an exclusive dataset of property market excess returns. To the best of our knowledge, this is the most extensive cross-section of international commercial real estate markets, containing information at the city-level in 26 countries from 2001 to 2013. Our identification strategy is based on a spatial econometric model. We exploit transparency differentials between the marginal market and its more transparent benchmark portfolio as the implied transmission channel through which local macroeconomic shocks and price changes are propagated. This specification allows us to empirically test whether transparency differentials across property markets imply cross-sectional dependence and return co-movements.

First, we find empirical evidence of the connectivity between the marginal market and its more transparent reference portfolio. A large variation in excess returns in the marginal market is explained by the exposure to markets with a higher pre-trade transparency. Based on a portfolio sorting approach, we show that investors can obtain abnormal returns in opaque markets relative to the benchmark portfolio. This empirical result provides some evidence for the investors' incentive to enter less transparent markets. Second, we estimate spillover effects and feedback loops that are transmitted through the imposed linkage mechanism to show how differences in the pre-trade transparency serve as a trigger mechanism for return co-movements. Finally, as implied by our economic intuition, we identify the cultural and geographic proximity between markets as a further possible channel of the return co-movements. We interpret the observed cross-sectional dependence between markets with a similarly perceived culture in favor of our hypothesis that investors benefit from a higher familiarity to mitigate the ambiguity in less transparent property markets.

We also apply several tests to rule out alternative explanations for the cross-sectional dependence in commercial real estate markets. First, we use the government bond OTC market as a control sample to show that the return dependence is specifically related to the limited pre-trade transparency in real estate markets. We do not find a similar dependence structure within international fixed-income markets. Second, we test for potential return co-movements within transparent, mature property markets that might arise from potential diversification strategies of investors. When we do not explicitly impose restrictions derived from transparency differentials, our findings suggest a lower dependence within global markets. We conclude that the proximity in pre-trade transparency serves as a channel to learn about the marginal market and provides the main source of co-movements across markets. We exploit the financial crisis period 2007-2008 as a quasi-experiment to show that the exposure to the reference portfolio remains relatively stable between the pre- and post-crisis period. In contrast, the return dependence within global markets increased after the crisis because of investment flows into global markets considered as safe havens. Third, we show that the observed cross-sectional dependence across property markets cannot be merely explained by global systematic risk factors. The return dependence, implied by transparency differentials, remains when we control for potential co-movements among macroeconomic fundamentals.

We extend the literature in several directions: First, we contribute to the understanding of information transmission in OTC markets under limited pre-trade transparency. Several studies analyze the implication of transparency in the corporate and government bond market (e.g., Bessembinder and Maxwell (2008), Schultz (2012)). This paper sheds light on the implications of limited transparency in segmented commercial real estate markets. Second, our proposed reference portfolio is in line with theoretical predictions that arise from investors' behavior under ambiguity (e.g., Massa and Simonov (2006), Cao, Han, Hirshleifer, and Zhang (2011), Mele and Sangiorgi (2015)). Third, we also build on the literature of investment decisions under perceived familiarity and cultural distance (e.g., La Porta, de Silanes, Shleifer, and Vishny (1998), Grinblatt and Keloharju (2001), Chan, Covrig, and Ng (2005), Beugelsdijk and Frijns (2010)). For instance, foreign investors benefit from a similar cultural background to mitigate hidden market entry and information acquisition costs in international financial markets.

This paper also provides implications for institutional investors. If local risk factors dominate, investors benefit from an optimal diversification of risk in international commercial real estate. However, our findings imply that limited pre-trade transparency is related to co-movements in property market excess returns that offset potential diversification benefits. Our results are also important for financial market regulation. Our proposed linkage mechanism serves as a breeding ground for correlated price bubbles and potential instabilities across seemingly segmented property markets. The construction sector cannot dampen the emergence of demand-driven price bubbles by providing additional supply because of its short-term inelasticity. To prevent the instability of private property markets and the inherent systemic risk for the commercial real estate sector, policy regulation is required. International transparency standards in commercial property markets must be established and enforced by policymakers to reduce the amount of ambiguity in opaque property markets (see, e.g., Easley and O'Hara (2010)).

The remainder of the paper is structured as follows. Section 2 provides the institutional background and derives testable hypotheses. Section 3 presents our econometric methodology and discusses the identification assumptions. Section 4 introduces our data. Section 5 shows the empirical results. Section 6 concludes.

2 Market Transparency in Commercial Real Estate

This section describes the institutional background of international commercial real estate markets. We derive testable hypotheses on the market implications of limited pre-trade transparency.

2.1 Institutional Background

For commercial real estate, pre-trade transparency comprises the access to costly information about the legal and regulatory framework (e.g., the enforcement of property rights), transaction executions (e.g., the fairness and efficiency of the transaction process), and performance measures. Limited pre-trade transparency hinders foreign direct property investments in less transparent property markets. First, commercial real estate markets are geographically segmented due to the immobility of the asset. Consequently, foreign investors have to be familiar with the country-specific regulatory framework. The degree of pre-trade transparency and the amount of available information for investors varies across international property markets. In opaque markets, the legal restrictions are often vague and differ for foreign and domestic investors. Second, commercial real estate is privately traded. Investments in less transparent markets are related to higher information acquisition and market entry costs because uninformed investors face adverse selection costs. Foreign investors are confronted with better-informed local brokers, traders, or real estate agents. Transaction prices depend on the bargaining power of the counterparties. A lower degree of pre-trade transparency improves the bargaining position of the domestic trader. As a consequence, foreign investors might pay a markup to the domestic trader, thereby lowering expected returns.

Compared to centralized trading platforms and other OTC markets, the disclosure of post-trade information to other market participants is slower. Transaction prices are not immediately revealed. Due to the high transaction volumes of individual properties, commercial real estate markets are dominated by large institutional investors, such as hedge, pension, or real estate funds.[4] For instance, international media covered the deal of a sovereign wealth fund from Qatar in Singapore (June 2016) at a reported transaction price of 2.5 billion U.S. dollars. Competitors use the revealed trade and price information to learn about the market. However, to properly exploit the revealed post-trade signals, investors have to reduce the uncertainty from the limited pre-trade transparency that veils the efficient pricing.

The real estate specific pre-trade transparency differs from that of other OTC markets. In OTC markets, investors learn from revealed bid and offer prices about the relation between macroeconomic fundamentals and the market price.[5] Using a unique prior belief, they assign probabilities to the observed information signals. In contrast to this calculable risk, lack of information (implied by the limited pre-trade transparency in commercial real estate) is more related to ambiguity. Bid and offer prices are not publicly available in international property markets. Hence, investors cannot assign probabilities from a unique prior belief to uncertain events, but are confronted with multiple probability functions, and assess information signals only within a range of precision (see, e.g., Epstein and Schneider (2007, 2008)). For example, a foreign investor assigns the value of a heterogeneous property to a set of market-specific observable fundamentals. The exact pricing kernel is unknown because of the limited pre-trade transparency. Limited information about country-specific legal and regulatory requirements or taxation creates ambiguity about potential cash flows that can be obtained from income-producing properties. This ambiguity veils the true mapping of the state variables to the efficient price.

[4]Institutional Real Estate, Inc. reports that the two largest companies, Brookfield and Blackstone, manage 10.6 percent of the collective assets under management (AuM), while the top 10 and 20 real estate companies represent 33% and 53% of AuM, respectively (Gray (2016)).

[5]For instance, regulatory efforts enhanced the availability of quotes at which dealers are willing to trade in bond markets. In the U.S. bond market, the enforcement of pre-trade transparency has started with the implementation of the Transaction Reporting and Compliance Engine (TRACE) in 2002 (Bessembinder and Maxwell (2008)). Similar attempts have been initiated in Europe, with its latest transparency regime installment of the Markets in Financial Instruments Directive (MiFID) II in 2014.

2.2 Economic Hypotheses

As implied by the differences in the amount of available pre-trade information, investors should not perceive the same reference market to price risk. When confronted with ambiguity, investors prefer a familiar benchmark as a comparable reference portfolio (Cao, Han, Hirshleifer, and Zhang (2011)). Following this intuition, we define a global portfolio that is perceived as familiar by investors from the perspective of a local market. We define the local market as the marginal market and compute its individually perceived benchmark portfolio. This benchmark portfolio comprises all property markets with a higher pre-trade transparency level compared to the marginal market. Data vendors promote the pre-trade transparency in these global markets by collecting information on realized transaction prices for index construction. Similarly, brokers share costly knowledge of the transaction process and legal requirements with their clients. Intuitively, a larger portfolio weight is given to markets that are closer to the marginal market in terms of their pre-trade transparency. Investors who are more familiar in markets with a similar transparency level have a comparative advantage to assess the hidden information acquisition or monitoring costs on discounted cash flows. Consequently, they exploit this source of information to assess potential price ranges and expected returns in the marginal market.

Hypothesis 1. *The expected property market return in the marginal market is exposed to the return performance of an individually perceived weighted benchmark portfolio with a higher pre-trade transparency.*

The market entry of a large institutional investor as a first-mover establishes the interrelation between limited pre-trade transparency and revealed post-trade information signals, and serves as a potential trigger mechanism for co-movements and spillovers among returns. The transaction signal constitutes revealed post-trade information to competitors, who enter the marginal market with a lag. However, the limited pre-trade transparency dampens the information content of the post-trade signal. The followers, or second-movers, invest in information acquisition to overcome this ambiguity. Our intuition is in line with Mele and Sangiorgi (2015), who argue that, under ambiguity, investors have an incentive to strategically invest in information acquisition if other investors are better informed. Given the inelastic short-term supply of the construction sector, the additional demand from the followers drives up property prices. As a consequence, the first-mover can realize higher expected returns from buying properties in one period and selling them at a higher price in the subsequent one. The price information serves as a benchmark for expected returns in markets with similar pre-trade transparency levels and attracts the entry of investors in these markets. For instance, large investors can diversify their risk by investing in multiple markets. Small investors might invest within a small transparency spectrum around the marginal market according to their risk preferences. Hence, the revealed post-trade signal leads to herding of additional investors, driving up demand, and results in a cascade of return co-movements. Intuitively, the better-informed investors exploit the potential emergence of a property price bubble by strategically delaying its inevitable crash (see, e.g., Abreu and Brunnermeier (2003)).

Hypothesis 2. *The interrelation between limited pre-trade transparency and revealed post-trade information signals in the marginal market leads to a cascade of return co-movements, spillover effects, and feedback loops across markets with similar degree of post-trade transparency.*

An investor might benefit from a higher perceived familiarity to enter a marginal market as an informed first-mover. Learning-based familiarity can be acquired in several ways: First, an institutional investor can utilize economies of scale because of its size (Eichholtz, Koedijk, and Schweitzer (2001)). Large real estate companies or hedge funds can pre-test opaque markets by investing small capital amounts without having an impact on their overall performance. Second, investors can learn by investing in shares of foreign (private or public) property investments, such as real estate private equity or REITs, who exploit information advantages in their home markets. Third, cultural proximity between countries could be another potential channel for the cross-sectional dependence between property markets. Familiarity-based investment decisions are a rational response to restrictions in the amount of available information (Massa and Simonov (2006)). For instance, a larger degree of cultural familiarity might help foreign investors to contact important networks and to acquire the relevant information at lower acquisition costs in less transparent property markets. In general, cultural proximity explains the preference of international investors in specific markets (Beugelsdijk and Frijns (2010), Guiso, Sapienza, and Zingales (2009)). For instance, investors focus on countries within the same legal system (La Porta, de Silanes, Shleifer, and Vishny (1998)) or that have a common language (Grinblatt and Keloharju (2001), Chan, Covrig, and Ng (2005)). If investors benefit from a perceived cultural familiarity to enter less transparent property markets, we expect a higher return dependence between markets that are culturally more proximate.

Hypothesis 3. *A higher cultural proximity between two countries implies a larger return dependence, since investment decisions are based on the perceived familiarity to overcome the limited pre-trade transparency in international real estate markets.*

3 Econometric Framework

This section presents our spatial econometric model. We first define a pre-specified weighting matrix to capture the interconnectedness between the marginal market and the reference market portfolio. In a second step, we derive the spatial multiplier from the reduced-form specification for the estimation of local spillover effects and feedback loops. Third, we discuss the identifying economic assumptions. Finally, we describe our estimation strategy.

Our spatial regression model is specified as

$$r^e_{nt} = \lambda W_{nt} r^e_{nt} + X_{nt}\beta + \eta_n + \varepsilon_{nt}, \tag{1}$$

where r^e_{nt} is a $n \times 1$ vector of property market excess returns, pooled over all j sectors (industrial, office, and retail), and $i = 1, \ldots, M$ cities in all $k = 1, \ldots, K$ countries. The $n \times k$ matrix X_{nt} contains the set of k risk factors. We impose parameter homogeneity, $\beta_{ij} = \beta, \forall\, i, j$, because of the limited data availability in international commercial real estate markets. The estimates of the parameter vector β can be interpreted as population average effects.[6] We include fixed effects (η_n with $n = ij$ for city i and property sector j) to control for time-invariant, individual-specific effects that might be correlated with explanatory variables.[7] The spatial lag parameter λ measures the exposure of the expected returns r^e_{nt} of the marginal markets to its individually perceived reference market portfolio $W_{nt}r^e_{nt}$.

Specification of Weighting Matrix. We model the interconnectedness of the marginal market to its individually perceived reference portfolio in the time-varying weighting matrix W_{nt}. This benchmark portfolio is defined as the weighted average of all property markets with a higher pre-trade transparency compared to the marginal market. Intuitively, international investors exploit the available information about the return performance from markets with a higher pre-trade transparency to assess the expected returns in the marginal market. The exposure of the marginal market to each market in the reference portfolio results in an over-parametrization. We therefore impose economic restrictions in the weighting matrix to reduce the dimensionality to the single spatial lag parameter λ. These restrictions are captured in the time-varying weights $\omega_{kl,t}$ of the weighting matrix W_{nt} and are based on the transparency differential between the marginal market k and each property market l in the portfolio. Furthermore, we use the transparency differentials as the pre-specified linkage mechanism in our identification strategy to empirically test the implied transmission channel for spillover and feedback effects across commercial real estate markets.

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

[7] We follow the Mundlak (1978) correlated random effects approach to simplify the estimation of the spatial lag model with fixed effects using an unbalanced panel. Therefore, we specify an auxiliary regression term $\eta_{ij} = \bar{x}_{ij}\xi + \alpha_{ij}$ with time averages $\bar{x}_{ij}$ of the explanatory variables. Based on the conditional expectation, $E\left(\varepsilon_{ij} = \alpha_{ij} + e_{ij} \mid x_i\right) = 0$, the random effect α_{ij} is uncorrelated with the regressors.

We follow a two-step approach to construct the weighting matrix. For each time period t we first build a contiguity matrix with $\omega_{kl,t} = 1$ for each global market l that contains a higher pre-trade transparency compared to the marginal market k and zero otherwise.[8] Less transparent markets than the marginal markets are not included in the reference portfolio. Intuitively, investors are confronted with higher uncertainty in these markets and, therefore, cannot use them as an additional source of information for the marginal market.

In a second step, we calculate the inverse of the transparency differential, i.e.,

$$w_{kl,t} = d_{kl,t}^{-1} \; for \; k, l = 1, \ldots, N, \tag{2}$$

between the marginal market k and each global market l for each element $w_{kl,t} = 1$ of the contiguity matrix.[9] A smaller transparency differential to the marginal market implies a larger weight of the more transparent market in the reference portfolio. Diagonals of the weighting matrix are restricted to zero. We also normalize the rows of the weighting matrix to a unit sum. Each element is defined as

$$w_{kl,t}^{*} = \frac{w_{kl,t}}{\sum^{N} w_{kl,t}}. \tag{3}$$

Spillover Effects and Feedback Loops. We derive a reduced-form specification from our econometric model to estimate the magnitude of spillover effects and feedback loops across international property markets. The reduced-form

$$r_{nt}^{e} = \left(I_n - \lambda W_{nt}\right)^{-1} \left(X_{nt}\beta + \eta_n + \varepsilon_{nt}\right), \tag{4}$$

[8]The contiguity matrix with binary weights, which take either the value of zero or one, constitutes an equally-weighted benchmark portfolio that is individually perceived for the marginal market.

[9]The transparency level is aggregated at the country level, but property markets are available at the city-level. We normalize the transparency differential between two cities within a country with identical transparency levels to the smallest possible distance in period t, such that $d_{k',l',t} < min(d_{kl,t})$ for markets $k^{'}, l^{'}$ that are located in the same country. We justify this by the geographic proximity as a proxy for potential information advantages (e.g., Coval and Moskowitz (2001), Garmaise and Moskowitz (2004)).

represents the steady-state equilibrium specification. Local shocks and changes in the macroeconomic fundamentals are transmitted through the spatial multiplier

$$S(\lambda)^{-1} = (I_n - \lambda W_{nt})^{-1} \approx I_n + \lambda W_{nt} + \lambda^2 W_{nt}^2 + \lambda^3 W_{nt}^3 + \ldots + \lambda^q W_{nt}^q. \tag{5}$$

Given the interconnectedness between local markets, as implied by the weighting matrix, shocks originating in one location first spill over to directly linked markets (first-order W), then transmit to the markets that are linked to these markets (second-order W^2), including feedback loops, and so forth. Hence, the magnitude of spillovers on local markets is geometrically decreasing. The strength of how local price adjustments are transmitted to other markets depends on the magnitude of the spatial lag parameter λ, the connectivity of private markets implied by the transparency differentials, and the strength of local shocks. Driven by the underlying portfolio rebalancing of international investors, the simultaneous adjustment process lasts several rounds until a new equilibrium across property markets is reached.

To summarize the spillover effects and feedback loops, we compute three different measures: the average direct, the average total, and the average indirect effect (LeSage and Pace (2009)). The *average direct effect* is computed as $(nT)^{-1} \sum_i^{nT} \frac{\partial r_i^e}{\partial X_{is}} = (nT)^{-1} trace\,(S(\lambda)^{-1} I_{nT} \beta_s)$ and measures the effect of parameter β_s for $s = 1, \ldots, k$, on its own local property market, taking into account spillovers and feedback loops. The spatial lag multiplier amplifies local shocks in macroeconomic fundamentals through which price adjustments are mediated to a new equilibrium. The *average total effect* measures the average impact of a unit change of the explanatory variable in the marginal market on all other markets. We calculate the total effect as the average of the row sum of the reduced-form, $(nT)^{-1} \sum_{ij}^{nT} \frac{\partial r_i^e}{\partial X_{js}} = (nT)^{-1} \iota_{nT}' S(\lambda)^{-1} I_{nT} \beta_s \iota_{nT}$, where we denote the unit vector as ι_{nT}. This measure can also be interpreted as a local market change caused by a hypothetical unit change in all other private markets. The *average indirect effect* on the local market from the other markets is measured as the difference between the average total and direct impact, i.e., $(nT)^{-1}\sum_{i\neq h}^{nT}\frac{\partial r_i^e}{\partial X_{hs}} = (nT)^{-1}[\iota_{nT}' S(\lambda)^{-1} I_{nT}\beta_s \iota_{nT} - trace\,(S(\lambda)^{-1} I_{nT}\beta_s)]$ and reflects the pure spillover effect.

Identification. In the following, we discuss the identification assumptions. Our model specification resembles a CAPM-type global market portfolio. However, the CAPM-implied portfolio reflects a common factor for all markets and does not provide information about the underlying source of spatial dependence. In our model, the spatial weights are defined by economic restrictions to explicitly test the implied economic transmission channel. The weights impose the linkage mechanism through which local shocks are transmitted across markets. We therefore follow Blume, Brock, Durlauf, and Jayaraman (2015) and assume *a priori* knowledge about the structure of the transmission channel. The parameters are identified because of the underlying reduced-form specification as implied linkage mechanism (e.g., Pinske and Slade (2010), Gibbons and Overman (2012)). $W_{nt}r_{nt}^e$ does not merely serve as an estimate for the weighted average, as implied by an unspecified CAPM-based market portfolio. The transmission channel explicitly arises from the conditional expectation of the reduced-form specification $E(r_{nt}^e|X_{nt}) = (I_n - \lambda W_{nt})^{-1}[X_{nt}\beta + \eta_n]$ with the spatial lag multiplier as the intended explanatory variable.

The weighting matrix W_{nt} fulfills the exogeneity assumption for the identification (Manski (1993)). We allow for time-varying spatial weights to capture the changes in the pre-trade transparency level within each country. At an annual frequency, the transparency adjustment is too sluggish to be endogenously driven by the trading activity of investors. Hence, the time-varying weighting matrix mitigates the potential reverse causality from the return performance to the pre-trade transparency. Furthermore, the imposed transparency differentials are unrelated to the performance of macroeconomic fundamentals. This allows us to disentangle the economic transmission channel of spillover effects from local macroeconomic shocks as their potential source. We follow our economic intuition to justify our model specification. The spatial multiplier effect through which local shocks are transmitted arises from the endogenous spatial lag $W_{nt}r_{nt}^e$. Investors exploit the available pre-trade transparency to learn from observed price signals in markets with higher pre-trade transparency and use the benchmark portfolio as a reference for expected returns in the less transparent marginal market. The portfolio weights are based on transparency differentials between markets through which post-trade information signals are transmitted. Investors learn from observable price information and trading activity in more transparent markets about the pricing kernel, i.e., the functional form between future cash flows of income-producing properties and macroeconomic fundamentals, in the marginal market. Based on this justification, we impose an exclusion restriction of the exogenous spatial lag $W_{nt}X_{nt}$. This exclusion restriction allows us to use the reduced-form $S(\lambda)^{-1}X_{nt}$ as instrument for $W_{nt}r^e_{nt}$.

The specification of our model leads to the potential reflection problem (Manski (1993)). The cross-sectional dependence of property market excess returns r^e_{nt} could merely reflect the correlation of observed or unobserved, explanatory variables in the matrix X_{nt}. As a robustness test, we attempt to resolve this identification problem by adding common factors that capture the potential correlation from the explanatory variables. Particularly, we choose common factors that are correlated with the explanatory variables and therefore remove some of the cross-sectional dependence in X_{nt}. This strategy is valid since the strong-form dependence that is implied by the common factor absorbs the weak-form spatial dependence (see, e.g., Pesaran and Tosetti (2011), Sarafidis and Wansbeek (2012)). Conditional on these common factors, we mitigate the spatial correlation in $W_{nt}X_{nt}$ that dominantly comes from the explanatory variables. The prevailing variation mainly arises from the differences in the pre-trade transparency in the weighting matrix that is unrelated to the exogenous regressors. We exploit this source of variation in our instrument to identify the endogenous spatial lag. Furthermore, we reduce the potential risk of correlated unobserved variables by including additional common global factors at different aggregation levels in the model to isolate the endogenous dependence from spatially unobserved variables.

Estimation. The estimates are based on a generalized method of moments (GMM) estimator to avoid the endogeneity between the spatial lag $W_{nt}r^e_{nt}$ and the vector of error terms. We follow Wang and Lee (2013a,b) who propose a GMM estimator for spatial models with randomly missing values of the endogenous variable. Missing dependent variables are replaced by predicted values based on the covariates and spatially correlated endogenous variables. This imputation strategy is empirically valid under the missing at random (MAR) assumption (Rubin (1976)). Real estate performance data is systematically missing in less transparent markets. To satisfy the MAR condition, we assume that conditional on explanatory variables, particularly on the level of pre-trade transparency, the probability of observing missing observations is unrelated to the underlying value of the unobserved endogenous variable. As a robustness check, we also apply the 2SLS and the NLS estimator, as proposed by Wang and Lee (2013b), to rule out that the observed dependence structure is driven by the imputation strategy. GMM and 2SLS are based on the imputation of predicted values. The NLS estimator uses only observed values of the dependent variable.[10] As suggested by Kelejian and Prucha (2007), we compute heteroscedasticity and autocorrelation consistent (HAC) standard errors.[11]

4 Market Returns and Pre-Trade Transparency

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

[10]We compare the three estimators in Appendix A of the Internet Appendix.

[11]Standard errors, as proposed by Driscoll and Kraay (1998), would be more appropriate to be fully robust against cross-sectional dependence. However, the limited time dimension of our panel and the poor finite sample properties of their variance-covariance matrix prevent us from applying them.

[12]Table B.1 of Appendix B in the Internet Appendix shows the market coverage of our sample. Table C.1 of Appendix C provides an overview of the construction of the data in our sample.

U.S., Europe, and Asia-Pacific (DTZ (2015)). We also have emerging market data for Asian and Eastern European countries, including the likes of China, South Korea, the Czech Republic and Hungary.

Market Returns. We use nominal total returns as a proxy for capital appreciation and net cash flows earned by investors.[13] We measure total returns in local currency to avoid the contamination of returns with potential common exchange rate movements. Excess returns are calculated relative to the risk-free rate. We use the annualized three-month U.S. Treasury Bill rate as the risk-free benchmark for all markets to abstain from isolating the risk premiums from country-specific short-term interest rates. For a similar reason, we use the three-month Treasury Bill instead of long-term government bonds as the risk-free rate, because bond yields are not risk-adjusted. Table 1 provides a descriptive summary of the country-specific private market excess returns, calculated as average returns over all cities and sectors for each country. Mean excess returns vary from 15.6% (Hong Kong), 11.8% (South Korea), and 9.8% (China) to -3.9% (Greece), and -9.5% (Ireland). Property market volatility is highest in Ireland with a standard deviation of 23.6%, followed by Hong Kong (21.4%), Singapore (20.7%), and Japan (18.7%).

[INSERT TABLE 1 HERE]

Figure 1 illustrates the variation of the average commercial real estate market performance over time. Unsurprisingly, private markets follow a systematic downward trend in the aftermath of the recent financial crisis. This pattern is in line with studies, such as Levitin and Wachter (2013) and Duca and Ling (2015), who find empirical evidence of a commercial real estate bubble burst that subsequently followed the turmoil in the U.S. real estate housing market. We also observe a recovery of the return performance in 2010 that is only slightly below the mean excess return of the pre-crisis period. The overall

[13] To mitigate the potential measurement problems of the return proxy, we allow for an error ν_{ijt} in sector $j = 1, \ldots, J$ for city $i = 1, \ldots, M$ at time t, defined as the difference between the true, unobservable return y'_{ijt} and its observed proxy $y_{ijt} = y'_{ijt} + \nu_{ijt}$. We assume that the measurement error and the explanatory variables are uncorrelated in our sample and capture ν_{ijt} in the residuals of the regression model.

low standard deviations are in line with the observed sustained growth in property prices over the sample period, except during the crisis years.

[INSERT FIGURE 1 HERE]

Pre-Trade Transparency. The level of pre-trade market transparency, as proxied by the Jones Lang LaSalle (JLL) transparency index in 2012, is provided in column 7 of Table 1. The index captures the degree of available information on performance measures, market fundamentals, financial disclosures, legal frameworks, as well as fairness and efficiency of the transaction process in international commercial real estate markets.[14] The score values range from 1.0 (for the most transparent markets) to 5.0 (for opaque markets). Based on the transparency scores, we distinguish between markets with pre-trade transparency that is "high" (scores from 1.00 to 1.70), "medium" (from 1.71 to 2.45), and "low" (from 2.46 to 3.46).[15] Despite the small numerical differences in the scores among the markets, they are economically significant. Although the index values are updated every two years, they have been relatively stable in most countries. The transparency level has increased in Eastern European markets, such as in the Czech Republic, Hungary, and Poland. Italy and Portugal have also improved from a low to a medium transparent market. In 2012, China, Greece, and South Korea are the only markets in our sample with a low transparency level. Fully opaque markets provide only insufficient or no market information. Due to this limited data availability, in particular on market performance, these markets cannot be included in our sample.

5 Empirical Results

In this section, we show that the exposure to the reference portfolio explains a large portion of the cross-sectional dependence among property markets. We also provide evidence of

[14] We list the components in Appendix D of the Internet Appendix.

[15] We follow the JLL classification that distinguishes between the categories "highly transparent", "transparent", and "semi-transparent".

abnormal returns in opaque markets. Further, we estimate spillover effects and feedback loops to illustrate the emergence of co-movements. Finally, we demonstrate that a higher perceived familiarity as a potential transmission channel between markets implies return co-movements.

5.1 Risk Exposure to the Benchmark Portfolio

We first provide evidence of the risk exposure of the marginal market to its individually perceived reference portfolio. This portfolio includes all property markets with a higher pre-trade transparency compared to this marginal market. We use the corresponding specification of the weighting matrix to test whether the return dependence is related to the learning behavior of investors. They exploit the available pre-trade information in more transparent markets to overcome the limited pre-trade transparency in marginal markets. Table 2 compares the results between the model with country-specific fundamentals (Model I) and the model including a spatial lag parameter (Model II). Models III to V present the spatial lag model with additional control variables as robustness tests.[16] We use fixed effects in each model to capture the heterogeneous, time-invariant components that affect excess returns. The spatial lag coefficient λ is statistically significant (0.660 in Model II). A large portion of the return performance over time can be explained by this risk exposure of the marginal market to its global reference portfolio. We observe an adjusted R^2 of 37.1% compared to 25.8%, when we regress excess returns on country-specific fundamentals without spatial lag (Model I). The spatial lag significantly reduces the value of the Pesaran (2004) CD test statistic of unexplained residual dependence.

The weighting matrix of our baseline model represents a weighted reference portfolio with larger portfolio weights for markets with a smaller transparency differential to the marginal market. When we compare this model to a specification based on an equally-

[16]The estimation of the models is based on GMM. For robustness, we re-estimate the models based on 2SLS and NLS in Table E.1 of Appendix E in the Internet Appendix. These estimators use alternative imputation strategies for the missing values. However, the estimated coefficients are comparable.

weighted portfolio, including more transparent markets, we find a lower explanatory power and a higher unexplained residual dependence for the latter weighting scheme.[17] Our finding suggests that small transparency differentials serve as a potential source of the dependence structure in property markets. We relate this channel to an information advantage of investors who specialize in less transparent markets in the portfolio and, therefore, have superior knowledge or trained skills in information acquisition in the marginal market compared to their competitors.

[INSERT TABLE 2 HERE]

We include macroeconomic risk factors that reflect the opportunity cost of capital in the asset market and influence the local market conditions on the underlying cash flow of the property investment.[18] We borrow them mainly from the previous literature (e.g., Chen, Roll, and Ross (1986)). The signs of the coefficients confirm our economic intuition. Property excess returns are positively correlated with stock market returns relative to the annualized three-month U.S. Treasury Bill rate. Investors require a higher risk premium for holding income-producing properties if the opportunity costs of capital increase. Discounted expected cash flows from property investments are driven by household consumption growth. For instance, a consumption growth increases the demand for commercial real estate, such as shopping centers or warehouses. Higher consumption is also reflected in additional industrial and office space required by the employment sector. For instance, a 1%-increase in consumption expenditure instantaneously raises local property market excess returns by 1.32% annually. We also find a positive effect of expected inflation, providing evidence that commercial real estate serves as a hedge against inflation (e.g., Fama and Schwert (1977)). The positive effect of the term spread on private markets can be explained by two channels: First, investors demand a risk premium

[17] See Table E.2 of Appendix E in the Internet Appendix.

[18] We discuss their construction in Table C.1 of Appendix C in the Internet Appendix. Table E.3 of Appendix E shows the correlation matrix of the fundamentals. All variables are determined in nominal local currency values. We apply the Im, Pesaran, and Shin (2003) panel unit root test for stationarity, that is robust against cross-sectional dependence and the unbalanced panel structure.

as compensation for higher refinancing costs and lower expected payoffs from discounted future rental cash flows. Second, a higher term spread is reflected in an increasing risk aversion of investors about the future economic performance and translates into higher expected returns.

The results are robust when we control for confounding factors that jointly affect the property excess returns r^e_{nt} and the weighted average portfolio $W_{nt}r^e_{nt}$. Model III of Table 2 controls for funding liquidity risk. The commercial real estate boom has been accompanied by an expansion of the securitization industry, providing funding liquidity through pooled mortgage loans sold as commercial mortgage-backed securities (CMBS) in the credit market (Levitin and Wachter (2013)). Dry-outs in funding liquidity negatively affect the performance of commercial real estate, as observed in the aftermath of the recent financial crisis (Brunnermeier (2009)). For instance, a higher credit risk, implied by a larger spread between the CMBS yield relative to the long-term government bond, decreases the amount of debt-financed capital inflows to the real estate sector. We also control for equity-based funding liquidity provided by publicly traded real estate vehicles, such as REITs (Bond and Chang (2012)). Therefore, we use excess returns on REIT shares that are positively related with private market excess returns. The spatial lag parameter (0.654) is similar to the spatial lag model (Model II). We conclude that the underlying source of cross-sectional dependence is not driven by a systemic liquidity risk component. In Models IV and V, we add the construction sector and commercial real estate investment inflows as controls, respectively.[19] The degree of dependence is around 0.705% when we capture the capital value component that is related to the supply of the construction sector. We also find that a 1%-increase in construction reduces the expected return by 0.35%. Investment inflows are positively related to expected returns. The confounding factor partially absorbs the source of cross-sectional dependence. The estimated spatial lag parameter decreases from 0.660 (Model II) to 0.375 (Model V). We

[19]Due to data limitations, we use aggregated investment inflows to the U.S., Asia-Pacific, and Western, Central, and Eastern Europe.

interpret this reduction in the magnitude as empirical evidence of international investment flows as the underlying source of the cross-sectional dependence across property markets. We conduct further robustness tests in the Internet Appendix.[20]

5.2 Abnormal Returns in Opaque Markets

We also test for return opportunities in opaque markets relative to the benchmark portfolio. Empirical evidence of abnormal returns in less transparent markets suggests that investors have an incentive for market entry as a first-mover. Based on the transparency level, we sort markets into the three groups that are ranked "high", "medium", and "low" to show that abnormal returns can be obtained in opaque markets. We regress excess returns on its reference market portfolio, dummy coefficients for the transparency level (high, medium, and low), and their interaction terms with the portfolio. The model specification empirically replicates the portfolio sorting approach and is conceptually similar to a time series regression of cross-sectional average excess returns for each group on a set of risk factors (Hoechle, Schmid, and Zimmermann (2015)).[21]

Model I in Table 3 shows the risk-adjusted performance of each group, estimated by the corresponding dummy variable. Investors can earn an abnormal excess return of 3.9% on income producing properties in opaque markets. In contrast, abnormal returns in the high and medium ranked transparency groups are statistically insignificant. The estimated intercepts of Models II to IV separately replicate the abnormal returns for each sorted group. In Model V, we show the performance difference between the sorted groups

[20] Table E.4 of Appendix E in the Internet Appendix tests for sector-specific heterogeneity. Compared to the retail sector (with a spatial lag of 0.633), we find a higher degree of dependence for the office sector (0.706), which is more attractive for international investors. The magnitude is smaller in the more local, owner-occupied industrial sector (0.563). In Table E.5, we re-estimate the model with country-specific average excess returns. We show that the dependence structure prevails across countries and is not merely driven by the geographic proximity between markets within a country.

[21] Given the limited time dimension of our panel, we do not estimate time series regressions. For this reason, we also do not follow the suggested Driscoll and Kraay (1998) approach for statistical inference. Their standard errors are fully robust against cross-sectional dependence, but they suffer from a poor finite sample performance. We use clustered standard errors to mitigate the cross-sectional dependence within the sorted groups.

with the lowest and the highest transparency level (Low minus High). The risk-adjusted performance in opaque markets is 3.3% higher than what investors can earn in transparent markets.[22]

[INSERT TABLE 3 HERE]

5.3 Spillover Effects and Feedback Loops

The estimated coefficients presented in Table 2 can only be interpreted as an immediate local market price effect of changes in the explanatory variables. They do not capture the dependence structure that arises from the linkage between the marginal market and its benchmark portfolio. Therefore, we compute the average direct, the average indirect, and the average total effect of each risk factor in Table 4. Compared to the immediate expected return elasticity of 1.318%, resulting from a 1%-increase in consumption expenditures, we estimate an average direct effect of 1.38%. We interpret the immediate impact as a change in fundamentals that is incorporated into property prices during the bargaining process of the first-mover and the subsequent herding behavior of investors. They are attracted by the post-trade information from the first-mover and affect the market price. The magnitude of the average direct effect of the explanatory variables is larger than their immediate effect because of subsequent feedback loops from other markets. For instance, local shocks in the marginal market indirectly affect property prices in more opaque markets. From the perspective of these markets, the marginal market is included in their reference portfolio. Competitive investors use the revealed post-trade information to adjust the expected return of their benchmark portfolio. This adjustment triggers a cascade of investors entering less transparent markets in expectation of higher expected returns. However, price movements in the marginal market can also lead to market entry

[22]The outperformance of the opaque market is not a specific result of the individually perceived reference portfolio. In Table E.6 of Appendix E in the Internet Appendix we find a performance difference of 3.9% between opaque and transparent markets, when we use a market size based value-weighted global portfolio.

in more transparent markets. Intuitively, this can be explained by different types of investors. For instance, large institutional investors diversify their portfolio. Attracted by the revealed signal from the first-mover, they can invest in markets within a spectrum of pre-trade transparency around the level of the marginal market. Small investors can invest according to their risk preference. Risk-seeking investors consider markets that are more opaque than the marginal market. More risk-averse investors or investors who cannot bear the information acquisition costs prefer markets with a marginally higher pre-trade transparency level. In both cases, the market entry forces feedback loops to the marginal market as both effects reinforce each other. We interpret the empirically observed average indirect impact of 2.5% as a pure spillover effect from the marginal market to other markets. The sum of the average direct and the average indirect effect equals 3.88% and can be interpreted as the average total impact on all markets that arise from a 1%-change of consumption expenditures in the marginal market.

[INSERT TABLE 4 HERE]

To illustrate how these spillover effects and feedback loops lead to co-movements, we partition all three effects (average direct, average indirect, and average total effect) by the order of their neighbors in Figure 2. The concept of neighbors, as implied by the weighting matrix, is defined in terms of the linkage between two markets. For instance, all markets with a higher pre-trade transparency are first-order neighbors of the marginal market. More transparent markets that are connected via spatial weights to these markets are defined as second-order neighbors of the marginal market, their neighbors are defined as third-order neighbors, and so forth. Conceptually, the marginal market is a second-order neighbor to itself, as local shocks can be transmitted and reinforced through the feedback loops.

All three effects of a local shock arising in the marginal market are geometrically decaying by the order of its neighbors. This transmission of shocks is implied by the spatial multiplier and leads to co-movements across property markets. Due to the geometric decay, the co-movements are predominantly across markets of low-order neighbors. We show the partitioning for a change in local consumption expenditures, since this is the main explanatory variable of expected property market returns. For instance, the direct effect reflects the immediate (or first-round) impact of a shock on the local market price (W^0). Intuitively, this immediate effect with the estimated direct effect of 1.318% can be interpreted as the impact of a first-mover and the subsequent herding behavior. There is no spillover effect and the total effect equals the direct effect. The revealed post-trade information leads to an indirect spillover effect to its direct neighbors (W^1) with magnitude of 0.870 and equals the total effect. The estimated spillover effect can be explained by investors who invest in markets with a similar pre-trade transparency. Via the first-order neighbors, the local shock has also a total effect of 0.575 on markets that are linked to them (W^2) because of the portfolio re-adjustment of investors. The total effect can be decomposed into a spillover effect (0.542) and a direct effect of 0.033 to the marginal market because of feedback loops. When the local shock reaches neighbors of order 4, 80.86% of the indirect effect or pure spillover effect, an accumulated magnitude of 2.024 out of 2.503, is explained. Economically, a 1%-change in local consumption expenditure increases the average excess return in markets up to order 4 by 2.024%. Similarly, the accumulated magnitude, reaching neighbors of order 4, explains 87.41% of the total effect (3.394 out of 3.883). Co-movements are higher across low-order neighbors compared to markets that are neighbors of a higher order.

[INSERT FIGURE 2 HERE]

5.4 Return Co-Movements based on Familiarity

Subsection 5.1 shows the exposure of local property markets to their perceived reference portfolio with a higher pre-trade transparency and provides empirical evidence of abnormal returns in opaque markets. In Subsection 5.3, we show how spillover effects and feedback loops lead to return co-movements. In this section, we test whether a higher familiarity between two countries is related to the observed cross-sectional dependence. For instance, a higher perceived familiarity serves as a possible source that might help investors overcome the limited pre-trade transparency. We use economic distance measures as proxies for the familiarity between two countries. The selected measures are highly correlated with the level of transparency in property markets.[23]

We first test for cultural distance. Investors who are more familiar with the culture in less transparent markets might benefit from their experience or have an advantage to invest in relevant business relations, thereby reducing the information acquisition costs. In Models I to VI of Table 5, we use cross-sectional differentials in the Hofstede index as elements of the weighting matrix. We consider country-specific differences in how individuals perceive uncertainty (*Ambiguity Aversion*), the extent to which society accepts unequally distributed power (*Power Distance*), or prefers individual responsibility in favor of collectivism (*Individualism*). Countries with a higher degree of uncertainty avoidance share a more complex and developed legal system, while similarities in the Arabic, Spanish, and Asian languages are reflected in a lower degree of individualism and a higher power distance (Tang and Koveos (2008)). We also compare societies in their orientation towards ideals that are considered as masculine attributes, such as competition, personal achievements, or rewards for success (*Masculinity*), and test for similar consideration of the future (*Long-Term Orientation*) and strict norms (*Indulgence*). The magnitudes of the spatial lag parameters are comparable to the results in Table 2 or even slightly higher when we test for the proximity in the degree of individualism and indulgence between societies as a potential channel for return co-movements in international commercial real estate.

In Model VII we test for the geographic distance as a possible explanation for the observed return dependence between nearby located markets (see, e.g., Coval and Moskowitz

[23] We explain their construction in Table C.1 of Appendix C of the Internet Appendix. Table E.7 in Appendix E depicts the Spearman rank correlation coefficient (top triangle) and the Bravais Pearson correlation coefficients (bottom triangle).

(2001), Garmaise and Moskowitz (2004), Seasholes and Zhu (2010)). The estimated spatial lag of 0.499 is smaller compared to the other specifications. Geographic distance might proxy information advantages at a national level, but internationally, the cultural familiarity seems to be a more intuitive source of information for investors who aim at investing in less transparent markets. Our finding is also supported by the results in Models VIII and IX, where we explicitly test for the connectivity of property markets related to their proximity in the level of corruption (*Corruption Perception*) and economic freedom (*Economic Freedom*), reflecting investors' general uncertainty in terms of property rights, political stability, and investment freedom. We find estimated spatial lag parameters of 0.535 and 0.658, respectively. The magnitudes are in line with our intuition.

[INSERT TABLE 5 HERE]

5.5 Alternative Explanations

In this section, we address several robustness tests to rule out alternative explanations for the cross-sectional dependence in international commercial real estate markets.

Comparison with Government Bond Markets. We use government bond OTC markets as a control sample to test whether the empirically observed return comovements across markets are specifically related to the pre-trade transparency in commercial real estate. In Table 6, we regress country-specific government bond yields on its reference portfolio and on macroeconomic fundamentals (e.g., Diebold, Piazzesi, and Rudebusch (2005); Ludvigson and Ng (2009)). The weighting matrix imposes the linkage between the marginal market and the more transparent benchmark portfolio based on transparency differentials as weights. As proxy for the ex-ante transparency, we use indices that are highly correlated with the real estate market specific transparency index, but are aggregated at the country level. We use the Corruption Perception Index (correlation of -81% with the transparency index), and the EIU Country Risk (correlation of 66%), which is composed of currency risk, banking risk, and sovereign risk. For both measures, the estimated spatial lag coefficient is economically and statistically insignificant for bond yields (Panel A). When we re-estimate the model specifications based on country-specific property market excess returns (Panel B), we find statistically significant spatial lag coefficients with similar magnitude (0.644 for the Corruption Perception Index and 0.591 for the Country Risk) to the results in Table 2.

We hypothesize that the diverse results between both OTC markets is related to their different pre-trade transparency. In bond markets, closing prices are collected in trading platforms and brokers provide quotes at which they are willing to trade on this pre-trade information. Beginning with the Trade Reporting and Compliance Engine (TRACE) in 2002 in the U.S., the degree of pre-trade transparency has increased in bond markets (see, e.g., Schultz (2012)). Hence, investors learn about information signals by updating a unique prior belief from available bid and offer prices. In commercial real estate markets, information about price offers is proprietary and privately bargained. To improve their bargaining position, investors have to learn about the country-specific legal and regulatory framework that affects the return on income-producing properties. The limited pre-trade transparency makes the underlying pricing kernel more ambiguous, allowing for potential price ranges and multiple likelihood functions that make the interpretation of information signals more challenging. The learning channel from markets with higher pre-trade transparency generates the cross-sectional dependence. Market participants derive a reference value from the revealed post-trade information in less opaque markets and benefit from their experience to acquire information advantages at lower costs.

[INSERT TABLE 6 HERE]

Global Markets as Safe Havens. Table 7 compares the co-movements within the global markets (Model I) to the cross-sectional dependence implied by the linkage of the marginal market to its reference portfolio (Model II). The weighting matrix in Model I connects all highly and medium transparent markets in two separate global market segments.[24] The weighting matrix is flexible enough to reflect the potential diversification strategies of investors, but does not depend on transparency differentials. The degree of dependence (the spatial lag coefficient of 0.345 in column 1) might be related to co-movements in global markets that arise from the preference of risk-averse investors to invest in the most transparent global markets with less perceived ambiguity. However, the magnitude is smaller than the spatial lag of 0.660 in Table 2. The results support a stronger linkage mechanism from our learning-based transmission channel. Comparing the adjusted R^2 and the Pesaran CD test, we conclude that potential co-movements within global commercial real estate markets only explain a small portion of the cross-sectional dependence.

We use the financial crisis period 2007-2008 as a quasi-natural experimental shock to test for changes in the dependence structure during the aftermath of the crisis. We split the sample into a pre-financial crisis (2002-2006) and a post-financial crisis period (2009-2013).[25] We compare the results of Model I (columns 2 and 3) with the baseline specification (Model II) where the weighting matrix captures the interconnectedness between the marginal market and the perceived reference portfolio (columns 4 and 5). For robustness, we contrast them to the OLS specification (Model III) without taking into account the dependence structure (columns 6 and 7). If our economic intuition is true and the dependence is mainly driven by transparency differentials between the marginal market and the reference portfolio, we expect that the degree of dependence should be the same in both periods for Model II. Intuitively, the learning-based transmission channel to the marginal market should be unaffected by the crisis period. In contrast, the dependence within global markets might be higher in the post-crisis period because of the potential flight to quality of international investors who consider more transparent,

[24]We compute two equally-weighted portfolios that are obtained from the row-normalization of the weighting matrix with binary weights w_{ij} equal to one if the pre-trade transparency of the markets i and j are either both classified as "high" (scores from 1.00 to 1.70) or "medium" (from 1.71 to 2.45).

[25]We exclude the crisis period 2007-2008. We also remove the year 2001 from the sample to avoid a potential contamination of the results from the dot-com bubble burst.

global markets as a safe haven.[26] The findings are in line with our intuition. We find no evidence of a significant dependence in Model I before the financial crisis period (column 2). This result implies that investors can use global markets for risk diversification as the high pre-trade transparency and the available information allows them to enter these markets easily. However, we find a statistically significant spatial lag after the crisis period (column 3), which might be related to a potential flight to quality of investors to global and medium transparent markets during times of turmoil. When we compare the results to Model II (columns 4 and 5), we find a significant spatial lag in both sub-samples with a slightly smaller degree of dependence in the post-crisis period.

[INSERT TABLE 7 HERE]

Common Systematic Risk Factors. We also address the reflection problem (Manski (1993)) that might arise from the correlation among macroeconomic fundamentals. To mitigate this problem, we include additional common factors whose strong-form dependence absorbs the weak-form dependence among the explanatory variable. In Model I of Table 8, we control for the weighted average of national GDP, the TED spread, and the effective exchange rate. We choose these variables because of their economic relation to the macroeconomic fundamentals in our baseline model. The globally-weighted GDP average also serves as a common factor that controls for a global commercial real estate trend (e.g., Case, Goetzmann, and Rouwenhorst (1999)). The GMM estimator uses the reduced-form specification $S(\lambda)^{-1}X$ in the vector of instruments to compute the spatial lag coefficient. Exploiting the remaining variation that arises from the transparency differentials slightly reduces the spatial lag to 0.523. When we explicitly control for the variation of $W_{nt}X_{nt}$ and remove most of the variation in the instrumental variable, the spatial lag decreases to 0.326 and 0.396, respectively. Model II uses average values of the explanatory variables as proxies. Model III includes the first latent factor of the principal

[26] Gelos and Wei (2005) find a similar effect of capital flight from equity investments in opaque markets back to more transparent safe havens during crisis periods.

component analysis for each regressor. A combination of year dummies and fixed effects (Model IV) approximates a common factor representation that, by construction, sweeps away the cross-sectional dependence without explaining its underlying source (Sarafidis and Wansbeek (2012)).

We also compare our baseline model to a standard CAPM specification (Model V), where we use the IPD global market portfolio with weights based on the market capitalization. This model reflects only a common factor representation without explicitly modeling the underlying transmission channel of the dependence structure. Compared to the baseline model (Model II in Table 2), the CAPM-type specification has a lower adjusted R^2 (0.347) and a higher unexplained residual dependence as indicated by the Pesaran CD test (12.122).

[INSERT TABLE 8 HERE]

In Table E.8 of Appendix E in the Internet Appendix we rule out additional global systematic risk factors as the main source of return co-movements across commercial real estate. Compared to the results in Table 2, a large portion of the cross-sectional correlation remains unexplained in the error term. We compare different models where we control for common real exchange rate effects, since the global risk factors are denominated in U.S. dollars. We use clustered-robust standard errors to ensure a robust inference (Petersen (2009)). Private market excess returns are positively correlated with the global stock market portfolio. However, the explanatory power (adjusted R^2 of 8.5%) is low. The explanatory power is even lower (6.4%), when we use global consumption growth as a common risk factor. We also test for the impact of the TED spread as a proxy for global credit risk and the three-month Eurodollar rate to capture investors' expectation about the future global economy (see, e.g., Bekaert and Harvey (1995)). Credit risk has a negative impact on the commercial real estate market performance. An increase in the Eurodollar rate is reflected in higher expected returns. The common factor model has a very low explanatory power of 7.7%. However, the variation in private market excess returns can partly be explained by real estate specific funding liquidity, proxied by excess returns on U.S. REITs and the spread in CMBS yields. The adjusted R^2 increases to 25.2%. Additionally accounting for global investment inflows in the real estate sector improves the adjusted R^2 to 31.6%. We control for these variables in Table 2 to disentangle their impact from the effect of pre-trade transparency.

6 Conclusion

This paper provides empirical evidence of cross-sectional dependence and implied co-movements across international commercial real estate markets. We relate these co-movements to cross-sectional differences in the level of pre-trade transparency. Due to limited pre-trade transparency, international investors are confronted with high market entry as well as information acquisition costs, and face investment decisions under ambiguity. We propose a global benchmark portfolio that contains property markets with a higher pre-trade transparency as the individually perceived reference to assess the expected returns in the less transparent marginal market. We impose transparency differentials, i.e. differences in the level of pre-trade transparency, between the marginal market and each market with a higher transparency level being part of the reference portfolio. In so doing, we explicitly test this linkage mechanism as the underlying transmission channel through which local shocks are transmitted across property markets. Implicitly, investors who focus on less transparent markets in the benchmark portfolio have an information advantage to mitigate the information acquisition and market entry costs in the marginal market.

We find a positive and statistically significant exposure of the marginal market to its individually perceived reference portfolio. For instance, higher expected returns in the reference portfolio imply higher expected returns in the marginal market. We also show that investors can earn abnormal returns in less transparent markets based on this reference portfolio. Our result implies that investors can strategically exploit the first-mover advantage in opaque markets. From the reduced-form specification and the implied spatial lag multiplier of our model, we show empirical evidence of spillover effects and feedback loops across property markets that are transmitted through our identified transparency based transmission channel. This effect prevails even when conditional on common systematic risk factors. We also show that the cultural proximity as perceived by investors serves as a potential source to overcome the limited pre-trade transparency in less transparent markets.

Our results also provide general insights and important implications for institutional investors and policymakers. First, limited pre-trade transparency distorts investors' capital allocation and leads to higher return co-movements across markets. It thus might render risk diversification strategies obsolete. Second, we identify market opacity as a source of potential instability in commercial real estate markets. This trading friction serves as an intuitive explanation for the emergence of multiple price bubbles that might, in the event of a crash, culminate in transmission across international commercial real estate markets. Particularly, our model suggests downward spirals in the performance of similarly opaque private markets during turmoil periods. To prevent either these bubbles or the transmission of shocks that originate locally but spread systemically, the establishment of international transparency standards is required. The enforcement of such standards helps to prevent concentrated investment behavior and the emergence of potential property price bubbles. It reduces trading frictions, market entry costs, and 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 the descriptive summary of country-specific market excess returns for the 26 countries in our sample. For each country, we calculate the excess return as the average over all three sectors (industrial, office, and retail) and all cities based on the market coverage. We compute the mean and standard deviation over an annual time series from 2001 to 2013. Minimum and maximum indicate the lowest and the highest performance during this time period. The total number of observations in column 6 illustrates the market coverage for each country. Column 7 indicates the transparency level (and the corresponding score) as published by Jones Lang LaSalle (JLL) in 2012. The transparency index is updated every two years. Property markets are ranked between "highly transparent" (scores from 1.00 to 1.70), "transparent" (from 1.71 to 2.45), and "semi-transparent" (from 2.46 to 3.46).

Country	**Mean**	**Std.Dev.**	**Min.**	**Max.**	**Obs.**	**JLL Transparency**
Australia	0.081	0.125	-0.275	0.605	104	Highly Transparent (1.36)
Austria	0.042	0.080	-0.121	0.299	26	Transparent (2.22)
Belgium	0.039	0.064	-0.112	0.215	52	Transparent (2.07)
China	0.098	0.115	-0.170	0.432	68	Semi-Transparent (2.83)
Czech Republic	0.064	0.096	-0.170	0.432	39	Transparent (2.34)
Denmark	0.038	0.115	-0.237	0.312	39	Transparent (1.86)
Finland	0.024	0.074	-0.135	0.117	13	Highly Transparent (1.57)
France	0.061	0.088	-0.301	0.247	156	Highly Transparent (1.57)
Germany	0.035	0.069	-0.204	0.236	221	Transparent (1.80)
Greece	-0.039	0.152	-0.400	0.268	26	Semi-Transparent (2.84)
Hong Kong	0.156	0.214	-0.396	0.693	39	Transparent (1.76)
Hungary	0.038	0.122	-0.278	0.265	39	Semi-Transparent (2.53)
Ireland	-0.095	0.236	-0.704	0.399	39	Transparent (1.96)
Italy	0.033	0.083	-0.255	0.285	91	Transparent (2.16)
Japan	0.058	0.187	-0.377	0.566	73	Transparent (2.39)
Netherlands	0.037	0.065	-0.141	0.286	65	Highly Transparent (1.38)
Norway	0.072	0.176	-0.263	0.273	13	Transparent (2.08)
Poland	0.084	0.110	-0.235	0.319	39	Transparent (2.11)
Portugal	-0.004	0.077	-0.175	0.136	39	Semi-Transparent (2.54)
Singapore	0.055	0.207	-0.382	0.677	35	Transparent (1.85)
South Korea	0.118	0.098	-0.158	0.304	23	Semi-Transparent (2.96)
Spain	0.026	0.131	-0.330	0.358	91	Transparent (2.06)
Sweden	0.038	0.115	-0.234	0.204	39	Highly Transparent (1.66)
Switzerland	0.027	0.124	-0.144	0.261	13	Highly Transparent (1.67)
UK	0.043	0.115	-0.288	0.351	182	Highly Transparent (1.33)
USA	0.058	0.125	-0.516	0.457	416	Highly Transparent (1.26)

Table 2: Spatial Lag Models based on Pre-Trade Transparency

This table shows the results of the spatial lag model. We regress property market excess returns on the reference portfolio (Spatial Lag) and country-specific fundamentals. The reference portfolio includes all markets with a higher pre-trade transparency. The weights are based on their transparency differential to the marginal market. We use the JLL Transparency Index as a proxy for the pre-trade transparency. Model I represents the baseline model without spatial lag. Model II shows the baseline model with spatial lag. Models III to V control for funding liquidity, construction, and investment flows, respectively. The spatial lag parameter measures the degree of spatial dependence. Stock ER reflects excess returns on the national stock market portfolio. Personal consumption expenditure (ΔConsumption) is measured per capita. Changes in the consumer price index (ΔCPI) proxy expected inflation. The Term Spread measures the difference between long-term government bond yields and short-term interbank rates. REIT ER denotes excess returns on publicly traded REIT shares. 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 stock supply (Construction) and Investment are used to control for market-specific characteristics. Model I is based on the within-estimator, using cluster-robust standard errors. Models II to V are based on the Mundlak (1978) model specification using GMM. 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 parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Model I	**Model II**	**Model III**	**Model IV**	**Model V**
	Country-Specific Fundamentals	**Spatial Lag Model**	**Conditional on Funding Liquidity**	**Conditional on Construction**	**Conditional on Investments**
Spatial Lag		0.660***	0.654***	0.705***	0.375**
		(0.060)	(0.066)	(0.079)	(0.142)
Stock ER	0.153***	0.062***	0.063***	0.0567***	0.057**
	(0.015)	(0.014)	(0.015)	(0.021)	(0.021)
ΔConsumption	2.503***	1.318***	1.288***	1.414***	1.440***
	(0.184)	(0.187)	(0.189)	(0.317)	(0.316)
ΔCPI	1.068***	0.577**	0.471*	0.351	0.252
	(0.308)	(0.236)	(0.244)	(0.349)	(0.348)
Term Spread	0.664***	0.302*	0.181	0.381	0.180
	(0.209)	(0.155)	(0.163)	(0.288)	(0.290)
REIT ER			0.003		
			(0.004)		
U.S. CMBS Spread			0.018**		
			(0.007)		
Construction				-0.352***	
				(0.152)	
Investment					0.081***
					(0.024)
Observations	1980	2041	2041	880	880
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Pesaran CD	50.57***	2.99***	2.54**	-0.36	0.64
Adj.-R^2	0.258	0.371	0.385	0.471	0.486

Table 3: Abnormal Returns

This table shows the abnormal returns of sorted portfolios using pooled OLS regressions as proposed by Hoechle, Schmid, and Zimmermann (2015). The sorted portfolios are based on the JLL transparency index. Property markets are grouped as "High" (for scores from 1.00 to 1.70), "Medium" (from 1.71 to 2.45), and "Low" (from 2.46 to 3.46). To replicate the abnormal excess returns we regress property market excess returns on the reference portfolio (Spatial Lag), dummy variables for the sorted transparency levels (High, Medium, Low), and their interaction with the global market excess return. The dummy variables in Model I (Pooled) measure the performance of the sorted portfolios. The reference portfolio includes all markets with a higher pre-trade transparency. The weights are based on their transparency differential to the marginal market. We use the JLL Transparency Index as a proxy for the pre-trade transparency. The intercepts in Models II to IV (High, Medium, Low) replicate the risk-adjusted performance for each portfolio separately. The dummy variable (Low) in Model V (Low-High) measures the performance difference between the sorted portfolio of opaque markets and grouped markets with high pre-trade transparency. The unbalanced panel pools the three sectors (industrial, office, and retail), and all cities in 26 countries over the years 2001 to 2013. Clustered-robust standard errors are given in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Model I	**Model II**	**Model III**	**Model IV**	**Model V**
	Pooled	**High**	**Medium**	**Low**	**Low-High**
Constant		0.006	0.004	0.039***	0.006
		(0.006)	(0.006)	(0.015)	(0.006)
High	0.006				
	(0.006)				
Medium	0.004				
	(0.008)				
Low	0.039**				0.033**
	(0.015)				(0.017)
Spatial Lag		0.684***	0.874***	0.710***	0.684***
		(0.060)	(0.095)	(0.130)	(0.060)
Spatial Lag × High	0.684***				
	(0.060)				
Spatial Lag × Medium	0.874***				
	(0.095)				
Spatial Lag × Low	0.710***				0.027
	(0.134)				(0.149)
Observations	1732	1033	430	245	1278
Adj.-R^2	0.221	0.230	0.295	0.252	0.216

Table 4: Spillover Effects and Feedback Loops

This table shows the average direct, total, and indirect effect of shocks in explanatory variables from the reduced-form specification of the following models: We regress property excess returns on the reference portfolio (Spatial Lag) and country-specific fundamentals. Models II to IV control for funding liquidity, construction, and investment flows, respectively. The reference portfolio includes all markets with a higher pre-trade transparency. The weights are based on their transparency differential to the marginal market. We use the JLL Transparency Index as a proxy for the pre-trade transparency. The three measures are based on LeSage and Pace (2009): The *average direct impact* is computed as $(nT)^{-1}\sum_{i}^{nT}\frac{\partial r_i^e}{\partial X_{is}} = (nT)^{-1} trace\left(S(\lambda)^{-1}I_{nT}\beta_s\right)$ and measures the effect of parameter β_s for $s = 1, \ldots, k$, on its own local property market taking into account spillovers and feedback loops. The *average total impact* measures the average effect of a unit change of the explanatory variable in the marginal market on all other markets. The total effect is calculated as the average of the row sums of the reduced-form, $(nT)^{-1}\sum_{ij}^{nT}\frac{\partial r_i^e}{\partial X_{js}} = (nT)^{-1}\iota_{nT}^{'}S(\lambda)^{-1}I_{nT}\beta_s\iota_{nT}$, where we denote the unit vector as ι_{nT}. The *average indirect effect* captures the pure spillover effect from the local market on all other markets and is defined as the difference between the average total and direct impact, i.e., $(nT)^{-1}\sum_{i\neq h}^{nT}\frac{\partial r_i^e}{\partial X_{hs}} = (nT)^{-1}[\iota_{nT}^{'}S(\lambda)^{-1}I_{nT}\beta_s\iota_{nT} - trace\left(S(\lambda)^{-1}I_{nT}\beta_s\right)]$. The corresponding standard errors are based on simulations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Model I	**Model II**	**Model III**	**Model IV**
Average Direct Impact				
Stock ER	0.063	0.065	0.072	0.046
ΔConsumption	1.380***	1.338***	1.519***	1.444***
ΔCPI	0.608***	0.494***	0.373	0.239
Term Spread	0.313	0.191**	0.404	0.190
REIT ER		-0.007		
U.S. CMBS Spread		0.019		
Construction			-0.379	
Investment				0.087
Average Total Impact				
Stock ER	0.158	0.193	0.230	0.073
ΔConsumption	3.883***	3.748***	4.817***	2.279***
ΔCPI	1.708***	1.357***	1.184	0.377
Term Spread	0.890*	0.527**	1.280	0.299
REIT ER		0.029		
U.S. CMBS Spread		0.026		
Construction			-1.202	
Investment				0.138
Average Indirect Impact				
Stock ER	0.096	0.128	0.157	0.027
ΔConsumption	2.503***	2.410***	3.298***	0.835***
ΔCPI	1.100**	0.863***	0.811	0.138
Term Spread	0.577	0.336	0.876	0.110
REIT ER		0.036		
U.S. CMBS Spread		0.008		
Construction			-0.823	
Investment				0.051

Table 5: Spatial Lag Model based on Cultural Proximity

This table provides regression results of the spatial lag model using different weighting matrices. Spatial weights are based on the inverse economic distance. The weighting matrices in Models I to VI reflect the differences in the Hofstede Cultural Sub-Indices. We use the geographic Haversine distance in Model VII. The weighting matrices of Models VIII and IX are based on the Corruption Perception Index and the Index of Economic Freedom, respectively. Excess returns are regressed on the spatial lag and macroeconomic fundamentals. The spatial lag parameter 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 expenditure (ΔConsumption) is measured per capita. Changes in the consumer price index (ΔCPI) proxy expected inflation. The Term Spread measures the difference between long-term government bond yields and short-term interbank rates. Estimates are based on GMM using the Mundlak (1978) specification. 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 parentheses. ***, **, and * indicate statistical significance at the 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	Ambiguity Aversion	Power Distance	Individualism	Masculinity	Long-Term Orientation	Indulgence	Geographic Distance	Corruption Perception	Economic Freedom
Spatial Lag	0.604***	0.622***	0.758***	0.642***	0.656***	0.804***	0.449***	0.535***	0.658***
	(0.113)	(0.148)	(0.103)	(0.125)	(0.137)	(0.070)	(0.153)	(0.088)	(0.090)
Stock ER	0.072***	0.062**	0.039**	0.062***	0.063***	0.037**	0.088***	0.079***	0.060***
	(0.022)	(0.024)	(0.019)	(0.022)	(0.024)	(0.015)	(0.023)	(0.017)	(0.017)
ΔConsumption	1.051***	1.192***	0.887***	1.305***	1.042***	0.762***	1.713***	1.502***	1.090***
	(0.282)	(0.330)	(0.305)	(0.287)	(0.324)	(0.214)	(0.334)	(0.230)	(0.243)
ΔCPI	0.742**	0.419	0.063	0.455*	0.465*	0.323	0.619**	0.703***	0.418*
	(0.293)	(0.263)	(0.225)	(0.256)	(0.242)	(0.227)	(0.256)	(0.251)	(0.227)
Term Spread	0.257*	0.219	0.163	0.231	0.125	0.232	0.351*	0.486***	0.284*
	(0.156)	(0.163)	(0.158)	(0.151)	(0.150)	(0.152)	(0.180)	(0.159)	(0.154)
Observations	2041	2041	2041	2041	2041	2041	2041	2041	2041
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pesaran CD	5.23**	5.52***	0.98	4.02***	4.32***	0.32	15.32***	6.67***	3.22
Adj.-R^2	0.364	0.382	0.411	0.391	0.389	0.428	0.354	0.347	0.392

Table 6: Comparison with Government Bond Markets

This table compares the government bond OTC and the commercial real estate markets. In Panel A, we estimate the spatial lag model for government bond yields. In Panel B we replicate the model for property market excess returns based on country-specific average values. The reference portfolio (Spatial Lag) includes all markets with a higher pre-trade transparency. The weights are based on their transparency differential to the marginal market. We use the Corruption Perception and the EIU Country Risk Index as a proxy for the country-specific pre-trade transparency, respectively. The spatial lag measures the degree of spatial dependence. Stock ER reflects excess returns on the national market portfolio. Personal consumption expenditure (ΔConsumption) is measured per capita. Changes in the consumer price index (ΔCPI) proxy expected inflation. The Term Spread measures the difference between long-term government bond yields and short-term interbank rates. Estimates are based on GMM using the Mundlak (1978) specification. HAC-robust standard errors are given in parentheses. ***, **, and * indicate statistical significance at the 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: Government Bond Yields		
	Corruption	**Country Risk**
Spatial Lag	-0.024	-0.094
	(0.079)	(0.132)
Stock ER	-0.009***	-0.010***
	(0.003)	(0.003)
ΔConsumption	-0.154**	-0.156**
	(0.065)	(0.066)
ΔCPI	-0.138*	-0.145*
	(0.079)	(0.080)
Term Spread	-0.050	-0.049
	(0.102)	(0.103)
Observations	338	338
Fixed Effects	Yes	Yes
Pesaran CD	22.12***	22.95***
Adj.-R^2	0.530	0.524
Panel B: Commercial Real Estate		
	Corruption	**Country Risk**
Spatial Lag	0.644***	0.591***
	(0.020)	(0.113)
Stock ER	0.064**	0.066**
	(0.028)	(0.028)
ΔConsumption	1.548***	1.524***
	(0.311)	(0.320)
ΔCPI	0.231	0.193
	(0.499)	(0.457)
Term Spread	0.382	0.225
	(0.279)	(0.281)
Observations	338	338
Fixed Effects	Yes	Yes
Pesaran CD	-1.54	-1.40
Adj.-R^2	0.439	0.403

Table 7: Global Property Markets as Safe Havens

This table extends the results of the baseline model in Table 2. The weighting matrix in Model I separately connects all global markets that are defined as "Highly" (JLL scores from 1.00 to 1.70) and "Medium" transparent (scores from 1.71 to 2.45) with an equal portfolio weighting. Model II is based on the reference portfolio that includes all markets with a higher pre-trade transparency and portfolio weights based on the transparency differential to the marginal market. Models I and II are compared to a baseline model specification without spatial lag (Model III). We split the sample into a Pre-Crisis and Post-Crisis period. The Pre-Crisis Period ranges from 2002 to 2006 (excluding the year 2001 to mitigate potential effects of the dot-com bubble burst). The Post-Crisis Period ranges from 2009 to 2013. The spatial lag parameter measures the degree of spatial dependence. Stock ER reflects excess returns on the national market portfolio. Personal consumption expenditure (ΔConsumption) is measured per capita. Changes in the consumer price index (ΔCPI) proxy expected inflation. The Term Spread measures the difference between long-term government bond yields and short-term interbank rates. Models I and II are based on GMM using the Mundlak (1978) specification. Model III is based on the within-estimator with clustered-robust standard errors. HAC-robust standard errors are given in parentheses for Models I and II. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Model I			Model II		Model III	
	Full Sample	**Pre-Crisis Period**	**Post-Crisis Period**	**Pre-Crisis Period**	**Post-Crisis Period**	**Pre-Crisis Period**	**Post-Crisis Period**
Spatial Lag	0.345***	-0.0360	0.468***	0.924***	0.716***		
	(0.056)	(0.088)	(0.086)	(0.156)	(0.092)		
Stock ER	0.118***	0.158***	0.041*	0.009	0.047**	0.144***	0.037
	(0.013)	(0.024)	(0.023)	(0.034)	(0.024)	(0.021)	(0.026)
ΔConsumption	2.177***	0.435	2.434***	0.203	1.574***	0.633	2.932***
	(0.183)	(0.552)	(0.294)	(0.429)	(0.304)	(0.629)	(0.314)
ΔCPI	0.864***	2.123***	0.774**	1.158*	0.169	1.371*	1.370***
	(0.254)	(0.639)	(0.379)	(0.627)	(0.367)	(0.702)	(0.421)
Term Spread	0.566***	-0.596*	-0.064	0.209	-0.210	-0.774*	0.131
	(0.158)	(0.350)	(0.448)	(0.286)	(0.432)	(0.441)	(0.530)
Observations	2041	785	942	785	942	740	785
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pesaran CD	23.77***	9.49***	9.29***	2.30**	-0.43	-	35.03***
Adj.-R^2	0.301	0.194	0.341	0.348	0.423	0.115	0.222

Table 8: Spatial Lag Model Conditional on Common Systematic Risk

This table replicates the results of the baseline spatial lag model conditional on common systematic risk factors. The reference portfolio (Spatial Lag) includes all markets with a higher pre-trade transparency. The weights are based on their transparency differential to the marginal market. We use the JLL Transparency Index as a proxy for the pre-trade transparency. Stock ER reflects excess returns on the national market portfolio. Personal consumption expenditure (ΔConsumption) is measured per capita. Changes in the consumer price index (ΔCPI) proxy expected inflation. The Term Spread measures the difference between long-term government bond yields and short-term interbank rates. Global CRE ER represents the IPD global property market portfolio with portfolio weights based on market capitalization. ΔGDP Average captures the cross-sectional average of country-specific GDP. The TED Spread is the difference between the annualized three-month LIBOR rate and the corresponding three-month U.S. Treasury Bill rate. ΔXR Effective reflects changes in the national currency relative to a basket of other currencies. $\overline{\Delta X_{nt}}$ represents additional cross-sectional averages of the macroeconomic fundamentals. We also include the first latent factor from a principal component analysis for each explanatory variable (PCA X Factors). Estimators are based on GMM using the Mundlak (1978) representation. The Pesaran (2004) CD test shows t-statistics of the null hypothesis of residual independence. The panel pools 26 countries from 2001 to 2013. Estimates are based on GMM. HAC-robust standard errors are given in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Model I	**Model II**	**Model III**	**Model IV**	**Model V**
Spatial Lag	0.523***	0.326**	0.396**	0.084	
	(0.108)	(0.163)	(0.165)	(0.299)	
Global CRE ER					0.810***
					(0.066)
Stock ER	0.074***	0.059***	0.068***	0.056***	0.100***
	(0.017)	(0.019)	(0.020)	(0.019)	(0.016)
ΔConsumption	1.321***	1.430***	1.529***	1.538***	1.440***
	(0.192)	(0.208)	(0.222)	(0.212)	(0.162)
ΔCPI	0.419*	0.530*	0.483*	0.303	0.302
	(0.251)	(0.272)	(0.262)	(0.292)	(0.288)
Term Spread	0.416**	0.273	0.398**	0.344*	0.157
	(0.165)	(0.179)	(0.184)	(0.185)	(0.192)
ΔGDP Average	0.565*				
	(0.288)				
TED Spread	-0.370				
	(0.419)				
ΔXR Effective	-0.226***				
	(0.068)				
Observations	1980	1980	1980	1980	1980
$\overline{\Delta X_{nt}}$	No	Yes	No	No	No
PCA X Factors	No	No	Yes	No	No
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Dummies	No	No	No	Yes	No
Pesaran CD	6.163***	15.393***	15.282***	2.295**	12.122***
Adj.-R^2	0.384	0.379	0.365	0.390	0.347

Figure 1: Illustration of Time-Varying Effects

This figure illustrates the systematic variation of property market excess returns from 2001 to 2013. For each year, we compute the average of the property market excess returns from all sectors and cities. The sample is based on the PMA market coverage. We show a systematic downward trend in all private markets in the aftermath of the recent financial crisis 2007/2008. The markets recover in 2010, providing returns that are only slightly below the average excess return of the pre-crisis period.

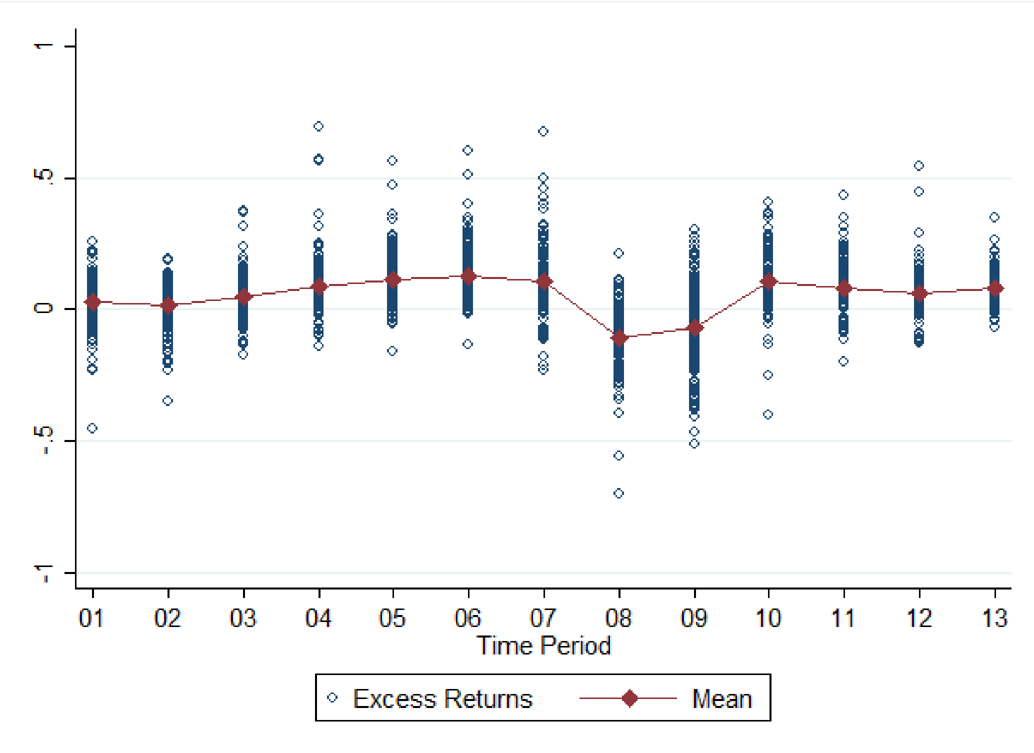

Figure 2: Spatial Partitioning

This figure illustrates the magnitude of the average total effect for neighbors of different orders based on a shock in personal consumption expenditures. We decompose the average total effect into the average direct and the average indirect (pure spillover) effect for higher order neighbors. The three measures are based on LeSage and Pace (2009): The *average direct effect* is computed as $(nT)^{-1}\sum_{i}^{nT}\frac{\partial r_i^e}{\partial X_{is}} = (nT)^{-1} trace\left(S(\lambda)^{-1} I_{nT}\beta_s\right)$ and measures the effect of a %-change in personal consumption expenditures on its own local property market taking into account spillovers and feedback loops. The *average total effect* measures the average effect of a %-change in consumption expenditures in the marginal market on all other markets. The total effect is calculated as the average of the row sums of the reduced-form, $(nT)^{-1}\sum_{ij}^{nT}\frac{\partial r_i^e}{\partial X_{js}} = (nT)^{-1}\iota_{nT}^{'} S(\lambda)^{-1} I_{nT}\beta_s \iota_{nT}$, where we denote the unit vector as ι_{nT}. The *average indirect effect* captures the pure spillover effect and is defined as the difference between the average total and direct impact, i.e., $(nT)^{-1}\sum_{i\neq h}^{nT}\frac{\partial r_i^e}{\partial X_{hs}} = (nT)^{-1}[\iota_{nT}^{'} S(\lambda)^{-1} I_{nT}\beta_s \iota_{nT} - trace\left(S(\lambda)^{-1} I_{nT}\beta_s\right)]$. Neighbors of order 1 (W1) are all markets that are directly linked to the shock-originating marginal market. Neighbors of order 2 (W2) are markets that are linked to these markets, and so on. Therefore, each market is its neighbor's neighbor.