Information Asymmetries and Learning in Commercial Real Estate Markets

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Abstract

This paper empirically tests information asymmetries and learning in global commercial real estate markets. We find that foreign investors pay a premium of 3.7%, on average, relative to local investors for comparable properties in local markets. The premiums reflect information disadvantages of foreign investors, which are not correlated with the hiring of agents, anchoring to prices in their home market and selection bias. We show that learning from prior acquisition experience significantly reduces information disadvantages of foreign investors. Foreign investors could offset their initial disadvantages relative to the first-time local investors after four acquisition experiences in local markets. Quality of learning through more distant past acquisitions, acquisitions of real estate of the same type and in the same city could also reduce information asymmetries of foreign investors. Foreign investors learn to pick out the counterparties of same-nationality to reduce the information asymmetry. Also, language proximity, other than geographic and economic proximity facilitates foreign investors' learning effect in cross-border transactions. In follow-on investments, we find that foreign corporate investors are learning about the locations.

Keywords: Learning, Information Asymmetry, Foreign Investors, Commercial Real Estate Markets, Cross-border Investments

JEL Code: D82, F21, G15, R30

1 Introduction

Information asymmetry between investors, especially foreign versus domestic investors, has been extensively debated among economists. The predominant argument is that domestic investors possess information advantage over their foreign counterparts due to domestic investors' geographical proximity to local markets and their familiarities with local language, culture, economic condition, and social network (Brennan and Cao, 1997; Coval and Moskowitz, 1999; Choe et al., 2005; Dvořák, 2005; Agarwal et al., 2009; Van Nieuwerburgh and Veldkamp, 2009). Asserting a different view, the information-based literature, however, argues that foreign investors with better market knowledge outperform local investors (Grinblatt and Keloharju, 2000; Seasholes, 2000; Cohen et al., 2002; Froot and Ramadorai, 2008). While the information literature abounds, few studies have examined the dynamics in information asymmetry and the associated economic effects.

The existing literature implicitly assumes that information asymmetry between foreign and local investors is time-invariant. For instance, Portes and Rey (2005), Coval and Moskowitz (2001), and Baik et al. (2010) consider the distance as a valid measure of information asymmetry between informed and uninformed investors. Choe et al. (2005), Dvořák (2005), Van Nieuwerburgh and Veldkamp (2009), Andrade and Chhaochharia (2010), and Chinco and Mayer (2015) suggest national boundary and/or investor ownership destination (country) as measures of the information asymmetries between local and non-local investors. In real estate market, Garmaise and Moskowitz (2003) employ the quality of property tax assessment as an exogenous measure of asymmetric information. Kurlat and Stroebel (2015) argue that the information asymmetry between sellers and buyers in the housing market depends on characteristics of both the neighborhood and the housing characteristics.

While allowing for cross-sectional variations in the distances between asset markets and investors, the existing literature invariably assumes that the distance measures remain constant across time. In this regard, the information asymmetry across investors is time-invariant when distance between properties and investors proxies for the information. Besides, once the ownership comparison (e.g., local vs non-local, and seller vs buyer) is given, then the information asymmetry follows and remains constant until the ownership changes. However, an investor's information about a market should be dynamic other than constant, especially when the investors are able to learn the market. It makes less sense assuming a frequent investor's information regarding a market would be the same as a first-time investor's information. In other words, the less informed investors could increase his/her information with transaction experience and even become the informed ones.

Subsequently, it is puzzling to think that investors continue to ignore information disadvantages and pay premiums for assets in foreign markets. We believe that learning is a dynamic process, where investors' market knowledge and information is an accumulation of past acquisition experiences in local markets, and learning could be magnified through acquisitions of the same asset classes and the assets within a district. The dynamic learning from past experience is consistent with the information immobility hypothesis of Van Nieuwerburgh and Veldkamp (2009), which argues that investors have selected preference for learning in the home market.

This paper aims to answer three questions: (1). Do foreign investors pay higher prices than local investors for comparable assets? (2). Do foreign investors learn to reduce the price premiums? (3). What foreign investors are learning about?

We obtain a comprehensive dataset comprising commercial real estate transactions by institutional investors from an established commercial data source to test the effects of dynamic "learning" (both time-dependent and quality-dependent) in the global commercial real estate markets. There are three key features of the dataset. First, it contains a large sample of cross-border and domestic commercial real estate transactions with detailed information on investors and properties, which enable us to match the transactions to investors' details and their past real estate transaction activities. The matched dataset could be used to track investors' cumulative acquisition experience and hence quantify investors' learning effecr. More important, the data enables us to identify the learning quality and the learning mechanism by taking a closer look at the property type, property location and investor type. Second, the long time-series of the database spanning over 15 years from 2001 to 2015 allow us to test the dynamic learning process of investors. Third, the wide coverage of commercial real estate transactions across 5,000 cities in 146 countries worldwide makes it possible for us to separate the effects of national boundaries from information asymmetries, which remains one limitations in many early studies that focuses only in a single real estate market (Garmaise and Moskowitz, 2003; Lambson et al., 2004; Kurlat and Stroebel, 2015; Chinco and Mayer, 2015)[1].

We begin the analysis by showing that foreign investors pay a price premium of 3.7%, on average, relative to local investors after controlling for those observable characteristics of investors, properties, countries, and a rich set of fixed effects. Further, we show that the price premium cannot be explained by the "Agent" effect, "Anchoring" effect, and selection bias. We also rule out the competing explanation for foreign investors paying premiums for local properties is that they select and purchase better-quality properties than those acquired by local investors. Using a 2-step matching process, we further rule out the location heterogeneity in acquired properties that could possibly correlate with the price premiums paid by foreign investors. The results do not reject the hypothesis that local investors have

[1]These studies used only commercial and residential real estate data within the US when measuring geographic distance.

information advantages over foreign investors.

We next use the number of investors' previous transactions, indicated as "Regular Learning Effect (RLE)", as the proxy for learning, and find that the inclusion of the RLE variable explains away the price premiums paid by foreign investors. For every 1% increase in acquisition experience in the destination city, investors could reduce the log-unit price by 0.11%, and the price bias by 0.07%. In sum, the results show that the difference of learning from historical experience between foreign and local investors, which serves as a proxy for the information asymmetry, explains the price discrepancy between properties acquired by foreign and local investors. For robustness check, we also adjust the learning effects to the model by using an alternative learning measure indicated by "Weighted Learning Effects (WLE)". WLE adds more weight to distant past acquisitions (see detailed discussion in Section 2.2). The results are consistent with baseline results using RLE. Also, the results of falsifications tests show that the experience gap between foreign and local investors other than other unobserved dimensions drives the price gap paid by foreign investors for comparable properties. In the heterogeneous tests, we categorize the investors into Corporate and Finance investors and group the properties into Senior Housing & Care, Apartment, Hotel, Office, Retail, Development Site, and Industrial. The results show that Corporate investors and investors who purchase location-valued properties learn more from historical acquisitions.

When investigating the home-turf advantages (initial information advantage) of first-time local investors, we find that foreign investors reduce the information gap with local investors through their learning from prior acquisitions in the local market. Specifically, we show that foreign investors nullify their initial information disadvantage by accumulating at least four acquisition experiences in host cities.

The natural question followed is what and how investors learn from past transaction experience? To answer this question, we study the learning quality and learning mechanism. First, we differentiate the learning in the same property type ("RLE-Type") from the learning in different property types; and differentiate the learning in the same city ("RLE-Outcity") from the learning in different cities. The results show that learning effects in the same property type are substantially larger than learning effects in different types of properties. Similarly, learning effects in the same host cities are found to be larger than learning effects in other cities. The results point to the importance of learning quality, implying that investors should be discriminatory in their acquisitions, such that they obtain information advantages more effectively through learning from the same type of property acquisitions than through non-discriminatory learning from acquisitions of different types of properties in local markets. Second, we find foreign investors learn to pick out the counterparties of same-nationality to reduce the information asymmetry. However, we do not find the learning effects for foreign investors in exploiting the joint venture strategy to reduce information asymmetry.

Third, following Sarkissian and Schill (2003) and Andrade and Chhaochharia (2010), we control for geographic, language, and economic proximity to refine the learning effect from historical acquisitions in cross-border transactions. We find that language proximity, other than geographic and economic proximity facilitates foreign investors' learning effect in cross-border transactions. To further study what foreign investors are learning when they choose to engage in follow-on investments, we move to investigate the effect of learning on the distance dimension and find that foreign corporate investors are learning about the locations.

Our paper makes three main contributions to the literature. First, it adds to the literature by examining the question of whether investors "learn" to reduce information asymmetries. For assets that is geographically fixed and immobile in location, such as real estate, local investors who are familiar with preference, culture, and idiosyncrasies in the home markets will have information advantage over foreign investors (Brennan and Cao, 1997; Coval and Moskowitz, 1999; Choe et al., 2005; Dvořák, 2005; Andrade and Chhaochharia, 2010; Baik et al., 2010). However, for assets in more liquid capital markets, such as stocks, foreign investors who access to global data and are more knowledgeable to information on macro-fundamentals, such as exchange rate risks, taxation policies, and labor markets, would have information edge over local investors in buying and selling the assets (stocks) (Grinblatt and Keloharju, 2000; Seasholes, 2000; Cohen et al., 2002; Froot and Ramadorai, 2008). Unlike the existing studies that invariably assume that information asymmetries are static and time-invariant, we use the learning mechanism to show that information revelation is a dynamic process, such that foreign investors could reduce information disadvantages through experience accumulated from the past transactions.

The second contribution is related to the growing literature by examining the question on "how" foreign investors learn to reduce information asymmetries. While the majority of the studies show that learning from prior experiences enhances performance in asset acquisitions and other economic activities (Camerer, 2011; Nadler et al., 2003; Loewenstein and Thompson, 2006; Barkema and Schijven, 2008; Reuer and Ragozzino, 2008; Knill et al., 2015; Cuypers et al., 2017)[2], few other studies, however, find no effects of learning in reducing information asymmetries in asset acquisitions (Kroll et al., 1997; Hayward, 2002; Porrini, 2004). We use two measures of learning, which include the cumulative number of prior transactions, and the quality of learning putting more weights on acquisitions of the same asset class and in the same city. In the same line of thought as the selective learning model of Van Nieuwerburgh and Veldkamp (2009), we show that foreign investors continue to improve their local knowledge with more acquisitions, and reduce the premiums paid in real estate transactions relative to local investors.

[2]Barkema and Schijven (2008) provide a comprehensive review of the literature on firms' learning and past acquisition experiences.

The third contribution add new evidence to the literature on information asymmetries in real estate investments. Studies that use commercial real estate data are far and few; and many of them focus either only in a single market, mostly in the US (Garmaise and Moskowitz, 2003; Lambson et al., 2004; Choi et al., 2014; Chinco and Mayer, 2015), or a single asset class, such as apartments (Turnbull and Sirmans, 1993; Lambson et al., 2004) and offices (Liu et al. 2015). While single-market and single-sector studies reduce unobserved heterogeneity in the samples, they lack cross-sectional variations to cleanly test the treatment effects (e.g., information asymmetries) that influence investors' preferences and investment behaviors. However, our empirical tests are built on a large sample of commercial real estate transactions covering 146 destination countries and 7 industry sectors; and coupled with the 15 years of transaction data, we could empirically test both cross-sectional and temporal dynamics in learning in commercial real estate markets using the comprehensive database.

The remainder of this paper is organized as follows: Section 2 discusses data sources and summary statistics, Section 3 presents our empirical strategy, Section 4 reports the results, and Section 5 concludes the study.

2 Data Sources and Variables

We obtained a unique dataset of commercial real estate transactions in different countries from Real Capital Analytics (RCA)[3]. RCA collects the sales data for commercial properties and portfolios transacted at a minimum price of US$1 million. Unlike studies in a single country and a single sector of the market, the RCA dataset contains commercial real estate transactions from 146 countries across the globe[4]. More specifically, our dataset contains 212,078 commercial real estate transactions across 146 countries covering a sample period from January 2001 to December 2015. Each transaction contains information on total transaction price, price per square foot (psf), transaction date, property size, distance to CBD, building age, investor name and address, property address, investor type and property type. There are 7 types of institutional investors: Corporate, Equity Fund, Government, Institutional Finance, Public Firms, Private Firms, and Institutional Fund. Commercial properties are classified into 7 types: Apartment, Development Site, Hotel, Industrial, Office, Retail, and Senior Housing Care.

[3]RCA is an independent real estate data analytics firm headquartered in New York, with offices in San Jose, London and Singapore. It collects data on commercial property transactions with a minimum size of US$1 million across 146 countries. The database contains, cumulatively, US$18 trillion in commercial property transactions linked to over 200,000 investors and lenders. Source: https://www.rcanalytics.com/.

[4]Having the largest and most comprehensive database on global commercial real estate transactions estimated at US$18 trillion in aggregate, RCA guarantees the integrity and the quality of commercial property transactions data through collaborations with various data partner companies whose data supplement RCA's database.

Based on investor identity (either a local or a foreign investor) in each transaction record, we define a "*Foreign*" dummy that assigns a value of 1 to a foreign investor if the investor's headquarters location (country) is different from that of a property; otherwise, an investor is identified as a local investor, and a value of 0 is assigned. Given our intent to empirically test price differences in properties purchased by foreign investors and local investors, we drop countries that contain either only domestic transactions or only foreign (cross-border) transactions from the sample. We reduce the sample to 159,923 transactions, comprising 120,192 local purchases and 39,731 foreign purchases. Local transactions are around three times as large as foreign transactions, implying the dominant role of local investors in commercial real estate market in the sample countries. The 159,923 transactions are distributed across 5,219 cities in 59 countries, and 16,268 institutional investors from 110 home countries are involved in the transactions. Like Chinco and Mayer (2015)[5], we also divide the investors in the same country into "out-of-city" and "in-city" investors based on the city identifier. The diversity of the dataset in terms of country coverage, investor type, and property type offers a perfect laboratory for us to set up natural experiments to test the effects of investors' learning from acquisition experiences on their following pricing strategies.

The dataset also reports transaction details on whether a joint venture arrangement is formed and whether a professional brokerage (agent) firm is appointed in a transaction. We compute the physical distance (in km) between each investor's headquarters location and the location of the property purchased by translating the addresses into spatial coordinates (Coval and Moskowitz, 1999; Garmaise and Moskowitz, 2003). Of the 159,923 transacted properties, 29,099 properties are resold at least once by the investors during the sample period, and the remainder are held by investors up to the end of the sample period (e.g., December 2015). Based on the repeat sales sub-sample, we compute the holding period and holding period return for each property.

2.1 Outcome Variables

Like most of the early literature, information advantage (asymmetry) is not directly observable. We test the information gap between local and foreign investors, using two price indicators. The first indicator is the unit price (measured in term of US$ psf), as denoted by $P_{i,p,j,ym}$. Where i, p, j, and ym index investors, properties, host cities, and year-month, all of which are directly observed from the transaction data. We test the hypothesis that foreign investors pay no significant price premiums relative to local investors for comparable properties, (e.g., "the law of one price" holds). If the hypothesis is rejected, and foreign investors pay a price premium in a transaction, we infer that local investors do possess significant

[5]Chinco and Mayer (2015) use the state level identifier from the house and property bill addresses to sort the housing buyers into "out-of-state" and "in-state" groups.

information advantages relative to foreign investors.

The second indicator, $PB_{i,p,j,ym}$, is an indirect measurement defined as the price bias. It is computed as:

$$PB_{i,p,j,ym} = \frac{PB_{i,p,j,ym} - \frac{1}{n}\sum_{p=1}^{n} P_{p,j,ym}}{\frac{1}{n}\sum_{p=1}^{n} P_{p,j,ym}} \tag{1}$$

Given a cumulative n acquisitions that occurred in a host city j in year-month ym, $\frac{1}{n}\sum_{p=1}^{n} P_{p,j,ym}$ represents the average unit price in the host city j in year-month ym. Therefore, $PB_{i,p,j,ym}$ is a percentage of the deviation of $P_{i,p,j,ym}$ from the average unit price $\frac{1}{n}\sum_{p=1}^{n} P_{p,j,ym}$ in the host city j in year-month ym. The information advantages of local investors, if exist, are reflected in a smaller $PB_{i,p,j,ym}$ in their real estate transactions, relative to foreign investors.

2.2 Learning from Prior Transactions

We define two variables for the effectiveness of investors' learning, which is measured based on the extent to which knowledge and information are accumulated from previous transactions. The first learning variable, "Regular Learning Effect (RLE)", is the number of past transactions in a specific host city j before the current acquisition. An investor' information about a market is assumed to increase with his/her cumulative acquisitions in the past. For illustration, UBS's[6] RLE at the point of purchasing the Equitable Building, an office building in New York City, in July 2011 is computed at 5, based on its records of five completed acquisitions, specifically one office building, three apartments, and one hotel, prior to the Equitable Building deal.

The second learning variable, "Weighted Learning Effect (WLE)", adds a quality dimension to learning by assigning different weights to past acquisition experiences. Unlike RLE, which treats every past acquisition equally as one unit (equal weight), WLE takes into account of the number of years spanning past acquisitions. Differing from an approach that assigns more weight to recent transactions versus more to distant past transactions, we assume that knowledge in commercial real estate grows with time[7] and that earlier-entered investors are more established in a market than investors who have only entered the market for a relatively short period. Therefore, our WLE variable places more weight on distant past acquisitions relative to recent acquisitions when measuring the effectiveness of learning

[6]UBS is a Swiss global financial services company headquartered in Basel, Switzerland. According to our data, UBS has made 253 acquisitions in 172 host cities in the US.

[7]Unlike speculators, investors taking a long-term perspective to acquire commercial properties for steady, long-term income-generating purposes. They set up asset management teams to oversee the operations of the acquired properties; thus, the property management experience represents a valuable source of information to support future acquisitions.

experiences for investors. There are three advantages using WLE: (1). It better captures an investor's experience in the host city by considering both the quantity and duration; (2). It serves as a robustness test for our baseline results; (3). It mitigates the possible endogeneity problem caused by the reverse causality between transaction price and transaction experience. Since the lower transaction price might be attractive to investors, more acquisitions could ensue. Therefore, the transaction price could gives rise to the change of prior acquisition experience other than the opposite direction. However, the transaction price is less likely to affect a property's length of existence after its transaction. To our best knowledge, we are the first to take into account of both quantity and duration of prior acquisitions in constructing the learning measurement. The following formula is proposed to calculate WLE:

$$WLE_{i,j,ym} = \sum_{p=1}^{k} \left(\frac{month_{i,p,j,ym}}{180}\right) \tag{2}$$

where $WLE_{i,j,ym}$ is investor i's weighted learning effect in city j in year-month ym; $month_{i,p,j,ym}$ is the duration (in months) between the time of acquisition of property p and the time of current acquisition; and k is the total number of investor i's property acquisitions up to the time ym. The denominator "180" is the full sample period measured in months, which is computed as $12 * 15\ years = 180\ months$.

Using the same UBS example for illustration, UBS purchased five properties prior to the purchase of "Equitable Building" in July 2011. The five acquisition experiences are recorded in chronological order as follows: "The Gershwin" in August 2005, "Waterside Plaza" in September 2005, "The Montrose" in March 2006, "Sports Illustrated Building" in June 2006, and "Buckingham Hotel" in June 2010. As of July 2011, the durations (in months) since the acquisitions of "The Gershwin", "Waterside Plaza", "The Montrose", "Sports Illustrated Building", and "Buckingham Hotel" were estimated at 71 months, 70 months, 64 months, 61 months, and 13 months, respectively. For the current "Equitable Building" acquisition, the experience from "The Gershwin" acquisition is most valuable and therefore is assigned the largest weight of $(\frac{71}{180})$ in the WLE, followed by "Waterside Plaza" $(\frac{70}{180})$, "The Montrose" $(\frac{64}{180})$, "Sports Illustrated Building" $(\frac{61}{180})$, and "Buckingham Hotel" $(\frac{13}{180})$. Thus, the WLE for UBS purchasing "Equitable Building" in July 2011 is computed as $[\frac{71}{180} + \frac{70}{180} + \frac{64}{180} + \frac{61}{180} + \frac{13}{180} = \frac{279}{180}]$.

2.3 Sample Matching Procedure

Local investors' commercial real estate transactions in our data are three times as many as transactions by foreign investors. Therefore a matching process is necessary to remove possible price variations between foreign investors and local investors, which are unrelated to information asymmetries. We apply a 2-step matching approach to minimize biases caused by sampling distribution and selection problems. We first sort the properties acquired by foreign investors into the treatment group, and then find the matching properties acquired by local investors to form the control group. The 2-step sampling matching process is described below.

In Step 1, we compute the pairwise distance of any two properties, specifically one that is purchased by a foreign investor and another one purchased by a domestic investor, based on the coordinate data. Since real estate business is about "location, location, location", understanding spatial and local legal systems that determine property values and sales is critical. Therefore, we use a 2-km radius circle as a guide to find matching properties acquired by foreign investors and local investors to better control for the confounding effects associated with spatial discontinuity and unobserved characteristics of the sample properties. We exclude properties for which a matching property is not found within a 2-km radius circle. Thus, based on a circle with a 2-km radius with a reference property "A" purchased by a foreign investor as the center, property "A" is excluded from our sample if we do not find any other property purchased by local investors within the 2-km radius. Similarly, using a reference property "B" purchased by a local investor as the center, property B is also excluded from our sample if we do not find any property purchased by foreign investors within the 2-km radius. We also tried radius of 1 km and 3 km, and found the cutoff does not change our primary results in empirical tests. The selection of cut-off involves a trade-off between bias and efficiency. Bias is reduced with using a smaller radius, but efficiency is reduced as fewer observations are kept. We employ the 2-km radius for compromise between bias and efficiency.

In Step 2, we run a propensity matching procedure to identify properties with observably similar characteristics to form a treatment group consisting of properties acquired by foreign investors and a control group consisting of properties acquired by local investors. This approach is similar to a study by Asker et al. (2015), which investigated behavioral differences between public and private firms. We compute the propensity scores using a logistic regression with the key property characteristics, such as property size, CBD distance, property types, and host country, acting as the covariates. We perform the nearest-neighbor matching based on the computed propensity scores. The resulting matched sample contains 62,183 transactions, of which 25,881 are local transactions and 36,302 are foreign transactions.

We admit that it is impossible to find two commercial properties that are exactly the same. The 2-step matching process presented here tries to reduce the differences in location, type, and size between two property groups as much as possible.

2.4 Descriptive Statistics

Table 1 reports the descriptive statistics of variables used in the analyses. The definitions of all variables are reported in Appendix A. The table is organized into two sections that include the full sample (Panel A) and the matched sample (Panel B) of properties acquired by both foreign investors and local investors. The sample period ranges from January 2001 to December 2015. The full sample results show that, in terms of the average US$ price psf, foreign investors pay an estimated US$ 340.031 compared to local investors who pay US$ 315.540 in their property acquisitions, which translates into a significant price premium of US$24.491 psf. For the matched samples that control for observable characteristics such as property size, CBD distance, property types, and host country as reported in Panel B of Table 1, foreign investors pay a positive premium of US$31.382 psf, e.g., [US$357.255 psf - US$325.873 psf] on average for comparable properties relative to local investors. Figure 1 shows the dynamics of unit price over the sample periods. With the exception of 2005 to 2007, foreign investors consistently pay higher prices relative to local investors. In terms of total price (US$), the average price gap between foreign purchases and local purchases falls from US$11.85 million (Panel A) to US$4.26 million (Panel B) after controlling for heterogeneity in property- and country-related attributes.

[Insert Table 1 and Figure 1 here]

Aside from the unit price gap, price bias is another outcome variable used to identify information asymmetries; it measures the deviation of investors' acquisition prices from the average prices in the host city. A positive (negative) price bias indicates that an investor pays a price that is higher (lower) than the average price in the host city. The statistics show that price bias in foreign acquisitions is significantly positive at 0.01 and 0.018 compared to the negative price biases of -0.043 and -0.009 in local acquisitions in the full sample (Panel A) and the matched sample (Panel B), respectively. The results are consistent with the higher average psf price paid by foreign investors and provide suggestive evidence for information asymmetries between the two groups of investors.

We define a dummy variable, "Agent", which has a value of 1, if a professional broker/agent is hired by an investor in a transaction and 0 otherwise. "Anchoring" is defined as the average unit price (psf) of properties in the home country of an investor in the year of the current acquisition[8]. The fraction of foreign investors' hiring agents is slightly higher at 21.6% compared to 18.2% of local investors in the full sample; the fraction increases to 24.5% for local investors in the matched sample. The anchoring effects do not differ significantly between foreign and local investors. For the two learning variables, RLE and WLE, we find significantly stronger learning effects by local investors relative to foreign investors in both

[8]See Northcraft and Neale (1987) and Lambson et al. (2004) for detailed introduction of Anchoring effect.

the full sample and the matched sample. The results may reflect the strong domination of local investors in commercial real estate markets, which thus enhances the learning effect for local investors relative to foreign investors. For risk mitigation purposes, we find that foreign investors (31.5%) are more likely to engage in joint ventures (JVs) in property acquisitions relative to local investors (17.6%) in the full sample, but the ratio of JV deals between the two types of investors in the matched sample does not differ significantly from zero.

In terms of property size, properties acquired by foreign investors are 28,804.6 sf smaller than properties acquired by local investors in the full sample (Panel A). Regarding the CBD distance, we find properties acquired by foreign investors located slightly closer to the city center. The differences in size and CBD distance between properties acquired by the two types of investors decrease substantially and turn to be statistically insignificant after matching (Panel B). Figure 2 plots the distributions of property size (in the top graph) and property's distance to CBD (in the bottom graph) for both foreign investors and local investors after the PSM. The matched sample shows similarities in property size and property's distance to CBD between foreign properties (darkened line) and local properties (dashed line), suggesting that the matching process significantly reduces the observable differences between foreign and local samples.

[**Insert Figure 2 here**]

We also include a set of variables for transactions and investors to control for observed variations in the sample. In Table 1, we find the number of foreign investors' holding assets is larger than that of domestic investors', suggesting that foreign investors are larger than their domestic counterparts. This is in line with the evidence in literature and reality: foreign investors are generally more capitalized, and less of liquidity constraint than domestic investors (Grinblatt and Keloharju, 2000; Seasholes, 2000; Audretsch and Elston, 2002). In the matched sample, the average number of asset holdings by local investors increases to 439.2, whereas the average number of asset holdings by foreign investors only increases to 414.6, relative to the full sample numbers of 368.91 and 439.20, respectively. "Volume", the amount of transactions in the destination cities, which serves to proxy the market demand in the host city, is almost the same for foreign and local investors.

In terms of country characteristics, the full and the matched samples share similar levels of information transparency, as measured by the Transparency Index (TI), and the national income level (per capita GDP).

3 Empirical Methodology and Results

3.1 Specifications for the Information Asymmetry Model

We begin the empirical analyses by testing the "local investors are better informed" hypothesis that foreign investors will pay higher prices relative to local investors for comparable commercial properties in the destination market. The hypothesis, if not rejected, implies that local investors possess information advantages over foreign investors, and the log-unit price (or the price bias) function for the global commercial real estate investment model is written as:

$$Y_{i,p,j,ym} = \alpha Foreign + \beta X + \mu_j + \delta_f + \varphi_k + \sigma_{ym} + \epsilon_{j,ym} \tag{3}$$

$Y_{i,p,j,ym}$ is the dependent variable, which is represented either by price psf or price bias. The subscripts p, i, j, f, k and ym denote properties, investors, host cities, investor types, property types, and year-month, respectively. The treatment variable, *Foreign*, if economically positive and statistically significant, supports the "local investors are better informed" hypothesis, which implies that foreign investors pay higher prices than local investors for comparable properties in the local market. X is a vector of control variables that captures heterogeneity in terms of property attributes, investor attributes and host-country attributes. These control variables include property size (in square feet), CBD distance, investor size (measured by the number of assets in an investor's holding), a binary JV dummy[9], per capita GDP[10] of the host country, perceived corruption level[11], and volume of acquisitions[12]. Price psf, property size, CBD distance, number of assets in an investor's holding, per capita GDP, and volume of acquisitions are expressed in logarithmic terms throughout our estimations. α and β are estimated parameters.

The coefficient of the volume of acquisitions is expected to be positive to support the liquidity constraint story that predicts a positive relationship between prices and trading volume (Stein, 1995; Berkovec and Goodman Jr, 1996). The marginal diminishing effects of property size are reflected by its negative coefficient on the unit price. The CBD distance is expected to be negatively associated with the transacted price. The JV dummy is expected to have a negative sign in the pricing model because investors form a JV with local partners

[9]JV is a binary variable that takes a value of 1 if the transaction is done via a JV and is 0 otherwise.

[10]Per capita GDP is used as a proxy for economic development or the purchasing power of local consumers (Morck et al., 2000; Ferreira et al., 2009; Javorcik and Wei, 2009)

[11]The Perceived Corruption Index, obtained from Transparency International, ranges from 0 to 10, with 0 indicating the least corruption and 10 indicating the most corruption (Wei, 2000; Wei and Shleifer, 2000; Javorcik and Wei, 2009)

[12]Volume of acquisitions is the number of all acquisitions at the host-city level in one year. It serves as a proxy for the demand for commercial properties in the host city

to reduce information asymmetries[13], particularly in an unfamiliar market. The number of assets in an investor's holding is a proxy for the market capitalization of the investor, and a larger investor is less likely to have liquidity-constraint in acquisitions; therefore, the "Asset" coefficient is expected to have a positive sign (Choi et al., 2014).

We account for variations in the destination country using two control variables. The first variable is the corruption perceptions index ("TI") published by Transparency International[14], which measures transparency, institutional quality, and uncertainty in the host country. Investors expect high returns to compensate for potential corruption risks and thus pay relatively lower prices for properties in highly corrupt countries. The sign on "TI" is expected to be negative. The second country variable controlled is the per capita GDP, of which coefficient is expected to have a positive sign, implying that purchasing power is positively associated with property transaction price (Case and Shiller, 1990, 2003).

In addition to the control variables listed above, we also include a rich set of fixed effects to rule out the possible contamination of unobserved characteristics of investors, properties, host markets, and investors' countries of origin. The investor-type fixed effect absorbs the time-invariant difference across different types of investors. As we know, investors differ dramatically from each other along a series of dimensions, such as risk attitude, investment preference, and investment objectives. For example, government investors seek for strategical entry in cross-border investment, while private investors look for maximization of profit. The inclusion of investor-type fixed effect helps to eliminate the effect of investors' intention on the price difference between foreign and domestic investors. Besides, price varies largely between property types. For instance, the price of industrial building is way lower than the office building. Therefore, we include property-type fixed effect in our specifications to remove unobserved heterogeneities associated with the category of property. Since the host-city characteristics might also affect the transaction prices of commercial real estate assets, it is necessary to control for the host-city fixed effect to reduce the time-invariant difference across different cities. Another point that might bias our estimation of information asymmetry is investors' countries of origin. To mitigate this concern, we include the country of origin fixed effect. The year-month fixed effect is also included to control for time trends. We cluster the standard errors at the host-city level because errors in property price variance are correlated within cities.

[13]In highly corrupt countries, foreign investors use JV arrangements as a risk-mitigating strategy to reduce investment risks (Balakrishnan and Koza, 1993; Inkpen and Beamish, 1997; Javorcik and Wei, 2009).

[14]Transparency International's Corruption Perceptions Index has been widely used in the literature to capture corruption levels and information opaqueness for 176 countries around the world. Source: https://www.transparency.org/news/feature/corruption_perceptions_index_2016.

3.2 Difference in Acquisition Price

We begin the analysis by estimating the price difference using Equation (3) and report the results in Table 2, with Panel A corresponding to full sample regressions and Panel B corresponding to matched sample regressions. Column (1) shows the baseline results: *Foreign* is positive and statistically significant in predicting the log(unit price) after controlling for a set of structural control variables and fixed effects. Economically, foreign investors pay 3.7% more on average than local investors, which translates into a price of US$ 11.90 in psf or US$ 4,733,516 in total, for comparable properties[15]. The price premium amounts to approximately 10% of the mean total transaction price for properties purchased by local investors in the full sample, e.g., US$44.119 million. Therefore, the 3.7% premium in price psf is not economically trivial. Our results are consistent with early results describing premiums paid by out-of-state buyers in local real estate markets (Turnbull and Sirmans, 1993; Lambson et al., 2004; Chinco and Mayer, 2015)[16].

[Insert Table 2 here]

The coefficients on ln(Size), ln(CBD Distance), ln(Assets), ln(PerGDP), JV, and ln(Volume) are all statistically significant, and their signs are consistent with expectations. Property size and CBD distance are negatively associated with the psf price, and the sign are stable and robust in all model specifications in Table 2. The JV dummy coefficient is statistically significant, indicating that JV-transactions are 14.2% lower in the psf price than transactions without JV arrangements. Large investors holding more assets in their portfolios ("Asset") pay higher prices for comparable properties in local markets than small institutional investors. The "Volume" coefficient is significantly positive, which implies that high local market demand bids up transaction prices. This evidence supports the liquidity constraints scenario described by Stein (1995). The per capita GDP is statistically significant and positive, indicating that property transactions are positively correlated with income level in the economy. "TI", which is a proxy for market transparency, is insignificant.

3.3 Tests for Learning Effects

We next explore the underlying reasons behind the premiums paid by foreign investors for local real estate transactions. We hypothesize four possible mechanisms: high search costs (agent), biased beliefs (anchoring), learning (information asymmetry) and selection bias

[15]The mean values of price psf, property size, and total price in our sample are US$321.689, 397,744.5 square feet, and US$47.095 million, respectively. Thus, the 3.7% premium for price psf translates into 3.7% x 321.689 = US$11.90 psf. A foreign investor pays 11.581 x 397,774.5 = US$4,733,516 more than a domestic investor on a property of 397,774.5 sf, on average.

[16]Home bias evidence is also observed in stock markets, where foreign investors over-pay for comparable stocks compared local investors (Brennan and Cao, 1997; Hau, 2001; Dvořák, 2005; Choe et al., 2005; Agarwal et al., 2009; Ferreira et al., 2009).

(property quality), all of which could widen information asymmetries and distort the law of one price for real estate investments.

Real estate agents, who are familiar with local property markets and have significant information advantages, are sometimes hired for a fee by either buyers or sellers to facilitate real estate transactions (Garmaise and Moskowitz, 2003; Levitt and Syverson, 2008; Hendel et al., 2009). Professional real estate brokerage firms offer a wide range of services, including property searching, buyer prospecting, interest matching, and negotiation to the closing of a deal and conveyance of real estate assets. Do real estate agents help foreign investors bridge the information gap with local investors? If so, we expect that hiring real estate agents reduces the risk of foreign investors overpaying for properties in local markets.

The anchoring effect denotes a cognitive bias that results in a tendency for investors to overly rely on a first piece of information when making decisions. The real estate literature has found evidence of anchoring bias, where buyers form price beliefs based on home market price information when acquiring foreign real estate assets (Northcraft and Neale, 1987; Lambson et al., 2004). If the hypothesis holds, foreign buyers from high price markets are more likely to overestimate mean prices of properties in other markets. The biased belief of buyers is one potential source of information asymmetry between foreign buyers and local sellers.

The third hypothesis concerns information immobility and learning by investors (Van Nieuwerburgh and Veldkamp, 2009; Andrade and Chhaochharia, 2010). Investors who have more transaction experience in the market should have accumulated more information through the trading experience, and subsequently become the advantageous party relative to those investors with less historical transaction experience. If investors learn from their past acquisition experiences, they should be able to reduce information asymmetries in current or future acquisitions and reduce price premiums paid for local assets relative to other investors. In this regard, the difference of learning points directly to the information asymmetry between foreign and domestic investors.

Selection bias suggests that the properties purchased by foreign investors might be substantially different from those purchased by domestic investors. We address the selection bias through two ways: (1). We employ a 2-step matching approach as aforementioned in Section 2.3 to minimize biases caused by sampling distribution and location heterogeneity[17].

[17]To remove the unobserved differences between foreign-owned and local-owned properties, we have tried different methodologies suggested by literature. First, we include observed characteristics of properties as many as possible, as well as the property type fixed effects. Second, following the methodology of Murphy and Topel (1990) and Levitt and Syverson (2008), we can estimate the unexplained variation in the outcome variable. To save space, we do not report the tables here. The principle is to infer the estimated coefficient according to the benchmark coefficients and R-squares in a series regressions with/without fixed effects included. The methodology is discussed in detail in Murphy and Topel (1990) and Levitt and Syverson (2008). To sum up, it appears that unobserved heterogeneity may explain some small portion of our findings,

(2). We examine whether the foreign investors earn higher returns than do the domestic parties when reselling the acquired properties. If the result is negative, it suggests that the properties purchased by foreign investors are not better than the properties purchased by domestic investors. This step aims to examine whether the difference of property quality other than the information gap leads to the difference of transaction price of properties acquired by different groups of investors.

We continue the analysis by investigating the incremental explanatory effects of "Agent", "Anchoring", and "Learning":

(1) "Agent" is a dummy variable for agent effects, which has a value of 1 if a real estate agent or broker is engaged in a transaction or 0 otherwise;

(2) "Anchoring" is a continuous variable that measures the anchoring effect based on average psf prices of commercial properties transacted in investors' home markets in the year of the current (referenced) transaction; and

(3) "RLE", or the regular learning effect variable, which is computed as the number of past acquisitions prior to the current acquisition.

Our empirical strategy here is to include "Agent", "Anchoring", and "RLE" separately, and see whether the inclusion explains away, either partially or fully, the price premium paid by foreign investors in Column (1) of Table 2.

Columns (2) to (4) in Panel A of Table 2 add the variables "Agent", "Anchoring" and "RLE" independently to the baseline model, and the results indicate that the coefficients of the three variables are statistically significant, estimated at -0.183 (Column 2), 0.018 (Column 3), and -0.111 (Column 4), respectively. Notably, the inclusions of "Agent" and "Anchoring" barely change the coefficient of the "*Foreign*" dummy in Columns (2) and (3), which remains positive and significant at approximately 0.037 and 0.034 compared to 0.037 in the baseline model (Column 1). The results imply that "Agent" and "Anchoring" effects do not explain away variations in price premiums paid by foreign investors.

However, interestingly, the inclusion of "RLE" not only accounts for 11.1% of the unit price but also takes away the explanatory effects of *Foreign* dummy by dragging the coefficient magnitude from positively significant at 0.037 down to statistically insignificant at -0.011. The results imply that the learning from past acquisition experiences, "RLE", helps to reduce the overpricing for real estate purchases by foreign investors, such that the price gap between the foreign investors and local investors disappears. By simply using the number of past acquisitions as an indicator of learning, we find economically that 1% increase in the number of past acquisition experience is associated with a decrease of 0.11% in the psf price in the current acquisitions. In sum, the results show that the difference of learning from historical experience between foreign and local investors, which serves as a proxy for

but cannot explain the overall patterns.

the information asymmetry, explains the price discrepancy between properties acquired by foreign and local investors.

We conduct further tests on the nonlinearity of learning effects by adding the squared learning term "RLE2" to Model (5), and the interaction of learning with the perceived corruption index "TI", represented by "RLE*TI", to Model (6). The "RLE" coefficient remains significant and negative, and the "RLE2" coefficient is positive and significant, suggesting that learning effects are concave and diminish with the number of properties acquired. The quadratic function implies that learning is most effective in the first few acquisitions, and wanes off gradually in subsequent purchases. We also show that learning from prior experience is less effective in corrupt countries with low transparency, as the interactive "RLE*TI" term appears to be positive. This is supportive of the argument that information asymmetries are expected to be more pronounced in corrupt countries, hindering learning by investors (Brennan and Cao, 1997; Javorcik and Wei, 2009). In Column (7), we include the "Agent", "Anchoring", "RLE", "RLE2", and interactive learning and corruption index ("RLE*TI") simultaneously, and find the learning effects are still significant, implying the information story is immune to other effects.

We also control another important characteristic of the commercial property, that is the building age denoted by *YearBuilt*, in the regressions reported in Appendix Table B1. As the information on building age is missing for some sample properties, the observations available for estimations are less than those in Table 2. Table B1 shows consistent learning effects.

The results alignt with the organizational learning literature, which primarily provides insights into how experience facilitates capability building, improved bargaining outcomes, and better performance (Fowler and Schmidt, 1989; Barkema and Schijven, 2008; Cuypers et al., 2017).

3.4 Correcting for Selection Bias

To prove that the information story is not contaminated by the selection bias, we first employ a 2-step matching approach as aforementioned in Section 2.3 to eliminate the sampling distribution and location heterogeneity. Then, we examine whether the foreign investors earn higher returns than do the domestic parties when reselling the acquired properties.

3.4.1 The 2-step Matching Process

The composition of the full sample, which is dominated by local investors, may be a potential source of selection bias in the results. Differences in observable and unobservable characteristics of investors, in the purchased properties, and in host cities in which properties are located potentially influence the distributions of the property sale samples as well as the selection of property types purchased by foreign and local investors. This selection, if not controlled for in the models, may bias estimates of foreign acquisition premiums and distort the explanation of information asymmetries between foreign and local investors.

We address sample selection bias by using a boundary strategy and propensity score matching (discussed in Section 2.3) to generate a more comparable sample. Based on the matched sample, we replicate the models depicted in Equation (3) and report the results in Panel B of Table 2. The results in Panel B are largely consistent and exhibit similar patterns to those reported in Panel A. In the baseline model in Column (1), the foreign investors' premium, as captured by the *Foreign* dummy, is still significant and positive, although the magnitude is slightly smaller at 3.3% relative to 3.7% reported in Panel A. The negative agent effect is still significant at 0.192 (Column 2), while the effect of anchoring disappears in Column (3). Learning effects are significant in all models (Columns 4 to 7), and turn out to be larger after controlling for other observed and unobserved variations in properties, cities and investors. Specifically, the coefficients on the learning variable "RLE" range from -12.5% to -18.8%. The effects on the marginal diminishing in the learning curve, "RLE2", and on the learning barrier in corrupt countries, "RLE*TI", persist in Models (5) and (6), respectively. The results in the matched sample regressions reaffirm earlier findings showing that information asymmetry exists in real estate markets, and investors can narrow their relative information disadvantages by learning from past acquisition experiences and reduce price premiums paid in local real estate markets.

3.4.2 Do foreign investors acquired better quality properties?

Another competing explanation for foreign investors paying premiums for local properties is that they select and purchase better-quality properties than those acquired by local investors. We conduct further tests to falsify such claims that foreign investors have better knowledge than local investors in picking superior properties and subsequently re-selling the properties to yield higher holding period returns. Out of the full sample of 159,923 properties, we identify 29,099 properties that were sold more than once, commonly known as repeat sales in the real estate literature, and the remainder of the properties are held by investors at the end of the sample period. We are unable to determine the holding period (HP) and holding period return (HPR) for properties that are held to the end of the sample period, and the properties are dropped from the subsequent regressions.

Based on the repeat sales sub-sample, we compute the "HP" and "HPR"[18] for properties that were sold for the second time in the sample. Panel A of Table 3 shows the mean statis-

[18]Based on the repeat sale samples, we compute the holding periods (HPs), which is the difference between the first and the subsequent sale dates (in months), and the holding period return (HPRs), which is the percentage change in price relative to the original transaction price.

tics for the "HPR" and "HP". Unconditionally, "HPR" of local acquisitions is estimated to be 44.3%, which is approximately 1.4 times larger than the HPR (estimated at 18.2%) of foreign acquisitions. The unconditional difference of the "HPR" between local and foreign investors is statistically significant, consistent with the finding of Hendel et al. (2009) that local investors buy at discounts and sell at premiums. The lower returns of properties acquired by foreign investors provide us with suggestive evidence that the properties purchased by foreign investors are not better than those acquired by local investors. The "HP" of foreign properties is 3.6 months longer than that of local properties, but the difference between the two "HP" values is statistically insignificant.

[Insert Table 3 here]

We further test the conditional relationships between "HPR" and "*Foreign*" by performing the OLS and Heckman Two-step estimations separately in Panel B of Table 3. Since "HP" and "HPR" are only observable for properties that were resold within the sample period, simple OLS regressions may be subject to investors' choices to not sell their properties during the holding periods, which could cause bias to the "*Foreign*" dummy estimation. Therefore, we include the Heckman (1978) two-step model to address the selection bias in the OLS. Specifically, to determine whether selection is a problem, we first estimate the probability of being resold, (the probability of being treated) as a function of the original control variables and an additional identifying variable - the total price of the property. This variable is assumed to affect the probability of a property being resold in the sample period. We then model the step two "HPR" model using the standard OLS, controlling for "HP" and those observable characteristics used in Table 2.

The results in Panel B of Table 3 (both OLS and Heckman Two-setp models) are consistent with the findings in the literature: foreign investors underperform domestic investors by obtaining a lower return (Choe et al., 2005; Dvořák, 2005; Agarwal et al., 2009). In particular, foreign investors' "HPR" values are lower, estimated at -9.9% and -10.1% relative to local investors, respectively, in OLS and Heckman estimations. We can see that the inverse mills ratio estimated in the Heckman Two-step regression is statistically significant, which suggests that the error terms in the selection and primary equations are correlated. Overall, the results in Table 3 reject the competing explanation that the premium paid by foreign investors is correlated with selection bias.

In Table 3, we do not include learning effect in the regressions of returns for two reasons. First, the focus of this section is on the sign of *Foreign* dummy, which helps us to establish the conclusion that whether foreign investors pick out quality properties relative to local investors. Second, unlike the learning effect on price, which is calculated based on the buying point, the learning effect on returns depends on both buying and selling point. The count of historical transactions at the buying point could differs dramatically from the count of historical transactions at the selling point. Therefore, including learning effect in this section would make our results very confusing.

3.5 Price Bias

For robustness tests, we derive the "Price Bias" variable (Equation 1), which is defined as deviations in the acquisition price of a property from the average price of all acquisitions in the same host city in the referenced year-month, as an alternative outcome variable to the psf price in Equation (3).

Using "Price Bias" as the dependent variable, we re-estimate Equation (3) and report the results in Table 4 with Panel A corresponding to full sample regressions and Panel B corresponding to matched sample regressions. The overall results are consistent with those reported in Table 2, where the log-unit price (price psf) is used as the dependent variable. Specifically, the price bias in the foreign acquisition is estimated at 4.1% higher in the baseline model (Column 1 of Panel A), and the effects remain when an agent is hired (Column 2) and anchoring on home average prices (Column 3) is adjusted in the models. The inclusion of learning variables significantly explains the 4.1% higher price bias for foreign investors as reported in the baseline models (Column 1), and the coefficient of *Foreign* becomes statistically insignificant in Models (4) to (7). The "RLE" coefficients, ranging from -7.9% (Column 4) to -12.8% (Column 7), reflect learning effects, which are associated with a reduction in foreign investors' information disadvantages. The interactive term "RLE*TI" is statistically insignificant, implying that learning effects are indifferent when explaining variations in price bias in corrupt and non-corrupt countries.

We then control for selection bias using the matched sample in Panel B of Table 4, and the results are consistent with that in Panel A. We find the price bias in foreign acquisitions estimated at 4.3% higher in the baseline model (Column 1). The coefficients of the "Agent" and "Anchoring" variables are both statistically significant: hiring real estate agents reduces foreign investors' price bias by 15.5%, and anchoring to foreign investors' home market average prices increases the price bias in foreign acquisitions by 0.7%. The "RLE" coefficients substitute the *Foreign* dummy effects in Models (4) to (7) and significantly explain variations in the price bias. The learning effects are stronger, ranging from -9.2% and -12.7%, and independent of the sample selection bias. The statistically significant and positive quadratic term "RLE2" in Model (5) supports the marginal diminishing of learning effects. We do not observe differential learning effects in reducing price bias in corrupt and non-corrupt countries, as represented by the "TI" variable.

[Insert Table 4 here]

3.6 Falsification Tests

Tables 2 and 4 show that the premiums paid by foreign investors are explained by the information gap, which is proxied by the differences of RLE between foreign and domestic investors. However, people might still argue that international investors tend to purchase more expensive properties. On its own, this is not entirely surprising as foreign investors are likely to face a higher fixed cost of managing a distant property and therefore will be inclined to amortize this cost across more valuable properties. In this regard, the premium paid by foreigners could be explained by other unobservable characteristics (for instance better amenities, or amenities that are valued more by foreign buyers). Besides, the valuations on attributes of a property could be different, to some extent, between local and foreign investors. Foreign investors can be different along many unobservable dimensions that could justify why they pay a higher price on average. If they value more some expensive attributes (like being closer to a connection to an airport, closer to an international school or having larger open spaces), they will end up buying more expensive properties even if they have the same amount of information.

To address this issue, we conduct a falsification by adding the learning variable "RLE" to the second step in the propensity score matching criteria in addition to property size, CBD distance, property type, and host country variables. The new matching process technically creates a control sample consisting of local investors that share the same acquisition experiences as the treatment sample of foreign investors in the destination markets. If the information story (that is, learning reduces information asymmetry) holds, we should observe no price premiums paid by neither foreign nor local investors when their prior experiences are equivalent.

Using the new matched sample adjusted for learning, we re-estimate Equation (3) with the log-unit price (Column 1) and price bias (Column 2) as dependent variables and summarize the results in Table 5. Specifically, the coefficients on the *Foreign* dummy, which are estimated at 0.019 and 0.033 in Columns (1) and (2), respectively, are both statistically insignificant. Thus, foreign investors' premiums disappear if foreign and domestic investors share the same level of acquisition experience in the destination city. We are unable to reject the information asymmetry hypothesis that the experience gap between foreign and local investors other than other unobserved dimensions drives the price gap paid by foreign and local investors for comparable properties.

[Insert Table 5 here]

3.7 Heterogeneity Tests

In this section, we turn to examine the heterogeneity in learning effect across investor types and property types.

First, those typical companies like Starbucks and Apple (referred to as the Corporate investor), strive to learn which locations will maximize sales, whereas companies like a fund or a Real Estate Investment trust (referred to as the Finance investor) tries to learn which properties are under-priced. This implies that corporate follow-on investments depend more on how the previous locations have fared. Second, the locations of some types of properties, such as Apartment, Hotel, Office, and Industrial, are an investor's top concern in an acquisition. The two points suggest the learning effect could differ across investor types and property types.

We then investigate the differences in learning effect (RLE) between Corporate and Finance investors, and across these 7 types of properties. The results are reported in Table 6.

[Insert Table 6 here]

The reference group in Column (1) consists of properties acquired by Finance investors and the reference group in Column (2) are Housing & Care properties, respectively. The interaction term represents the difference in learning effect (RLE) between the interacted group and the reference group. Specifically, the learning effects of Finance investors and the learning effects on Senior Housing & Care are estimated at -0.098 and -0.099, respectively. The interaction, *RLE*Finance*, appears to be significantly positive at 0.042, suggesting that Finance investors learn less, relative to Corporate, from their historical acquisitions. In Column (2), the coefficients of 4 interactions terms (*RLE*Apartment*, *RLE*Hotel*, *RLE*Office*, *RLE*Retail*) are negative and statistically significant, which implies that investors' learning effects from the historical acquisitions of these 4 types of properties are larger than that from acquiring Senior Housing & Care. To the contrast, the interactions of *RLE*Dev_Site* and *RLE*Industrial* are either significantly positive or statistically insignificant. This suggests that investors learn more from the location-valued properties.

To sum up, the results shown in Table 6 reveal that the difference in location-value could explain the nature of learning that occurs differs across investor types and property types.

3.8 Weighted Learning Effects

To address possible endogeneity concerns caused by the reversal causality between transaction price and transaction experience and for robustness checks, we use WLE (defined in Equation 2) instead of RLE in Equation 3.

The results reported in Table 7 are stable and consistent with those reported for the

"RLE" models in Tables 2 and 4. Similar to the early results, information asymmetries as represented by the *Foreign* dummy disappear when "WLE" is added to the models. We also find that the "WLE" coefficient is significantly negative with values ranging from -8.3% (Column 1) to -15.7% (Column 2) for the log-unit price models and from -6.7% (Column 7) to -17.0% (Column 6) for the price bias models. However, the marginal effects of "WLE" are slightly smaller than those of "RLE" in Tables 2 and 4. We also find "WLE2" to be significant and positive, implying that learning effect diminishes at an increasing rate to reduce log-unit prices and price bias in real estate transactions. Additionally, the inclusions of "Agent" and "Anchoring" do not absorb the effect of "WLE". All models control for the characteristics of investors, properties, countries as shown in previous tables and the results are consistent. To save space, we do not report the results here.

[Insert Table 7 here]

3.9 When Do Foreign Investors Phase Out the Information Disadvantages

The home bias literature shows substantial home-turf (information) advantages[19] for local investors, who may obtain easier access to local information by reading local papers, chatting with local residents, and driving around the city. To test home-turf advantages related to information in the absence of learning, we only include transactions of first-time investors who have no prior experience in the host cities. Home-turf advantages are not rejected if non-local first-time investors pay significant premiums for comparable properties in local markets relative to local first-time investors; furthermore, the results imply that the law of one price does not hold.

We sort the first-time investors into three groups: in-city investors, out-of-city investors, and foreign investors. Using in-city investors as the reference group, we include two dummies, "*OutCity*" and "*Foreign*", in the log-unit price and price bias models. An "*OutCity*" dummy takes a value of 1 if an investor has his/her headquarters in a different city but within the same country relative to the property location and otherwise has a value of 0 if he is identified as an "in-city" investor with the headquarters and property located in the same city.

We include both the "*OutCity*" and "*Foreign*" dummies in the models and report the estimated results in Table 8; the models in Panel A are estimated using the full sample of all first-time investors, and the models in Panel B are estimated using the matched sample

[19] Local investors possess superior information regarding a wide range of local features such as zoning laws, school quality, local economic trends, condition of local infrastructure, and crime statistics. Other out-of-state (foreign) investors may need to spend more time, money, and effort to obtain the same set of information than local investors.

of first-time investors[20].

[Insert Table 8 here]

In the full sample (Columns 1 and 2), we find that first-time out-of-city investors pay 6.6% more in psf price relative to first-time in-city investors for comparable properties, whereas foreign investors pay an incremental premium of 5.0%, or an equivalent cumulative premium of 11.6%, [6.6% + 5.0%], for comparable properties compared with in-city buyers. In terms of price bias (Column 2), differences in out-of-city investors' local real estate purchases are estimated at 9.9% relative to in-city investors, and these differences increase to 14.6%, [9.9% + 4.7%] for foreign investors relative to in-city investors. The results are robust and consistent in the matched sample models (Columns 3 and 4), and the differential unit prices and price bias are larger between foreign investors and in-city investors, which are estimated at 13% and 14.7%, respectively. Our results are consistent with the propositions of Van Nieuwerburgh and Veldkamp (2009) and Andrade and Chhaochharia (2010), which state that investors choose to learn and specialize in local markets where they have an initial information endowment to magnify their home-turf advantages. We show that in-city investors are able to capitalize on their information advantages to purchase properties at lower prices in local markets than out-of-city and foreign investors, even in the absence of learning.

Next, we further explore whether foreign investors' learning reduces the information gap and at which stage the information gap is wiped out. Using first-time domestic investors (both in-city and out-of-city) as the reference group, we test the effectiveness of learning in reducing information asymmetries of matched foreign investors by increasing "RLE" one unit by one unit. The logic of this test is, given the home-turf information advantage of first-time local investors versus first-time foreign investors, how many transactions the first-time foreign investors should accumulate to offset the home-turf information advantage of first-time local investors. We add nine interactive terms for "Foreign" based on the number of cumulative prior purchases, which ranges from two to ten (for example, "Foreign*Two" indicates foreign investors with two past acquisitions in the local market), in the log-unit price and price bias models, and we summarize the results in Table 9.

[Insert Table 9 here]

The log-unit price premium and price bias premium paid by first-time foreign investors relative to first-time local investors are estimated at 18.9% and 15.7%, respectively. However, when learning is added cumulatively through prior acquisitions, we find that the price premiums paid by foreign investors relative to the first-time local investors are fully offset after

[20] The matched sample that uses foreign investors with prior acquisition experience may under-estimate information asymmetries in the models. However, a matched sample of investors with the same experience is difficult to construct due to small sample size of foreign investors with only one-time acquisition experience (without prior acquisition experience).

four prior acquisitions, at which point the net log-unit price and the net price bias for foreign real estate acquisitions turn negative at -20.6%+18.9%=-1.7% and -17.6%+15.7%=-1.9%, respectively. The results imply that foreign investors erase home-turf advantages (first-time purchases in the absence of learning) of local investors through learning, and on average, experience with four prior acquisitions is sufficient for foreign investors to obtain necessary local information that enables them to compete on equal footing with local investors without paying higher prices for local properties. The results are consistent with the information learning literature (Van Nieuwerburgh and Veldkamp, 2009; Andrade and Chhaochharia, 2010). Adding to Van Nieuwerburgh and Veldkamp (2009), we show that not only do local investors who use learning widen their information advantages, but foreign investors also use learning to reduce information gaps and pay lower premiums in commercial real estate purchases. More past acquisition experience reduces the risks of foreign investors overpaying in local commercial real estate markets.

4 What Are Investors Learning About

In previous sections, we have shown the existence of learning effects in global commercial real estate transactions. The natural question followed is: what are investors learning about?

In this section, we attempt to answer this question by taking a closer look at the changes in different dimensions of investors' behaviors after investors have accumulated experience in the market. We first examine the efficiency of learning by differentiating familiar assets (or familiar locations) from unfamiliar ones. Then, we move to investigate the nature of foreign investors' learning process in the cross-border transactions.

4.1 The Quality of Learning

In Tables 2 and 4, we reveal that RLE significantly accounts for the premium paid by foreign investors. The RLE used in Tables 2 and 4 is calculated as the number of an investor's all historical acquisitions in the host city before the focal acquisition. A natural question regarding the calculation of RLE is: to what extent does the RLE precisely capture the effects of an investor's learning from his/her historical acquisitions on the investor' information? If RLE is a valid and trustworthy measure of learning effect, we should observe estimated variation of RLE in different learning scenarios.

For illustration, we use the example of UBS, who has made five acquisitions in New York comprising one office, three apartments, and one hotel. Based on the "RLE", UBS undertook five past acquisitions in New York before purchasing the "Equitable Building" in July 2011. However, given that the "Equitable Building" is an office building, UBS's experience with the early acquisition of another New York office building is more relevant than its experience with the previous acquisitions of three apartments and one hotel in New York. Thus, we should assign more weight to the past office acquisition than to the other four acquisitions when adjusting for the quality of UBS learning in July 2011. Similarly, we hypothesize that investors' experience in the same destination city is likely to be more valuable than their experience in other cities when measuring the effectiveness of learning. UBS made 5 acquisitions in New York and 112 acquisitions in other US cities prior to acquisition of the "Equitable Building" in July 2011. We assume that UBS' experience in the 112 acquisitions in other US cities still contributes to increasing its information in New York real estate market, but is less useful than the experience in the 5 acquisitions in New York.

We therefore extend the "RLE" in two ways to differentiate the quality of learning from the experience. First, to adjust for the quality dimension of learning for the same type of property, we construct the "RLE-Type" variable, which counts only the number of past acquisitions of the same property type in the same destination city. In the UBS case, the quality-adjusted "RLE-type" is 1 versus the quality-neutral "RLE" of 5 used in the early regressions (Tables 2 and 4). Second, we construct another variable, "RLE-Outcity", which measures the number of historical acquisitions by an investor outside the current destination city (but still in the same host country). We use the "RLE-Outcity" variable to test the effectiveness of learning from out-of-city acquisition experiences versus "RLE", which is technically a proxy of the in-city acquisition experience.

We compare the three types of learning ("RLE", "RLE-Type" and "RLE-Outcity") in the log-unit price and price bias models, and the results are reported in Panels A and B of Table 10, respectively. In the baseline models for log-unit price and price bias, the coefficients of "RLE" are statistically and economically significant, and the values are estimated at -11.1% (Column 1) and -7.9% (Column 4), respectively. When we adjust for the quality of learning, "RLE-Type" coefficients are estimated at -7.7% (Column 2) for the log-unit price model and -5.7% (Column 5) for the price bias model. Type-specific learning coefficients are approximately 30% smaller than type-neutral "RLE" coefficients. More specifically, we may infer that the learning effects for acquisitions of the same type of property are -0.077/(-0.111 + 0.077) = 2.26 (log price) to -0.057/(-0.079 + 0.057) = 2.59 (price bias) times as large as the learning effects for different types of properties[21]. The results point to the importance of learning quality, implying that investors should be discriminatory in their acquisitions, such that they obtain information advantages more effectively through learning from the same type of property acquisitions than through non-discriminatory learning from acquisitions of different types of properties in local markets.

[21]The reductions in learning effect after adjusting for the same type of property acquisition experience are estimated at [-0.111 + 0.077 = -0.034] and [-0.079 + 0.057 = -0.022] for the log-unit price and price bias models, respectively.

[Insert Table 10 here]

For the out-of-city learning experience, the coefficients of the "RLE-Outcity" variable are statistically significant but have smaller estimated values of -2.2% (Column 3) and -1.8% (Column 6) in the log-unit price and the price bias models, respectively. Therefore, the learning effects from past acquisitions in the same host cities are (-0.079/-0.018)=4.38 (price bias) to -0.111/-0.022=5.04 (log price) times as large as the effects from acquisitions in other cities. The results imply that investors' experiences from past acquisitions in the same destination city are more effective for enhancing learning than acquisitions in other cities.

All models in Table 10 control for the characteristics of investors, properties, countries as shown in previous tables and the results are consistent. To save space, we do not report the results here.

4.2 Same-nationality Matches of Foreign Investors

Given the existence of price premiums paid by foreign investors in global commercial real estate market, as well as the existence of learning and quality of learning, what information can foreign investors infer from their past transactions to reduce the price premiums.

Due to the cultural or linguistic links, or those links that are physically proximate, foreign investors have a tendency to match sellers of same-nationality to reach a good deal (Nunn, 2007; Badarinza et al., 2019). In Appendix Table B2, we study whether same-country matching reduces the transaction price in cross-border commercial real estate deals. *Same-BS* is a dummy equal to 1 if the buyer and seller are from the same country. It is negative and statistically significant in predicting the price and price bias in cross-border transactions, implying that the same-country matching reduces the transaction price and hence the price premiums paid by foreign investors relative to local investors.

Therefore, the foreign investors may learn to pick out the counterparties of same-nationality to reduce the information asymmetry. To test this, we then examine whether experienced foreign investors are more likely to make a deal with sellers of same-nationality. In Columns (1) and (2) of Table 11, we employ a logit model and regress the *Same-BS* on the two learning measures, RLE and WLE. We find the coefficients of RLE and WLE are significantly positive, which are supportive of the hypothesis that experienced foreign investors incline to buy commercial properties from sellers of same-nationality.

[Insert Table 11 here]

Since the joint venture is also a way for foreign investors to reduce information asymmetry in cross-border transactions, we also test whether experienced foreign investors are more likely to exploit the joint venture strategy. The results are reported in Columns (3) and (4) of Table 11. However, the estimated coefficients of learning measures are indifferent from zero, indicating that foreign investors do not learn to use joint venture strategy. This can be explained by an investor's contradictory attitudes on joint venture. On the one hand, the joint venture serves as strategy for investors to reduce risk and information asymmetry in cross-border acquisitions (Balakrishnan and Koza, 1993; Inkpen and Beamish, 1997). On the one hand, the risk of technological leakage also increases in a joint venture (Javorcik and Wei, 2009). Therefore, the foreign investors become less dependent on joint venture when they accumulate enough transaction experience.

4.3 Language Proximity of Foreign Investors

Differing from the investors in domestic transactions, foreign investors in cross-border transactions confront the information asymmetry along three dimensions: geographically, linguistically, and economically. Following Sarkissian and Schill (2003) and Andrade and Chhaochharia (2010), we control for geographic, language, and economic proximity to refine the learning effect from historical acquisitions in cross-border transactions. Geographic proximity is defined as the inverse of physical distance in kilometers between the headquarter city of the investor and the host city of the property. Economic proximity is defined as the ratio of the volume of bilateral trade between home and host country to the total trade of the home country. Language proximity is a dummy that takes value 1 if home country shares a same official language with the host country, 0 otherwise. Our object in this section is to explore how proximities in geography, language, and economics between the home and destination countries affect foreign investors' learning effect in cross-border transactions.

Table 12 reports the results, with Panels A and B using log price and price bias as the dependent variable, respectively. We find the RLE is economically and statistically significant in all specifications in both Panels A and B. The coefficients of RLE for log price and price bias in cross-border transactions are estimated at around -0.14 and -0.10.

[Insert Table 12 here]

From Column (2) in both panels, we add three proximity variables, and find RLE remaining negative and significant. For log price, the geographic proximity is significantly negative in all specifications, while the other two proximity variables turn out to be insignificant. For price bias, all three proximity variables are insignificant. We also interact RLE with each of the three proximity variables and add the interaction term to the regression, separately. The aim is to explore how RLE varies under different conditions. We find only the interaction terms of RLE and language proximity are negative and significant in both panels, implying that the RLE of a foreign investor, who comes from a home country that uses the same official language as in the host country, is larger than that of those investors coming from home countries that use different official languages. In another word, language proximity, other than geographic and economic proximity facilitates foreign investors' learning effect in cross-border transactions.

4.4 Location Choices of Foreign Investors

Thanks to the rich information on investors and properties in our data, we can categorize the investors into Corporate and Finance investors[22], and group the properties into Senior Housing & Care, Apartment, Hotel, Office, Retail, Development Site, and Industrial. Figure 3 presents the distances to CBD for properties acquired by Corporate and Finance investors. As shown, the properties acquired by Corporate investors are, on average, 8.09km way from the city center, compared to a 13.26km CBD distance for properties acquired by Finance investors. Figure 3 also shows that the Development Sites locate farthest from the city center, estimated at 15.83km, followed by Industrial (13.22km), Retail (11.27km), Hotel (10.32km), Apartment (9.93km), Senior Housing & Care (8.91km), and Office (7.92km).

To further study what foreign investors are learning when they choose to engage in follow-on investments, we move to investigate the effect of learning on the location (CBD distance) dimension. Specifically, we examine whether corporate investors engage in follow-on investments differently from finance investors. In Panel A of Table 13, we find that the *CBD Distance* of properties purchased by the foreign corporate investors at the first time are around 8.098 km, which is 0.514 km smaller than the *CBD Distance* (estimated at 8.612 km) of properties purchased by the foreign finance investors at the first time. The difference in *CBD Distance* of the first-time purchase between corporate and finance investors is insignificant. When we look at the non-first-time purchases, we find that corporate investors, relative to finance investors, choose to buy properties that are closer to CBD in the destination city. In particular, corporate investors choose to engage in follow-on investments by purchasing properties that are 6.360 km away from CBD, while finance investors still purchase properties that are over 8 km away from CBD. The difference in *CBD Distance* of the non-first-time purchase between corporate and finance investors is statistically significant.

[**Insert Table 13 here**]

We also conduct the econometric regressions to see whether corporate investors incline to purchase properties closer to CBD with the accumulation of transaction experience, holding other variables constant. If this is the case, then it suggests that foreign corporate investors are learning about the locations. Model (1) of Panel B uses the sample consisting of first-time purchases only and shows that, at the first-time purchase, foreign corporate investors do not acquire geographically (measured by CBD distance) different properties, relative to finance investors. In Model (2), we find the interaction of Corporate*RLE negative and

[22]In our data, the Corporate includes two types of institutional investors: corporate and private firms. The Finance includes five types of institutional investors: equity fund, public fund, private fund, institutional finance, and institutional fund.

statistically significant at -0.06, which implies that one unit increase in learning experience decreases the CBD distance of properties acquired by corporate investors by more than 6% than that of properties acquired by finance investors. The results in Table 13 suggests that foreign corporate investors are learning about the locations.

5 Conclusions

This paper uses a unique transaction-level dataset to set up empirical tests on the dynamics of information asymmetries in the global commercial real estate markets. We find significant evidence to support the notion that learning via prior acquisition experiences reduces information asymmetries, and the results are in line with the learning choice argument proposed by the information immobility model of Van Nieuwerburgh and Veldkamp (2009), Andrade and Chhaochharia (2010) and Cuypers et al. (2017).

Our results do not reject the hypothesis suggesting that "local investors are better informed". We find that foreign investors pay 3.7% more on average than local investors in acquiring comparable properties in local markets. The premiums paid by foreign investors are uncorrelated with the effects of hiring real estate agents ("Agent") and anchoring on home prices ("Anchoring"), and the results are clear of possible sample selection bias. We also rule out the alternative explanations that location heterogeneity and property quality lead to the price premiums paid by foreign investors.

However, we are unable to reject the hypothesis that learning from prior acquisitions significantly increases the information level of investors. The learning effects as represented by "RLE", which is based on the number of historical acquisitions by an investor before the current acquisition in the host city, significantly reduce the log price by -11.1% and the price bias by -7.7%. When we adjust the learning effects by adding more weight to distant past acquisitions in the "WLE", the learning effects remain robust and significant. More important, the inclusion of the RLE or the WLE variable explains away the price premiums paid by foreign investors. This suggests that the difference of learning from historical experience between foreign and local investors, which serves as a proxy for the information asymmetry, explains the price discrepancy between properties acquired by foreign and local investors. The results of heterogeneous tests show that Corporate investors and investors who purchase location-valued properties learn more from historical acquisitions. Moreover, when investigating the home-turf advantages (initial information advantage) of first-time local investors, we find that foreign investors reduce the information gap with local investors through their learning from prior acquisitions in the local market. Specifically, we show that foreign investors nullify their initial information disadvantage by accumulating at least four acquisition experiences in host cities.

We then take a closer look at what and how investors learn from past transaction experience? First, we find that learning effects in the same property type are substantially larger than learning effects in different types of properties. Similarly, learning effects in the same host cities are found to be larger than learning effects in other cities. Second, we find foreign investors learn to pick out the counterparties of same-nationality to reduce the information asymmetry. However, we do not find the learning effects for foreign investors in exploiting the joint venture strategy to reduce information asymmetry. Third, the results show that Corporate investors and investors who purchase location-valued properties learn more from historical acquisitions. Third, we find that language proximity, other than geographic and economic proximity facilitates foreign investors' learning effect in cross-border transactions. Further, we find that foreign corporate investors are learning about the locations.

The results imply that foreign investors' prior acquisition experience is a necessary step to reduce their information disadvantages relative to local investors in the global real estate markets. Information immobility does not impose barriers on cross-border investments into local markets. Information asymmetries of foreign investors are uncorrelated with selection bias, the hiring of third-party agents, and anchoring to home market prices. Foreign investors learn via prior acquisitions to reduce the information gap against local investors.

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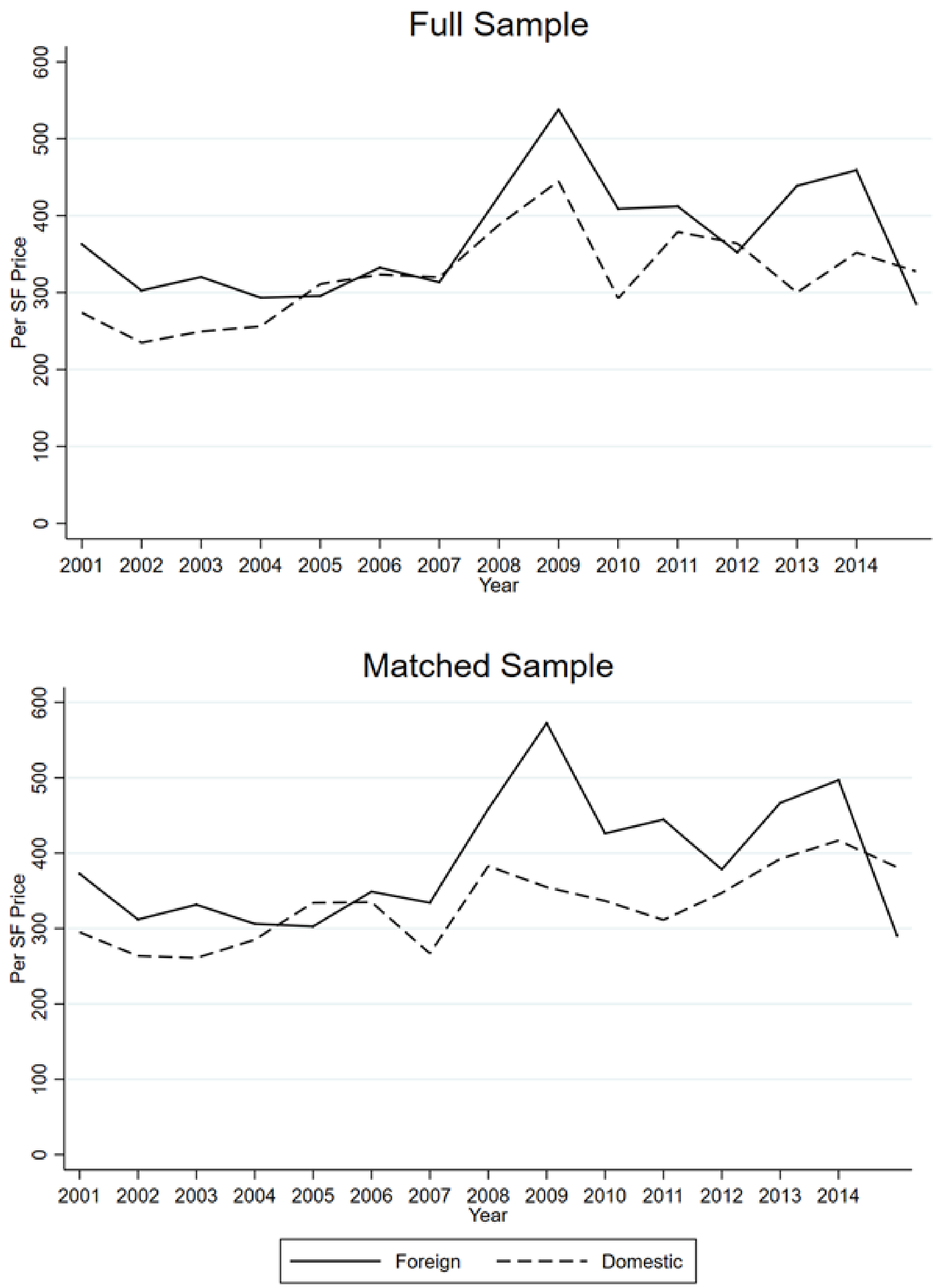
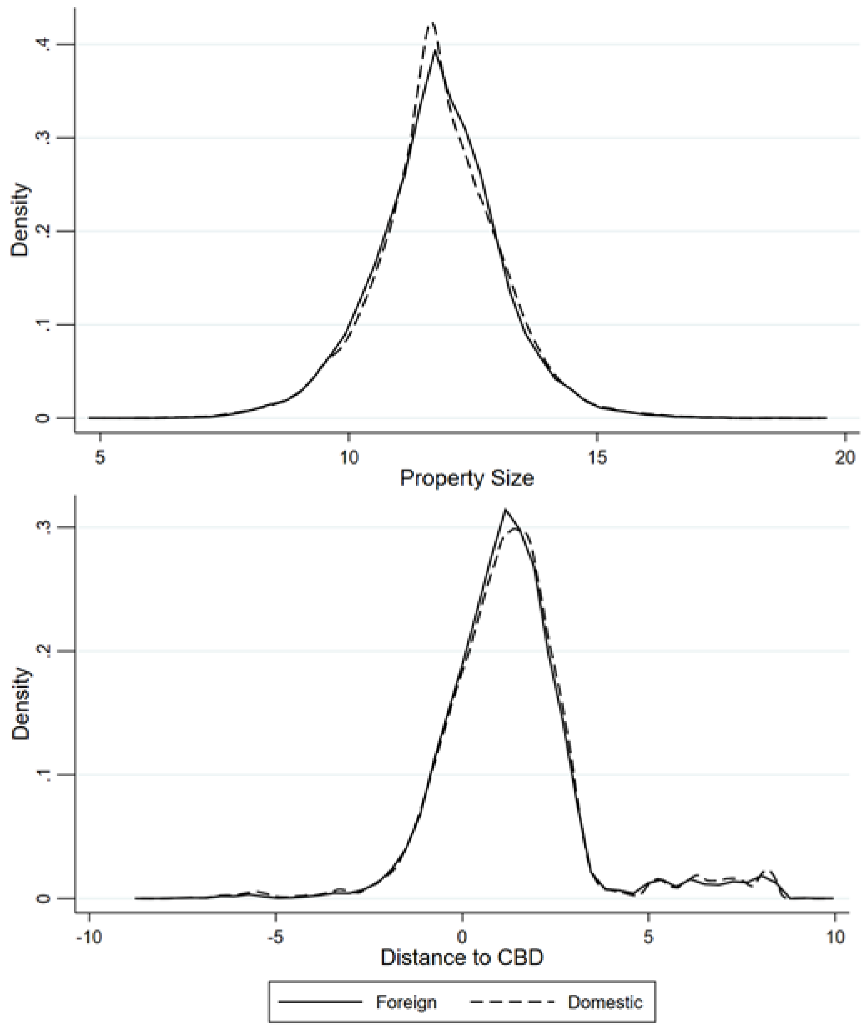
Figure 1: Comparison of Acquisition Prices between Foreign and Domestic Investors



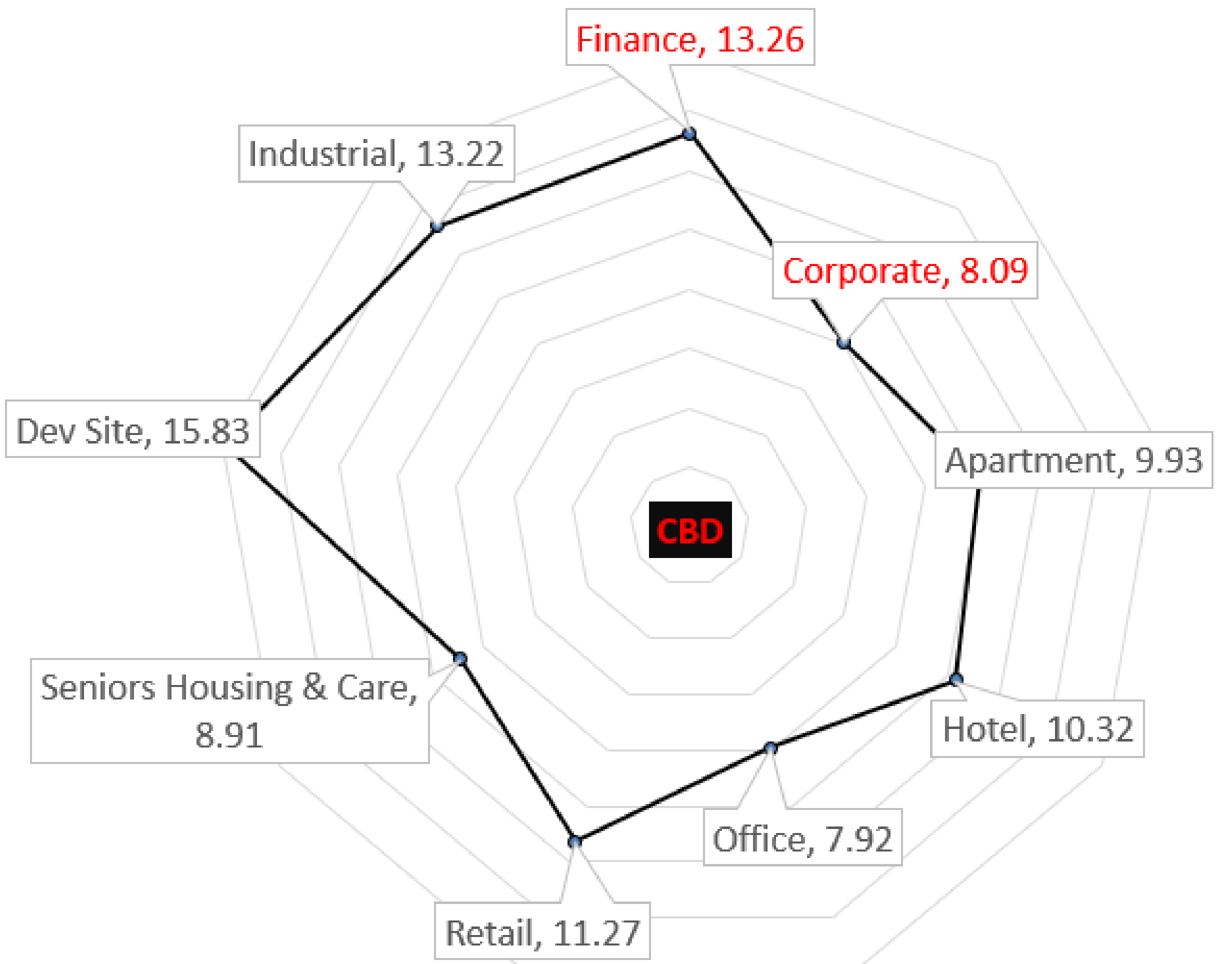
Notes: The top graph shows the comparison of acquisition price between foreign and local investors along the sample period based on the full sample. The bottom graph shows the comparison of acquisition price between foreign and local investors along the sample period based on the matched sample.

Figure 2: Kernel Density Plots of the Matched Sample



Notes: This figure presents the kernel distribution of property size in psf (top graph) and property's distance to CBD (bottom graph) of foreign investors versus local investors after the PSM.

Figure 3: Distance to CBD



Notes: This figure presents distances (in km) to CBD for different types of properties. Finance and Corporate stand for the properties acquired by Finance and Corporate investors, respectively. Apartment, Hotel, Office, Senior Housing & Care, Development Site, and Industrial represents the acquired properties in respective categories.

Table 1: Descriptive Staitstics

	Panel A: Full sample			Panel B: Matched sample		
	Local	Foreign	Diff. in Means	Local	Foreign	Diff. in Means
Unit Price (US$)	315.54	340.031	-24.491***	325.873	357.255	-31.382***
Total Price (Million US$)	44.119	55.969	-11.85***	53.355	57.615	-4.26***
Price Bias	-0.043	0.01	-0.054***	-0.009	0.018	-0.027***
Distance (km)	934	5,820	-4,886***	877	5,862	-4985***
Agent	0.182	0.216	-0.034**	0.245	0.215	0.03*
Anchoring	321.625	321.882	-0.257	323.064	327.688	-4.624
RLE	8.818	4.114	4.704***	7.885	4.288	3.597***
WLE	1.304	0.828	0.476***	1.252	0.862	0.39***
JV	0.176	0.315	-0.139**	0.298	0.294	0.004
Size (square feet)	404,976.80	376,172.20	28,804.6***	360,875.30	345,797.40	15,077.90
CBD Distance (km)	9.961	8.791	1.170**	8.353	7.874	0.479
No. of Assets	368.912	406.798	-37.886***	439.2	414.6	24.6**
Volume	76.116	66.575	9.541	66.499	70.478	-3.979
TI	3.978	3.978	0	3.978	3.978	0
PerGDP	29,299	29,299	0	29,299	29,299	0
Number of Observations	120,192	39,731		25,881	36,302	
Number of Investors	14,297	3,595		4,754	3,398	
Number of Countries		59			59	
Number of Cities		5,219			4,532	

Notes: This table presents the summary statistics for the full samples and the matched samples of foreign investors and local investors during the period from 2001 to 2015. The definifions of the variables are reported in Appendix A. This table reports the mean of the key variables used in our empirical analysis as well as pairwise differences in means, with *** indicating a difference that is significant at the 1% level, ** indicating the significance at the 5% level, and * indicating the significance at the 10% level.

Table 2: Log-Unit Price in Local and Foreign Real Estate Investments

Panel A: Regressions on Full Sample

Dep. Variable	ln(Unit Price)						
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign	0.037*	0.037*	0.034***	-0.011	-0.011	-0.013	-0.015
	(0.020)	(0.019)	(0.010)	(0.019)	(0.019)	(0.020)	(0.020)
Agent		-0.183***					-0.176***
		(0.023)					(0.022)
Anchoring			0.018***				0.019***
			(0.004)				(0.005)
RLE				-0.111***	-0.134***	-0.155***	-0.182***
				(0.007)	(0.010)	(0.018)	(0.020)
RLE2					0.007**		0.008***
					(0.003)		(0.003)
RLE*TI						0.015***	0.016***
						(0.005)	(0.004)
ln(Size)	-0.308***	-0.316***	-0.309***	-0.317***	-0.318***	-0.318***	-0.326***
	(0.014)	(0.013)	(0.006)	(0.014)	(0.014)	(0.014)	(0.014)
ln(CBD Dis.)	-0.059***	-0.058***	-0.058***	-0.058***	-0.058***	-0.058***	-0.057***
	(0.006)	(0.006)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
ln(Assets)	0.008***	0.008***	0.008***	0.030***	0.030***	0.030***	0.029***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
ln(PerGDP)	0.606***	0.591***	0.686***	0.694***	0.700***	0.621***	0.692***
	(0.167)	(0.166)	(0.101)	(0.159)	(0.159)	(0.162)	(0.162)
TI	-0.003	0.006	-0.006	-0.000	0.000	-0.020	-0.015
	(0.043)	(0.042)	(0.023)	(0.043)	(0.043)	(0.044)	(0.044)
JV	-0.142***	-0.140***	-0.141***	-0.150***	-0.151***	-0.150***	-0.146***
	(0.020)	(0.020)	(0.012)	(0.020)	(0.020)	(0.020)	(0.021)
ln(Volume)	0.261***	0.260***	0.261***	0.273***	0.273***	0.273***	0.273***
	(0.010)	(0.010)	(0.005)	(0.010)	(0.010)	(0.010)	(0.010)
Constant	-2.754	-2.403	-3.698***	-3.800**	-3.857**	-3.003*	-3.667**
	(1.846)	(1.834)	(1.119)	(1.756)	(1.760)	(1.791)	(1.804)
Observations	159,923	159,923	157,882	159,923	159,923	159,923	157,882
R-squared	0.643	0.645	0.647	0.648	0.648	0.648	0.650
Fixed Effect	YES	YES	YES	YES	YES	YES	YES

Panel B: Regressions on Matched Sample

Dep. Variable	ln(Unit Price)						
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign	0.033*	0.033*	0.032*	-0.006	-0.006	-0.007	-0.006
	(0.018)	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)
Agent		-0.192***					-0.187***
		(0.029)					(0.027)
Anchoring			0.001				0.003
			(0.004)				(0.004)
RLE				-0.125***	-0.149***	-0.160***	-0.188***
				(0.009)	(0.012)	(0.018)	(0.020)
RLE2					0.008**		0.010***
					(0.004)		(0.004)
RLE*TI						0.014**	0.014***
						(0.005)	(0.005)
ln(Size)	-0.252***	-0.264***	-0.254***	-0.265***	-0.265***	-0.265***	-0.278***
	(0.015)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)
ln(CBD Dis.)	-0.055***	-0.054***	-0.054***	-0.054***	-0.054***	-0.054***	-0.052***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)
ln(Assets)	-0.001	-0.002	0.000	0.018***	0.019***	0.018***	0.019***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
ln(PerGDP)	0.718***	0.694***	0.716***	0.744***	0.748***	0.713***	0.693***
	(0.199)	(0.197)	(0.202)	(0.193)	(0.194)	(0.194)	(0.195)
TI	-0.034	-0.025	-0.040	-0.039	-0.039	-0.052	-0.049
	(0.049)	(0.048)	(0.049)	(0.047)	(0.047)	(0.047)	(0.048)
JV	-0.163***	-0.159***	-0.161***	-0.171***	-0.172***	-0.171***	-0.167***
	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
ln(Volume)	0.265***	0.263***	0.266***	0.277***	0.278***	0.278***	0.277***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
Constant	-4.563**	-4.122*	-4.563**	-4.853**	-4.889**	-4.498**	-4.131*
	(2.200)	(2.174)	(2.224)	(2.142)	(2.145)	(2.152)	(2.159)
Observations	62,183	62,183	60,357	62,183	62,183	62,183	60,357
R-squared	0.658	0.661	0.662	0.664	0.664	0.664	0.666
Fixed Effect	YES	YES	YES	YES	YES	YES	YES

Notes: This table reports the results of estimating Equation (3) using ln(Unit Price) as the dependent variable. Panel A and B report the results of estimations on full sample and matched sample, respectively. RLE2 is the square of RLE, which captures the quadratic relationship between RLE and acquisition price. RLE*TI is an interaction used to test how learning effect changes in association with corruption in the host city. Other variables mean the same as defined in Table 1. Investor type fixed effect, property type fixed effect, host city fixed effect, country of origin fixed effect and year-month fixed effect are included in all regressions. Heteroscedasticity-consistent standard errors clustered at the host city level are shown in parentheses under the coefficients estimated. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

Table 3: Are Properties Purchased by Foreign Investors Better than Those Purchased by Domestic Investors

Panel A: Unconditional Comparison

	Domestic	Foreign	Diff. in Means
Holding Period Return	0.443	0.182	0.261***
Holding Period	48.497	52.144	-3.647

Panel B: Regressions of Holding Period Return

Model	OLS	Heckman Two-Step	
		First-step	Second-step
	(1)	(2)	(3)
Foreign	-0.099**		-0.101*
	(0.038)		(0.059)
Holding Period	-0.026		-0.020
	(0.029)		(0.031)
ln(Size)	0.079***	-0.021***	0.146***
	(0.025)	(0.004)	(0.042)
ln(CBD Dis.)	-0.049***	-0.005**	-0.040**
	(0.015)	(0.002)	(0.019)
ln(Assets)	0.012	0.067***	0.366***
	(0.008)	(0.002)	(0.082)
ln(Per GDP)	-2.185*	0.663***	-3.662***
	(1.210)	(0.017)	(0.842)
TI	0.156	0.048***	-0.249***
	(0.109)	(0.005)	(0.067)
JV	0.154*	0.234***	0.217***
	(0.081)	(0.010)	(0.044)
ln(Volume)	-0.258***	0.021***	-0.189***
	(0.041)	(0.003)	(0.030)
ln(Total Price)		-0.005	
		(0.005)	
Inverse Mills Ratio			-7.401***
			(1.583)
Constant	26.515**	-7.661***	50.044***
	(12.185)	(0.198)	(10.924)
Observations	28,657	160,375	160,375
R-squared	0.213		
Rho			-1.000
Sigma			7.401
Fixed FE	YES	YES	YES

Notes: This table examines whether the properties purchased by foreign investors are better than those purchased by domestic investors. Panel A reports the summary statistics for Holding Period Return (HPR) and Holding Period (HP) in the sample of repeat sales. Panel B reports the results of estimations of HPR on Foreign dummy, with Column (1) corresponding to OLS estimation, and Columns (2) and (3) corresponding to Heckman Two-step estimation, respectively. Investor type fixed effect, property type fixed effect, host city fixed effect, country of origin fixed effect and year-month fixed effect are included in all regressions. Heteroscedasticity-consistent standard errors clustered at the host city level are shown in parentheses under the coefficients estimated. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

Table 4: Price Bias between Local and Foreign Investors

Panel A: Regressions on Full Sample

Dep. Variable	Price Bias						
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign	0.041**	0.041***	0.040***	0.007	0.007	0.007	0.005
	(0.016)	(0.015)	(0.008)	(0.015)	(0.015)	(0.015)	(0.015)
Agent		-0.134***					-0.130***
		(0.017)					(0.016)
Anchoring			0.022***				0.022***
			(0.003)				(0.004)
RLE				-0.079***	-0.118***	-0.087***	-0.128***
				(0.007)	(0.010)	(0.012)	(0.012)
RLE2					0.011***		0.012***
					(0.003)		(0.002)
RLE*TI						0.002	0.004
						(0.003)	(0.003)
ln(Size)	-0.168***	-0.173***	-0.169***	-0.174***	-0.175***	-0.174***	-0.181***
	(0.009)	(0.010)	(0.005)	(0.010)	(0.010)	(0.010)	(0.010)
ln(CBD Dis.)	-0.044***	-0.043***	-0.043***	-0.043***	-0.043***	-0.043***	-0.042***
	(0.006)	(0.006)	(0.003)	(0.006)	(0.006)	(0.006)	(0.005)
ln(Assets)	0.004	0.004	0.004***	0.020***	0.020***	0.020***	0.020***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln(PerGDP)	0.216*	0.204	0.324***	0.279**	0.288**	0.267**	0.367***
	(0.129)	(0.127)	(0.073)	(0.130)	(0.132)	(0.133)	(0.128)
TI	-0.054**	-0.048*	-0.058***	-0.052**	-0.051**	-0.055**	-0.054**
	(0.025)	(0.024)	(0.016)	(0.024)	(0.024)	(0.026)	(0.025)
JV	-0.135***	-0.133***	-0.134***	-0.141***	-0.141***	-0.141***	-0.138***
	(0.015)	(0.015)	(0.011)	(0.015)	(0.015)	(0.015)	(0.015)
ln(Volume)	0.150***	0.150***	0.149***	0.159***	0.159***	0.159***	0.158***
	(0.006)	(0.006)	(0.004)	(0.007)	(0.007)	(0.007)	(0.007)
Constant	-3.090**	-2.833**	-4.341***	-3.841***	-3.937***	-3.711***	-4.735***
	(1.395)	(1.381)	(0.819)	(1.396)	(1.412)	(1.432)	(1.381)
Observations	159,923	159,923	157,882	159,923	159,923	159,923	157,882
R-squared	0.140	0.143	0.141	0.147	0.147	0.147	0.151
Fixed Effect	YES	YES	YES	YES	YES	YES	YES

Panel B: Regressions on Matched Sample

Dep. Variable	Price Bias						
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign	0.043***	0.043***	0.044***	0.015	0.015	0.015	0.016
	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
Agent		-0.155***					-0.153***
		(0.024)					(0.021)
Anchoring			0.007*				0.008**
			(0.004)				(0.004)
RLE				-0.092***	-0.107***	-0.108***	-0.127***
				(0.006)	(0.011)	(0.013)	(0.015)
RLE2					0.005		0.006**
					(0.003)		(0.003)
RLE*TI						0.006	0.007
						(0.005)	(0.005)
ln(Size)	-0.161***	-0.170***	-0.163***	-0.170***	-0.170***	-0.171***	-0.181***
	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
ln(CBD Dis.)	-0.046***	-0.046***	-0.044***	-0.045***	-0.045***	-0.045***	-0.043***
	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)	(0.009)
ln(Assets)	-0.004	-0.005	-0.003	0.010***	0.010***	0.010***	0.010***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
ln(PerGDP)	0.410**	0.390**	0.427**	0.429**	0.432**	0.415**	0.415**
	(0.182)	(0.180)	(0.181)	(0.186)	(0.186)	(0.188)	(0.184)
TI	-0.064*	-0.057*	-0.072**	-0.068**	-0.068**	-0.074**	-0.075**
	(0.035)	(0.034)	(0.034)	(0.033)	(0.033)	(0.033)	(0.033)
JV	-0.152***	-0.149***	-0.151***	-0.159***	-0.159***	-0.159***	-0.154***
	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.015)	(0.016)
ln(Volume)	0.172***	0.170***	0.171***	0.181***	0.181***	0.181***	0.178***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Constant	-5.038***	-4.682**	-5.225***	-5.250***	-5.274***	-5.090**	-4.954**
	(1.934)	(1.907)	(1.928)	(1.979)	(1.984)	(2.001)	(1.964)
Observations	62,183	62,183	60,357	62,183	62,183	62,183	60,357
R-squared	0.166	0.171	0.167	0.174	0.175	0.175	0.180
Fixed FE	YES	YES	YES	YES	YES	YES	YES

Notes: This table reports the results of estimating Equation (3) using Price Bias as the dependent variable. Panel A and B report the results of estimations on full sample and matched sample, respectively. RLE2 is the square of RLE, which captures the quadratic relationship between RLE and acquisition price. RLE*TI is an interaction used to test how learning effect changes in association with corruption in the host city. Other variables mean the same as defined in Table 1. Investor type fixed effect, property type fixed effect, host city fixed effect, country of origin fixed effect and year-month fixed effect are included in all regressions. Heteroscedasticity-consistent standard errors clustered at the host city level are shown in parentheses under the coefficients estimated. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

Table 5: Falsification Tests

Dep. Variable	Ln(Price)	Price Bias
	(1)	(2)
Foreign	0.019	0.033
	(0.018)	(0.031)
ln(Size)	-0.249***	-0.160***
	(0.014)	(0.022)
ln(CBD Dis.)	-0.058***	-0.052***
	(0.011)	(0.009)
ln(Assets)	-0.001	-0.006
	(0.004)	(0.006)
ln(PerGDP)	0.820***	0.558**
	(0.132)	(0.220)
JV	-0.162***	-0.160***
	(0.020)	(0.020)
ln(Volume)	0.261***	0.177***
	(0.011)	(0.009)
Constant	-5.528***	-6.803***
	(1.374)	(2.224)
Observations	61,851	59,273
R-squared	0.657	0.155
Fixed Effect	YES	YES

Notes: This table reports the results of falsifications. We perform the propensity score matching based on property size, CBD distance, property type, host country, and RLE. This matching principle would result in the same RLE between foreign investors and local investors. We then perform the OLS estimations, with Column (1) and (2) employing ln(Unit Price) and Price Bias as the dependent variables, respectively. The independent variables are defined as in Table 1. Investor type fixed effect, property type fixed effect, host city fixed effect, country of origin fixed effect and year-month fixed effect are included in all regressions. Heteroscedasticity-consistent standard errors clustered at the host city level are shown in parentheses under the coefficients estimated. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

Table 6: Heterogeneous Tests

Dep. Variable	ln(Unit Pirce)	
Model	(1)	(2)
Foreign	-0.011	-0.015
	(0.019)	(0.019)
RLE	-0.098***	-0.099**
	(0.009)	(0.040)
Investor Type		
RLE**Finance*	0.042***	
	(0.013)	
Property Type		
RLE**Apartment*		-0.146***
		(0.047)
RLE**Dev_Site*		0.101**
		(0.050)
RLE**Hotel*		-0.063***
		(0.009)
RLE**Industrial*		-0.018
		(0.026)
RLE**Office*		-0.091**
		(0.046)
RLE**Retail*		-0.037**
		(0.017)
Constant	-4.267**	-1.990
	(1.752)	(1.636)
Observations	159,923	159,923
R-squared	0.649	0.656
Fixed FE	YES	YES
Controls	YES	YES

Notes: This table reports the results of estimating the heterogeneity of learning effects across investor types and property types. The dependent variable is ln(Unit Price). Finance is a dummy equal to 1 if the investor is a Finance investor and 0 otherwise. In Column (1), the reference group is the Corporate investor. In Column (2), the reference group is the Senior Housing & Care. Other variables mean the same as defined in Table 1. The structural control variables are the same as in Table 2 and are included in all regressions in this table. To save space, we do not report here. Investor type fixed effect, property type fixed effect, host city fixed effect, country of origin fixed effect and year-month fixed effect are included in all regressions. Heteroscedasticity-consistent standard errors clustered at the host city level are shown in parentheses under the coefficients estimated. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

Table 7: Weighted Learning Effects (WLE)

Dep. Variable	**Panel A: Ln(Unit Price)**				**Panel B: Price Bias**			
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Foreign	-0.005	-0.009	0.010	0.009	-0.009	-0.006	0.003	0.007
	(0.019)	(0.020)	(0.031)	(0.015)	(0.015)	(0.015)	(0.014)	(0.013)
WLE	-0.083***	-0.157***	-0.061***	-0.111***	-0.086***	-0.170***	-0.067***	-0.133***
	(0.006)	(0.017)	(0.008)	(0.011)	(0.007)	(0.018)	(0.007)	(0.019)
WLE2		0.010***		0.012***		0.015***		0.017***
		(0.003)		(0.003)		(0.004)		(0.006)
WLE*TI		0.014***		0.003		0.014***		0.003
		(0.004)		(0.003)		(0.005)		(0.004)
Agent		-0.179***		-0.140***		-0.207***		-0.177***
		(0.022)		(0.017)		(0.029)		(0.024)
Anchoring		0.019***		0.023***		0.005		0.010**
		(0.005)		(0.004)		(0.004)		(0.005)
Constant	-3.571**	-3.531*	-3.650**	-4.652***	-4.099**	-3.249	-6.279***	-6.105***
	(1.782)	(1.821)	(1.678)	(1.398)	(2.053)	(2.064)	(2.244)	(2.313)
Observations	159,923	157,882	153,213	151,319	57,130	55,270	54,869	53,112
R-squared	0.646	0.648	0.149	0.153	0.674	0.677	0.167	0.174
Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table reports the results of estimating Equation (3) using WLE as the key explanatory variable. The headers in the first row indicate the dependent variables, and the headers in the second row denote the samples used for the estimations. WLE2 is the square of WLE, which captures the quadratic relationship between WLE and acquisition price. WLE*TI is an interaction used to test how learning effect changes in association with corruption in the host city. Other variables mean the same as defined in Table 1. The structural control variables are the same as in Table 2 and are included in all regressions in this table. o save space, Iwe do not report here. nveTstor type fixed effect, property type fixed effect, host city fixed effect, country of origin fixed effect and year-month fixed effect are included in all regressions. Heteroscedasticity-consistent standard errors clustered at the host city level are shown in parentheses under the coefficients estimated. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

Table 8: Home-Turf Advantage of Local Investors

	Panel A: Full Sample		**Panel B: Matched Sample**	
Dep. Variable	Ln(Price)	Price Bias	Ln(Price)	Price Bias
Model	(1)	(2)	(3)	(4)
OutCity	0.066***	0.099***	0.088**	0.107**
	(0.021)	(0.024)	(0.035)	(0.047)
OutCity*Foreign	0.050***	0.047***	0.042***	0.040***
	(0.011)	(0.010)	(0.011)	(0.010)
ln(Size)	-0.457***	-0.258***	-0.410***	-0.249***
	(0.011)	(0.011)	(0.015)	(0.012)
ln(CBD Dis.)	-0.036***	-0.026***	-0.038***	-0.032***
	(0.004)	(0.004)	(0.006)	(0.006)
ln(Assets)	0.007***	0.003*	0.005*	-0.001
	(0.002)	(0.002)	(0.003)	(0.002)
ln(PerGDP)	0.162	0.153	-0.118	0.246
	(0.117)	(0.110)	(0.130)	(0.186)
TI	-0.049**	-0.067***	-0.072***	-0.062**
	(0.021)	(0.018)	(0.027)	(0.029)
JV	-0.235***	-0.193***	-0.236***	-0.205***
	(0.019)	(0.012)	(0.018)	(0.015)
ln(Volume)	0.411***	0.244***	0.398***	0.256***
	(0.009)	(0.008)	(0.011)	(0.009)
Constant	1.287	-2.828**	3.889***	-3.982**
	(1.198)	(1.173)	(1.404)	(1.963)
Observations	60,152	60,152	31,334	31,334
R-squared	0.694	0.230	0.731	0.250
Fixed Effect	YES	YES	YES	YES

Notes: This table reports the results of estimating the home-turf advantage of local investors, with Panel A corresponding to the full sample and Panel B corresponding to the Matched sample. We only keep the transactions that are investors' first-time purchases in the host cities. An "out-town" dummy takes a value of 1, if an investor has his/her headquarter in a different city, but within the same country relative to the property location; and otherwise a value of 0, if he is identified as an "in-city" investor having the headquarter and property located in the same city. Other variables mean the same as defined in Table 1. Investor type fixed effect, property type fixed effect, host city fixed effect, country of origin fixed effect and year-month fixed effect are included in all regressions. Heteroscedasticity-consistent standard errors clustered at the host city level are shown in parentheses under the coefficients estimated. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

Table 9: Incremental Prior Acquisitions and Learning Effects

Dep. Variable Model	Ln(Price) (1)	Price Bias (2)
Foreign	0.189***	0.157***
	(0.038)	(0.041)
Foreign*Two	-0.111***	-0.094***
	(0.010)	(0.011)
Foreign*Three	-0.161***	-0.145***
	(0.016)	(0.014)
Foreign*Four	-0.206***	-0.176***
	(0.019)	(0.020)
Foreign*Five	-0.233***	-0.181***
	(0.025)	(0.027)
Foreign*Six	-0.247***	-0.171***
	(0.038)	(0.040)
Foreign*Seven	-0.226***	-0.185***
	(0.034)	(0.036)
Foreign*Eight	-0.234***	-0.183***
	(0.034)	(0.042)
Foreign*Nine	-0.241***	-0.183***
	(0.040)	(0.042)
Foreign*Ten	-0.235***	-0.173***
	(0.033)	(0.026)
Constant	-1.765	-4.622*
	(1.859)	(2.580)
Observations	31,334	31,334
R-squared	0.707	0.190
Fixed Effect	YES	YES
Controls	YES	YES

Notes: This table reports the results of the sensitivity analyses of price difference to foreign investors' incremental RLE. Using the first-time local investors (both in-city and out-town) as the reference (control) group, we test the effectiveness of learning in reducing information asymmetries of the matched foreign investors via the increasing "RLE". E.g. "Foreign*Two" indicates foreign investors with two past acquisitions in the local market. The headers in the first row denoting the dependent variable used in specifications. Other variables mean the same as defined in Table 1. The structural control variables are the same as in Table 2 and are included in all regressions in this table. To save space, we do not report here. Investor type fixed effect, property type fixed effect, host city fixed effect, country of origin fixed effect and year-month fixed effect are included in all regressions. Heteroscedasticity-consistent standard errors clustered at the host city level are shown in parentheses under the coefficients estimated. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

Table 10: The Quality of Learning

Dep. Variable	Panel A: Ln(Price)			Panel B: Price Bias		
Model	(1)	(2)	(3)	(4)	(5)	(6)
Foreign	-0.011	0.020	0.012	0.007	0.029*	0.020
	(0.019)	(0.020)	(0.019)	(0.015)	(0.015)	(0.014)
RLE	-0.111***			-0.079***		
	(0.007)			(0.007)		
RLE-Type		-0.077***			-0.057***	
		(0.009)			(0.007)	
RLE-OutCity			-0.022***			-0.018***
			(0.004)			(0.004)
Constant	-3.800**	-3.556**	-2.945	-3.841***	-3.681***	-3.248**
	(1.756)	(1.788)	(1.849)	(1.396)	(1.371)	(1.377)
Observations	159,923	159,923	159,923	159,923	159,923	159,923
R-squared	0.648	0.645	0.643	0.147	0.143	0.141
Fixed Effect	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

Notes: This table reports the results of estimating the quality of learning effects. RLE-Type is the number of investors' historical acquisitions aggregated by property type in the host city. RLE-Outcity is the number of investors' historical acquisitions outside the host city, but still in the host country. Other variables mean the same as defined in Table 1. The structural control variables are the same as in Table 2 and are included in all regressions in this table. To save space, we do not report here. Investor type fixed effect, property type fixed effect, host city fixed effect, country of origin fixed effect and year-month fixed effect are included in all regressions. Heteroscedasticity-consistent standard errors clustered at the host city level are shown in parentheses under the coefficients estimated. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

Table 11: The Nature of Learning Process

Dep. Variable	Same-BS		JV	
Learning Measure	RLE	WLE	RLE	WLE
Model	(1)	(2)	(3)	(4)
LE	0.054**	0.034*	-0.015	-0.013
	(0.026)	(0.018)	(0.016)	(0.015)
ln(Unit Price)	0.079**	-0.009	-0.056***	-0.056***
	(0.032)	(0.026)	(0.008)	(0.008)
ln(Volume)	0.134***	0.096***	-0.027***	-0.027***
	(0.024)	(0.023)	(0.009)	(0.009)
ln(CBD Dis.)	-0.046***	-0.047***	-0.002	-0.002
	(0.014)	(0.014)	(0.003)	(0.003)
ln(Assets)	0.076***	0.091***	0.002	0.002
	(0.013)	(0.011)	(0.002)	(0.002)
ln(PerGDP)	-1.305***	-1.203***	-0.192**	-0.191**
	(0.088)	(0.082)	(0.079)	(0.079)
TI	-0.289***	-0.366***	-0.002	-0.002
	(0.028)	(0.028)	(0.014)	(0.014)
ln(Volume)	0.003	-0.003	0.116***	0.116***
	(0.019)	(0.018)	(0.006)	(0.006)
Constant	8.146***	7.842***	0.400	0.387
	(1.106)	(1.041)	(0.817)	(0.816)
Observations	31,334	31,334	31,334	31,334
Fixed Effect	YES	YES	YES	YES

Notes: This table reports the results of logit models that regress *Same-BS* and JV on explanatory variables. *Same-BS* is a dummy equal to 1 if the buyer and seller are from the same country. Investor type fixed effect, property type fixed effect, host city fixed effect, country of origin fixed effect and year-month fixed effect are included in all regressions. Heteroscedasticity-consistent standard errors clustered at the host city level are shown in parentheses under the coefficients estimated. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

Table 12: Geographical Proximity in Cross-Border Transactions

Panel A. Dependent Variable: ln(Unit Price)

Dep. Variable	ln(Unit Price)				
Model	(1)	(2)	(3)	(4)	(5)
RLE	-0.153***	-0.142***	-0.148***	-0.131***	-0.148***
	(0.011)	(0.011)	(0.011)	(0.007)	(0.012)
Geographic Proximity		-1.462*	-1.933***	-1.487*	-1.465*
		(0.808)	(0.377)	(0.787)	(0.809)
Language Proximity		-0.031	-0.030	-0.012	-0.031
		(0.025)	(0.024)	(0.015)	(0.025)
Economic Proximity		0.014	0.001	0.012	-0.025
		(0.059)	(0.057)	(0.039)	(0.053)
RLE*Geographic Proximity			5.713		
			(4.433)		
RLE*Language Proximity				-0.023**	
				(0.010)	
RLE*Economic Proximity					0.054
					(0.053)
Constant	-0.063	0.997	1.043	0.898	1.109
	(1.969)	(2.025)	(2.008)	(0.933)	(1.999)
Observations	40,360	30,284	30,284	30,284	30,284
R-squared	0.720	0.721	0.721	0.721	0.721
Fixed Effect	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES

Panel B. Dependent Variable: Price Bias

Dep. Variable	Price Bias				
Model	(1)	(2)	(3)	(4)	(5)
RLE	-0.120***	-0.109***	-0.110***	-0.100***	-0.118***
	(0.008)	(0.009)	(0.010)	(0.014)	(0.011)
Geographic Proximity		-0.115	-0.222	-0.136	-0.119
		(0.740)	(0.729)	(0.745)	(0.736)
Language Proximity		-0.038	-0.038	-0.022	-0.038
		(0.026)	(0.026)	(0.020)	(0.026)
Economic Proximity		-0.068	-0.071	-0.070	-0.124**
		(0.063)	(0.061)	(0.089)	(0.056)
RLE*Geographic Proximity			1.297		
			(3.932)		
RLE*Language Proximity				-0.020*	
				(0.010)	
RLE*Economic Proximity					0.077
					(0.059)
Constant	-2.717	-2.661	-2.651	-2.744	-2.502
	(1.827)	(2.010)	(2.006)	(1.713)	(1.976)
Observations	40,360	30,284	30,284	30,284	30,284
R-squared	0.202	0.221	0.221	0.221	0.221
Fixed Effect	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES

Notes: This table reports the results of estimating Equation (3) with the sample of cross-border transactions. Panel A and B report the results of estimations using ln(Unit Price) and Price Bias as the dependent variable, respectively. Geographic Proximity is defined as the inverse of physical distance in kilometers between the headquarter city of the investor and the host city of the property. Economic Proximity is defined as the ratio of the volume of bilateral trade between home and host country to the total trade of the home country. Language Proximity is a dummy that takes value 1 if home country shares a same official language with the host country, 0 otherwise. Other variables mean the same as defined in Table 1. The structural control variables are the same as in Table 2 and are included in all regressions in this table. To save space, we do not report here. Investor type fixed effect, property type fixed effect, host city fixed effect, country of origin fixed effect and year-month fixed effect are included in all regressions. Heteroscedasticity-consistent standard errors clustered at the host city level are shown in parentheses under the coefficients estimated. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

Table 13: Effect of Learning on *CBD Distance* for Foreign Investors

Panel A: Unconditional Comparison of CBD Distance (in km)

	Corporate	Finance	Difference
First-Time Purchase	8.098	8.612	-0.514
non-First-Time Purchase	6.360	8.202	-1.842***

Panel B: Regression Results

Dep. Variable	ln(CBD Distance)	
Sample	First-time Purchase	All Purchases
Model	(1)	(2)
Corporate	0.289	
	(0.268)	
RLE		0.007
		(0.013)
Corporate*RLE		-0.060*
		(0.036)
Constant	-13.666***	-12.679***
	(3.584)	(2.520)
Observations	20,577	31,334
R-squared	0.704	0.665
Control	YES	YES
Fixed Effects	YES	YES

Notes: This table reports the results of estimating the effect of learning on *Distance to CBD* for foreign investors. Panel A reports the unconditional comparison of *CBD Distance* of first-time purchase and non-first-time purchase between Corporate and Finance investors. Panel B reports regressions results. The structural control variables are the same as in Table 2 and are included in all regressions in this table. Heteroscedasticity-consistent standard errors clustered at the host city level are shown in parentheses under the coefficients estimated. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

Appendices

Appendix A. The Definitions of Variables

Unit Price: is the price (in US$) per square foot.

Price Bias: as defined in Equation (1).

Total Price: is the transacted total price of a property measured in million US dollars.

Size: is short for property size in terms of square feet.

Distance: is the Euclidean distance of an acquired commercial property to the headquarter city of its institutional buyer.

CBD Distance: is the Euclidean distance of an acquired commercial property to the located city center of the property.

$YearBuilt$: is year that the property built.

Agent: is a dummy taking value of 1 if the investor hires an agent broker, 0 otherwise.

Anchoring: is a continuous variable used to measure the average price per square foot in the home country of the investor at the current the year of the focal acquisition.

RLE: is short for Regular Learning Effect, which is the number of an investor's historical acquisitions before the focal acquisition in the host city.

WLE: is short for Weighted Learning Effect, which takes into account of both the quantity and the duration of historical acquisitions.

JV: is short for joint venture, taking 1 if an investor employs joint venture strategy to acquire the focal property, 0 otherwise.

Assets: is the number of investors' holding assets before the focal acquisition, which proxies for investors' size or capitalization.

$Volume$: is the transaction volume of the focal year in the host city, which proxies for the demand of properties in the host city.

$PerGDP$: is the per capita GDP obtained from World Bank.

TI: is the corruption perception index obtained from international transparency.

Appendix B. Additional Tables

Table B1: Controlling for Building Ages

Sample	Full Sample		Matched Sample	
Dep. Variables	ln(Price)	Price Bias	ln(Price)	Price Bias
Model	(1)	(2)	(3)	(4)
Foreign	-0.019	0.002	-0.004	0.008
	(0.019)	(0.013)	(0.019)	(0.014)
RLE	-0.197***	-0.135***	-0.215***	-0.138***
	(0.021)	(0.014)	(0.019)	(0.018)
RLE2	0.010***	0.014***	0.018***	0.015***
	(0.003)	(0.002)	(0.005)	(0.004)
RLE*TI	0.017***	0.004	0.016***	0.002
	(0.004)	(0.003)	(0.005)	(0.005)
Agent	-0.185***	-0.134***	-0.196***	-0.152***
	(0.022)	(0.015)	(0.024)	(0.018)
Anchoring	0.018***	0.022***	0.001	0.009*
	(0.005)	(0.005)	(0.005)	(0.005)
ln(Size)	-0.350***	-0.179***	-0.297***	-0.169***
	(0.016)	(0.012)	(0.016)	(0.011)
ln(CBD Dis.)	-0.064***	-0.046***	-0.058***	-0.044***
	(0.006)	(0.005)	(0.010)	(0.008)
YearBuilt	0.002***	0.001**	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
ln(Assets)	0.032***	0.022***	0.019***	0.011***
	(0.003)	(0.003)	(0.003)	(0.003)
ln(PerGDP)	0.652***	0.341***	0.588***	0.298*
	(0.153)	(0.126)	(0.171)	(0.178)
TI	0.017	-0.043*	-0.028	-0.067**
	(0.050)	(0.026)	(0.051)	(0.034)
JV	-0.118***	-0.120***	-0.134***	-0.133***
	(0.023)	(0.018)	(0.019)	(0.018)
ln(Volume)	0.281***	0.158***	0.292***	0.182***
	(0.011)	(0.008)	(0.012)	(0.009)
Constant	-6.499***	-5.772***	-5.036***	-4.801***
	(1.653)	(1.341)	(1.766)	(1.861)
Observations	129,360	129,360	47,225	47,225
R-squared	0.657	0.159	0.672	0.181
Fixed FE	YES	YES	YES	YES

Notes: This table reports the results of extending the estimations of Equation (3) by including the building ages (denoted as *YearBuilt*) as an additional control. As the information on building age is missing for some sample properties, the observations available for estimations are less than those in Tables 2 and 4. The fixed effects and heteroscedasticity-consistent standard errors are included as in previous tables. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.

Table B2: Cross-border Transactions between the Same-country Counter-parties

Dep. Variable	Ln(Unit Price)	Price Bias
	(1)	(2)
Same-BS	-0.045***	-0.039**
	(0.017)	(0.017)
ln(Size)	-0.284***	-0.109***
	(0.003)	(0.004)
ln(CBD Dis.)	-0.050***	-0.033***
	(0.002)	(0.002)
ln(Assets)	-0.012***	-0.011***
	(0.002)	(0.002)
ln(PerGDP)	0.041	0.781***
	(0.076)	(0.078)
TI	-0.044***	-0.058***
	(0.016)	(0.017)
JV	-0.188***	-0.102***
	(0.010)	(0.010)
ln(Volume)	0.292***	0.079***
	(0.002)	(0.002)
Constant	2.555***	-7.606***
	(0.808)	(0.825)
Observations	38,232	38,232
R-squared	0.613	0.102
Fixed Effect	YES	YES

Notes: This table uses cross-border (foreign) transactions only to study the determinants of transaction price in foreign transactions. *Same-BS* is a dummy equal to 1 if the buyer and seller are from the same country. The fixed effects and heteroscedasticity-consistent standard errors are included as in previous tables. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level, respectively.