## Does the Law of One Price Hold in Heterogeneous Asset Markets?

# A Test Using the U.S. Commercial Real Estate Market\*

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#### Abstract

The law of one price is a common assumption in finance. Even for heterogeneous assets, the law holds at the level of factor prices. However, the law is sometimes violated when markets are segmented as a result of limits of arbitrage. We examine market segmentations across investor types for commercial real estate. We propose an elaborate procedure to test price discrepancies by distinguishing three types of market segmentation. We find strong evidence against the law of one price. First, transaction prices for comparable assets sometimes differ by investor type. Second, even if the average prices are not different, marginal factor prices sometimes differ by investor type. Third, when different investors operate in different domains of investments, the implied factor price function sometimes exhibits discontinuity. In particular, we obtain evidence for REIT price premia over corporate users, developers, and individual investors. Individual investors consistently pay lower prices except for multifamily. Our paper serves as a guide to judging whether one should include investor characteristics in a hedonic regression model.

(JEL Classification: G12, G14, R33)

Key words: limits of arbitrage, market segmentation, property market, heterogeneous goods, hedonic pricing, propensity score, matching estimation, REIT

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## I. INTRODUCTION

The law of one price (hereafter, LOOP) is one of the most fundamental assumptions in finance. The LOOP states that the assets with identical payoffs have the same price. The law is important because it ensures value additivity. It naturally holds for homogeneous goods and assets, but it also extends to heterogeneous goods at the level of factor price.

A heterogeneous good can be considered as a bundle of multiple factors. Rosen (1974) formally defines the hedonic equilibrium for heterogeneous goods, in which heterogeneous buyers and sellers trade away all arbitrage opportunities. In the hedonic equilibrium, there is an implicit factor price function for each attribute of the good. Thus, two assets with identical attributes have the same price. The LOOP, which is a slightly more general condition than the absence of arbitrage, does not hold when arbitrage is limited.<sup>1</sup>

In reality, price discrepancies occur for seemingly identical assets. The well-known examples are the stock price divergence between Royal Dutch and Shell and between Palm and 3Com.<sup>2</sup> When stocks for these merging or splitting companies were listed in multiple markets, the LOOP did not hold across stock exchanges. There is also considerable evidence for market segmentations.<sup>3</sup> Due to the existence of price discrepancies in practice, theories

<sup>1</sup> See Pliska (1997) on the relation between the LOOP and the absence of arbitrage.

<sup>&</sup>lt;sup>2</sup> See Rosenthal and Young (1990) for Royal Dutch/Shell and Lamont and Thaler (2003) for Palm/3Com.

<sup>&</sup>lt;sup>3</sup> For recent examples, see Vayanos and Vila (2009) and Garleanu and Pedersen (2011).

pertaining to limits of arbitrage have been developed. The survey by Gromb and Vayanos (2010) summarizes four types of costs that can prevent arbitrage: (1) non-fundamental risk for arbitrageurs, (2) short-selling costs, (3) leverage constraints, and (4) equity capital constraints. All of these costs make investors incapable of executing trades to exploit mispricing. Limits of arbitrage and market segmentation are regarded as a key to understanding asset pricing (Cochrane, 2011).

In this paper, we empirically test whether the LOOP holds for an important class of heterogeneous assets: commercial real estate (hereafter, CRE). In particular, we examine if the LOOP holds across different investor types. If it does, we can apply no-arbitrage models to standard CRE markets. If it does not hold, we will need to redefine markets by investor type for future research.

There are a number of reasons to expect limits of arbitrage in CRE markets. For example, idiosyncratic shocks to investor demand can have a larger impact on market prices since markets are typically thinner. There is no short-selling in direct CRE investments. Investors are more constrained in both debt and equity financing because of the large scale of real estate assets. Information acquisition is more costly than in financial markets. As a result, there are good reasons to suspect that the LOOP breaks down in some parts of markets. Since the current understanding of CRE markets is limited due to the heterogeneity of assets and data limitations, our study sheds some light on the workings of CRE markets.

Specifically, we examine four property types (office, retail, industrial, and multifamily) and six investor types (REITs, corporations, investment managers, developers, individuals, and other institutional investors) in ten major metropolitan areas in the U.S.A. By specifying three types of market segmentation, we propose a procedure of sequential testing on segmentation.

With Type I segmentation, different investor types share the common investment domain, but trade similar assets for significantly different prices. We use the propensity score matching estimation and hedonic regression to estimate overall price gaps for comparable assets. With Type II segmentation, even though there is no significant difference in average price level in the common domain, the marginal factor prices are different by investor type. We use the hedonic regressions to estimate differences in slope of the factor price function. With Type III segmentation, investors largely operate in different domains and the resulting factor price function exhibits discontinuity between the domains. We use hedonic regressions to estimate gaps in the factor price level evaluated at the mean value of each factor. The idea is analogous to the regression discontinuity design.

Figure 1 summarizes our estimation result. It shows strong evidence against the LOOP. For each property type, we observe all three types of market segmentation. Note that the idiosyncrasy of real estate assets makes it harder to detect any systematic discrepancies in price. We find a few cases of Type I and Type II segmentations for each property type. Type III segmentation is more frequently observed. Different investors often have different investment domains, and their transaction prices do not always form a single smooth price function for the entire market.

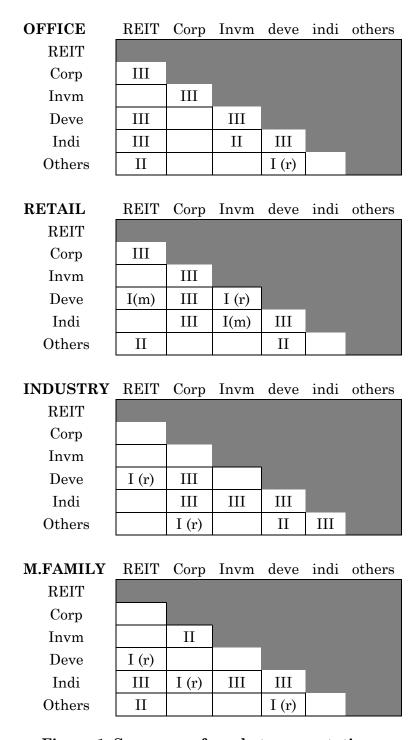


Figure 1. Summary of market segmentation.

Notes: The figure summarizes the test result on market segmentation by buyer type for four property types. I, II, and III stands for the type of segmentation as defined in the text. I(r) and I(m) correspond to regression and matching estimation, respectively.

We tend to find price premia for REITs, and price discounts for developers and individual investors. REIT premia, which is widely reported in the previous studies, are particularly large in magnitude in the office market, but also prevalent in the retail market and the multi-family market. A standard explanation is REITs' overpricing driven by low costs of capital. Discounts for individual investors may be consistent with price discrimination by seller due to lower willingness-to-pay (cf. student discount). Developer's lower prices may be associated with their opportunistic investment strategy. However, we do not have enough data to investigate the causes in more detail.

Our study also has a practical value for empirical research in urban and real estate economics. It is not uncommon to include some buyer and seller characteristics in hedonic equations. For example, a growing body of literature examines price premium or discount paid by different types of investors by including investor type dummies. Price premia are found for REITs (Hardin and Wolverton, 1999, Ling and Petrova, 2010, and Akin et al., 2011), tax-deferred exchanges (Holmes and Slade, 2001, and Ling and Petrova, 2010), and out-of-state buyers (Ling and Petrova, 2010). In contrast, price discounts are found for vacant homes (Harding et al., 2003).

However, an econometrician should not include buyer and seller characteristics in the equation unless markets are clearly segmented because the identification of implicit factor price functions relies on the existence of heterogeneous buyers and sellers. In the hedonic equilibrium, each transaction gives the maximum utility for the buyer and the seller. The implicit factor price function is tangent to the buyer's indifference curve as well as the seller's indifference curve for any transaction. In other words, the implicit hedonic price function represents a joint envelope of a family of value functions of heterogeneous buyers and another family of offer functions of heterogeneous sellers. If an econometrician perfectly controlled for the heterogeneity of buyers and sellers in an extreme case, she could not identify the implicit price function because there is only one transaction for each buyer type and seller type. In less extreme cases, it is not particularly meaningful to include imperfect controls for buyer and seller characteristics when the market is not segmented.

Figure 2 illustrates a problem arising from the partial control for investor characteristics. Buyer types A and B operate in different domains but they form a single factor price function (the solid line). Suppose an econometrician estimates a linear hedonic model by allowing for heterogeneous intercepts by buyer type while imposing the common slope restriction. Then, the econometrician would find a significant difference in intercepts (the gap between the dotted line and the dashed line). Without examining investment domains carefully, she would erroneously conclude that the market is segmented in such a way that buyer type A pays a higher price than type B.

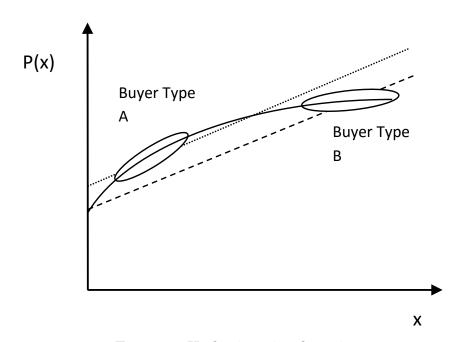


Figure 2. Hedonic price function

Notes: The figure illustrates a hedonic price function P(x) for a particular attribute x. The solid line represents the true price function, with buyer types A and B operating in different domains. The dotted and dashed lines represent fitted values of linear regression when heterogeneous constants are allowed but a common slope is imposed.

Furthermore, if the econometrician allowed for heterogeneous slopes by buyer type, the price gap would flip; the intercept for type A is lower than that for type B. She would also find a significant difference in slope. Now, she would erroneously conclude that the market is segmented in such a way that buyer type A pays a lower price even though two types are forming a single market. There are other cases where a single market appears to be segmented. Our testing procedure will help econometricians avoid these errors.

The primary contribution of this study is to show significant price discrepancies between investor types by using an elaborate testing procedure. The distinction of segmentation type and the proposed testing procedure are also contributions. Due to the large variance of error terms, we can reject the null hypothesis of no segmentation only if the magnitude of price discrepancy is large. Still, we observe many cases of segmentation. The strong evidence of the violation of LOOP has important implications on the future analysis of CRE markets and CRE investments. In a market with segmentation, researchers need to control for investor types when estimating hedonic price functions. The segmentation also implies large arbitrage opportunities if the existing obstacles are circumvented. Although investigating the cause of market segmentation is beyond the scope of this study due to data limitations, it will be important and interesting both academically and practically.

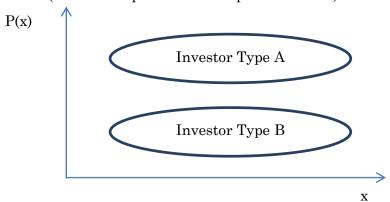
The remainder of the paper is organized as follows. Section two defines three types of market segmentation and builds research hypotheses. Section three describes data and

section four explains our empirical strategy. Section five presents the empirical result and section six concludes.

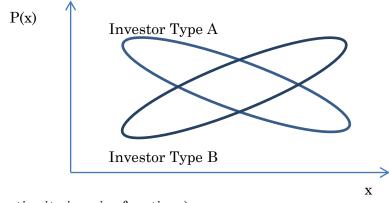
## II. SEGMENTATION TYPE

We define three types of market segmentation. In other words, we consider three cases in which a single smooth price function cannot exist. Figure 3 schematically summarizes segmentation.

Type I Segmentation (Price discrepancies for comparable assets)



Type II Segmentation (Discrepancies in marginal factor price)



Type III (Discontinuity in price functions)

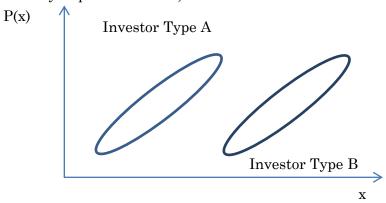


Figure 3. Three types of market segmentation.

Notes: x is a factor (i.e., an attribute) of the asset and P(x) is the factor price. Each oval represents the distribution of transactions made by a particular investor type.

First, if investors of different types trade similar assets for significantly different prices, the LOOP does not hold. With Type I segmentation, different investor types share the common investment domain, but Type A buyers systematically pay higher prices than Type B buyers for comparable assets. We test for price discrepancies in both factor prices and transaction prices.

Second, even if investors of different types trade similar assets for similar prices, there is a case where a single factor price function cannot exist. With Type II segmentation, different investor types share the common investment domain and, on average, trade assets at similar price levels. However, the marginal factor prices are significantly different by investor type. We test for differences in slope of factor price functions.

Third, when investors of different types do not trade similar assets, there may be a single smooth price function as depicted in Figure 2. However, if the price function is not smooth, it cannot be the joint envelope of buyers' value functions and sellers' offer functions, hence violating the LOOP. With Type III segmentation, investors largely operate in different domains but the resulting factor price function exhibits discontinuity between the domains, which is a stronger condition than non-smoothness. We test for discrepancies in factor price at the middle of investment domains.

#### III. DATA

We use the CoStar transaction price data for CRE in ten major markets in the United States: Los Angeles, Chicago, Phoenix, San Diego, Atlanta, Seattle, Dallas, Tucson, Boston, and Washington, D.C. The CoStar Group provides a wide coverage of for-sale

listings of CRE in the U.S., with detailed information regarding buyers, sellers, property characteristics, and locations. We augment the CoStar dataset by geocoding the property location. The property types are office, retail, industrial, and multi-family. The sample period covers from 1998 to 2011. The investor types are REITs, investment managers, individual investors, corporate users, developers, and other institutional investors.

The original sample size is 12,359 observations. We exclude non-arms-length transactions and portfolio sales. After trimming of the data with respect to a negative building age, price per square foot being less than \$1, the size of building being less than 2 square feet, and incorrect location information, the sample size becomes 11,512 observations. We further exclude transactions by banks to eliminate REO assets. The final sample size is 9,966.

Table 1 summarizes the investor types defined by CoStar. REITs refer to public real estate investment trusts. Investment managers operate separate accounts, sponsor funds, and other real estate investment programs for institutional investors. Developers are non-traded private development companies. Other institutional investors include pension funds, insurance companies, equity funds, and private REITs. Corporate users and Individual are self-evident. If we have multiple buyers or sellers for a transaction, we use the primary buyer & seller for our investor type.

In our dataset, property location is identified at the zip code level. In order to construct variables representing intra-city location, we add the geocode of the zip code center for each transaction. The intra-city location is extremely important for hedonic analysis although many studies just ignore them. It is often the basis for investment focus

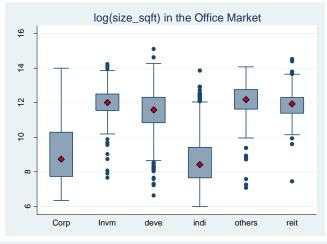
(e.g., CBD vs. suburbs) and it is the primary determinant of asset price in standard urban economic models. We construct the logarithm of distance to CBD, the logarithm of distance to the nearest subcenter of the MSA, and the direction from CBD (north/south and east/west).

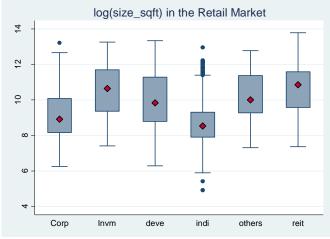
We convert transaction price to the logarithm of price per square foot of building for office, industrial, and retail. We construct the logarithm of price per unit for multy-family. We also take logarithm of building size and lot size. BldgAge is the age of the building calculated as the difference between the year it was built and the year sold. lnSize is the size of the building, which we calculate by taking a log of the total square footage of the building. lnland is the size of the plot of land, calculated by taking a log of the total acres. Stories refer to the number of stories a building.

Table 2 shows the descriptive statistics. Investment managers, REITs and other institutional investors invest in larger buildings in office, retail and industrial markets. As we expect, individuals tend to invest in smallest buildings across four markets. In respect to building age, REITs, and investment managers tend to invest in the newest buildings across four markets whereas corporation, developers and individuals take the oldest buildings. Investment managers, REITs and others invest in the tall buildings in the office and multi-family market. Retail and industrial market do not show variation in stories by investor type.

Figures 4 and 5 illustrate the logarithm of building size and the building age, respectively. There is some heterogeneity in investment domain. Individual investors and corporate users tend to buy smaller and older buildings. In contrast, REITs, developers,

investment managers, and other institutional investors operate in similar domains of larger and newer buildings. For example, in the office market, the median value of log building size is 8.42 for individual investors, and 11.93, 12.01, and 12.18 for REITs, investment managers, and other institutional investors, respectively. In the retail market, the median value of building age is 27 and 29 years for corporate users and individual investors, while 11 years for both other institutional investors and REITs.





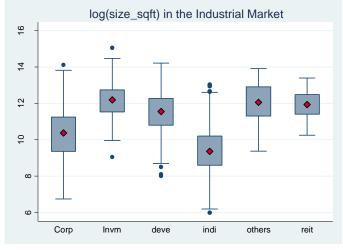


Figure 4. Box Plot for the log (size\_sf)

Notes: The diamond symbol represents the median value of each investor type. The line between the lowest adjacent limit and the bottom of the box represent one-fourth of the data. One-fourth of the data falls between the bottom of the box and the median, and another one-fourth between the median and the top of the box. The line between the top of the box and the upper adjacent limit represents the final one-fourth of the data observations. Dot represents the outliers.

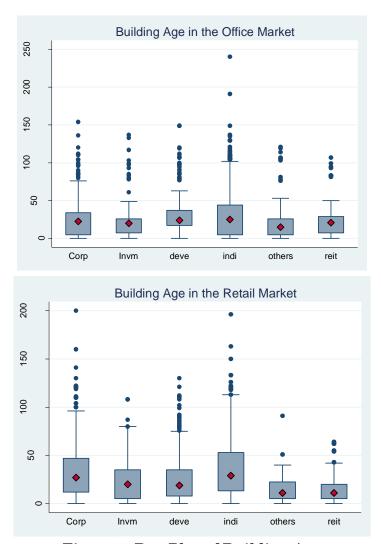


Figure 5. Box Plot of Building Age

The diamond symbol represents the median value of each investor type. The line between the lowest adjacent limit and the bottom of the box represent one-fourth of the data. One-fourth of the data falls between the bottom of the box and the median, and another one-fourth between the median and the top of the box. The line between the top of the box and the upper adjacent limit represents the final one-fourth of the data observations. Dot represents the outliers.

# IV. EMPIRICAL STRATEGY

## **Research Hypotheses**

On the basis of three types of market segmentation, we establish the following research hypotheses for our empirical analysis:

**H0** (No segmentation) There exists no market segmentation by buyer type.

- H1 (Type I segmentation) When two types of buyers exhibit similar distributions of transaction characteristics, price levels significantly differ by buyer type for comparable assets or for the asset with average characteristics.
- **H2 (Type II segmentation)** When two types of buyers exhibit similar distributions of transaction characteristics, and when H0 is not rejected against H1, the marginal factor prices are different by buyer type for at least one factor.
- H3 (Type III segmentation) When two types of buyers do not exhibit similar distributions of transaction characteristics, price levels significantly differ by buyer type for the asset with average characteristics.

Three alternative hypotheses are mutually exclusive. H1 corresponds to Type I segmentation; one buyer type systematically pays higher prices than another buyer type. H2 corresponds to Type II segmentation; even if price levels are not different, marginal prices are different. H3 corresponds to Type III segmentation; investors largely operate in different domains but the resulting price function exhibits discontinuity at the mean value of two domains. If we reject the null hypothesis for one of three alternative hypotheses, we conclude that the market is segmented and the LOOP does not hold.

## **Testing Procedure**

We propose the following sequential procedure to test these hypotheses (as illustrated in Figure 6). First, for each pair of buyer types, we check if distributions of transaction characteristics are similar. Since we have six buyer types, there are fifteen pairs in total. The specific procedure of this check is explained in Appendix A.

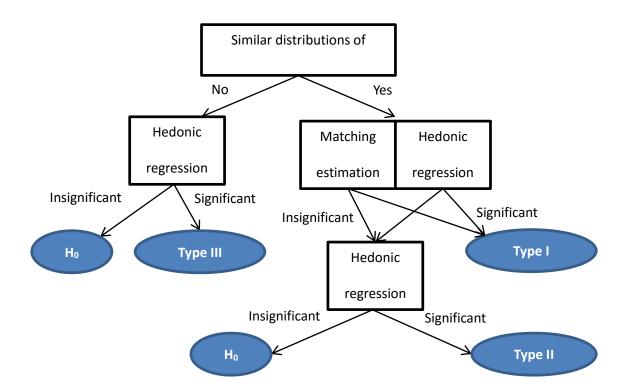


Figure 6. The Testing Procedure

Second, if distributions are similar, we test Type I segmentation by two estimation methods: propensity score matching and hedonic regression. With matching, we estimate price discrepancies for comparable (matched) assets between two buyer types. With hedonic regression, we evaluate price discrepancies at the mean value of each factor between buyer types. If we find significant price discrepancies for a particular buyer pair, we conclude that the market has Type I segmentation between the pair.

Third, if price discrepancies are not statistically significant, we test Type II segmentation by hedonic regression. If coefficients on one or more factors are different between a particular pair of buyer types, we conclude that the market has Type II segmentation between the types.

Finally, for the buyer pairs that do not show similar distributions of characteristics, we test Type III segmentation by hedonic regression. If we find significant price discrepancies at the mean value of each factor, we conclude that the market has Type III segmentation between the buyer pair.

#### **Matching Estimation**

The details of matching estimation are the following. In the first stage, we compute propensity scores for each of fifteen buyer pairs by using logit model:

$$p(x) \equiv Prob(w = 1|x) = \frac{e^{x'\beta}}{1 + e^{x'\beta}} = \Lambda(x'\beta),$$

where

$$\begin{split} x^{'}\beta &= \alpha_0 + \alpha_1 lnSize_i + \alpha_2 BldgAge_i + \alpha_3 Stories_i + \alpha_4 \ lnland_i + \sum_{m=1}^6 \tau_m * YearDummy_m + \\ \sum_{n=1}^9 \varphi_n MSA_n + \sum_{n=1}^9 \omega_n MSA_n * DistCBD_i + \varepsilon_i. \end{split}$$

w is the dummy variable for one of two buyer types regarded as the "treatment group." The list of variables is explained at the end of this section.

Given the propensity score, in the second stage we estimate the "average treatment effect on the treated" (hereafter, ATT) although there is no actual treatment in our project. Treatment is a convention to distinguish one buyer type from the other. Under the assumptions that 0 < p(x) < 1,  $E(y_0|x,w) = E(y_0|x)$ , and  $E(y_1|x,w) = E(y_1|x)$ , ATT is defined as:

$$ATT = E\{y_1 - y_0 | w = 1\} = E[E\{y_1 | w = 1, p(x)\} - E\{y_0 | w = 0, p(x)\} | w = 1],$$

where  $y_0$  and  $y_1$  are log price per square foot for the control group and the treatment group, respectively.

The identification requires the balancing property. Balancing property means that observation with the same propensity score must have the same distribution of observable (and unobservable) characteristics independent of treatment status. Then, for a given propensity score, exposure to treatment is random. We adopt the procedure of Becker and Ichino (2002) to check the balancing property. We also impose a restriction on the common support of propensity scores. If the number of observations is reduced by more than half by limiting to the common support, we do not run the matching. After confirming that the common support is wide enough, we estimate ATT for the entire sample.

The ATT is calculated as the difference of counterfactual outcome between the treatment and control group given similar propensity scores. Because getting identical propensity scores is unlikely, we consider three approaches to matching: nearest-neighbor (based on the single control observation closest to the treatment observation), kernel matching (based on a distance-weighted average of all the observations in the control group), and

stratification (based on dividing the support of propensity scores in intervals). We report the result of kernel matching for brevity, but other results are generally consistent. Other results are available upon request. The kernel matching estimator is given by

$$\tau^{K} = \frac{1}{N^{T}} \sum_{i \in T} \left\{ Y_{i}^{T} - \frac{\sum_{j \in C} Y_{j}^{C} G\left(\frac{p_{j} - p_{i}}{h_{n}}\right)}{\sum_{k \in C} G\left(\frac{p_{k} - p_{i}}{h_{n}}\right)} \right\}$$

where  $\tau$  is the ATT,  $N^T$  is the number of units in the treatment group,  $Y_i^T$  and  $Y_j^C$  are outcomes for the treated and the control, respectively,  $G(\cdot)$  is a kernel function, and  $h_n$  is a bandwidth parameter.

Once we estimate ATTs for all pairs, we switch the treatment group and the control group and estimate the second ATT for all pairs. We take the weighted average of two ATTs for each pair to obtain the mean price difference for matched samples. In computing standard errors of the mean price difference, we take a conservative approach of by assuming perfect correlation between two ATTs.

#### **Hedonic Regression**

The details of hedonic regression are the following. We run pairwise regressions for all buyer type pairs. We use demeaned regression model as follows:

$$E(y|w,x) = \gamma + \alpha w + x\beta + w(x - \varphi)\delta + \lambda Z,$$

where w is dummy variable for a buyer type in the pair, x is the vector of factors, Z is the

vector of control variables,  $\varphi \equiv E(x)$ , and y is log transaction price per square foot. The identifying assumption is  $E(y_0|x,w) = E(y_0|x)$  and  $E(y_1|x,w) = E(y_1|x)$ . We demean x in all interaction terms with w so that we can interpret  $\alpha$  as the price discrepancy if w = 1, when evaluated at the sample mean of each factor x.<sup>4</sup>

The vector of factors x is composed of *lnSize*, *BldgAge*, *Stories*, and *lnland*. The vector of The vector of control variables z is composed of *yeardummy*, *MSA*, *DistCBD*, *DistCBD\*MSA*, *DirectN*, *DirectE*, *MSA\*DirectN*, *MSA\*DirectE*. The list of variables are the following.

#### List of Variables

*lnsp* is a log of price per square foot, log(sale price per square foot),

*Insize* is the size of the building, which we calculated by taking a log of the total square footage of the building.

*Inland* is the size of the plot of land, calculated by taking a log of the total acres.

Stories refer to the number of stories of the building.

*Bdage* is the age of the building calculated as the difference between the year it was built and the year sold.

LogDist is a log of miles distance between the subject property and the first principal city of each metropolitan statistical area (MSA), a proxy for the Central Business District (CBD) at each MSA.

DistSubc is a log of subcenter distance, which is equal to the minimum miles distance

<sup>&</sup>lt;sup>4</sup> See Wooldridge (2002).

between the subject property and the sub-center, i.e., a principal city which shows the minimum distance from a subject property.

*DirectN* is a dummy variable which takes the value of 1 if the difference of latitude between the subject property and the principal city shows a positive sign and otherwise, 0.

Direct E is a dummy variable which takes the value of 1 if the difference of longitude between the subject property and the principal city shows a positive sign and otherwise, 0.

MSA is dummy variables for Boston, Chicago, Dallas, LA, Phoenix, San Diego, Seattle, Tucson, and Washington. The reference MSA is Atlanta.

Before 2006 is a dummy variable if a sold year of property is before 2006, and otherwise, 0. yr2006 through yr2011 represent year dummies if sold years of properties are 2006 through 2011, respectively, and otherwise, 0.

us is a unit size, i.e., a log of square foot per the number of units of multi-family property  $(\log(\frac{\text{size\_sf}}{\# \text{of unit}}))$ .

*Units* are total number of units of multi-family property.

## V. ESTIMATION RESULTS

## Type I segmentation

Table 3 shows the test result for Type I segmentation. We use matching estimation and hedonic regression. The estimated price discrepancies are shown only when a buyer pair exhibits similar distributions of transaction characteristics. We report the result for four pairs in office, five pairs in retail, seven pairs in industry, and six pairs in multi-family.

Having many blank cells indicate that different investor types tend to have different domains of investment, as observed in the descriptive statistics. The full results of matching and regression for all buyer pairs are summarized in Appendices B and C.

We do not find many significant price discrepancies of this type. Due to large heterogeneity of CRE, standard errors are rather large. As a result, we obtain significant price discrepancies only when the estimated price gap is quite large. If a larger number of observations were used, we could find smaller discrepancies to be statistically significant. Large heterogeneity of CRE makes our estimates conservative.

In the office market, other institutional investors pay a higher price than developers based on both matching estimation and hedonic regression. The price discrepancy is 0.29 (roughly 34%) by matching and 0.18 (roughly 20%) by regression. The difference in magnitude probably arises because of different evaluation points. Matching estimation uses the average for all observations while regression uses a single evaluation point.

In the retail market, a few pairs exhibit significant price discrepancies by both matching and regression. Matching and regression results generally agree on the price ordering of {investment manager, REIT} > {developer} > {individual investors}. The magnitude of price discrepancies are roughly 20-30% between developers and investment managers or REITs. The gap between investment managers and individual investors reaches 0.43 by matching estimation.

In the industrial market, two pairs exhibit significant price discrepancies by regression though no pair does by matching. Developers pay a lower price than REITs by 0.14 (13%) and other institutional investors pay a higher price than corporate users by 0.20 (22%)

based on regression. If we include insignificant results, other institutional investors consistently pay higher prices in industrial properties.

In the multi-family market, three pairs exhibit significant discrepancies by regression though no pair does by matching. Based on regression, developers pay a lower price by 0.11 than REITs, but pay a higher price by 0.16 than other institutional investors. Individual investors pay a lower price than corporate users by 0.11. The higher price paid by corporate users and the lower price paid by individual investors can be consistent with sellers' price discrimination provided that the corporate user's demand is inelastic and individual investors have lower WTP. However, what kind of market power enables the sellers to price discriminate is a question to be answered.

Overall, developers' tendency to pay lower prices is puzzling given that they have the ability to renovate or redevelop acquired properties. The option value to developers can rationalize a higher price rather than a lower price for comparable assets. Developers may be self-selecting into opportunistic investments in poor performing assets, while REITs focus on similar assets with better performance. Unfortunately, we do not have performance data to investigate this issue further.

The REIT price premia, which are widely reported in the previous studies, are not prevalent in this type of segmentation. In retail, industrial, and multi-family properties, we find REIT price premia against developers. But this can also be seen as developer discounts. We do not find significant REIT premia for other pairs. The limited evidence of REIT price premia as Type I segmentation is a manifestation of the effectiveness of our rigorous testing procedure. Even if there are significant differences in intercepts of hedonic

regression, it does not directly indicate price discrepancies or market segmentation. We evaluate price discrepancies at the mean value of factors after confirming distributional similarities. We will discuss REIT price premia as Type III segmentation in the next section.

### Type III segmentation

We discuss Type III segmentation before discussing Type II because the former is more similar to Type I. The difference is that Type III is for the buyer pair with dissimilar distributions of characteristics. To detect Type III segmentation, we test the price discrepancies at the mean value of x in hedonic regressions. The full result for all buyer pairs is summarized in Appendix C.

Table 5 shows the test result for Type III segmentation. We observe more cases of segmentation of this type than Type I. Investors often operate in different domains of investment and also their transaction prices do not always form a continuous function for the whole market.

In the office market, we find Type III segmentation for six pairs. The most consistent result is REIT premia. REITs pay 0.44 higher than corporate users, 0.26 higher than developers, and 0.49 higher than individual investors. Investment managers also pay 0.21 higher corporate users and 0.21 higher than developers. Individual investors pay even 0.14 lower than developers. If we combine all of these results, we have an ordering of {REITs and investment managers} > {developers and corporate users} > {individual investors} in terms

of price discrepancies. We find discounts for developers and individuals and premia for REITs as in Type I segmentation.

In the retail market, we again find premia for REITs and investment managers and discounts for individual investors. REITs pay 0.28 higher than corporate users and investment managers pay 0.35 higher than corporate users. Individual investors pay 0.1 lower than corporate users and 0.18 lower than developers. Thus the ordering is {investment manager} > {REIT} > {developers} > {corporations} > {individuals}.

In the industrial market, we don't observe REIT premium but do observe individual investor discounts. Individual investors pay 0.16 lower than corporate users, 0.23 lower than investment managers, 0.35 lower than developers, and 0.35 lower than other institutional investors.

Interestingly, in the multi-family market, we observe some premia paid by individual investors. Individuals pay 0.31 higher than REITs and 0.17 higher than Investment managers. Individual's demand can be inelastic for the multi-family properties.

Overall, we tend to observe higher prices paid by REITs and investment managers, and lower prices paid by individuals. This general tendency is consistent with that in the Type I case.

### Type II segmentation

Type II segmentation is associated with discrepancies in marginal factor prices when a buyer pair exhibits similar distributions of characteristics. We test coefficients on four factors: log floor area (lnsize), building age (bdage), number of stories (stories), and log lot size (lnland). Table 4 presents the test result. The full results for all buyer pairs are summarized in Appendix D.

Overall, we do not observe many segmentations of this type. In the office market, there are only three pairs on the building size and one pair on the number of stories. In the retail market, there are two pairs on the building size, two pairs on the number of stories, and a pair on the lot size. In the industrial market, there are a pair on the building age, three on the number of stories, and two pairs on the lot size. In the multi-family market, there is one pair on the building size and one pair on the number of stories.

## VI. CONCLUSION

Our empirical results provide strong evidence that the law of one price is violated by market segmentation in the commercial real estate market. The primary contribution of this study is to show significant price discrepancies between investor types by using an elaborate testing procedure. The distinction of segmentation type and the proposed testing procedure are also contributions. The result has important implications on the future research and investment.

However, our current study does not explain what causes these market segmentations. By the theory of limits of arbitrage, we speculate that different costs of arbitrage in a general sense would be playing a role. In a future study, we will extend the current study and further examine the microstructure of market segmentation in heterogeneous asset markets.

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Table 1. Definition of Investor Types

Our type	Costar's description	Examples	Definition			
REIT	Traded on a public market, must have REIT type tax status	Prologis Liberty Property Trust, SimonProperty Group, Inc.	A real estate investment trust, or REIT, is a company that owns, and in most cases, operates income-producing real estate. Some REITs also engage in financing real estate. The shares of many REITs are traded on major stock exchanges.			
Corporate	Corporate user or retailer or business or company user	Adobe Systems Inc	A company that purchases real estate to operate a business. The corporation can be a small private manufacturer or a large publically traded company.			
Investment managers	Investment manager or advisor	RREFF AEW Capital Management	This group provides real estate investment strategy and operating knowledge to various groups of equity institutional investors.  Investment managers operate separate accounts, sponsor funds and other real estate investment programs as well as develop and manage the assets in which they invest. They serve the investment goals of public and corporate pension funds, foundations, endowments, insurance companies and individuals.			
developers	Non-traded privately held development/property manager/owner/operator that owns properties	Adler Realty Investments Inc	A private real estate company owner that can also develop, manage and operate it's assets. The company buys and sells properties.			
individuals	Individual or a small group of individual investors	Chawla Properties, LLC	Individual or small group of individuals that invest directly and own real estate property.			
others	Pension Fund Insurance Equity fund Private REIT	Prudential Insurance Group Federal Capital Partners	Eqiuity fund established by an employer to facilitate and organize the investment of employees' retirement funds contributed by the employer and employees. The pension fund is a common asset pool meant to generate stable growth over the long term, and provide pensions for employees when they reach the end of their working years and commence retirement.  A public or private insurance company purchases real estate for income or increase return of capital upon sale. The purchases are not user intended as a location to operate a business.			

#### **Table 2. Descriptive Statistics**

The table summarizes descriptive statistics by buyer type in each property market. Lnsp is a log of price per square foot, log(sale price per square foot). Insize is the size of the building, which we calculated by taking a log of the total square footage of the building. lnland is the size of the plot of land, calculated by taking a log of the total acres. Stories refers to the number of stories a building has. LogDist is a log of miles distance to the Central Business District (CBD) at each metropolitan statistical area (MSA)) Bdage is the age of the building calculated as the difference between the year it was built and the year sold.

		О	ffice	Retail							
Variable	Obs	Mean	Std. Dev.	Min	Max	Ob	s Mean	Std. Dev.	Min	Max	
		R	EITs	REITs							
lnsp	133	5.38	0.53	3.57	6.53	130	5.39	0.66	3.55	6.96	
lnsize	133	11.86	0.95	7.45	14.53	130	3 10.61	1.48	7.37	13.78	
bdage	93	25.67	25.76	0.00	107.00	98	14.93	15.07	0.00	64.00	
stories	93	7.32	7.07	1.00	50.00	99	1.90	5.68	1.00	57.00	
lnland	127	1.15	1.40	-2.12	5.24	129	9 1.51	1.57	-2.30	7.01	
logDist	133	1.74	1.34	-1.19	3.68	13	7 2.68	0.88	-0.40	3.98	
		Corp	orations			Corporations					
lnsp	273	4.99	0.72	2.90	6.85	400	5.19	0.88	2.57	7.18	
lnsize	273	9.08	1.64	6.34	14.00	400	9.16	1.30	6.25	13.21	
bdage	232	27.45	29.68	0.00	154.00	35	1 35.49	31.00	0.00	200.00	
stories	242	2.97	4.08	1.00	41.00	359	9 1.28	1.36	1.00	24.00	
lnland	244	0.07	1.58	-3.51	5.14	39	5 0.07	1.49	-3.91	5.38	
logDist	276	2.42	1.15	-1.15	4.10	400	2.54	0.95	-1.12	4.14	
Investment Managers							Inv	restment Mar	nagers		
lnsp	245	5.48	0.55	3.42	6.72	82	5.49	0.75	3.44	7.36	
lnsize	245	11.98	0.97	7.65	14.24	82	10.50	1.39	7.42	13.25	

bdage	186	22.65	23.86	0.00	137.00	57	26.04	27.64	0.00	108.00				
stories	186	8.60	7.78	1.00	52.00	57	1.89	2.08	1.00	12.00				
lnland	236	1.16	1.26	-1.61	3.98	70	0.90	1.69	-2.81	4.69				
logDist	246	1.84	1.37	-1.29	4.10	82	2.37	1.10	-1.19	3.57				
	Developers							Developers						
lnsp	410	5.10	0.80	1.65	6.70	419	5.31	0.89	2.39	8.65				
lnsize	410	11.44	1.38	6.64	15.10	419	9.94	1.47	6.29	13.34				
bdage	327	32.28	28.85	0.00	149.00	321	25.60	26.16	0.00	130.00				
stories	328	7.72	10.51	1.00	100.00	336	1.33	1.29	1.00	16.00				
lnland	398	0.77	1.50	-3.51	4.81	402	0.73	1.59	-3.51	4.72				
logDist	410	1.81	1.46	-2.40	4.10	419	2.46	1.06	-1.50	4.05				
		Indiv	riduals			Individuals								
lnsp	971	5.18	0.70	2.46	7.12	1599	5.31	0.92	1.43	8.53				
lnsize	971	8.66	1.36	5.99	13.86	1599	8.67	1.09	4.93	12.95				
bdage	880	31.01	30.27	0.00	240.00	1399	36.49	29.39	0.00	196.00				
stories	898	2.43	2.77	1.00	27.00	1458	1.24	1.23	1.00	29.00				
lnland	861	-0.46	1.56	-4.61	3.65	1569	-0.49	1.25	-3.91	3.89				
logDist	974	2.34	1.09	-1.50	4.18	1600	2.48	0.93	-1.29	4.66				
		Ot	hers					Others						
lnsp	133	5.43	0.70	1.88	6.77	70	5.43	0.73	1.68	7.22				
lnsize	133	12.04	1.24	7.09	14.08	70	10.15	1.42	7.31	12.77				
bdage	93	24.01	29.74	0.00	121.00	52	15.27	15.96	0.00	91.00				
stories	94	11.09	11.76	1.00	62.00	52	1.52	2.42	1.00	18.00				
lnland	126	1.06	1.47	-3.51	4.37	67	1.10	1.56	-2.53	5.26				
logDist	133	1.65	1.57	-1.50	4.10	70	2.78	0.72	-0.21	3.93				

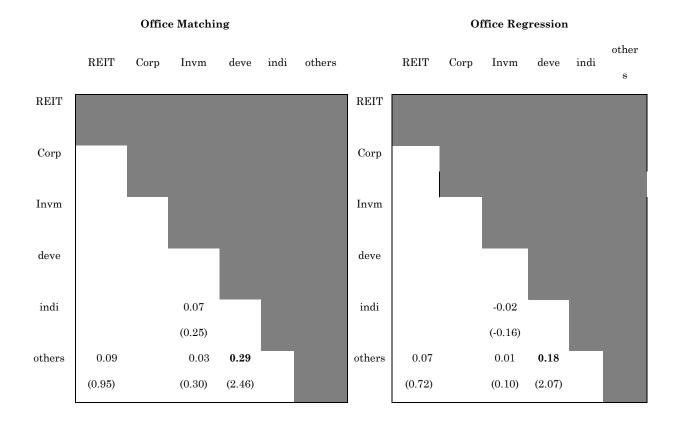
Industry	Multi-Family	

Variable	Obs	Mean		Min	Max	Obs	Mean	Std. Dev.	Min	Max
REITs								REITs		
lnsp	84	4.21	0.57	2.59	5.27	100	4.99	0.66	2.77	6.35
lnsize	84	11.96	0.82	10.25	13.39	100	12.24	0.82	8.99	13.67
bdage	69	18.20	18.65	0.00	100.00	93	20.11	18.43	0.00	102.00
stories	69	1.25	0.60	1.00	4.00	87	4.69	5.25	1.00	40.00
lnland	83	2.19	1.01	-0.31	4.61	99	1.71	1.25	-1.83	4.04
logDist	84	2.66	0.72	0.60	4.05	100	2.26	0.98	-0.86	4.04
		Corp	orations					Corporation	ns	
lnsp	594	4.16	0.72	0.77	7.52	93	4.70	0.83	2.09	6.87
lnsize	594	10.37	1.29	6.75	14.11	93	10.18	1.63	6.33	13.60
bdage	556	26.28	19.00	0.00	111.00	80	51.09	35.31	1.00	211.00
stories	564	1.09	0.41	1.00	8.00	77	2.84	3.10	1.00	26.00
lnland	579	0.99	1.32	-2.66	4.49	92	-0.04	1.95	-3.00	4.32
logDist	594	2.65	0.85	-1.29	4.14	93	2.17	1.02	-1.15	3.89
	I	nvestme	nt Manager	s		Investment Managers				
lnsp	175	4.10	0.59	2.20	6.21	180	4.76	0.74	2.65	7.73
lnsize	175	12.12	0.98	9.05	15.05	180	11.94	1.16	8.28	14.42
bdage	128	20.86	18.04	0.00	88.00	172	24.95	20.88	0.00	94.00
stories	129	1.10	0.53	1.00	6.00	163	4.56	7.69	1.00	82.00
lnland	170	2.42	1.05	-0.92	5.16	179	1.71	1.65	-2.30	4.56
logDist	175	2.72	0.64	-0.22	3.94	180	2.26	0.97	-1.12	4.10
		Dev	elopers					Developers	3	
lnsp	248	4.11	0.74	1.72	7.10	704	4.61	0.75	0.38	8.54
lnsize	248	11.49	1.11	8.01	14.22	704	11.71	1.24	7.33	14.74
bdage	207	25.80	20.26	0.00	111.00	650	31.25	24.97	0.00	190.00
stories	204	1.20	0.52	1.00	5.00	621	3.44	4.15	1.00	52.00
lnland	244	1.95	1.14	-1.31	5.26	697	1.52	1.69	-4.61	5.22
logDist	248	2.74	0.80	-0.40	4.22	704	2.33	0.89	-2.40	4.09
		Indi	viduals					Individuals	8	
lnsp	950	4.44	0.77	0.28	6.96	1517	4.87	0.72	1.18	8.98
lnsize	950	9.47	1.19	5.99	13.03	1517	9.35	1.10	6.21	13.30
					4					

bdage	875	28.46	22.47	0.00	211.00	1454	48.05	23.24	0.00	132.00
stories	884	1.13	0.58	1.00	12.00	1404	2.19	1.34	1.00	27.00
lnland	919	0.17	1.24	-4.61	5.27	1519	-0.90	1.29	-4.61	4.79
logDist	952	2.45	0.94	-1.29	4.29	1523	2.11	0.85	-1.50	4.69
		Ot	hers					Others		
lnsp	70	4.00	0.59	2.59	5.35	69	4.65	0.81	2.71	6.65
lnsize	70	12.00	1.04	9.37	13.91	69	12.24	1.06	9.03	13.94
bdage	54	22.59	20.95	0.00	95.00	66	24.39	22.60	0.00	114.00
stories	55	1.35	1.62	1.00	12.00	64	4.98	7.30	1.00	49.00
lnland	69	2.31	1.26	-1.83	4.67	69	1.86	1.64	-2.41	4.44
logDist	70	2.78	0.65	-0.22	3.55	69	2.13	0.95	-0.40	3.79

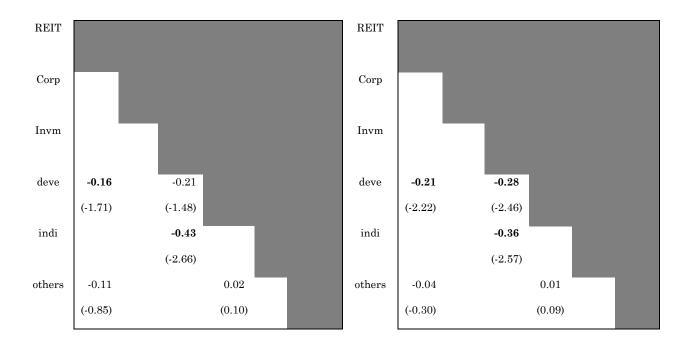
#### Table 3. Type I Segmentation.

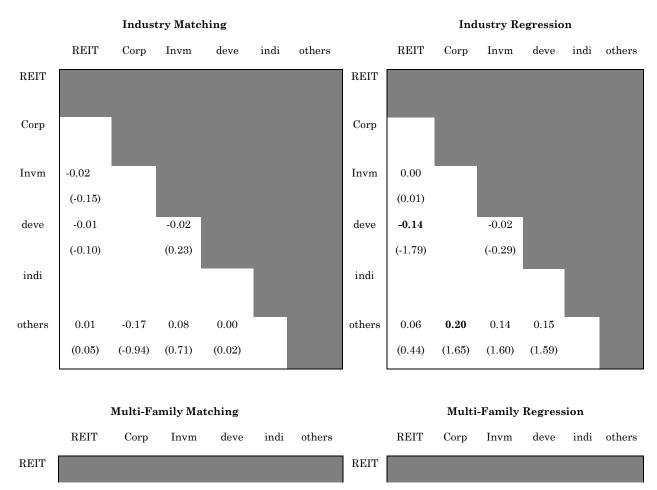
Notes: The estimated price discrepancies between different buyer pairs are shown in the matrix form. The left panels show the result of matching estimation and the right panels show the result of hedonic regressions. Positive numbers mean that buyers on the left (row) pay a higher price than buyers on the top (column). Blank cells represent the buyer pairs that do not satisfy the similarity condition. In each cell, the upper row shows price discrepancies and the lower row shows the t-statistics in parenthesis. The price discrepancy by matching estimation is the weighted average of ATTs as explained in the text. Control variables in regressions are: yeardummy, MSA, DistCBD, DistCBD\*MSA, DirectN, DirectE, MSA\*DirectN, MSA\*DirectE.

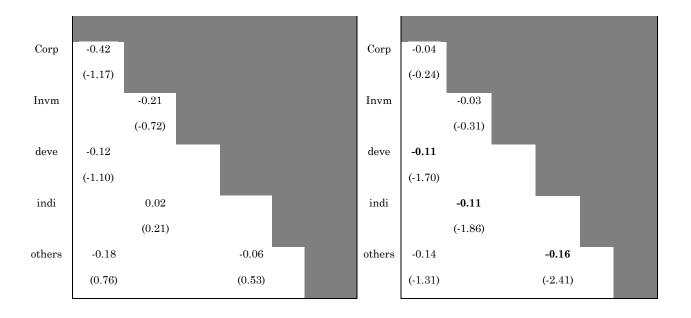


Retail Matching Retail Regression

REIT Corp Invm deve indi others constant REIT Corp Invm deve indi others



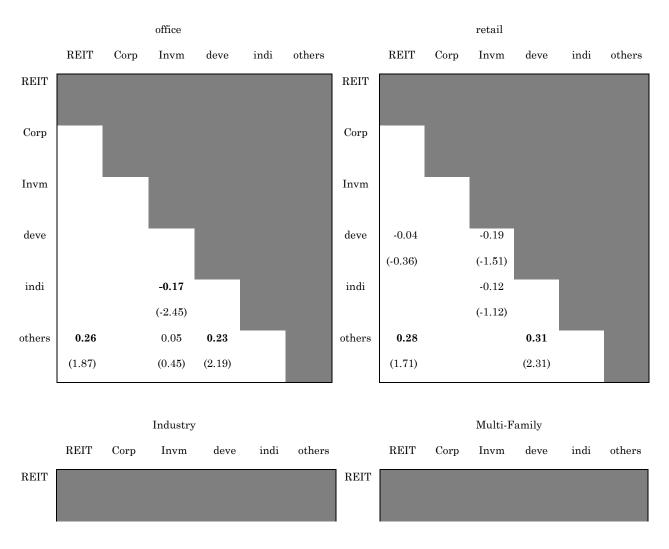


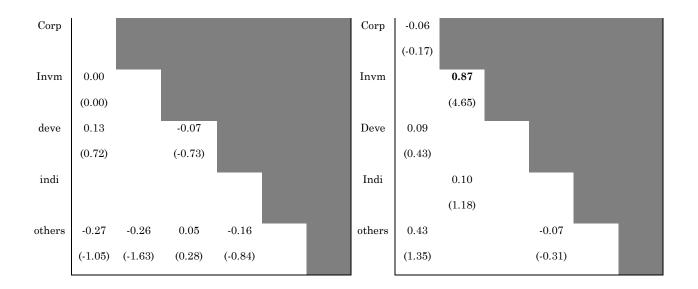


#### Table 4. Type II Segmentation.

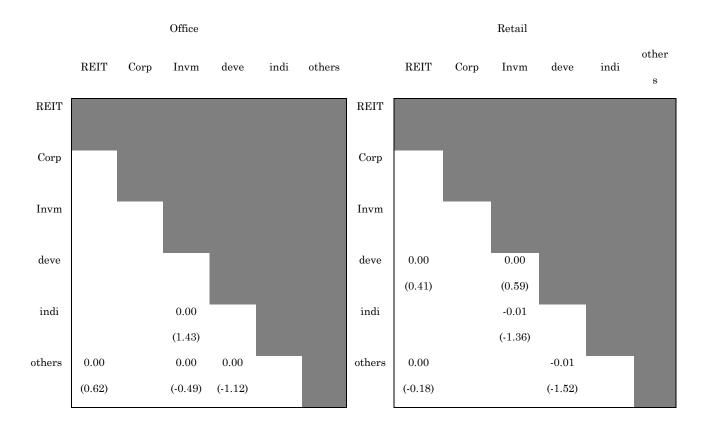
Notes: This table is the result of all pairwise regressions irrespective of the segmentation type. A part of the result is used for Type II segmentation. Positive numbers mean that buyers on the left (row) have a higher marginal factor price (a steeper slope) than buyers on the top (column). In each cell, the upper row shows the difference in coefficient and the lower row shows the t-statistics in parenthesis. Control variables are: yeardummy, MSA, DistCBD, DistCBD\*MSA, DirectN, DirectE, MSA\*DirectN, MSA\*DirectE.

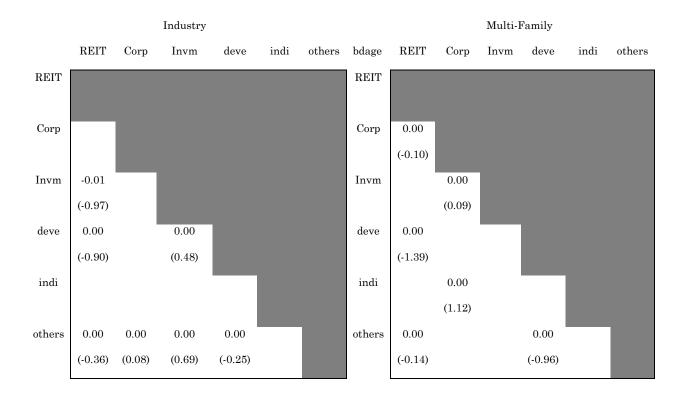
#### A. The difference in the coefficient on the log building size (Insize)



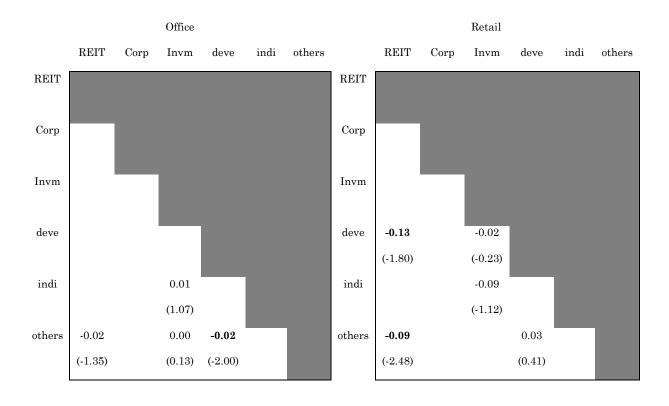


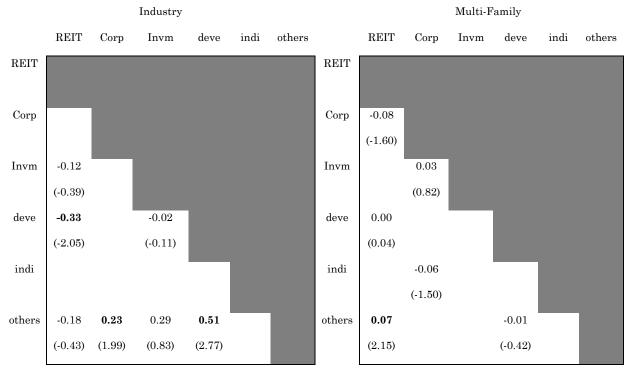
## B. The difference in the coefficient on the building age (bdage)



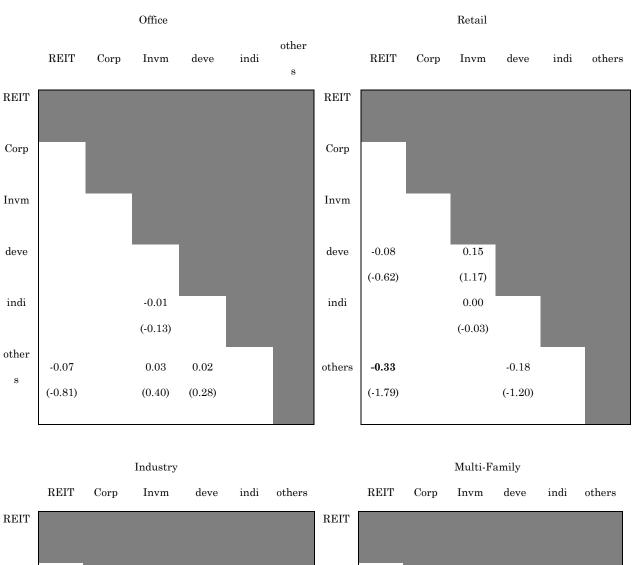


#### C. The difference in the coefficient on stories (stories)





## D. The difference in the coefficient on the log lot size (lnland)

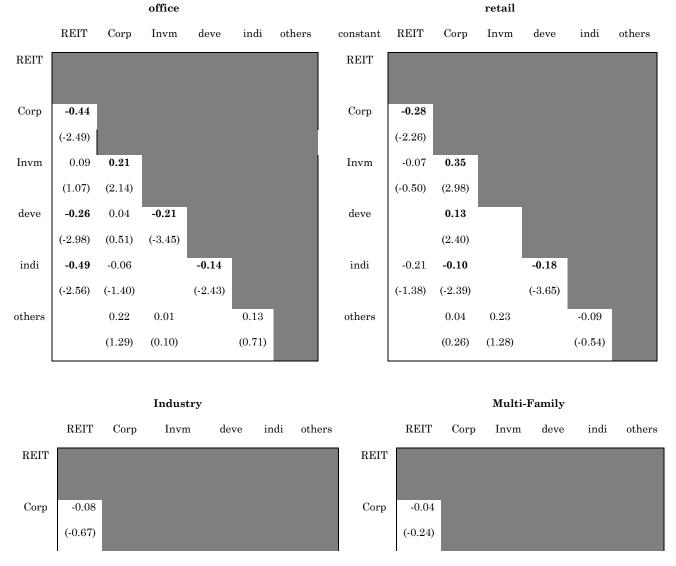


others	0.15	0.29	-0.08	0.26	others	0.09	0.07	
	(0.59)	(1.93)	(-0.46)	(1.37)		(0.77)	(1.18)	

#### Table 5. Type III Segmentation

Notes: The estimated price gap between different buyer pairs are shown in the matrix form. Positive numbers mean that buyers on the left (row) pay a higher price than buyers on the top (column) when evaluated at the mean of every factor. Blank cells represent the buyer pairs that satisfy the similarity condition, thus not Type III. In each cell, the upper row shows price gap and the lower row shows the t-statistics in parenthesis.

Control variables are: yeardummy, MSA, DistCBD, DistCBD\*MSA, DirectN, DirectE, MSA\*DirectN, MSA\*DirectE.



Invm	0.00	0.08				Invm	-0.07					
	(0.01)	(1.12)					(-1.29)					
deve		0.19	-0.02			deve		-0.01	0.02			
		(4.07)	(-0.29)					(-0.14)	(0.40)			
indi	-0.34	-0.16	-0.23	-0.35		indi	0.31		0.17	-0.08		
	(-1.61)	(-4.52)	(-1.91)	(-5.18)			(1.90)		(2.42)	(-2.25)		
others	0.06				0.35	others		-0.06	-0.06		-0.12	
	(0.44)				(1.77)			(-0.35)	(-0.94)		(-0.89)	
	, ,										` '	

## Appendix A. Criteria of similar distributions of transaction characteristics.

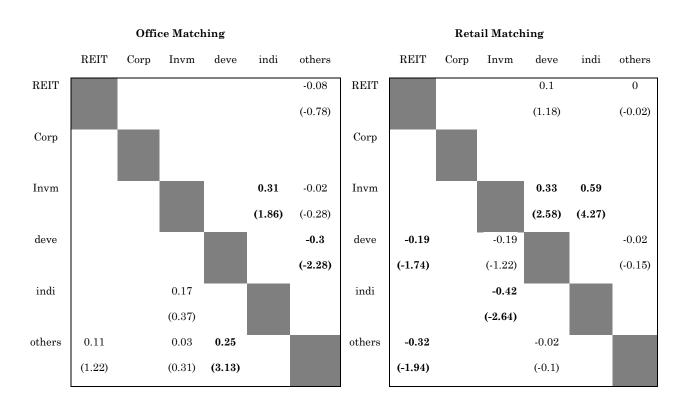
To compare transaction characteristics between two buyer types, we run a logit regression and obtain propensity scores for all transactions in each combination. The propensity score can be seen as a single-index variable which summarizes transaction characteristics.

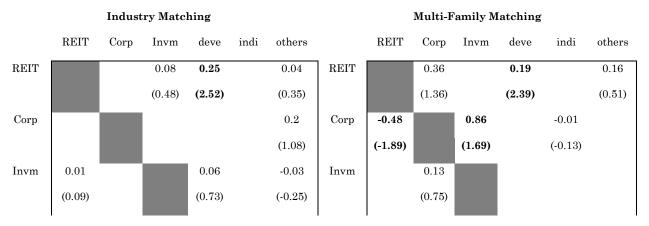
To check if two buyer types make similar transactions, we employ two commonly used measures in propensity score matching: common support and balancing property. Our first criterion is based on the support of propensity scores. We require that the number of observations is not reduced by 50% or more when we restrict ourselves to the common support of propensity scores. Significantly different supports of propensity scores indicate that transaction characteristics are not similar. Our second criterion is that two buyer types satisfy the balancing property defined by Becker and Ichino (2002). It requires that observations with the same propensity score have similar distributions of factors between two buyer types. If both criteria are met, we conclude that distributions of transaction characteristics are similar.

<sup>&</sup>lt;sup>1</sup> For details, see Becker and Ichino (2002).

## **Appendix B. Average Effect of Treatment on the Treated (ATT)**

The below table summarizes the Average treatment effect on the treated (ATT). Each column (top) represents the control group and each row (side) represents the treatment group. The t-values are shown in the parenthesis.

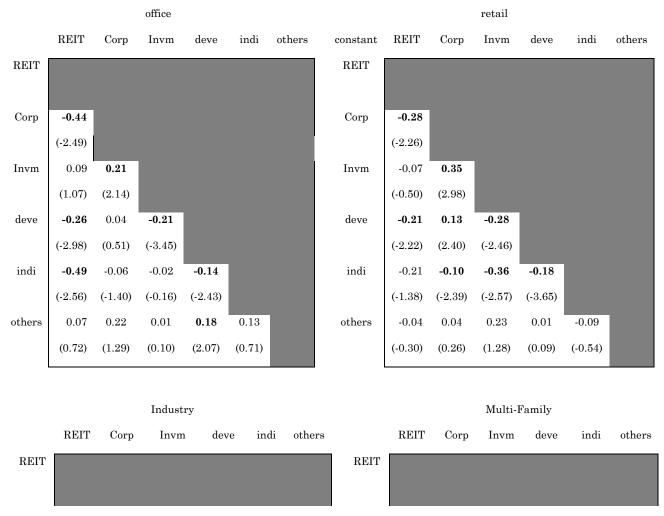




deve	0.07		0.01		0.01	deve	-0.11		0.07
	(0.44)		(0.06)		(0.09)		(-0.86)		(0.59)
indi						indi	0.02		
							(0.18)		
others	0.06	0.14	0.22	0.06		others	-0.21	-0.01	
	(0.54)	(1.41)	(1.92)	(0.55)			(-1.49)	-0.12	

# Appendix C: Coefficients on buyer type dummies in hedonic regressions (all pairs)

Notes: This table is the result of all pairwise regressions irrespective of the segmentation type. A part of the result is used for Type I segmentation, and another part is used for Type III segmentation. Positive numbers mean that buyers on the left (row) pay a higher price than buyers on the top (column) when evaluated at the mean of every factor. In each cell, the upper row shows price gap and the lower row shows the t-statistics in parenthesis. Control variables are: yeardummy, MSA, DistCBD, DistCBD\*MSA, DirectN, DirectE, MSA\*DirectN, MSA\*DirectE.

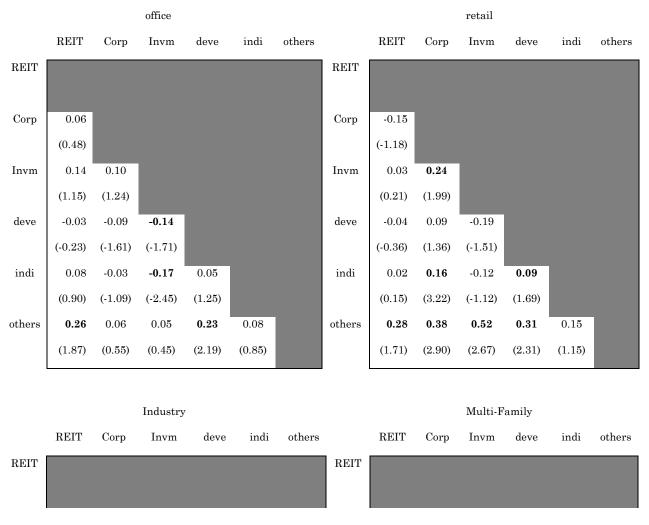


$\operatorname{Corp}$	-0.08					$\operatorname{Corp}$	-0.04					
	(-0.67)						(-0.24)					
Invm	0.00	0.08				Invm	-0.07	-0.03				
	(0.01)	(1.12)					(-1.29)	(-0.31)				
deve	-0.14	0.19	-0.02			deve	-0.11	-0.01	0.02			
	(-1.79)	(4.07)	(-0.29)				(-1.70)	(-0.14)	(0.40)			
indi	-0.34	-0.16	-0.23	-0.35		indi	0.31	-0.11	0.17	-0.08		
	(-1.61)	(-4.52)	(-1.91)	(-5.18)			(1.90)	(-1.86)	(2.42)	(-2.25)		
others	0.06	0.20	0.14	0.15	0.35	others	-0.14	-0.06	-0.06	-0.16	-0.12	
	(0.44)	(1.65)	(1.60)	(1.59)	(1.77)		(-1.31)	(-0.35)	(-0.94)	(-2.41)	(-0.89)	

## Appendix D: Coefficients on four factors in hedonic regressions (all pairs)

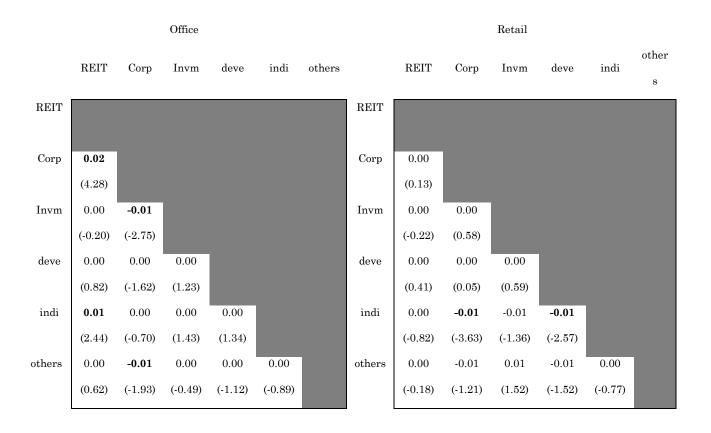
Notes: This table is the result of all pairwise regressions irrespective of the segmentation type. A part of the result is used for Type II segmentation. Positive numbers mean that buyers on the left (row) have a higher marginal factor price (a steeper slope) than buyers on the top (column). In each cell, the upper row shows the difference in coefficient and the lower row shows the t-statistics in parenthesis. Control variables are: yeardummy, MSA, DistCBD, DistCBD\*MSA, DirectN, DirectE, MSA\*DirectN, MSA\*DirectE.

#### A. The difference in the coefficient on the log building size (Insize)



Corp	0.04					Corp	-0.06					
	(0.26)						(-0.17)					
Invm	0.00	-0.17				Invm	0.03	0.87				
	(0.00)	(-2.14)					(0.13)	(4.65)				
deve	0.13	-0.17	-0.07			Deve	0.09	-0.02	-0.13			
	(0.72)	(-3.01)	(-0.73)				(0.43)	(-0.23)	(-0.87)			
indi	0.25	0.09	0.29	0.24		Indi	0.32	0.10	-0.09	0.09		
	(1.32)	(2.57)	(3.23)	(4.02)			(1.52)	(1.18)	(-0.58)	(1.52)		
others	-0.27	-0.26	0.05	-0.16	-0.39	others	0.43	-0.18	-0.27	-0.07	-0.09	
	(-1.05)	(-1.63)	(0.28)	(-0.84)	(-2.00)		(1.35)	(-0.47)	(-1.05)	(-0.31)	(-0.38)	

## B. The difference in the coefficient on the building age (bdage)



			Industry							Multi-I	Family		
	REIT	Corp	Invm	deve	indi	others	bdage	REIT	$\operatorname{Corp}$	Invm	deve	indi	others
REIT							REIT						
Corp	-0.01						Corp	0.00					
	(-1.60)							(-0.10)					
Invm	-0.01	0.00					Invm	-0.01	0.00				
	(-0.97)	(1.42)						(-2.81)	(0.09)				
deve	0.00	0.00	0.00				deve	0.00	0.00	0.00			
	(-0.90)	(1.54)	(0.48)					(-1.39)	(-0.48)	(1.09)			
indi	0.00	0.00	0.00	0.00			indi	0.01	0.00	0.01	0.00		
	(0.23)	(3.18)	(1.07)	(0.27)				(1.76)	(1.12)	(2.28)	(3.00)		
others	0.00	0.00	0.00	0.00	0.00		others	0.00	0.00	0.00	0.00	0.00	
	(-0.36)	(0.08)	(0.69)	(-0.25)	(-0.85)			(-0.14)	(0.20)	(0.43)	(-0.96)	(-1.24)	
							l						

# C. The difference in the coefficient on stories (stories)

			Office							Retail			
	REIT	Corp	Invm	deve	indi	others		REIT	$\operatorname{Corp}$	Invm	deve	indi	others
REIT							REIT						
$\operatorname{Corp}$	-0.02						$\operatorname{Corp}$	0.00					
	(-0.81)							(-0.08)					
Invm	-0.01	-0.01					Invm	0.04	-0.07				
	(-0.82)	(-0.64)						(0.56)	(-1.03)				
deve	0.00	0.00	0.02				deve	-0.13	-0.05	-0.02			
	(0.29)	(0.31)	(2.08)					(-1.80)	(-0.81)	(-0.23)			
indi	-0.02	-0.02	0.01	-0.02			indi	-0.15	-0.15	-0.09	-0.08		
	(-1.54)	(-1.37)	(1.07)	(-1.61)				(-2.35)	(-2.56)	(-1.12)	(-1.22)		
others	-0.02	0.01	0.00	-0.02	0.01		others	-0.09	-0.09	-0.15	0.03	0.11	
	(-1.35)	(0.74)	(0.13)	(-2.00)	(0.70)			(-2.48)	(-1.69)	(-2.56)	(0.41)	(1.39)	

			Industry							Multi-F	amily		
	REIT	Corp	Invm	deve	indi	others		REIT	Corp	Invm	deve	indi	others
REIT							REIT						
$\operatorname{Corp}$	-0.42						Corp	-0.08					
	(-2.62)							(-1.60)					
Invm	-0.12	0.38					Invm	0.00	0.03				
	(-0.39)	(3.72)						(0.16)	(0.82)				
deve	-0.33	0.08	-0.02				deve	0.00	0.01	0.01			
	(-2.05)	(0.66)	(-0.11)					(0.04)	(0.34)	(0.69)			
indi	-0.29	0.09	-0.39	0.08			indi	-0.08	-0.06	-0.05	-0.07		
	(-1.76)	(1.34)	(-3.60)	(0.81)				(-3.82)	(-1.50)	(-2.80)	(-4.62)		
others	-0.18	0.23	0.29	0.51	0.38		others	0.07	0.07	0.03	-0.01	0.07	
	(-0.43)	(1.99)	(0.83)	(2.77)	(3.72)			(2.15)	(1.54)	(2.80)	(-0.42)	(3.38)	
							l						

# D. The difference in the coefficient on the log lot size (lnland)

			Office							Retail			
	REIT	Corp	Invm	deve	indi	other s		REIT	Corp	Invm	deve	indi	others
REIT							REIT						
Corp	0.03						Corp	-0.02					
	(0.30)							(-0.11)					
Invm	-0.13	0.03					Invm	-0.13	-0.18				
	(-1.81)	(0.40)						(-0.85)	(-1.37)				
deve	-0.03	0.04	0.03				deve	-0.08	-0.03	0.15			
	(-0.39)	(0.68)	(0.56)					(-0.62)	(-0.45)	(1.17)			
indi	-0.01	0.03	-0.01	0.02			indi	-0.20	-0.21	0.00	-0.17		
	(-0.19)	(1.03)	(-0.13)	(0.52)				(-1.46)	(-4.21)	(-0.03)	(-2.81)		
other	-0.07	0.11	0.03	0.02	0.06		others	-0.33	-0.19	-0.41	-0.18	0.06	
s	(-0.81)	(1.31)	(0.40)	(0.28)	(0.98)			(-1.79)	(-1.24)	(-2.01)	(-1.20)	(0.41)	

			Industry							Multi-F	amily		
	REIT	Corp	Invm	deve	indi	others		REIT	Corp	Invm	deve	indi	others
REIT							REIT						
Corp	-0.19						Corp	-0.11					
	(-1.27)							(-0.85)					
Invm	-0.03	0.29					Invm	-0.06	0.08				
	(-0.19)	(3.54)						(-0.96)	(1.14)				
deve	-0.29	0.13	-0.12				deve	-0.10	0.06	0.00			
	(-1.72)	(2.45)	(-1.36)					(-1.58)	(1.01)	(-0.07)			
indi	-0.33	-0.11	-0.40	-0.23			indi	-0.26	-0.05	-0.09	-0.09		
	(-1.97)	(-3.29)	(-4.55)	(-3.88)				(-3.74)	(-0.80)	(-2.01)	(-3.21)		

others	0.15	0.29	-0.08	0.26	0.45	others	0.09	0.23	0.01	0.07	0.11	
	(0.59)	(1.93)	(-0.46)	(1.37)	(2.46)		(0.77)	(1.92)	(0.14)	(1.18)	(1.59)	