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Office Market Segmentation in Emerging Markets

A Study of Sao Paulo

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Working Paper

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Abstract

This study uses a unique dataset from Sao Paulo, Brazil, to investigate how corporate and smaller occupiers differ in their willingness to pay for principal office rent determinants. We partition our sample of buildings based on the average size of leasable units to test whether rent premiums associated with property attributes, locational submarkets and economic change can be generalized or are localized to each group. Results from hedonic regressions show that corporate and smaller occupier properties form both spatial and non-spatial submarkets, but not in terms of temporal changes in market rent which are found to be highly correlated across office market segments. These findings suggest that these property-type segments can be classified as imperfect substitutes with distinct underlying pricing differences for building vintage, specification, size and location, but not as independent real estate markets.

Key Words: Commercial real estate, office buildings, market segmentation.

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1. Introduction

The goal of this study is to evaluate the relationship between building characteristics, locational submarkets and economic change across different property-type segments of the office market. We split properties based on the average size of leasable units and test whether rent premiums associated with these set of determinants can be generalized or are specific to each group. The breakdown allows us to assess how different users value ordinary property features. The contributions are twofold. First, we outline some of the practical motivations and develop a conceptual grounding to explain why different office users may not necessarily value hedonic characteristics in similar ways. Our theoretical framework shows that pricing discrepancies may arise from transaction costs (objective and subjective) which limit the ability of different users to arbitrage across property-type segments. Although office buildings serve for the same purpose, they are not readily suitable for all types of uses. Ultimately we may view certain relocation costs (subjective) as an endogenous component of each firm's capital allocation choice (Black et al., 1997). The optimal assignment of building characteristics would thus be dictated by the productive activity carried out at an office property.

In the empirical analysis, we compare pricing schedules of occupational prices (rents) accross two different property-type segments using a standard log-linear hedonic model. Buildings with larger office space are compared to a sample of other properties in the same submarket areas. For the whole sample, rents are related to three sets of features: building attributes, locational submarkets and temporal changes in market rent. The hedonic model considers a sample of 747 properties with average leasable units larger than 100 sqm as well as 875 buildings with smaller office space. Preliminary evidence from the estimates suggests that different users do not value building features and locational submarkets homogeneously. Nonetheless, economic change affects these two office segments in a very similar way. These findings are confirmed by tests of structural stability of coefficients.

The present research contributes to the literature by confirming that the 'law of one price' only applies to local office markets in a very limited fashion. Other studies have drawn a similar conclusion on residential (Wolverton et al., 1999; Berry et al., 2003), industrial (Black et al.,1997) and retail markets (Hardin and Carr, 2006), but previous work has not typically sought to explore the underlying reasons for the violations of the 'law of one price' such as different requirements or utility functions of user groups. Our results also highlight complex interactions between regional submarkets and different uses of office properties. Investors and real estate advisors should pay attention to the segmented reality of the price generation process directly at microeconomic level.

This article is organized as follows. The second section provides a background discussion focusing on the literature development on market segmentation with respect to office markets. This is followed by a set practical motivations and a theoretical grounding for localized valuation of hedonic attributes. Next, the main empirical section outlines the data and methodology used in the study. Finally, conclusions are drawn.

2. Motivation and Background

Office buildings are not commodities: each has unique features that appeal different users, lenders and landlords. The confluence of location, function (degree to which a property can physically accommodate different occupier demands and configurations), form (exterior and interior design, finish quality, and configuration of common and private areas) and cost drive suitability for any given user. At the same time, different occupiers may not necessarily weight these features in similar ways.

Clapp et al. (1992) show that cross sectional and dynamic variables are relevant determinants of patterns in office market prices. Intra-metropolitan location reflects substantial spatial specialization by type of office activity and growth in selected industries, such as finance, insurance and real estate. Using a sample of 5189 headquarters, Shilton and Stanley (1999) find a significant degree of spatial concentration of headquarters, especially when considering companies from similar industries. Clapp (1993) suggests that office location decisions lead a given market participant to value different locations heterogeneously. Put differently, distinct users may value a given location unalike based on their intrinsic space requirements.

In the context of residential real estate, Wolverton et al. (1999) and Berry et al. (2003) investigated the existence of apartment niches determined by unit type. These authors suggest that distinct submarkets that may be differentiated by neighbourhood location, property features and temporal changes in market rent. These findings challenge the traditional property-type segmentation in which apartments are sufficiently homogeneous to be modelled as an aggregate real estate segment.

Dunse and Jones (2002) and Dunse et al. (2002) test whether city-level office markets, often assumed as a unitary market, can be divided as intra-metropolitan submarkets using data from Glasgow and Edinburgh. The authors conclude that the office market consists of a set of submarkets which are best defined upon real estate agent´s views of market fragmentation as property attributes do not remain constant across different regions of these cities. Locational segmentation based on a priori information from experts is found to provide better in-sample performance than statistically determined clusters (Chen et al., 2009; Bourassa et al., 2003). By contrast, Fuerst and Marcato (2010) find more mixed evidence of statistically determined clusters for the UK commercial property market. Applying both discriminant and neural network analysis, the authors conclude that statistical clustering is more suitable for identifying investment opportunities and risks while the expert-based sector-region classification is sufficient for describing the broad characteristics of a real estate portfolio. Recent research from White and Ke (2014) validates that certain office locations, such as Pixi and Pudong, located in Shanghai, cannot be viewed as homogeneous or perfect substitutes as the autors do not find convergence in rental performance or interactions among these submarkets.

While literature on the distinction of office markets based on locational segmentation is considerably developed, there is little empirical research on niches *inside* the traditional property-type segmentation of CRE. In the "industrial" segment, Black et al. (1997) differentiate distribution and manufacturing niches. Hardin and Carr (2006) propose a formal distinction of "retail" properties into neighbourhood and community centres. These authors show that rental rates determinants are different in each of these unit-type segments using hedonic regression analysis.

As far as our research allows, the commercial real estate (CRE) literature does not directly consider the fragmented reality of office properties. It does; however, provide some intuitive insights regarding property-type segmentation based on building class. For instance, Olayonwa et al. (2012) use rent distribution intervals to identify office quality classes, but do not test for the existence of market niches linked to these cathegories. Fuerst et al. (2015) find that the spread between high and low quality properties increases in recessionary periods due to illiquidity among low-tier buildings. In a similar context, Slade (2000) shows that price premiums linked to features of office properties are valued differently in distinct periods of business cycles. Robinson and McAllister (2015) investigate whether price premiums associated with environmental certification exist across different value segments or are localized to specific niches. The authors suggest that a positive premium may not be uniformly distributed across value segments. The concentrated supply of eco-labelled properties in higher-end buildings can actually lower price premiums in this segment.

In summary, while these studies reinforce the fragmented nature of office properties, they do not investigate how different users value traditional office rent determinants, namely building features, location and economic variables. Our analysis goes one step further as we compare property-type pricing schemes and distinguish which sets of determinants can be generalized across large and smaller occupiers and which are specific to each group.

3. Rationale for the Existence of Corporate and Smaller Occupier Segments

Strong supply-side rigidity is a feature that renders the market for office space unique relative to other real estate markets. Studies that focus on rent dynamics show that different property types return to equilibrium at substantially different speeds. Ibanez and Pennington-Cross (2013) compare rent dynamics for office, industrial, flex and retail markets in the US using appraisal-based data. The sluggish adjustment process is consistent with a property type that takes a long time to build or renovate and has long lease terms spanning from 3 to 5 years. The overall supply of office space in saturated areas is even less dynamic as it may take years to obtain construction or redevelopment approvals. The amount and speed of construction activity is impacted by demand volatility and the extent to which the investment in the development is irreversible or sunk (e.g. Holland et al., 2000; Schwartz and Torous, 2007; Bulan et al., 2009).

Once an office building is delivered, it will be bound to physical and locational constraints. The characteristics in place will attract different occupiers, such as large and smaller firms. Hence, segmentation of demand by unit type could potentially translate in different pricing for features, such as physical attributes, location and economic change captured by temporal changes in market rent (Wolverton et al., 1999).

Demand for office space is highly heterogeneous; however, it may be grouped according to basic space requirements. Classification based on structural features, such as the size of leasable units or floor plate, is a common way of segregating office properties into niches. For simplification, buildings with large leasable units will henceforth be denominated *corporate* and the remainder *smaller occupier (non-corporate).* Another possible seggregation strategy, as suggested by the CRE literature, is to consider building classes (e.g. letter grades).

Large local and multinational companies typically occupy properties in the *corporate* segment. These buildings are often located in priviledged areas and have central air conditioning, environmental certifications, excellent electricity supply, modern and innovative design, large floor plate and bigger office units. Smaller service firms and liberal professionals, such as lawyers and accountants, usually choose *non-corporate* properties.

Corporate and *smaller occupier* buildings can also be distinguished on the supply side. Developers of *non-corporate* properties often sell most units in the launch of the project and only after that begin to build. This feature is analogous to that of residential markets. At the same time, developers of *corporate* buildings typically build and lease their properties prior to selling them at higher prices. Institutional investors and REITs are usual buyers of such assets. Hence it is common to see *corporate* properties with a single or very few owners in the market. In contrast, *smaller occupier* buildings can be owned by several retail investors and non-investors (in some cases hundreds). Landlord segmentation based on property attributes, such as size, is highlighted by Bischoff and Maennig (2011).

The different ownership structure and investor profiles also have implications to users. Contractual negotiations of larger office space can be burdensome due to the variety of owners in a single *non-corporate* property. Rent values and lease clauses are often not standardized among these owners and can delay occupation. In some cases, tenants have to bear transaction costs to renovate, adapt and unify the space. These costs can be substantially higher if the occupier has to negotiate with multiple landlords at the same time. Similarly, a small tenant also faces diseconomies of scale when leasing space which is larger or better than needed. These features limit the ability of different occupiers to rellocate from *corporate* to *smaller occupier* buildings and *vice versa*.

The relationship between owners and developers also varies considerably depending on the property-type segment. Owners of *corporate* buildings usually have a stable long run connection with developers (when they are not the same entity), rendering managerial processes a lot smoothier. At the same time, retail landlords have a smaller capacity to bargain with each other and with developers. Long term planning is a key issue when it comes to property maintenance and renovation. Consistent with this, the literature on construction adaptability shows that developers tend to deliver less adaptable properties when they are built for sale to investors than when they are built for renting and management (Arge, 2005). One explanation to such effect is the higher upfront cost of adaptability and uncertainty regarding the time span of its benefits (Gosling et al., 2013)). Obsolete properties are the most likely to be penalized by customers with higher expectations (Slaughter, 2001).

Allen et al. (1995) suggest that examination of a price function requires consideration of the aggregate market in which properties compete. Nonetheless, as the evidence aforementioned suggests, the structure of the price generation process may not be homogeneous across *corporate* and *non-corporate* buildings. Thus we cannot necessarily infer that these market niches are perfect substitutes.

3.1. Do Office-type Segments form Distinct Markets?

Urban locational theory suggests that the relative prices between intra-urban regions remain stable overtime irrespective of cyclical oscilations in absolute prices (constant ratio hypothesis). Such stability is associated to the large degree of mobility of office occupiers, a high price elasticity of demand and arbitrage opportunities in a situation of mispricing (DiPasquale and Wheaton, 1996). In our context, larger and smaller office users could *theoretically* arbitrage rental price differentials based on relocation costs associated with rent determinants. That being the case, we would find similarity in their hedonic schedules.

On one hand, *corporate* and *smaller occupier* properties may not be perfect substitutes because they are not readily suitable for all types of users. At the same time, they may not be sufficiently heterogeneous to be treated as two independent markets because the purpose of these two types of property is to provide office space. For this reason, the following arbitrage condition could be satisfied if office users were indiferent to move from one property-type segment to the other:

$$P_c + \Theta_c = P_{st} + \Theta_{st} \tag{1}$$

Where P is the price (or rent) of a given property, Θ is the relocation cost of moving to another building in a different submarket and "c" and "st" denominate *corporate* and *small occupier* properties, respectively. The arbitrage logic is as follows. If the occupancy costs (rent) related to a *corporate* building (P_c) are higher than that of renting a *non-corporate* property and the rellocation cost differential ($P_{st} + \Theta_{st} - \Theta_c$), then large tenants could migrate to *smaller occupier* office space until the arbitrage condition is satisfied. In this scenario, demand for *non-corporate* buildings would shift outwards.

Based on Rosen's analytical framework, the price of an office building consists of a vector of utility-bearing features $(z_1, z_2, \dots, z_k)$, which make the hedonic price function (Rosen, 1974). Substituting (1) into the quintessential hedonic equation and solving for $P_c(z)$, we get:

$$P_c(z_1, z_2, \dots, z_k) = P_{st}(z_1, z_2, \dots, z_k) + \Theta_{st}(z_1, z_2, \dots, z_k) - \Theta_c(z_1, z_2, \dots, z_k) \tag{2}$$

Hence the hedonic price function for a *corporate* user depends on the pricing schedule of a smaller tenant ($P_{st}(z_1, z_2, \dots, z_k)$) and on the cost differential to relocate to a *non-corporate* building ($\Theta_{st}(z_1, z_2, \dots, z_k) - \Theta_c(z_1, z_2, \dots, z_k)$). Note that Θ cannot necessarily be interpreted as an isolated attribute z_θ. A large tenant user may need to revamp some of the existing features in order to use a *non-corporate* building. For instance, such user will almost certainly have to unify units to occupy a bigger space or adapt some of the existing installations in order to ensure sufficient electricity supply. These are objective (observable) relocation costs associated with attributes $(z_1, z_2, \dots, z_k)$. There are also subjective (not observable) costs embedded in these features. Because larger tenants may be more concerned with overall property quality, they may also have a different willingness to pay for certain amenities, such as location, building design, technological infrastructure, occupancy profile, *inter alia*. Not surprisingly, the marginal price of a given attribute z_i also depends on these subjective relocation costs.

$$\frac{\partial P_c(z)}{\partial z_i} = p_i^c(z_i, z_{-i}) = p_i^{st}(z_i, z_{-i}) + \theta_i^{st}(z_i, z_{-i}) - \theta_i^c(z_i, z_{-i}) \tag{3}$$

While attempts to arbitrage based on objective relocation costs seems relatively straightforward, establishing an arbitrage relationship for subjective relocation costs can be a daunting task. We can alternatively view these subjective costs as an endogenous component of each firm's capital allocation choice (Black et al., 1997). The optimal assignment of building characteristics would then reflect the productive activity which will be carried out at an office property. If the business of large companies is sufficiently different from that of than smaller service firms, then these two types of users may not necessarily price rent determinants in a similar manner. At one extreme, if large companies only consider occupying *corporate* properties and if smaller users only occupying *non-corporate* buildings, then the two uses compete in two independent markets. Conversely, an aggregate market exists if these buildings are close substitutes. In other words *corporate* and *smaller occupier* properties would not be priced independently. Given these considerations, we may question which implicit prices can be generalized across these property-type segments.

4. Empirical Assessment of Office-type Segmentation

Following Wolverton et al. (1999), Berry et al. (2003) and Hardin and Carr (2006), we define three sets of determinants to compare how different users value *corporate* and *smaller occupier* properties: physical attributes, location and response to economic fluctuations. These authors suggest that distinct segments can be defined based on implicit pricing differentials across these categories of variables.

We assess these gaps by stratifying data based on the average size of office units as defined by the *Corporate* dummy. Robinson and McAllister (2015) adopted a similar approach to investigate rent premiums associated with eco-labelled properties in different value segments. We employ a quintessential log-linear hedonic model that takes the following form:

$$P_{imt} = c_{imt} + \beta_n Z_{imt} + \beta_n D_m + \beta_n D_t + e_{imt} \tag{4}$$

Where P_{imt} is the natural logarithm of *Rent* per square foot for asset "i" on submarket "m" at time "t" and Z_{imt} is a vector of asset-specific variables, namely *Rating, Size, Age* and *Vacancy*. These covariates are explained in Tables 1 and 3. The remaining controls, D_m, a vector of location dummies used to capture the impact of submarket "m" which may be common to all assets in a given region, and D_t, a vector of time dummies used to isolate macroeconomic shocks common to all assets at a given period. c_{imt} and e_{imt} are a constant and an error term, respectively. The hypothesis of a generalized pricing schedule is validated if β_n is equal across the two property-type segments considered.

4.1. Data

The baseline dataset was extracted from CRE Tool, a system which offers an extensive appraisal dataset for office properties located in various Brazilian cities. This system is provided by Buildings[1], a company solely specialized in real estate research. According to Buildings, all data from CRE Tool is collected from landlords, brokers or through visits in each property and is updated on a quarterly basis.

The data covers 20,562 property-period observations (1,622 buildings) in the Sao Paulo office market from 2005:Q3 to 2014:Q3. The sample is divided in 14 locational submarkets inside the city (see Figure 1) and contains the property-characteristics characteristics described in Table 1.

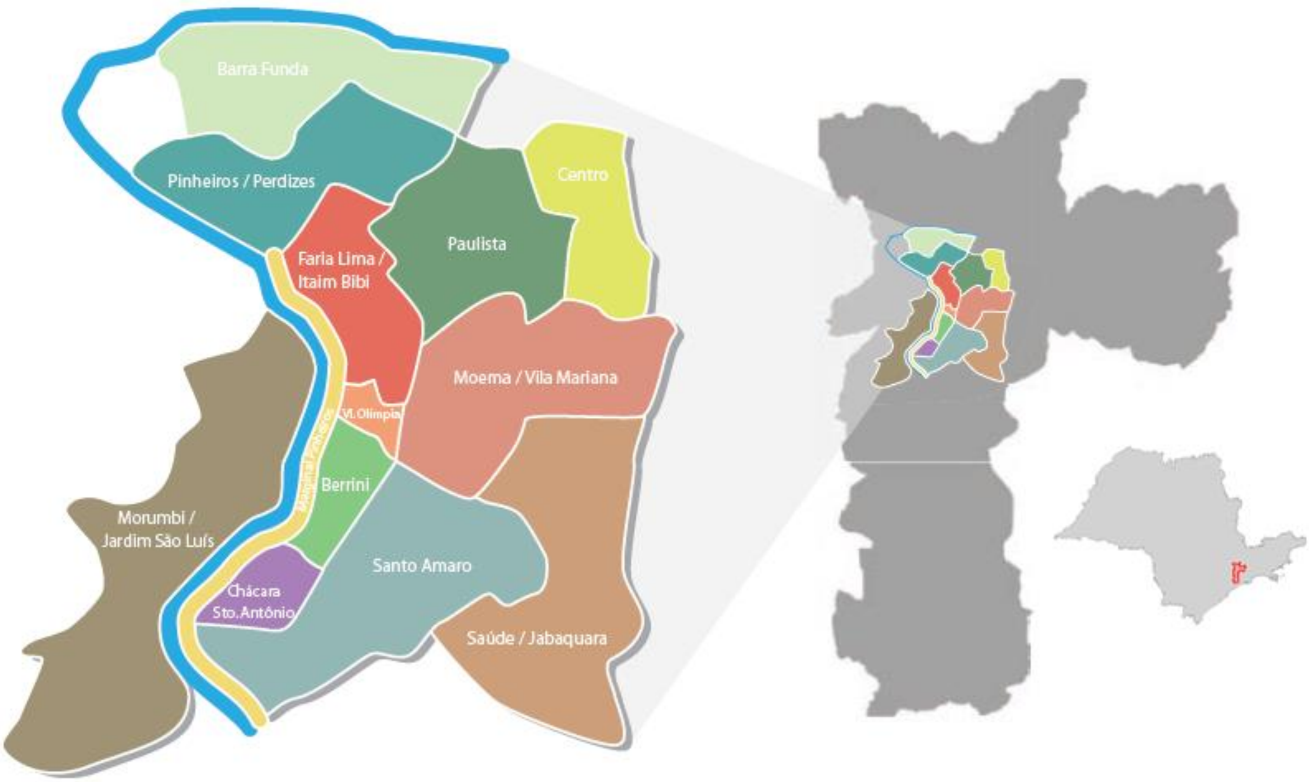
Table 1: Definition of Variables

Rent	= the natural logarithm of nominal asking rent per square foot denominated in Brazilian real (BRL)
Corporate	= a dummy defining whether a property belongs to the *corporate* or *smaller occupier* market niche. Buildings defines these segments based on the average size of units inside a given property. The cut-off threshold is 100 sqm. Properties above this number are considered *corporate* and the remainder *smaller occupier (non-corporate)*. This variable is set to one when an asset belongs to the first segment at a given period of time and zero otherwise.
Rating	= a dummy to capture each building class (standard categories AAA, AA, A, BB, B and C) as defined by the data provider. This variable is set to one when an asset belongs to a certain class at a given period of time and zero otherwise. All C class buildings were set to zero to avoid perfect colinearity. Thus all other classes are measured as premiums relative to this class.

[1] For more details regarding Buildings, please visit their website: http://www.buildings.com.br

Age	= measured from the year of construction or the year of a major refurbishment (whichever occurred more recently). We define age cohorts to account for potentially time-varying age effects. If a building belongs to a certain age group, this variable takes the value of one and zero otherwise. All properties that are less than 5 years old were set to zero to avoid perfect collinearity. Hence parameters for all age thresholds represent discounts relative to new assets.
Size	= the natural logarithm of the gross leasable area measured in squared meters
Vacancy	= the percentage of vacancy relative to the gross leasable area multiplied by one hundred

Figure 1: Definition of Locational Submarkets



We considered a dummy called *Corporate* to differentiate property-type segments based on the average size of leasable units inside a building. Segmentation based on a structural feature is generally subjective; however, this variable may serve as a proxy to capture the unobserved interaction between segmented demand (*corporate* vs. *non-corporate*) and the differentiated stock (supply) of office units. Ideally we would need occupier-related information to classify these niches more accurately. Nonetheless, such data is not available.

Practitioners often use a given feature or set of features to classify market participants as alternative to overcome this type of limitation. For instance, JLL (2016) defines prime rent when office properties have a floor plate above 10,000sqft. The implicit underlying assumption of such threshold is that institutional investors (supply) and *corporate* occupiers (demand) interact in properties that have a large floor plate. A potential critique to this backdoor approach is that a building with a large floor plate can have many units per floor in order to accommodate smaller tenants.

The advantage of using *Corporate* as opposed to other structural features, namely gross leasable area or floor plate, is that a leasable unit is the closest definition of usable office space inside a property. The caveat linked to this measure is that c*orporate* occupiers may still wish to unify leasable units and occupy a set of adjacent spaces within a *smaller occupier* building. Nonetheless, this is the exception rather than the rule. As explained in the previous section, transaction costs to unify spaces are often higher than that of finding an adequate unit elsewhere.

The data provider defines *corporate* and *smaller occupier* niches by setting a cutoff threshold of 100sqm for the average size of leasable areas. Properties with average leasable units above this number are defined as *corporate* (1) and the remainder as *non-corporate* (0). The dichotomous nature of our niche variable also brings about some caveats to our empirical estimates, especially when we consider buildings that are very close to this threshold. It may be preferable to test other cutoffs (e.g. 200sqm or 300sqm) or have several unit size categories. However, the lack of alternative and potentially imprecise cutoffs does not jeopardize the empirical testing of our broader hypothesis that *corporate* and *non-corporate* tenants have fundamentally different underlying valuation functions for the same property characteristics. Table 2 shows details of the property classification system.

Table 2: Details of the Property Classification System in the Baseline Dataset

	Macro Classification	A			B		C
	Micro Classification	AAA	AA	A	BB	B	C
Objetive Criteria	Floor Plate (sqm)	>=1500	>=1000	>=500	>=500	>=250	NA
	Gross Leasable Area (sqm)	>= 20,000	>= 10,000	>=5,000	>=5,000	>=2,500	NA
	Age (Deliver/Retrofit)	<=20 Years			<=40 Years		NA
Subjective Criteria (Grades)	Sum of Grades	>=13	>=11	>=8	>=5	>=5	>=3
	Technical Specifications	1 to 5	1 to 5	1 to 5	1 to 5	1 to 5	1 to 5
	Corporate Image	1 to 5	1 to 5	1 to 5	1 to 5	1 to 5	1 to 5
	Occupation Profile	1 to 5	1 to 5	1 to 5	1 to 5	1 to 5	1 to 5

While this table sheds some light on the objective criteria, it would have been useful to understand the methodology behind the subjective criteria but the data provider does not provide further detail. Technical specifications, corporate image and occupation profile are useful information for real estate investors. Nevertheless, these variables are qualitative in nature and there are many details to be considered due to the heterogeneous nature of office properties. An interesting feature of this classification system is that it does not take location into account.

The CRE database from Buildings is the largest and perhaps the most detailed non-proprietary source of data for office properties in Brazil. Many institutional investors and real estate companies use this information to make investment decisions. As far as our investigation allows, CRE Tool has not yet been widely used by in academic research.

4.2. Descriptive Statistics

The descriptive statistics are displayed in Table 3. At a glance, there are some discrepancies on attributes when we evaluate properties based on building classes and office units. Buildings with bigger office units also tend to be larger, but this is not necessarily true across all building classes. The mean size of *corporate* buildings is 7,935 sqm while that of *smaller occupier* properties is 4,182 sqm; however, AA- and BB-rated assets in the *non-corporate* segment are on average slightly larger than their *corporate* peers.

Top-tier properties also tend to be larger and newer regardless of the segmentation based on office units. *Corporate* AAA and AA buildings have, respectively, mean sizes of 36,973 and 19,952 sqm. The comparable figure for *non-corporate* AA properties is 21,644 sqm. The average age of higher-end buildings in both segments is well below the sample mean. These stylized facts reinforce the need to consider property-type segments when studying building attributes. Table 3 shows summary statistics.

Table 3: Summary Statistics of Variables

Market Niche/ Building Class	Building Class		Rent (in BRL)		Size (in sqm)		Age (in Years)	
	No. Obs	%	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Corporate	**8,141**	**39.6**	**53.34**	**36.71**	**7,935.56**	**7,985.78**	**22.66**	**17.84**
AAA	161	0.8	114.80	42.23	36,973.82	13,629.25	3.34	3.45
AA	301	1.5	106.95	47.04	19,952.01	5,957.87	6.19	4.84
A	1,367	6.6	79.29	35.68	11,480.33	6,295.23	7.68	6.01
BB	1,142	5.6	49.71	25.88	11.853.95	7,225.21	25.86	8.34
B	2,543	12.4	52.01	30.48	4,823,65	1,668.59	18.23	11.35
C	2,628	12.8	32.73	24.79	4,211.76	5,522.96	36.44	20.62
Smaller Occupier	**12,421**	**60.4**	**39.18**	**22.33**	**4,182.61**	**3,746.67**	**21.88**	**18.94**
AAA	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
AA	56	0.3	84.87	25.25	21,644.95	9166.74	1.37	1.18
A	454	2.2	63.51	24.65	9,058.92	3,993.47	4.80	4.74
BB	337	1.6	37.59	23.06	13,633.93	5,984.07	33.60	3.90
B	4,515	22.0	43.89	21.72	4,605.66	1,482.62	14.91	10.54
C	7,059	34.3	34.32	20.35	3,008.66	3,194.7	27.04	21.72
Total	**20,562**	**100.0**	**44.79**	**29.71**	**5,668.94**	**6,091.12**	**22.19**	**18.51**

Table 3 shows summary statistics of Rent, the asked rent per square meter of a given property, Age, measured from the year of construction or the year of a major refurbishment (whichever occurred more recently), and Size, gross leasable area measured in squared meters. Corporate is a dummy defining whether the asset belongs to the corporate or smaller occupier segments. Properties with average leasable units above 100sqm are classified as corporate and the remainder as smaller occupier (non-corporate). Rating is a dummy for each building class (standard categories AAA, AA, A, BB, B and C). The data covers commercial towers in the city of Sao Paulo from 2005:Q3 to 2014:Q3.

Without controlling for differences between building classes, top-tier properties have higher asking rent than lower-end peers. Nevertheless, this indicator is not uniformly distributed across office space segments. Mean *Rent* figures on C-rated buildings are fairly similar in both *corporate* and *smaller occupier* niches (BRL 32.73 vs. 34.32). At the same time, BB-rated properties have on average larger *Rent* in the *corporate* segment (BRL 49.71 vs. 37.59). This gap continues to widen as we compare higher-end buildings. For instance, mean *Rent* on AA-rated buildings the *corporate* and *smaller occupier* niches are, respectively, BRL 106.95 and 84.87. These preliminary indicators suggest that segmentation solely based on building class may not be sufficient as high-end properties could have an incremental premium associated with larger office space.

4.3. Regression Estimates

Table 4 reports regression results of equation (4). Standard errors in all estimates are clustered at submarket level as in Reichardt et al. (2012). Regression (1) highlights the significance and sign directions of building attributes and locational submarkets. *Ceteris paribus*, larger and older properties carry a rent premium and discount, respectively, relative to other properties (e.g. Clapp (1980), Glascock et al. (1990), Bollinger et al. (1998)). Among the control variables, A class assets have positive link with our left-hand side variable and this link is larger than that of B class properties. The results suggest that rent premiums are generally increasing among properties with higher *Rating*. These outcomes are consistent with those found by Eichholtz et al. (2010), Fuerst and McAllister (2011) and Reichardt et al. (2012). The sign of *Vacancy* is not statistically different than zero. The locational submarkets are measured relative to Faria Lima/Itaim region. Not surprisingly, most locations offer a significant rent discount relative to this more convenient office submarket. Spatial differentiation based on submarket dummies is reinforced by many studies in the literature (e.g. Dunse and Jones, 2002; Dunse et al., 2002; Bourassa et al., 2003; Chen et al., 2009).

Table 4: Regression Estimates of ln(Rent/sqm)

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	**Total Sample**	**Corporate Sample**	**Smaller Occupier Sample**	**Total Sample**	**Corporate Sample**	**Smaller Occupier Sample**
Constant	2.5347***	2.4886***	2.6916***	2.0505***	1.9850***	2.6800***
	(8.40)	(12.91)	(7.11)	(6.29)	(8.51)	(10.00)
ln (Size)	0.1210***	0.1435***	0.0920*	0.1900***	0.2176***	0.0934***
	(3.50)	(6.06)	(2.00)	(5.39)	(9.62)	(3.15)
Age (years)						
5 to 9	-0.0740**	-0.0845***	-0.0862***	-0.0971***	-0.0903**	-0.0855***
	(-2.81)	(-3.37)	(-4.62)	(-3.18)	(-2.90)	(-4.52)
10 to 14	-0.1956***	-0.2167***	-0.2119***	-0.2255***	-0.2238***	-0.2111***
	(-8.64)	(-5.34)	(-8.96)	(-8.24)	(-5.47)	(-7.58)
15 to 19	-0.2928***	-0.3427***	-0.3137***	-0.3255***	-0.3531***	-0.3129***
	(-11.16)	(-7.69)	(-10.11)	(-11.12)	(-9.73)	(-8.35)
20 to 24	-0.3436***	-0.4636***	-0.3301***	-0.3822***	-0.4718***	-0.3291***
	(-9.74)	(-8.55)	(-10.84)	(-11.47)	(-10.94)	(-9.78)
25to29	-0.4286***	-0.5364***	-0.4097***	-0.4686***	-0.5465***	-0.4076***
	(-18.30)	(-9.48)	(-12.77)	(-22.82)	(-13.85)	(-13.30)
30+	-0.5120***	-0.6432***	-0.4541***	-0.5607***	-0.6842***	-0.4521***
	(-14.72)	(-16.22)	(-12.54)	(-13.47)	(-17.49)	(-9.84)
Rating (Grades)						
AAA	0.3184***	0.2047**				
	(4.67)	(3.00)				
AA	0.3493***	0.2962***	-0.0395			
	(5.53)	(6.29)	(-0.18)			
A	0.2154***	0.2004***	0.0043			
	(4.17)	(4.91)	(0.06)			
BB	0.1514**	0.2081***	0.0164			
	(2.48)	(3.29)	(0.23)			
B	0.0364	0.1086**	0.0003			
	(1.19)	(2.53)	(0.01)			
Vacperc	0.0007	0.0002	0.0007	0.0011	0.0004	0.0007
	(1.06)	(0.43)	(0.72)	(1.77)	(1.11)	(0.82)
Vila Olimpia	-0.0180***	-0.1218***	-0.0152	-0.0292**	-0.1230***	-0.0155
	(-3.22)	(-14.05)	(-1.59)	(-2.98)	(-32.09)	(-1.68)
Saude & Jabaquara	-0.3561***	-0.2248***	-0.2641***	-0.3878***	-0.2136***	-0.2641***
	(-25.96)	(-9.92)	(-17.35)	(-24.84)	(-9.57)	(-18.21)
Santo Amaro	-0.3427***	-0.5376***	-0.2065***	-0.3594***	-0.5506***	-0.2066***
	(-66.29)	(-42.16)	(-18.24)	(-60.36)	(-42.37)	(-19.70)
Chacara Santo Antonio	-0.2366***	-0.2668***	-0.2759***	-0.2252***	-0.2566***	-0.2761***
	(-32.50)	(-26.01)	(-29.20)	(-25.66)	(-50.46)	(-29.62)
Morumbi/Jd Sao Luis	-0.3460***	-0.5013***	-0.1824***	-0.3314***	-0.4931***	-0.1858***
	(-36.01)	(-26.21)	(-6.92)	(-27.08)	(-30.03)	(-10.82)
Centro	-0.8121***	-0.8965***	-0.7559***	-0.8463***	-0.9525***	-0.7570***
	(-42.66)	(-48.13)	(-26.12)	(-40.61)	(-46.74)	(-35.55)
Marginal Pinheiros	-0.0918*	-0.1651***	-0.1018	-0.0487	-0.1786***	-0.1247**
	(-2.11)	(-8.12)	(-1.06)	(-1.01)	(-8.05)	(-2.20)

Moema/Vila Mariana	-0.2041***	-0.1997***	-0.1235***	-0.2258***	-0.2204***	-0.1236***
	(-18.25)	(-19.55)	(-12.52)	(-18.77)	(-20.92)	(-13.30)
Paulista	-0.0615***	-0.0339***	-0.0544***	-0.0790***	-0.0423***	-0.0543***
	(-10.42)	(-3.75)	(-10.72)	(-20.16)	(-3.76)	(-30.17)
Pinheiros/Perdizes	-0.2899***	-0.2024***	-0.2411***	-0.3085***	-0.2236***	-0.2412***
	(-18.28)	(-9.61)	(-18.42)	(-16.42)	(-10.16)	(-16.76)
Berrini	-0.0425***	-0.1437***	0.0608***	-0.0341***	-0.1423***	0.0603***
	(-5.55)	(-20.61)	(4.27)	(-4.52)	(-27.32)	0.0603***
Barra Funda	-0.4776***	-0.5167***	-0.4122***	-0.4916***	-0.5024***	-0.4124***
	(-51.14)	(-41.00)	(-28.44)	(-61.18)	(-43.63)	(-31.60)
Other	-0.5497***	-0.8273***	-0.4183***	-0.5638***	-0.8305***	-0.4183***
	(-48.46)	(-68.02)	(-36.99)	(-41.11)	(-51.79)	(-39.06)
Time Dummies	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
R-squared	**0.78**	**0.84**	**0.75**	**0.77**	**0.83**	**0.75**
Number of Properties	**1,622**	**747**	**875**	**1,622**	**747**	**875**
Observations	**20,562**	**8,141**	**12,421**	**20,562**	**8,141**	**12,421**

*Table 4 shows regression results. T-statistics are reported in parenthesis. ***, ** and * indicate whether coefficients are significant at 1%. 5% and 10% level, respectively. Standard errors are clustered at submarket level. All variables and submarkets are defined in Table 1 and Figure 1. The data covers commercial towers in the city of Sao Paulo from 2005:Q3 to 2014:Q3. The time dummy coefficients from these regressions are reported in the appendix.*

4.3.1 Differentiation based on Building Attributes

Hedonic estimations (2) and (3) test whether the aforementioned determinants can be generalized across property-type segments. *Size* and *Age* are significant and parameters remain as expected when we consider the stratified samples. Nonetheless, property size appears to have a larger rent premium among *corporate* properties (14.4% vs. 9.2% in *smaller occupier* buildings). *Age* parameters suggest that physical depreciation may have a greater impact on lease values for properties with larger leasable units. Rent discounts are relatively similar when we consider newer properties (up to 14 years); however, they can yield distinct results as office space become more obsolete. For instance, a *25 to 29* year-old *corporate* building offers an average rent discount of 53.6%. The comparable figure for a corporate property is 40.9%. The graphs in Figure 2 indicates that implicit rents might be statistically different in the *Age 30 plus* cohort.

Note that the sign of *Rating* also varies across property-type segments. On one hand, building class appears to be more relevant among *corporate* buildings. There are a few exceptions to this rule. Regression (2) reports that rent premiums associated with AAA class buildings may be smaller than that AA-rated peers. At the same time, results from regression (3) suggest that *Rating* is on average not different than zero among *non-corporate* properties. Although these outcomes reinforce the existence of localized rent premiums, we have to be careful when interpreting them. Most AAA *corporate* properties and upper class *smaller occupier* buildings, namely AA, A and BB, are highly clustered in developed submarkets. Therefore, it is possible that our locational dummies soaked part of the variation associated with *Rating*. Robinson and McAllister (2015) find different letter grade premiums across strata based on property sales value, but do not discuss these results.

Figure 2: Depreciation and Quality Paths of Corporate and Smaller Tenant Properties

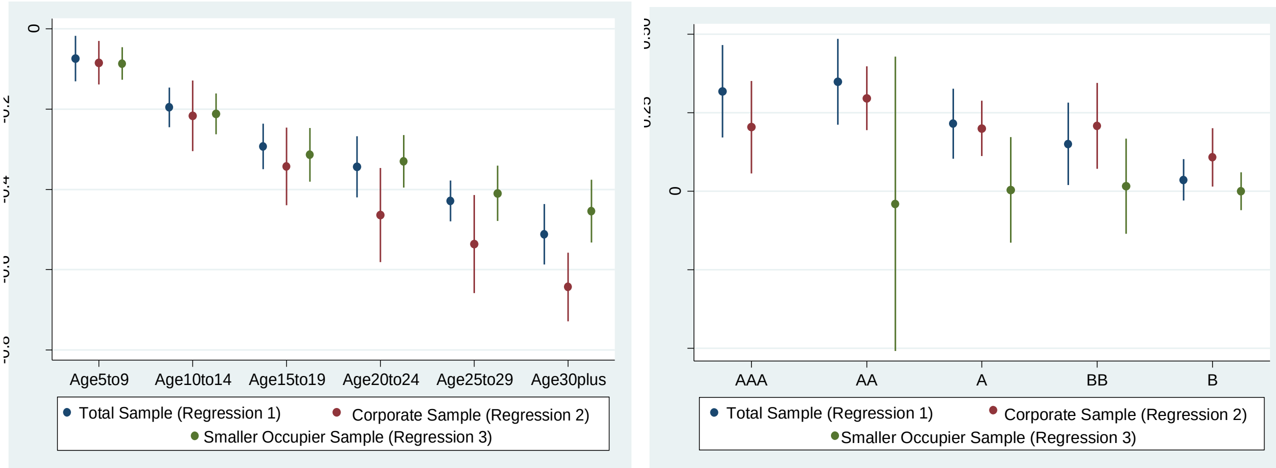


Figure 2 shows Age and Rating cohort estimates from regressions (1), (2) and (3) and their standard errors. Age cohorts (left) were benchmarked against buildings which are up to 4 years-old. Rating cohorts (right) are measured as premiums relative to C class properties.

Sheff (2006) and Fuerst et al. (2015) criticize the use of ordinal rankings (e.g. Class A, B or C) because they are composite indicators of a number of attributes of CRE assets. The way Buildings classifies office a property is not without problems as it takes *Age* and *Size* into account when assigning letter grades. As a robustness check we ran regressions (4), (5) and (6) without the *Rating* variable. The results are qualitatively similar to those found in regressions (1), (2) and (3); however, the premium (discount) associated with *Size* (*Age*) increased. For instance, the shadow price associated with *Size* for *corporate* buildings rose from 14.4% in regression 2 to 21.8% in regression 5. The same figure for smaller tenant properties remained almost unchanged (9.2% in regression 3 and 9.3% in regression 6). The parameters for submarket and time dummies remained fairly stable. Although these drifts in *Size* and *Age* further corroborate to the hypothesis of localized premiums linked to property features, there is an omitted variable problem in removing *Rating* from our model. This covariate also contains relevant information regarding the subjective classification developed by the data provider (e.g. technical specification, corporate image and occupation profile). Therefore it is not possible to distinguish potential "double counting" from the extent to which *Rating* adds information to the model. Unfortunately Buildings did not provide us with specific details from its classification system.

4.3.2 Differentiation based on Submarkets

We now turn our attention to locational submarkets. Regressions (2) and (3) report shadow rents for each property-type rent relative to Faria Lima/Itaim. As in regression (1), most regions exhibit significant lower rent when compared to this location. Nonetheless, some discrepancies appear when we compare *corporate* and *smaller tenant* buildings. Larger occupiers seem to be less flexible when pricing less appealing office locations (e.g. Santo Amaro, Morumbi/Jardim Sao Luis, Centro and Other) or growth submarkets (e.g. Vila Olimpia, Berrini, Marginal Pinheiros and Barra Funda). For instance, the *corporate* average rent discount in Santo Amaro is 53.8% (regression 2) while the same figure for non-corporate is 20.7%. At the same time, some regions appear to have more similar discounts (e.g. Paulista, Pinheiros/Perdizes, Saude/Jabaquara and Chacara Santo Antonio). The results for regressions (4), (5) and (6) are quantitatively similar to those aforementioned.

We have to be careful when interpreting these results as submarket dummies do not control perfectly for unobserved spatial heterogeneity. Even though these locational indicators are intended to define relatively homogeneous market regions, it is possible that intra-submarket variations in locational quality may give rise to biased results if *corporate* properties were systematically located in the best locations within submarket level (Reichardt et al., 2012). In our hedonic framework, two conditions would have to be met for such bias to arise: (1) *corporate* properties are systematically located in the best micro-locations while smaller tenant are found in worse areas and (2) the price gap between the best and worse micro-locations varies across submarkets. Considering the relatively large number of *corporate* and *smaller tenant* properties in our sample and their co-existence in most locations a bias seems unlikely.

4.3.3 Differentiation based on Economic Variables

Before we proceed to the discussion on temporal changes in market rent, it is worth recalling that we use asking rents, which may be subject to criticism by some readers. The real estate literature recognizes that appraisal based indicators can be subject to measurement error, namely due to valuation smoothing (e.g. Fisher et al., 1994, and Geltner and Fisher, 2007). Studies that compare the performance of appraisal- and transaction-based indices document that the latter provides more timely information in market turning points (Fisher et al., 2007; Geltner and Fisher, 2007; Chegut et al., 2013). Cho et al. (2014) employ time-varying asset pricing models and find that appraisal smoothing is on average close to zero, but changes overtime. These findings suggest that overall trends for a given market are likely to be similar despite the type of data considered.

In our case, the use of asking rents is sufficient as our goal is to compare patterns across *corporate* and *smaller tenant* properties (and not to develop a measure that successfully captures short-term fluctuations in rent). An et al. (2016) show that indicators of rent dynamics can vary substantially across the broader definitions of CRE properties (e.g. office, industrial, retail, etc.) using appraisal data from the US. As suggested by the market segmentation literature, temporal changes in market rents are one way of classifying heterogeneous real estate markets.

The following graph shows parameters from regressions (1), (2) and (3) after exponentiation. We do not report the actual estimates for the sake of brevity, but detailed figures, including those from regressions (4), (5) and (6), can be found in the appendix of this study. Results from these latter regressions are similar to those reported in this section.

The hedonic indicators in Figure 3 show that economic changes affect the *corporate* and *smaller tenant* segments in very similar ways and reflect to some extent the cyclicality of rent. Until 2008, office markets have experienced a full growth cycle due to a strong economic environment. In 2008:Q3, nominal rents grew at a slower pace in the aftermath of the global financial crisis and only begun to recover in 2010 as economic activity rebounded and interest rates were historically low. From 2012 onwards, office rent stagnated – and even declined – as Brazil entered in a recession.

Figure 3: Hedonic Trends by Property-type Segment

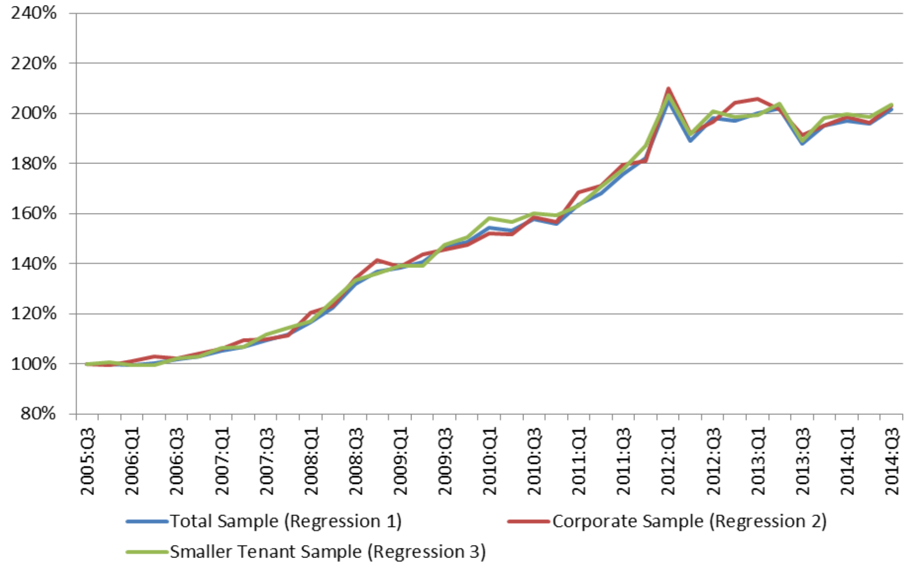


Figure 3 shows rent levels derived from quarter dummies in regressions (1), (2) and (3) after exponentiation. All quarters are benchmarked against 2005:Q3, which is normalized to 100%.

4.4. Testing which Hedonic Coefficients Differ

While an examination of coefficients reveals some evidence of differing shadow prices, it does not formally test the null hypothesis that individual parameters are similar across the *corporate* and *smaller tenant* segments. The existence of similarity in each regression coefficient estimate is examined by use of the Wald chi-squared test. The null hypothesis for each Wald test is $\beta_{i(Corporate)} = \beta_{i(Smaller\ Tenant)}$, where coefficient i = 1 to k. Adan and Fuerst (2015) employ a similar procedure to compare the effect of different energy efficiency measures in reducing household energy and gas consumption. These authors use distinct models with similar specification to compare the impact of each measure. The advantage of the Wald chi-squared test over the Chow (1960) and Tiao Goldberger (1962) tests is that former generalizes to different variance estimates of the variance-covariance matrix, whereas the latter tests do not offer such flexibility. This is particularly relevant in our case as we cluster standard errors at submarket level. Nonetheless, the Wald test is employed with the same objective as the Tiao-Goldberger (TG) test, which is to examine the structural stability of individual parameters across distinct regressions. The latter procedure has been more widely adopted in the real estate literature (e.g. Allen et al., 1995; Black et al. 1997; Wolverton et al. 1999; Slade; 2000; Berry et al., 2003; Hardin and Carr, 2006); however, none of these studies adopted clustered errors.

Table 5 shows the results of the Wald chi-square test for building attribute and locational coefficients across the *corporate* and *non-corporate* niches. The results for the time dummy parameters can be found in the appendix of this study. Some parameters are significantly different for building attributes and locational variables, but not for temporal changes in market rent.

Table 5: Comparison of Individual Coefficients across Office Segments

Regression	(2) Coefficients	(3)		(5) Coefficients	(6)	
Variables	**Corporate Sample**	**Smaller Occupier Sample**	**Wald Chi-Square Statistic**	**Corporate Sample**	**Smaller Occupier Sample**	**Wald Chi-Square Statistic**
Constant	2.4886	2.6916	0.29	1.985	2.68	12.32***
Building Attributes						
ln (Size)	0.1435	0.092	1.01	0.2176	0.0934	30.00***

5 to 9	-0.0845	-0.0862	0.01	-0.0903	-0.0855	0.04
10 to 14	-0.2167	-0.2119	0.01	-0.2238	-0.2111	0.06
15 to 19	-0.3427	-0.3137	0.31	-0.3531	-0.3129	0.71
20 to 24	-0.4636	-0.3301	7.37***	-0.4718	-0.3291	13.96***
25to29	-0.5364	-0.4097	3.10*	-0.5465	-0.4076	5.77**
30+	-0.6432	-0.4541	16.74***	-0.6842	-0.4521	24.35***
AA	0.2962	-0.0395	2.19			
A	0.2004	0.0043	3.89**			
BB	0.2081	0.0164	9.59***			
B	0.1086	0.0003	5.89**			
Vacperc	0.0002	0.0007	0.46	0.0004	0.0007	0.17
Submarkets						
Vila Olimpia	-0.1218	-0.0152	43.81***	-0.123	-0.0155	170.29***
Saude & Jabaquara	-0.2248	-0.2641	1.51	-0.2136	-0.2641	3.08*
Santo Amaro	-0.5376	-0.2065	289.76***	-0.5506	-0.2066	364.53***
Chacara Santo Antonio	-0.2668	-0.2759	0.32	-0.2566	-0.2761	3.25
Morumbi/Jd Sao Luis	-0.5013	-0.1824	79.36***	-0.4931	-0.1858	118.19***
Centro	-0.8965	-0.7559	15.18***	-0.9525	-0.757	83.15***
Marginal Pinheiros	-0.1651	-0.1018	0.4	-0.1786	-0.1247	1.45
Moema/Vila Mariana	-0.1997	-0.1235	23.77***	-0.2204	-0.1236	52.7***
Paulista	-0.0339	-0.0544	3.63*	-0.0423	-0.0543	1.23
Pinheiros/Perdizes	-0.2024	-0.2411	1.85	-0.2236	-0.2412	0.51
Berrini	-0.1437	0.0608	152.24***	-0.1423	0.0603	305.77***
Barra Funda	-0.5167	-0.4122	22.5***	-0.5024	-0.4124	21.25***
Other	-0.8273	-0.4183	471.57***	-0.8305	-0.4183	496.52***

*Table 5 shows results of Wald's chi-squared test of coefficient comparison across regressions 2 and 3 as well as regression 5 and 6. Chi square statistics are reported in parenthesis. ***, ** and * indicate whether differences among coefficient "i" in these regression are significant at 1%. 5% and 10% level, respectively. The statistic considers standard errors clustered at submarket level. All variables and submarkets are defined in Table 1 and Figure 1. The data covers commercial towers in the city of Sao Paulo from 2005:Q3 to 2014:Q3. The results for the time dummy coefficients are reported in the appendix.*

The Wald test for regressions (2) and (3) shows that older and higher-rated properties are valued differently by *corporate* and *smaller* tenants. When we exclude the *Rating* covariates from the regression, we can also reject the null hypothesis for *Size* (see results for regressions (4) and (5)). In light of this evidence, re-examination of the equations in Table 4 reveals that *corporate* users may be more sensible to overall levels of property quality than their *non-corporate* peers. The outcomes for the submarket dummies show that these two groups also value nine out of thirteen submarkets heterogeneously. As expected, growth and less convenient locations tend to face larger discounts by *corporate* occupiers. The test outcomes are fairly consistent for the regressions with and without the *Rating* dummies. Hence, shadow rental values not only vary substantially across regions but also vary by property type within a given submarket. The Wald test results for the time dummies indicate that economic change affects both types groups of properties in similar ways.

5. Conclusion

The impact of locational, physical features and economic variables on office rent levels has been the subject of several previous studies. This paper investigates whether the effect associated with these covariates can be generalized whether they or are fragmented across two niches of the office market: corporate and smaller occupiers. Contrary to previous real estate segmentation studies, we do not assume that segmentation is a purely spatial phenomenon but instead define these groups based on the mean size of leasable units inside a property and hence type of office user. This allows for segmentation within the same location. Our conceptual framework shows that pricing discrepancies may arise from transaction costs to relocate from one segment to another (objective relocation costs) and from endogenous capital allocation decisions associated with different users (subjective relocation costs). The empirical analysis confirms that office markets are not homogeneous as there are substantial differences in the height and slope of hedonic rent equations of corporate and non-corporate buildings. The results indicate that users of properties with larger units tend to be more sensitive to overall property quality and more selective in their locational decisions. For instance, rent discounts associated with physical obsolescence and less convenient office locations are significantly higher for corporate occupiers. At the same time, economic change affects these markets in a very similar way. We thus conclude that these submarkets can be classified as imperfect substitutes, but not as independent real estate markets.

Yet there are some caveats attached to the interpretation heterogeneous pricing of office market determinants. First, the controls for inherent heterogeneity are bound to be imperfect and correlated with unobserved variables (Campbell et al, (2011); Ghysels et al. (2013)). The omitted variable bias is pervasive in cross-sectional hedonic models as it is virtually impossible to control for all characteristics. Second, the definition of property-type niches is fairly subjective as the methodologies that define them vary from one database to another. Third, empirical studies only provide a snapshot of price differentials for a specific time period. It is reasonable to expect that certain price differentials may vary overtime and between segments.

Despite these considerations, this research implies that office markets may be too complex and disparate to be reliably examined with a simple aggregate approach as practiced in developed office market research since the 1980s. The fragmented reality of office properties has important implications for investment decisions and real estate valuation. As data availability as well as level of detail and accuracy is likely to improve in the future, researchers will be able to address a number of more specific issues, such as specific supply and demand factors that lead to localized valuation in office markets as well as pricing dynamics across property-type segments.

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6. Appendix

Table 4 (Cont'd): Regression Estimates of ln(Rent/sqm)

	(1)	(2)	(3)	(4)	(5)	(6)
Time Dummies	**Total Sample**	**Corporate Sample**	**Smaller Occupier Sample**	**Total Sample**	**Corporate Sample**	**Smaller Occupier Sample**
2005:Q4	-0.0012	-0.0040	0.0070	-0.0034	-0.0058	0.0069
	(-0.30)	(-0.63)	(1.21)	(-0.86)	(-0.94)	(1.17)
2006:Q1	-0.0065	0.0097	-0.0032	-0.0087	0.0068	-0.0033
	(-0.88)	(0.68)	(-0.27)	(-1.25)	(0.51)	(-0.28)
2006:Q2	0.0022	0.0280	-0.0037	-0.0018	0.0247	-0.0037
	(0.23)	(1.16)	(-0.46)	(-0.21)	(1.10)	(-0.47)
2006:Q3	0.0171**	0.0238	0.0214**	0.0127*	0.0190	0.0213**
	(2.31)	(0.89)	(2.20)	(1.80)	(0.78)	(2.19)
2006:Q4	0.0275***	0.0396	0.0279*	0.0221**	0.0355	0.0279*
	(3.44)	(1.32)	(2.12)	(2.80)	(1.25)	(2.13)
2007:Q1	0.0532***	0.0586***	0.0618***	0.0484***	0.0568***	0.0615***
	(5.04)	(3.41)	(5.01)	(4.87)	(3.54)	(4.84)
2007:Q2	0.0657***	0.0903***	0.0686***	0.0608***	0.0889***	0.0683***
	(4.72)	(5.32)	(3.32)	(4.64)	(5.37)	(3.23)

2007:Q3	0.0911***	0.0969***	0.1121***	0.0876***	0.0956***	0.1119***
	(10.88)	(6.36)	(9.99)	(11.39)	(6.76)	(9.61)
2007:Q4	0.1141***	0.1133***	0.1402***	0.1134***	0.1152***	0.1400***
	(10.72)	(5.01)	(9.53)	(10.56)	(5.70)	(9.07)
2008:Q1	0.1605***	0.1922***	0.1653***	0.1578***	0.1890***	0.1651***
	(19.31)	(11.22)	(11.46)	(20.38)	(11.91)	(11.45)
2008:Q2	0.2148***	0.2243***	0.2357***	0.2103***	0.2232***	0.2356***
	(25.07)	(8.19)	(16.64)	(22.61)	(8.74)	(16.42)
2008:Q3	0.2985***	0.3151***	0.3135***	0.2968***	0.3169***	0.3136***
	(16.53)	(13.95)	(11.85)	(17.02)	(14.63)	(11.64)
2008:Q4	0.3498***	0.3867***	0.3476***	0.3496***	0.3873***	0.3478***
	(17.15)	(16.47)	(12.82)	(18.19)	(16.79)	(12.74)
2009:Q1	0.3739***	0.3874***	0.3807***	0.3760***	0.3893***	0.3806***
	(21.32)	(17.92)	(14.98)	(22.20)	(19.28)	(14.82)
2009:Q2	0.3984***	0.4233***	0.3873***	0.3981***	0.4238***	0.3871***
	(16.96)	(14.56)	(14.83)	(17.14)	(15.61)	(14.84)
2009:Q3	0.4460***	0.4451***	0.4479***	0.4468***	0.4453***	0.4478***
	(19.26)	(12.48)	(19.98)	(19.48)	(13.00)	(19.34)
2009:Q4	0.4741***	0.4644***	0.4877***	0.4734***	0.4615***	0.4874***
	(19.90)	(10.55)	(21.95)	(19.74)	(10.67)	(21.31)
2010:Q1	0.5211***	0.5020***	0.5490***	0.5236***	0.5009***	0.5487***
	(28.44)	(11.83)	(23.87)	(26.13)	(11.43)	(23.18)
2010:Q2	0.5289***	0.5126***	0.5591***	0.5326***	0.5134***	0.5587***
	(23.07)	(11.44)	(20.10)	(21.91)	(11.36)	(19.15)
2010:Q3	0.5598***	0.5608***	0.5853***	0.5626***	0.5626***	0.5849***
	(23.20)	(10.60)	(21.78)	(22.39)	(10.48)	(20.38)
2010:Q4	0.5604***	0.5633***	0.5904***	0.5626***	0.5636***	0.5900***
	(22.26)	(10.87)	(19.49)	(21.60)	(10.87)	(18.57)
2011:Q1	0.6067***	0.6390***	0.6146***	0.6080***	0.6378***	0.6143***
	(24.06)	(11.56)	(24.49)	(22.41)	(11.37)	(23.45)
2011:Q2	0.6521***	0.6817***	0.6704***	0.6533***	0.6804***	0.6703***
	(39.56)	(21.06)	(35.26)	(36.51)	(21.32)	(37.44)
2011:Q3	0.7144***	0.7470***	0.7325***	0.7143***	0.7421***	0.7323***
	(24.17)	(16.10)	(27.80)	(22.47)	(16.01)	(27.91)
2011:Q4	0.7760***	0.7826***	0.8092***	0.7769***	0.7810***	0.8091***
	(24.48)	(10.09)	(29.73)	(24.26)	(10.61)	(28.77)
2012:Q1	0.9187***	0.9470***	0.9448***	0.9190***	0.9433***	0.9446***
	(30.13)	(18.66)	(23.88)	(29.69)	(19.31)	(22.36)
2012:Q2	0.9040***	0.9324***	0.9299***	0.9069***	0.9355***	0.9297***
	(37.46)	(18.66)	(28.66)	(36.31)	(19.22)	(27.42)
2012:Q3	0.9430***	0.9505***	0.9696***	0.9459***	0.9476***	0.9694***
	(32.69)	(22.59)	(30.13)	(32.27)	(23.74)	(29.03)
2012:Q4	0.9574***	0.9971***	0.9782***	0.9598***	0.9943***	0.9778***
	(38.60)	(33.57)	(32.70)	(37.78)	(33.30)	(31.21)
2013:Q1	0.9787***	1.0270***	0.9856***	0.9801***	1.0192***	0.9852***
	(35.91)	(32.86)	(29.75)	(35.28)	(36.27)	(28.67)
2013:Q2	0.9983***	1.0216***	1.0123***	1.0004***	1.0184***	1.0120***
	(36.25)	(27.09)	(35.28)	(36.38)	(29.44)	(34.10)
2013:Q3	0.9371***	0.9666***	0.9502***	0.9395***	0.9638***	0.9499***
	(30.41)	(24.92)	(24.25)	(30.96)	(28.04)	(23.48)
2013:Q4	0.9448***	0.9589***	0.9664***	0.9469***	0.9565***	0.9661***
	(34.95)	(29.64)	(29.83)	(34.66)	(31.54)	(28.51)
2014:Q1	0.9582***	0.9732***	0.9817***	0.9602***	0.9716***	0.9813***
	(37.97)	(31.89)	(33.22)	(38.23)	(35.60)	(31.17)
2014:Q2	0.9580***	0.9671***	0.9829***	0.9596***	0.9647***	0.9824***
	(39.01)	(32.15)	(31.69)	(38.89)	(38.02)	(29.59)
2014:Q3	0.9864***	0.9999***	1.0082***	0.9873***	0.9972***	1.0077***
	(40.49)	(34.70)	(32.80)	(41.19)	(39.70)	(31.06)

Table 5 (Cont'd): Comparison of Individual Coefficients across Office Segments

Regression	(2)	(3)		(5)	(6)	
	Coefficients			Coefficients		
Time Dummies	Corporate Sample	Smaller Occupier Sample	Chi-Square Statistic	Corporate Sample	Smaller Occupier Sample	Chi-Square Statistic
2005:Q4	-0.004	0.007	2.34	-0.0058	0.0069	2.68
2006:Q1	0.0097	-0.0032	0.59	0.0068	-0.0033	0.34
2006:Q2	0.028	-0.0037	1.36	0.0247	-0.0037	1.24
2006:Q3	0.0238	0.0214	0.01	0.019	0.0213	0.01
2006:Q4	0.0396	0.0279	0.08	0.0355	0.0279	0.04
2007:Q1	0.0586	0.0618	0.01	0.0568	0.0615	0.04
2007:Q2	0.0903	0.0686	0.46	0.0889	0.0683	0.42
2007:Q3	0.0969	0.1121	0.62	0.0956	0.1119	0.72
2007:Q4	0.1133	0.1402	0.82	0.1152	0.14	0.80
2008:Q1	0.1922	0.1653	1.16	0.189	0.1651	0.91
2008:Q2	0.2243	0.2357	0.12	0.2232	0.2356	0.15
2008:Q3	0.3151	0.3135	0.00	0.3169	0.3136	0.01
2008:Q4	0.3867	0.3476	1.43	0.3873	0.3478	1.45
2009:Q1	0.3874	0.3807	0.04	0.3893	0.3806	0.07
2009:Q2	0.4233	0.3873	1.46	0.4238	0.3871	1.50
2009:Q3	0.4451	0.4479	0.01	0.4453	0.4478	0.01
2009:Q4	0.4644	0.4877	0.25	0.4615	0.4874	0.30
2010:Q1	0.502	0.549	0.76	0.5009	0.5487	0.74
2010:Q2	0.5126	0.5591	0.67	0.5134	0.5587	0.60
2010:Q3	0.5608	0.5853	0.18	0.5626	0.5849	0.13
2010:Q4	0.5633	0.5904	0.24	0.5636	0.59	0.20
2011:Q1	0.639	0.6146	0.22	0.6378	0.6143	0.18
2011:Q2	0.6817	0.6704	0.14	0.6804	0.6703	0.10
2011:Q3	0.747	0.7325	0.15	0.7421	0.7323	0.06
2011:Q4	0.7826	0.8092	0.15	0.781	0.8091	0.18
2012:Q1	0.947	0.9448	0.00	0.9433	0.9446	0.00
2012:Q2	0.9324	0.9299	0.00	0.9355	0.9297	0.01
2012:Q3	0.9505	0.9696	0.21	0.9476	0.9694	0.29
2012:Q4	0.9971	0.9782	0.34	0.9943	0.9778	0.24
2013:Q1	1.027	0.9856	1.39	1.0192	0.9852	1.11
2013:Q2	1.0216	1.0123	0.07	1.0184	1.012	0.04
2013:Q3	0.9666	0.9502	0.13	0.9638	0.9499	0.11
2013:Q4	0.9589	0.9664	0.04	0.9565	0.9661	0.07
2014:Q1	0.9732	0.9817	0.06	0.9716	0.9813	0.07
2014:Q2	0.9671	0.9829	0.15	0.9647	0.9824	0.21
2014:Q3	0.9999	1.0082	0.05	0.9972	1.0077	0.09