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OFFICE RENT MODELING IN ISTANBUL: A GEOADDITIVE APPROACH

Sinem Güler KANGALLI UYAR*

Abstract

The objective of this research is to develop a hedonic model for office space rent prices in Istanbul, using a data set consisting of 2348 office spaces. The data includes information on office building and office space characteristics, as well as features related to the lease, location, and neighborhood that impact office rents. To examine the connection between office rent and these factors, a semiparametric geoadditive model was utilized, which allows for flexibility in functional form and captures location effects through geographical smoothing functions instead of location dummies. The results indicate that the link between office rent determinants and office space rents is nonlinear. The vacancy rate, a measure of office space demand, is the determinant with the greatest impact on office rents. The second most important determinant of office rents is that the office space is in an A-class office building, and the third most influential factor is that the office spaces have a view of the Bosporus.

Keywords: *Office rent, Hedonic price theory, Semiparametric, Geoadditive model, Istanbul office market.*

İSTANBUL'DA OFİS KİRA MODELLEMESİ: COĞRAFİ TOPLAMSAL BİR YAKLAŞIM

Öz

Bu araştırmanın amacı, 2348 ofis alanından oluşan bir veri seti kullanarak İstanbul'daki ofis alanı kira fiyatları için hedonik bir model geliştirmektir. Veriler, ofis binası ve ofis alanı özelliklerinin yanı sıra ofis kiralarını etkileyen kiralama, mekân ve komşuluk ile ilgili özellikleri içerir. Ofis kirası ile bu faktörler arasındaki ilişkiyi incelemek için, fonksiyonel formda esnekliğe izin veren ve mekânsal kuklalar yerine coğrafi düzgünleştirme fonksiyonları aracılığıyla mekân etkilerini yakalayan yarı parametrik bir coğrafi toplamsal model yaklaşımı kullanılmıştır. Sonuçlar, ofis kira belirleyicileri ile ofis alanı kiraları arasındaki ilişkilerin doğrusal olmadığını göstermektedir. Ofis alanı talebinin bir ölçüsü olan boşluk oranı, ofis kiraları üzerinde en büyük etkiye sahip belirleyicidir. Ofis kiralarının ikinci en önemli belirleyicisi, ofis alanının A sınıfı bir ofis binasında bulunması ve üçüncü en etkili faktör ise ofislerin boğaz manzarasına sahip olmasıdır.

Anahtar kelimeler: *Ofis kirası, Hedonik fiyat teorisi, Yarı parametrik, Coğrafi toplamsal model, İstanbul ofis piyasası.*

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1.INTRODUCTION

The hedonic price approach is useful for understanding the pricing behavior of heterogeneous goods. It allows a proper characterization of the heterogeneity of real estate goods by a limited number of attributes associated with different levels of quality (Rebelo, 2011). This approach has been widely applied to the analysis of housing markets, but its use in office markets is relatively uncommon. Previous research in this area has focused on individual markets. For example, Bottom et al. (1997) and Dunse and Jones (2002) studied the office markets in London and Glasgow, respectively. Other studies have investigated office markets in Munich (Nitsch, 2006), Paris (Nappi-Choulet et al., 2007), and Istanbul (Oven and Pekdemir, 2006a, 2006b; Ozus, 2009). However, there is still a lack of research on the application of hedonic models to office markets.

Accessing actual office rent data can be challenging for studies aimed at analyzing office rents, leading many researchers to rely on the asking rents instead (Brennan et al. 1984; Dunse and Jones 1998, 2002; Fuerst, 2008; Gat, 1998; Glascock et al. 1990; Nitsch, 2006; Ozus, 2009; Pekdemir and Dokmeci, 2011; Jennen and Brounen, 2009; Wheaton and Torto, 1988). Most of these studies employ cross-sectional data, with a few using temporal series (Tu et al. 2004; Nappi-Choulet et al. 2007). To the best of our knowledge, only Fuerst (2008) has examined office rent determinants using panel data.

Hedonic models can take on various functional forms. According to economic theory, the functional form of a hedonic price function depends on both the individual demand and supply functions of the good (Ekeland et al., 2004; Heckman et al., 2010; Koster et al., 2014a). When the exogeneity assumption of supply conditions is made, the functional form of the hedonic price function is determined solely by tenant preferences for property characteristics, according to Heckman et al. (2010). This is considered a reasonable assumption for the rental market (Glaeser and Gyourko, 2005).

Most office rent studies use hedonic models that include demand-side characteristics, such as physical features, location, and lease terms, assuming a logarithmic-linear pattern for the relationship between office rent and its determinants. However, Ekeland et al. (2004) found that the marginal willingness to pay for each characteristic is a nonlinear function of that characteristic. This suggests that significant differences in rents do not necessarily mean that the observations belong to different markets, as nonlinearity may be caused by locational differences in the same heterogeneous market. Empirical researchers have recognized the likelihood of hedonic functions being nonlinear in characteristics since Rosen (1974) developed the theory of hedonic price function (McMillen and Redfearn, 2010). Some office rent studies, such as Farooq et al. (2010), Čeh et al. (2012), Koster et al. (2014a), Bera and Kangalli Uyar (2019) have used nonparametric or semiparametric models to allow for functional form flexibility, rather than assuming linearity a priori. For example, Farooq et al. (2010) found a nonlinear relationship between office rent and distance to the central business district, while Koster et al. (2014a) discovered a highly nonlinear relationship between building height and office rents. Čeh et al. (2012) identified six input parameters that explain variations in office rents and used the nonparametric CAE method to estimate office rents as a function of those parameters. They found that the relationships between office rents and the six input parameters are highly nonlinear and linear regression does not work well to estimate office rents. Thus, they showed that ignoring high nonlinearity can lead to misleading findings. Bera and Kangalli Uyar (2019) used a semiparametric hedonic model (Mixed GWR model) that considers spatial heterogeneity to determine the factors affecting office rents in Istanbul. While there has been a notable rise in the utilization of nonparametric or semiparametric methods, which consider nonlinear relationships, in hedonic modeling studies concerning the housing market, using such flexible approaches in office market studies remains limited.

Except for a few studies mentioned earlier, it is typical to assume that there is a linear correlation between office rents and their determinants. This issue does not only pertain to office rent studies but also studies in the social sciences. Keele (2008) has noted that in social sciences, the linear functional form is generally preferred, and researchers often ignore verifying the linearity assumption. Even though much effort is devoted to checking assumptions about the nature of the error term, the issue is more often neglected by researchers when it comes to testing assumptions about the functional form of the model. The consequences of determining the incorrect functional form are considered severe regarding statistical inferences. Hence, coefficient estimates, and hypothesis tests are generally biased if the assumed form is incorrect (Bera and Yoon, 1993; Bera, 2000). Keele (2008) conducted a simulation study and observed that making the linearity assumption when the relationship between variables is indeed nonlinear can lead to researchers concluding that there is no relationship between variables, even though they are strongly related.

Nonparametric or semiparametric methods might overcome specification errors resulting from the wrong functional form. These methods do not make any a priori assumptions about the functional form, but they benefit from the distribution of data to infer the functional form (McMillen, 1996). In this study, we aim to investigate the relationships between office rents and their determinants by a semiparametric approach allowing functional form flexibility. Secondly, we attempt to make a comparison between the parametric and semiparametric models regarding their estimation performance. Finally, in the search for a better hedonic office rent model, we discuss the issue of including the geographical location for office spaces in the semiparametric model in a smooth interaction form and examine it by hypothesis tests.

The paper is structured as follows: Section 2 provides a concise overview of the existing literature on office rent determinants in the hedonic office rent domain. Section 3 outlines the model and methodology employed in this research. Section 4 discusses the data utilized in this study. Section 5 presents and interprets the empirical results. Finally, the last section presents the main findings and thoroughly discusses their implications.

2.LITERATURE REVIEW ON OFFICE RENT DETERMINANTS

The literature on office rent studies suggests that there are several variables that influence the level of rent. While both demand and supply-side variables may impact office rent, a considerable number of studies focus on demand-side variables. These variables, which fundamentally affect office rent, include physical, locational, and lease characteristics. Although there is no consensus on which variables to use and how they impact office rents, parametric methods are usually applied, with a few exceptions noted earlier. While there are many proxy variables for office rent determinants in office rent studies, this study focuses on the commonly used ones.

2.1.Physical characteristics

Physical characteristics imply the quality, internal services, amenities, prestige, and representativeness of office buildings. While building age is a common measure of office building quality in many studies (Bollinger et al. 1998; Clapp, 1980; Frew and Jud, 1988; Gat, 1998; Mills, 1992; Sivitanidou, 1995;1996; Slade, 2000; Wheaton, 1984; Wheaton and Torto, 1994), others have taken a more detailed approach to measuring building quality by conducting interviews and surveys with architects or property managers (Gat, 1988; Vandell and Lane, 1989; Webb and Fisher, 1996). After Glascock et al. (1990)'s study, the categorization of an office building into different classes has become a common approach to measuring quality (Bollinger et al. 1998; Laverne and Winson-Geideman, 2003; Bond et al. 2008).

Internal services and amenities are physical characteristics that pertain to the quality of the office building, too. In many studies, office building amenities and internal services have significant and positive influences on the level of rent (Clapp, 1980; Wheaton, 1984; Mills, 1992; Sivitanidou, 1996; Bollinger, 1998; Ozus,2009). Oven and Pekdemir (2006a) reported that building amenities such as day-care, bank, shop, conference room, health club, and restaurant are insignificant and parking facilities have little influence on the office rent for the investigated office market. Oven and Pekdemir (2006b) examined the influences of office rent determinants concerning the level of rent based on the influence scale which was established from the literature review. They found that the building amenities are not influential on office rents. Nitsch (2006) suggested that including physical characteristics only did not result in significant improvements and adding locational and neighborhood characteristics to the office rent model could improve its explanatory power.

Measuring the representativeness and prestige of an office building can be challenging, but some studies have suggested that building height could serve as a proxy for this factor (Clapp, 1980; Wheaton and Torto, 1994; Slade, 2000; Koster et al. 2014a). According to Sivitanidou (1995), the height of an office building is one of the most important factors affecting rent levels, even though it was not included as a variable in her office rent model.

2.2.Locational and neighborhood characteristics

Locational characteristics account for 30% of proposed office rent determinants in literature, making them the second most considered factor after physical characteristics (Oven and Pekdemir, 2006b). Companies are often willing to pay higher rents for certain locations, and this tendency may be associated with the concept of accessibility. Accessibility can be defined as proximity to transportation nodes, nearby labor markets, the quality of the surrounding environment, and neighborhood characteristics. Other locational characteristics include face-to-face contact opportunities and the representativeness of the location (Kempf, 2015).

The neighborhood characteristics and the quality of surroundings are other location factors that affect considerably office rents. Proximity to amenities such as shopping centers, restaurants, entertainment, and recreational parks is used to demonstrate the influence of the quality of surroundings on office rents (Bollinger et al. 1998; Colwell et al. 1998; Dunse and Jones, 1998; Ihlanfeld, 1990; Nitsch, 2006; Sivitanidou, 1996). Commonly used proxy variables for neighborhood characteristics include the average crime rate, average and median household income, concentration of blue-collar and college-educated households, and more (Wheaton, 1984; Sivitanidou, 1995; 1996; Bollinger et al. 1998; Ryan, 2005; Oven and Pekdemir, 2006a; 2006b). Even though the quality of surroundings and the neighborhood characteristics are important office rent determinants for metropolitan areas, there is no consensus concerning their impacts on the level of rent and which variables can serve as proxies (Kempf, 2015).

The prestige of location is one of the most important determinants in office tenants' decisions concerning office location. The prestige of location is measured by a dummy or distance variable. It is expected that the impact of this factor on office rent is positive. Some researchers use the dummy variables measuring the representativeness of location (Clapp, 1980; Sivitanidou, 1996), while others use the distance variables (Brennan et al. 1984; Oven and Pekdemir, 2006a; Oven and Pekdemir, 2006b; Nitsch, 2006). Most of the studies' empirical results indicate that office tenants are willing to pay a higher rent for prestigious locations.

2.3.Lease characteristics

Lease characteristics are proxied by factors such as the lease length, rental area size, rent review provisions, options, and incentives, as well as the type and quality of the tenant. Among them, the size of the rental area and lease length are commonly used office rent determinants in the literature. The hypothesis about the lease length is that landlords offer lower rents for longer leases in comparison to short leases (Kempf, 2015). Especially in a recessionary office market, this hypothesis can be valid due to the risk of vacancy. On the other hand, office tenants are willing to pay more for short leases since longer leases reduce flexibility.

The empirical findings related to the impact of lease length on office rent vary across the studies. Englund et al. (2004), Bond et al. (2008), as well as Stanton and Wallace (2009), found a positive and significant relationship between the level of rent and lease length. Brennan et al. (1984), Benjamin et al. (1992), and Desyllas (2000) reported the statistically insignificant effects of the lease length on office rents whereas Benjamin et al. (1990) found a negative and significant relationship between the level of rent and lease length.

The other lease factor is the size of the rental area. Like the other office rent determinants, the influence of this factor on office rents is still a discussion issue. If the office tenant rents large office space, his negotiating power might increase. In this case, the influence of the size of the rental area on office rents will be negative. On the other hand, it is stated that office buildings that have large and continuous space are highly appraised by large firms and are usually supplied in the short run (Kemph, 2015). The short-run supply of office buildings with large and continuous space might cause a positive influence on office rents. According to Wheaton and Torto (1994), the effect of the size of a rentable area on office rents depends on the market and its cycle stage. Accordingly, they found both positive and negative statistically significant relationships between office rents and the size of the rental area. However, Bond et al. (2008) and Benjamin et al. (1992) reported a negative and significant relationship, while Desyllas (2000) indicated an insignificant relationship.

The vacancy rate, closely associated with lease factors, is considered a significant determinant of office rent (Frew and Jud, 1988; Glascock et al., 1990; Hekman, 1985; Hendershott, 1996; Hendershott et al., 2002; Huynh, 2014; Pollakowski et al., 1992; Rosen, 1984; Shilling et al., 1987; Sivitanides, 1997; Wheaton and Torto, 1988; 1994). The vacancy rate represents the office space supplied at any given period and included in different forms to hedonic office rent models. These forms can include lagged vacancy rates, deviations from the natural vacancy rate, changes in vacancy rates, vacancy rates at the local level, and more. The impact of the vacancy rate on office rents might vary by different definitions of the vacancy rate. Ozus (2009) discovered that the vacancy rate at the local level has a negative effect on office rent, while the vacancy rate within buildings has a positive effect. Sivitanides (1997) noted that the influence of the vacancy rate seems to differ across markets. However, Glascock et al. (1990) examined the effect of the vacancy rate on rental changes in a medium-sized city. Their study covered A, B, C, and D-class office buildings located in six different areas with diverse characteristics. The findings revealed that, except for D-class office buildings, the vacancy rate is statistically significant regardless of the location or class of the office building. In contrast, Hekman (1985) argued that big cities exhibit strong responses to vacancy rates, while small cities show weaker ones. Shilling et al. (1987) obtained similar findings supporting Hekman's (1985) study.

3.MODEL AND METHODOLOGY

3.1.Model

Previous hedonic office rent studies are usually based on a parametric model which is in a log-linear form. This relationship might be demonstrated as follows:

$$\log y_i = X_i^* \beta^* + \varepsilon_i , i = 1,2,\dots,n \quad (1)$$

where $\log y_i$ represents the logarithmic asking rent for office space i, and β^* is a vector of coefficients. The independent variables, denoted as X_i^*, consist of various characteristics of the office space, and $X_i^* \beta^*$ represents the linear predictor that includes the constant term, discrete variables, and several continuous variables. This model assumes that the relationships between office rents and their determinants follow a log-linear pattern. However, it is important to note that this approach may be overly restrictive and may not necessarily align with theoretical principles. ε is the error term, which is distributed normally and independently with constant error variance and zero-mean, $\varepsilon \sim NID(0,\sigma^2)$.

This study seeks to enhance the previous analyses by introducing flexibility in the functional form of equation (1). To achieve this, we have introduced certain variables in a non-parametric form. These variables, denoted as $x_{1i}, x_{2i}, \dots, x_{ki}$, are incorporated into equation (1) in a non-parametric manner. As a result, we obtain the semi-additive model presented in equation (2). The semi-additive model is a variation of the semiparametric model that allows for the inclusion of additive components. Additivity enables us to ascertain the net effect of each independent variable on the dependent variable, similar to multiple linear regression models (Basile et al., 2015).

$$\log y_i = X_i^* \beta^* + s_1 (x_{1i}) + s_2 (x_{2i}) + \dots + s_k (x_{ki}) + \varepsilon_i \quad (2)$$

$s_k (.)$ are smooth function or nonparametric regression function and $\varepsilon \sim NID(0,\sigma^2)$.

The parametric part of the model, $X_i^* \beta^*$, allows discrete variables such as dummy variables or variables measured in ordinal scales. Moreover, any continuous variables which are supposed to have linear impacts on the dependent variable can be defined in a parametric manner in the model. The nonparametric part of the model, $s(x_{1i}), s(x_{2i}), \dots, s(x_{ki})$, provides the functional form flexibility for continuous variables by allowing nonlinear relationships. Consequently, the semi-additive model, which combines parametric and nonparametric terms, is formulated as equation (2). Although the semi-additive model captures nonlinear relationships between log(y) and the independent variables through the nonparametric component, it does not account for any spatial structure present in the data. To address this concern, we can introduce the geographical location (la_i, lo_i) as a covariate in equation (2), resulting in the formation of the semiparametric geoadditive (semi-geoadditive) model (Kammann and Wand, 2003; Geniaux and Napoléone, 2008).

$$\log y_i = X_i^* \beta^* + s_1 (x_{1i}) + s_2 (x_{2i}) + \dots + s_k (x_{ki}) + s(la_i , lo_i) + \varepsilon_i \quad (3)$$

The term $s(la_i, lo_i)$ represents the smooth spatial trend surface, which is a smooth interaction between latitude (la_i) and longitude (lo_i) . This component allows us to incorporate unobserved spatial variations into the model. In this case, the assumption for the error term can be relaxed by making the identically and independently distributed assumption: $\varepsilon \sim NID(0,\sigma^2)$.

Similar to the semi-additive model, the semi-geoadditive model enables the incorporation of nonlinear relationships and thresholds. However, Geniaux and Napoléone (2008) highlight several advantages of the semi-geoadditive model compared to other spatial econometric models. Firstly, it eliminates the need for an NxN spatial weight matrix in computations, allowing for efficient estimation even with large datasets. Secondly, instead of using locational dummies, the model captures locational effects through the smoothing function of geographical location. Thirdly, it can be utilized as a tool for specifying the process, providing valuable insights into the underlying relationships. Finally, the semi-geoadditive model addresses both the issues of nonlinearity and unobserved spatial heterogeneity simultaneously.

3.2.Methodology

The nonparametric elements of the semiparametric model in equation (2) can be estimated using the spline methodology. Splines perform by estimating separate regression curves that are connected at specific knots. There are different types of splines available, and in this case, we employ the methodology of penalized regression splines due to their computational efficiency. To apply the penalized spline regression methodology, we can express the nonparametric component of equation (2) in terms of a spline function basis.

$$s_k (x_k) = \sum_{qk} \beta_{qk} b_{qk} (x_k) \tag{4}$$

where β_{qk} are unknown parameters to be estimated and q_k indicates the knot number.

The semi-additive model presented in equation (2) can be expressed in matrix form as follows:

$$log\, y = X^* \beta^* + \sum_{q1} \beta_{q1} b_{q1} (x_1) + \sum_{q2} \beta_{q2} b_{q2} (x_2) + \ldots + \varepsilon$$

$$= X\beta + \varepsilon \tag{5}$$

where X comprises X^* and all spline function base; β includes β^* and all smooth coefficients, β_{qk}.

In a similar manner, the semi-geoadditive model can be rewritten in the matrix form. However, if s(la, lo) is defined using a tensor product, then the basis for s(la) +s(lo) is nested in the basis for s(la, lo). This means that the smooth bases can be represented as a multiplication of marginal spline function bases (Basile et al., 2015):

$$s(la,lo) = \sum_{qla} \sum_{qlo} \beta_{la,lo} b_{qla} (la) b_{qlo} (lo) \tag{6}$$

Hence, the semi-geoadditive model presented in equation (3) can be expressed in matrix form as follows:

$$log\, y = X^* \beta^* + \sum_{q1} \beta_{q1} b_{q1} (x_1) + \sum_{q2} \beta_{q2} b_{q2} (x_2) + \ldots + \sum_{qla} \sum_{qlo} \beta_{la,lo} b_{qla} (la) b_{qlo} (lo) + \varepsilon$$

$$= Z\theta + \varepsilon \tag{7}$$

where Z comprises X^* and all spline basis functions; θ includes β^* and all smooth coefficients, β_{qk} and $\beta_{la,lo}$.

It is important to choose an appropriate number of knots, q_k which are sufficiently large, to avoid misspecification issue. However, a challenge arises as there is a vast number of potential regression models to be estimated for a given number of knots. To address this issue, the penalized spline regression approach can be employed to minimize the influence of the knot number and position. This is achieved by imposing constraints on the estimation of smooth coefficients in equations (5) and (7). To do this, the parameter values (β) minimizing the following objective function are chosen for the model in equation (5):

$$min\{(logy - X\beta)^2 + \sum_k \lambda_k \beta' S_k \beta\} \tag{8}$$

Here, $\lambda_k \geq 0$ represents the smoothing parameters that control the trade-off between the distance to the data (represented by the first term) and the overall smoothness of the function (represented by the second term). The matrix S_k is a positive semidefinite matrix that relies on the components of the spline function base.

Upon minimizing the objective function in equation (8) for a given set of smoothing parameters, the penalized least square estimator can be derived as follows (Ahamada and Flachaire, 2010):

$$\hat{\beta} = (X'X + \sum_k \lambda_k S_k)^{-1} X' \log y \tag{9}$$

The covariance matrix of $\hat{\beta}$ is denoted as $V_{\hat{\beta}} = \sigma_\varepsilon{}^2 (X'X + \sum_k \lambda_k S_k)^{-1} X'X (X'X + \sum_k \lambda_k S_k)^{-1}$. Assuming ε follows a normal distribution $\varepsilon \sim N(0, I_n \sigma_\varepsilon{}^2)$, then $\hat{\beta}$ follows a normal distribution $\hat{\beta} \sim N(E(\hat{\beta}), V_{\hat{\beta}})$. However, the use of frequentist inference in semi-additive models based on penalized regression splines may result in the null hypothesis being rejected too frequently. To overcome this issue, Wood (2006a, 2006b) introduced a Bayesian approach, where the distribution of parameters is represented as follows:

$$\beta | \log y \sim N(E(\hat{\beta}), \sigma^2{}_\varepsilon (X'X + \sum_k \lambda_k S_k)^{-1}) \tag{10}$$

For the model presented in equation (7), the parameter values (θ) that minimize the following objective function are selected:

$$min\{(\log y - Z\theta)^2 + \sum_k \lambda_k \theta' S_k \theta\} \tag{11}$$

This expression represents the balance between minimizing the sum of squared residuals and achieving a smoother approximation of the function $s_k(.)$. The smoothing parameter λ_k regulates this trade-off. Here the objective function is solved by:

$$\hat{\theta} = (Z'Z + \sum_k \lambda_k S_k)^{-1} Z' \log y \tag{12}$$

The distribution of parameters (θ) is obtained by the Bayesian approach as follows:

$$\theta | \log y \sim N(E(\hat{\theta}), \sigma^2{}_\varepsilon (Z'Z + \sum_k \lambda_k S_k)^{-1}) \tag{13}$$

3.2.1.The Choice of optimal smoothing parameter: GCV criterion

When employing penalized spline regression in a semi-additive model, choosing the appropriate smoothing parameters,λ_k, becomes crucial. These parameters strike a balance between fitting the data closely and ensuring the smoothness of the spline functions, thereby mitigating the impact of knot placement and number. The question then arises as to how to determine the optimal smoothing parameter value. Several methods are available, such as mean squared error (MSE), cross-validation (CV), and generalized cross-validation (GCV) criteria. However, due to some limitations of MSE and CV, the GCV criterion is commonly used in practice (Ahamada and Flachaire, 2010). The optimal smoothing parameter value, λ_k, is determined by minimizing the GCV criterion. In the semi-additive model, the GCV criterion can be expressed as follows:

$$GCV(\lambda_k) = \frac{n(\log y - X\hat{\beta})^2}{[n - tr(H)]^2} \tag{14}$$

where n, is the number of observations; $H = X(X'X + \sum \lambda_K S_k)^{-1}) X'$ is the hat matrix of the semi-additive model. The effective degrees of freedom (edf) can be obtained by calculating the trace of H, denoted as tr (H). The edf provides a measure of the number of identifiable parameters in the model. It is important to note that all the definitions and concepts related to the GCV criterion are applicable to the semi-geoadditive model.

3.3.Hypothesis testing

In a linear regression model, F or LR tests are formulated by comparing alternative models. As the parametric model is nested in the semiparametric model, F or LR tests can be used to test various hypotheses about the comparison of these models, making it a natural framework for specification testing (Keele, 2008). These hypothesis tests in the nonparametric or semiparametric framework are also called nonlinearity tests (Fox and Weisberg, 2018). The F-test approach provides us for testing the statistical significance of each nonparametric variable via the F-test statistic that follows F distribution:

$$F = \frac{(RSS_{restricted} - RSS_{unrestricted})/(tr(H) - 1)}{RSS_{unrestricted}/df_{res,unrestricted}} \quad (15)$$

The terms $RSS_{restricted}$ and $RSS_{unrestricted}$ represent the total sum of squared residuals for the restricted and unrestricted models, respectively. The variable dfres is equal to n minus the trace of 2H-HH'. Under the null hypothesis there is no statistically significant difference between the RSS values of the restricted and unrestricted models.

In this study, it is important to highlight that while model (1) is present in both model (2) and model (3), model (2) is exclusively a component of model (3). Consequently, when comparing model (1) to model (2), model (1) is considered the restricted model, which omits nonparametric variables, while the latter is regarded as the unrestricted model. Conversely, when comparing model (2) to model (3), model (2) is designated as the restricted model, and the latter is identified as the unrestricted model.

Moreover, the likelihood ratio (LR) test can be utilized to assess whether the unrestricted model exhibits a higher level of explanatory power than the restricted model.

$$LR = -2(\log L R_{restricted} - \log L R_{unrestricted}) \quad (16)$$

The test statistic, which evaluates the equality of log-likelihoods under the null hypothesis, follows a distribution with degrees of freedom that corresponds to the difference in the number of parameters between the two models (Kanas et al., 2012). The test statistic under the null hypothesis that expresses the equal log-likelihoods follows a χ^2 distribution with degrees of freedom which is equal to the difference in the number of parameters across the two models (Kanas et al. 2012).

4.DATA

During the first quarter of 2018, this study examines a dataset comprising 2348 office spaces situated across 28 counties in Istanbul. The spatial distribution of office spaces within the study area is depicted in Figure 1.

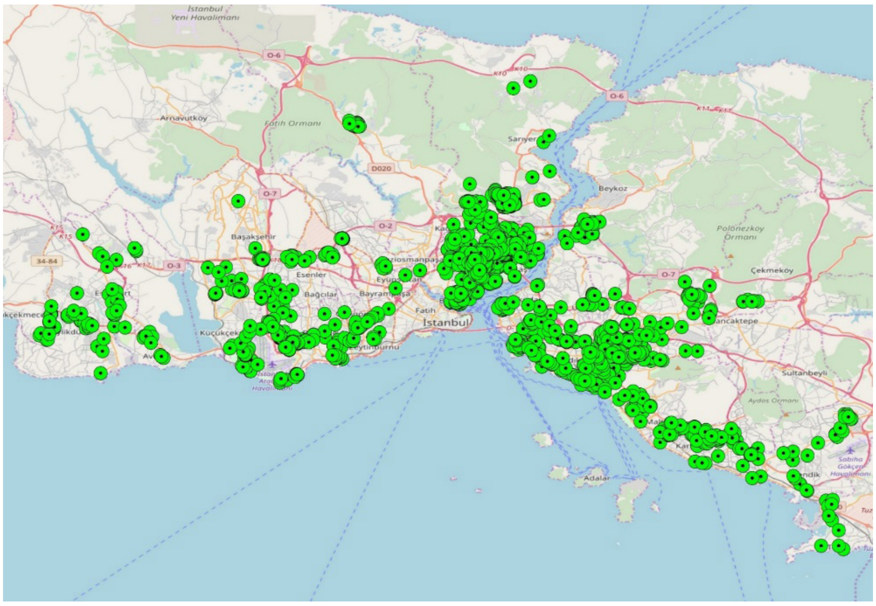

Figure 1: Spatial Distribution of Office Spaces.

The dataset utilized for this study offers extensive information on office spaces, including their asking rents, characteristics, and the buildings in which they are situated. To provide geographical context, geographical locations were also incorporated. The dataset was compiled from various sources, namely: 1) real estate agents who provided information on the geographical locations, rentable areas, asking rents, and characteristics of office spaces and buildings; 2) https://www.endeksa.com, an online real estate valuation website that furnished average unit rent and depreciation time data; 3) quarterly market reports from PROPIN, a real estate investment consultancy company that provided average vacancy rates; and 4) accessibility variables, which were computed by the author using the great circle distance formula. Table 2 in the Appendix contains detailed information on the definitions and sources of each variable.

5.EMPIRICAL RESULTS

Table 1 presents the estimation results for all models, including the log-linear model, semi-additive model, and semi-geoadditive model. The partial effect of each nonparametric variable on the office rent is illustrated in Figure 2 for the semi-additive model and Figure 3 for the semi-geoadditive model.

In the analysis, the dependent variable is the logarithm of asking rents for office spaces, denoted as Lrent. The independent variables include Number Room, Number Floor, Floor16_Floor20, Floor Area, Bosporus View, Class A, Security Guard, Generator, Parking Garage, Unit Rent, Depreciation Time, Vacancy Rate, Longitude, and Latitude. The definitions of these variables can be found in Table 2 in the Appendix. For the semi-additive model, the parametric part comprises Floor16_Floor20, Bosporus View, Class A, Security Guard, Generator, Parking Garage, and Vacancy Rate, while the nonparametric part includes Number Room, Number Floor, Floor Area, Unit Rent, Depreciation Time, Longitude, and Latitude. In contrast, the nonparametric part of the semi-geoadditive model involves Longitude and Latitude as a smooth interaction term. The significant independent variables impacting office space rents were identified using the backward elimination approach. Many of these variables are found significant, consistent with findings from other studies on the Istanbul Office Market. Additionally, prior to the regression analysis, local variance inflation factors (VIFs) were calculated to assess the collinearity. The local VIF values, ranging from 1.0569 to 2.9831, indicated the absence of significant local collinearity.

Table 1: Estimation Results

Variable	Log-Linear Model	Semiparametric Additive Model	Semiparametric Geoadditive Model
Intercept	-56.61***	8.168***	8.238***
	(-5.101)	(176.061)	(163.109)
Class A	0.233***	0.369***	0.399***
	(7.131)	(16.789)	(17.662)
Bosporus View	0.283***	0.152***	0.140***
	(5.023)	(4.435)	(4.146)
Vacancy Rate	-0.798***	-0.866***	-1.327***
	(-2.892)	(-4.057)	(-5.576)
Floor16_Floor20	0.164**	0.073*	0.068*
	(2.709)	(1.978)	(1.862)
Parking Garage	0.076*	0.053**	0.061**
	(0.054)	(2.178)	(2.570)
Security Guard	0.107***	0.038*	0.042*
	(2.924)	(1.682)	(1.908)
Generator	0.056	0.047**	0.055**
	(1.543)	(2.085)	(2.485)
Floor Area	0.002***	See Fig. 2	See Fig. 3
	(35.628)	F-stat: 743.870***	F-stat: 770.027***
Unit Rent	0.022***	See Fig. 2	See Fig. 3
	(20.035)	F-stat: 44.675***	F-stat: 21.354***
Depreciation Time	0.021***	See Fig. 2	See Fig. 3
	(8.016)	F-stat: 7.244***	F-stat: 6.266***
Number Floor	0.007***	See Fig. 2	See Fig. 3
	(5.126)	F-stat: 5.846***	F-stat: 5.415***

Number Room	0.084***	See Fig. 2	See Fig. 3
	(14.700)	F-stat: 4.404***	F-stat: 5.374***
Longitude, Latitude	-	-	See Fig. 3
	-	-	F-stat: 14.122***
Longitude	-0.211**	See Fig. 2	
	(-2.125)	F-stat: 20.685***	
Latitude	1.683***	See Fig. 2	
	(6.873)	F-stat: 10.220***	
Adj. R^2	0.66	0.88	0.89
GCV	-	0.104	0.100
Model	Log-linear vs. Semi-Additive	Log-linear vs. Semi-Geoadditive	Semi-Additive vs. Semi-Geoadditive
F test	94.031***	82.341***	9.749***
LR test	2531.5*** (df=16)	2644.868*** (df=16)	

***, **, * The coefficient displays statistical significance at levels of 1%, 5%, and 10%. The values in parentheses show t-statistics. In this table, t-values are given in parentheses. F-stats report the F-test statistics for the statistical significance of each nonparametric variable in the semiparametric additive, and geoadditive model.

The results of the log-linear model reveal that, except for Generator, all office rent determinants are statistically significant at various levels of significance. This finding suggests that possessing a generator does not influence the rent level. Additionally, the parametric model demonstrates an explanatory power of 66% (Adj.R^2) concerning these office rent determinants. However, the unexpected outcomes, such as an insignificant relationship and low explanatory power in the log-linear model, could potentially be attributed to an incorrect selection of the functional form. In such cases, employing methods that provide flexibility in the choice of functional form can be applied.

To investigate the reasons behind the unexpected results obtained from the log-linear model, the relationship between office rent and its determinants was re-evaluated using the semi-additive and semi-geoadditive models. The estimation results of the semi-additive model indicate that both the parametric and nonparametric independent variables are statistically significant. Unlike the log-linear model, the Generator variable is now significant at a 5% significance level. To compare the log-linear and semi-additive models, an F-test was conducted, which led to the rejection of the null hypothesis in favor of the semi-additive model $(F=94.031>F_{2233;2285.9;0.01})$. Furthermore, the explanatory power of the semi-additive model (Adj.R^2=88%) is relatively higher compared to the log-linear model (Adj.R^2=66%). To test the hypothesis that the log-linear model has better explanatory power than the semi-additive model, an LR test was performed, and the null hypothesis was rejected in favor of the semi-additive model (LR=2531.5> $\chi^2_{(16)}$). These findings suggest that the semi-additive model is preferred over the log-linear model. Supporting these results, Figure 2 demonstrates that the partial effect of each office rent determinant in the nonparametric part on the rent level is nonlinear. Specifically, Figure 2 displays the graphs of nonparametric functions, s(.), where solid curves represent estimated lines, and shaded areas indicate upper and lower 95% confidence intervals. The horizontal axis represents different levels of office rent determinants, while the vertical axis shows the smooth effects on office rents for varying levels of these determinants[1]. Thus, it is not possible to present estimated coefficients for the office rent determinants in the nonparametric part, as in the parametric part. Moreover, interpreting these effects is challenging compared to the marginal impacts of the office rent determinants in the parametric part, since the office rent determinants in the nonparametric part exhibit highly nonlinear relationships with office rents.

1 A total of 2348 coefficients, equal to the number of observations, were estimated for each office rent determinant in the nonparametric part.

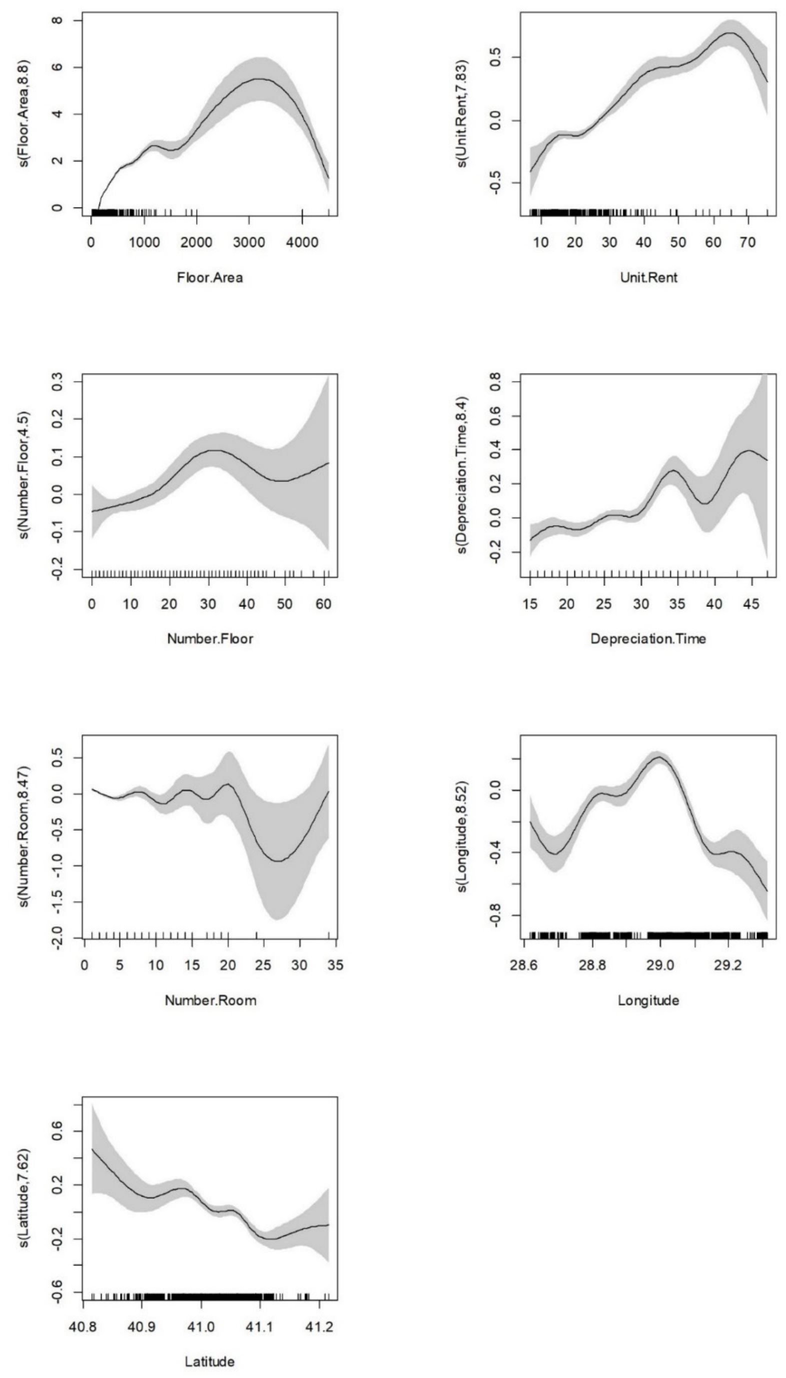

Figure 2: Nonlinear relationships in additive model

Including the geographical coordinates (longitude and latitude) is necessary to account for the impact of location on office rents. However, there is a question as to whether the geographical location should be included separately in the semi-additive model. According to the additive separability hypothesis, latitude and longitude can be included separately in the semi-additive model. On the other hand, capturing the interaction between longitude and latitude may provide a better representation of the locational effects on office space rents. In this scenario, the geographical location can be incorporated as a smooth interaction term within the nonparametric component of the semi-additive model. This modified model, known as the semi-geoadditive model, differs from the semi-additive model by including the geographical location as a smooth interaction term. To compare the semi-additive and semi-geoadditive models, an F-test can be utilized. Based on the F-test results, the null hypothesis is rejected in favor of the geoadditive model ($F=9.749>F_{2281.7;2270.2;0.01}$).

The estimation results of the semi-geoadditive model are presented in Table 1. These results indicate that both the parametric and nonparametric independent variables are statistically significant at various levels of significance. Comparing it with the semi-additive model, the geoadditive model (Adj.R^2 = 0.89) exhibits slightly better explanatory power and has a relatively low GCV value. Moreover, the impacts of office rent determinants in the parametric part are in line with theoretical expectations that were considered in the literature review. Therefore, we will consider the estimation results of the semi-geoadditive model to interpret the relationship between office rent and its determinants.

According to these estimation results, the Vacancy Rate emerges as the most influential determinant of office rent, with a negative impact. As highlighted by Kempf (2015), landlords may lower rents to mitigate the risk of vacancies, particularly during market downturns or when the office building lacks quality and construction standards. Therefore, the negative effect of the Vacancy Rate on office rent could be attributed to landlords' attempts to avoid vacancy risks.

The second most significant determinant of office rent in the parametric section is the Class A variable, which relates to the quality of the office building and categorizes buildings into Class A and Class B. Previous studies have shown mixed effects of Class A on office rent, with both positive and negative impacts. The estimated and adjusted coefficient of Class A indicates that renting an office space within a Class A building incurs an additional premium of 49.03%[2]. This positive effect aligns with the findings of previous studies conducted by Glascock et al. (1990) and Bond et al. (2008).

Similarly, office rent determinants in the parametric part can be interpreted in order of their importance. Having a Bosporus View leads to a 15.026% increase in office space rent. However, Oven and Pekdemir (2006a) discovered that proximity to the Bosporus has a minor negative impact on rent levels in the Istanbul Office Market. If the office space is situated on floors 16 through 20, the rent for that space will increase by 7.03%. The rents of office spaces located in high-rise buildings are higher compared to those in low-rise buildings. This is because height serves as a quality indicator for office buildings, so this finding aligns with expectations for the Istanbul Office Market.

The remaining determinants of office rent, such as Parking Garage, Generator, and Security Guard, represent characteristics of the office building. Since possessing these amenities indicates a higher quality office building, their positive impacts on office rent are anticipated. According to the estimation results, the presence of a Parking Garage increases the rent level by 6.29%. The increment for a Generator is 5.65%, and for a Security Guard, it is 4.29%.

2 To interpret the coefficients of dummy variables in a semi-log form, their adjusted coefficients can be calculated through the approach of Halvorsen and Palmquist (1980). In Table 1, the coefficients of all dummy variables were calculated by this approach.

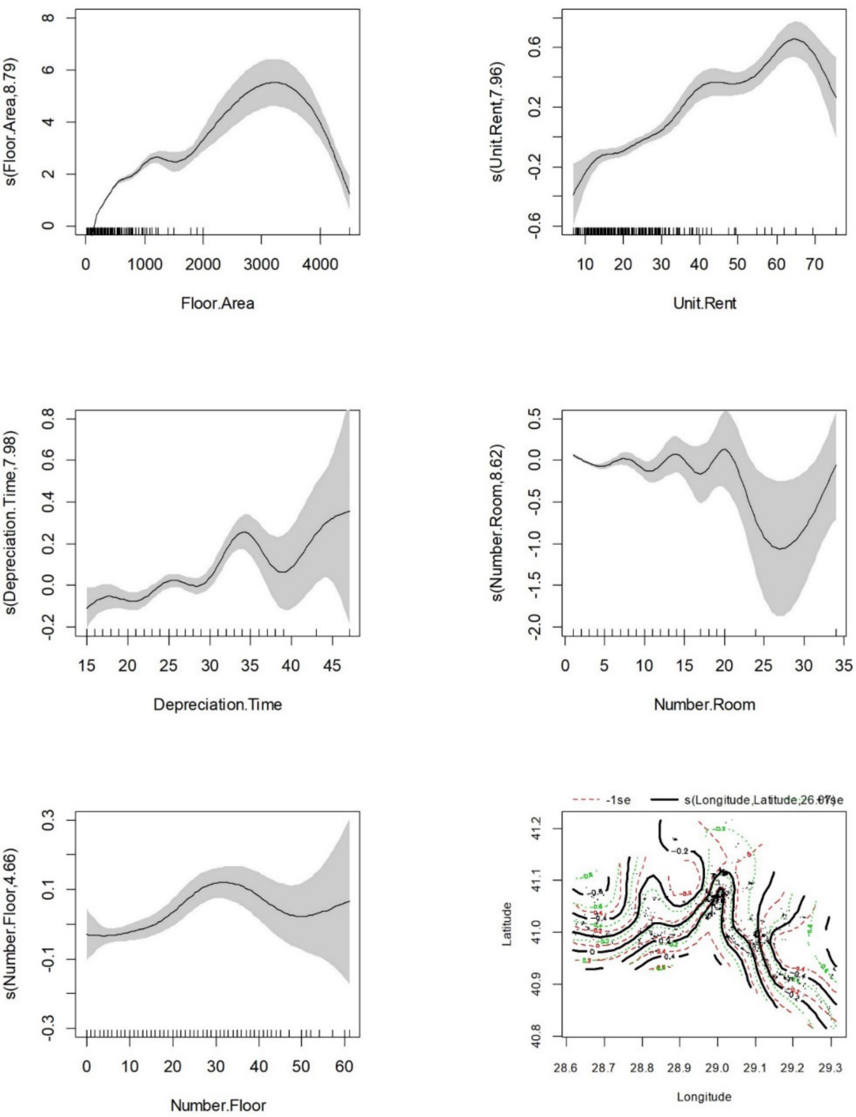

Figure 3: Nonlinear relationships in geoadditive model

Figure 3 illustrates the effects of office rent determinants in the nonparametric section on the rent level within the semi-geoadditive model. The solid curves represent the estimated lines, while the shaded areas indicate the upper and lower 95% confidence intervals. These graphs reveal that the partial effects of office rent determinants exhibit nonlinearity. It is evident that the confidence intervals tend to widen, particularly at the boundaries of the data, which is often due to a smaller number of observations at certain levels of independent variables.

As depicted in Figure 3, the Floor Area demonstrates a positive impact on the rent level up to a certain threshold. At this threshold, the effect reaches its maximum value. Beyond that threshold, the Floor Area begins to have a decreasing effect on the rent level.

Unit Rent and Depreciation Time are neighborhood characteristics that incorporate locational factors and the quality of the surrounding area. The average unit rent of housing within a given neighborhood serves as an indicator of the area's overall quality. When housing rents are high in a specific area, it suggests a superior quality of the surroundings. Consequently, other types of real estates, such as office spaces, may also command higher prices in the same location. This hypothesis finds support in the graph depicting Unit Rent in Figure 3. The graph illustrates that Unit Rent has a positive impact on the rent level[3], but this increase begins to diminish beyond a certain threshold of the variable.

Similarly, Depreciation Time can be viewed as a measure of the quality of the surrounding area. A higher average depreciation time of real estate in a particular area indicates that investments in that location are likely to remain profitable and usable for an extended period. This necessitates adherence to high construction standards for both real estate and office buildings. Consequently, the average depreciation time can serve as an indicator of the surrounding area's quality, which may contribute to an increase in office rents. In Figure 3, although the graph of Depreciation Time exhibits some fluctuations, it generally demonstrates a positive impact on the rent level.

It is expected that the variable "Number Room" will positively influence office rent, as office spaces with more rooms are likely to provide efficient utilization for tenants. However, the graph representing this variable indicates a nonlinear relationship between the Number Room and office rent. Specifically, the partial effect of the Number Room on office rent becomes negative after reaching a certain threshold of 20 rooms. Subsequently, the partial effect returns to being positive once the number of rooms exceeds 30.

Number Floor is an office rent determinant and its impact on office rents is controversial. Clapp (1980) suggests that the impact of this variable on office rent is implicitly determined by office tenants and may vary based on perceptions in different office markets. The graph representing the Number of Floors exhibits a positive partial effect on office rent, with the highest value observed when the number of floors reaches 33.

The final graph illustrates the effect of the interaction between Longitude and Latitude on office rent. Furthermore, this graph allows the observation of spatial variations in office rent.

6.CONCLUSION

This study introduces a hedonic model to estimate office space rent in the Istanbul market. The dataset consists of 2348 office spaces from 28 counties and includes various characteristics such as office space, office building, lease, locational, and neighborhood factors as determinants of office rent. The primary objective of this study is to find a model that can explain variations in rental prices for office spaces. Moreover, we suggest a modelling approach which provides more accurate pricing of commercial real estates. Overall, accurate pricing of real estate is crucial for ensuring fairness in the real estate market, facilitating efficient transactions, maintaining market stability, supporting financing and investment decisions related to real estate, obtaining appropriate insurance coverage, and enabling comparative analysis of real estates which have similar properties. To achieve this, three different models in log-linear, semi-additive, and semi-geoadditive functional forms were estimated and compared based on specific criteria. Selecting the correct functional form is crucial to ensure unbiased and consistent estimation results. Otherwise, findings derived from hedonic office rent analysis may be invalid. Therefore, this study adopts semiparametric approaches that provide flexibility in functional form, in contrast to many previous studies.

According to the estimation results, one of the office rent determinants is found to be insignificant in the log-linear form, whereas it becomes statistically significant in the semiparametric forms. Additionally, the estimation results obtained from the semi-additive and semi-geoadditive models indicate that office rent determinants in the nonparametric part exhibit nonlinear relationships with the rent level. These findings are further supported by nonlinearity tests. Consequently, the commonly used log-linear form in hedonic studies is deemed unsuitable for this study. Moreover, in the pursuit of a better model, the semi-geoadditive model is preferred over the semi-additive model. Nonlinearity tests indicate that the semi-geoadditive model provides a better explanation for rental variations by considering spatial effects.

The findings of this model reveal that the floor area, unit rent, number of floors, number of rooms, depreciation time, and geographical location are highly nonlinearly related to office space rents. The variables in the parametric part of the model include vacancy rate, class A, Bosporus view, floors 16 to 20, parking garage,

3 However, individual office space rents do not increase the average unit rent of housings in a certain neighborhood. Therefore, we can say that these variables are not cross-sectionally endogenous.

generator, and security guard. Among these variables, the most influential determinant of office rent is the vacancy rate, which serves as a proxy for office space demand. The second most effective determinant is Class A, which indicates the quality of the office building. Other important variables include the presence of a Bosporus view, office spaces located on floors 16 to 20, the availability of a parking garage, generator, and security guard in the office building, respectively.

This model can be expanded by adding different office characteristics. It might be observed how the energy identity information of office buildings is effective in the valuation of commercial real estate such as offices. Although this is not a common determinant in hedonic office rent studies for recent, it will be an important feature in office valuing in the green economy transition.

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