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Energising Property Valuation in Europe

Putting a value on energy efficient buildings

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Abstract

Key words like sustainability, green building, energy efficiency, Triple Bottom Line, Corporate Social Responsibility are just some key words, which increasingly affect the real estate businesses and therefore most of the related decision making processes. But what is about properties market value, when comparing sustainable and non-sustainable properties? A lot of discussions and research already was undertaken to analyze possible impacts of sustainable characteristics on properties values. Until now less significant quantitive empirical evidence could be found. At the most these are related to US real estate markets and the sustainability certifications of LEED and Energy Star.

In 2002 the EU Energy Performance of Buildings Directive (EPBD) was adopted to improve the energy efficiency of buildings. The IMMOVALUE-project, granted by the program of Intelligent Energy Europe, analyzed the possibility of implementing characteristics of energy efficiency into property valuation practice, while using data from the mandatory energy performance certificates. One result of the project was that if detailed property market data are available regression analysis and hedonic pricing models could be used to consider and empirically establish the effects of energy efficiency characteristics on properties values.

1 Introduction

Inevitably, the sustainability movement entered the real estate industry. Since the publication of the "Stern Review" in 2006 governments all over the world are trying to reduce their most obvious ecological hazards responsible for climate change. Currently, the existing building stock accounts for around 40% of the overall energy consumption within the real estate industry. Consequently, the sustainability movement has real estate researchers and professionals discussing phrases like "green buildings", "sustainable buildings", Triple Bottom Line (TBL) and corporate social responsibility (CSR).

In Europe the European Energy of Buildings Directive (EPBD - 2002/91/EC) launched in 2002. Due to the Directive, EU member states had to develop specific measurable values, which illustrate the overall energy-efficiency of a building. Additionally, from 2006 onward the directive mandates the creation of Energy Performance Certificates (EPC's) when buildings are sold or let. Finally, the EPC illustrates the status quo of the overall energy-efficiency of a subject existing or newly developed building. However, the ongoing activities such as energetic refurbishments beg the question as to whether energy efficient buildings are able to achieve a higher market value than non-efficient buildings. Therefore, the European Commission launched the IMMOVALUE project aimed at using key figures of the EPC to assess the energy-efficiency of a building and put them into value.

But how could it be possible to integrate this single issue into property valuation? The project collected and assessed the existing valuation methodologies while also examining the configuration of some launched national EPC's. International measuring scales, like the sustainability certifications BREEAM or LEED, are quite different and therefore not comparable. Furthermore, one can say the same about the comparability of national EPC's all over Europe.

Basically every property valuation reflects the subject property in the local property market. The task of the valuer is to compile all property facts and estimate their quality and marketability in comparison to the property market to demonstrate the valuation process in a transparent and replicable way. One aspect should be the status quo of the energy-efficiency and/or the sustainable characteristics of the property being valued. Besides the descriptive integration, the valuer should prove if some quantitative, i.e. monetary premium or discount on value were applicable in valuation.

While focusing on the income related valuation approaches we tested the possibility of using regression analysis and hedonic pricing models in the valuation of a property benchmarking stock. The nature of the analysis method is thus that it can examine a specific characteristic i.e. "energy efficiency" and its related features while keeping other price regulating characteristics stable or changed via controlled steps. This paper will focus on the possibility of integrating aspects of energy-efficiency into property valuation when there is a significant correlation to other market value influencing parameters.

2 Linkages energy efficiency and property valuation

The basic idea of the income related approaches is to estimate the property's value with the aid of the expected future rental income streams. Therefore, they are mainly used for income producing properties such as office buildings or commercial properties.

In contrast to the other known valuation approaches (the sales comparison approach and the cost approach) the income approach offers a broad range of possibilities to integrate energy efficiency and/or sustainability characteristics. Figure 1 illustrates the direct capitalization approach in combination with potential reasons for the adaptation of the single valuation parameters.

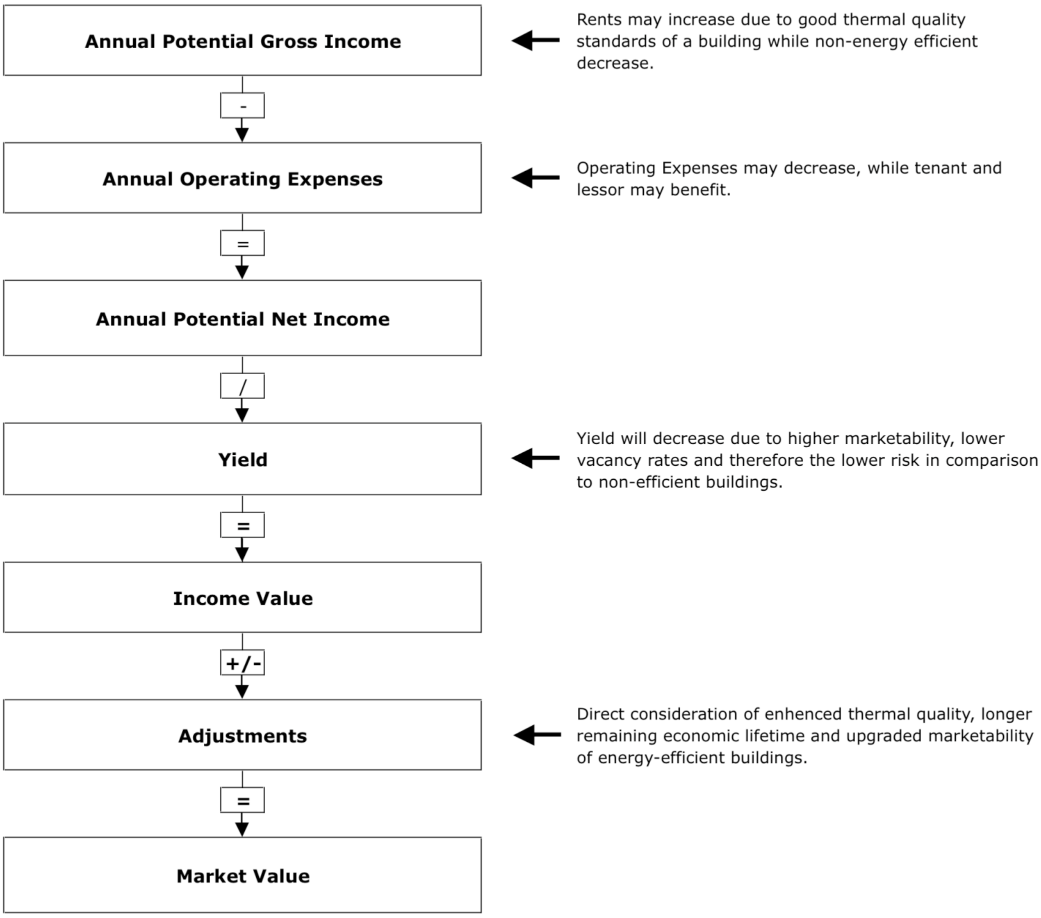

Figure 1: Potential Linkages for including energy efficiency characteristics into the Direct Capitalization Approach.

In theory it is widely spread that revenue savings due to energy related refurbishments could be seen as a rental bid in the hands of occupying tenants.[1] Further, the savings could reduce long-term risks, thus increasing future marketability while decreasing the exposure of energy efficient properties to the volatility of the property market.

While the valuer gathers property related energy efficiency information he must differentiate between direct and indirect value influencing characteristics. Direct impacts affect the energy consumption and its related emerging costs or maintenance costs of a property. Indirect impacts such as tenant churn rates or tenant retention are harder to isolate and measure. Furthermore, other value influencing impacts of public origin exist such as like tax savings or subventions.

3 Hedonic Pricing Model

3.1 Basic microeconomic methodology

Real estate is considered a differentiated or composite good in economic theory. In general, buildings or flats consist of a wide range of characteristics, which makes each property unique. The characteristics are considered to be one commodity that trades in bundles on an implicit market. The explicit market, with observed prices and transactions, is for the bundles themselves and include several implicit markets for the property's characteristics.[2] Originally developed for automobiles by Court[3], hedonic pricing models

[1] Sayce S., Sundberg A. (2009)

[2] Cf. Sheppard, S. (1999)

have been used extensively in applied economics since the seminal work of Rosen[4]. Lancaster[5] and Griliches[6] are also often cited. The theoretical underpinnings are well described in Follain and Jimenez[7] as well as Sheppard[8]. In his 2002 paper, Malpezzi[9] presented a review of the hedonic price literature, and Sirmans et al.[10] provided a review of specifications and characteristics that have most frequently been used in hedonic pricing studies.

Since a property is fixed in space, by selecting a specific object, a household implicitly chooses many different goods and services. A hedonic price function is able to describe how the quantity and quality of several characteristics determine its price in a particular market. Basically, the hedonic price function maps the equilibrium of supply and demand. The implicit prices for the variety of the property's characteristics while considering the quality and quantity of the different characteristics that are supposed to clear the market. This implicitly includes that prices for properties vary over time and depend on local and structural features. I. e. the hedonic price function can be seen as a reduced kind of supply and demand in a specific local property market.

In order to facilitate better understanding, we will show a simplified example. A property is described by a vector of k characteristics.

$$\mathbf{Z} = (z_1, z_2, \ldots, z_k)$$

A potential buyer selects/prefers a set of values for each of the properties characteristics. Therefore the price of the property is a function dependent on the entire bundle of property features. This functional dependency generates the hedonic price function

$$P = P(\mathbf{Z}) .$$

Due to the assumption that differentiated goods (which properties are) cannot be easily untied and thus the impossibility of arbitrage, marginal prices of properties' characteristics are not constant.[11] Furthermore, the price of one characteristic may depend on the quantity and/or quality of another. Therefore, we might expect to observe nonlinear relationships between the market price and its measured attributes.

To illustrate this interrelationship, consider the left panel of Figure 2, which shows how the price of a flat changes if the quantity of a certain characteristic, e.g. the area of the flat, is increased, all other characteristics held constant. Obviously, we face decreasing marginal prices of this characteristic.

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[3] Cf. Court, A.T. (1939)
[4] Cf. Rosen, S. (1974)
[5] Cf. Lancaster, K. (1966)
[6] Cf. Griliches, Z. (1971)
[7] Cf. Follain, J., Jimenez, E. (1985)
[8] Cf. Sheppard, S. (1999)
[9] Cf. Malpezzi, S. (2002)
[10] Cf. Sirmans, G., et al. (2005)
[11] Cf. Rosen, S. (1974)

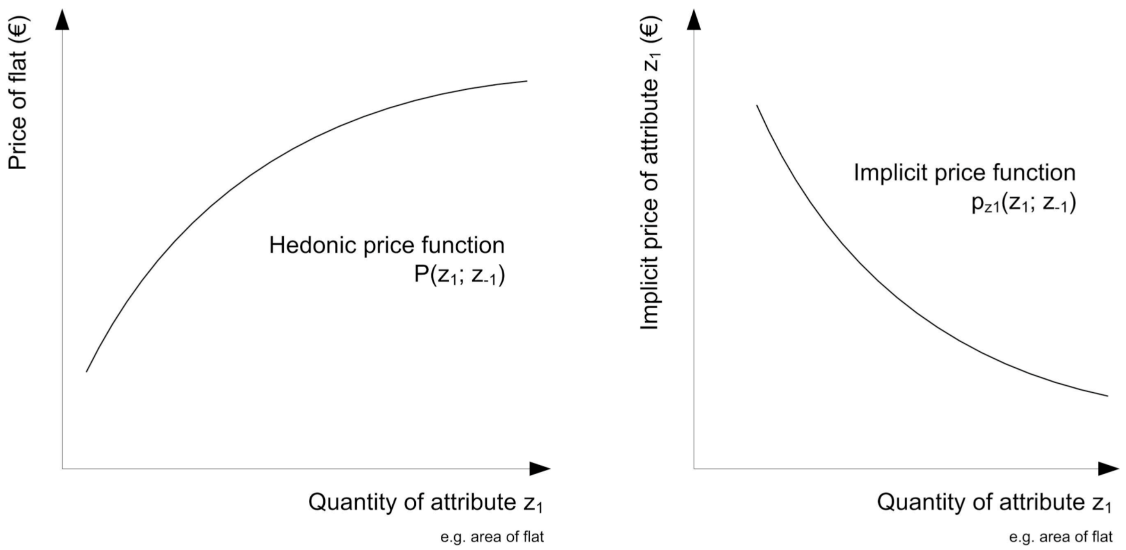

Figure 2: Hedonic price function vs. implicit price function.

The right side of Figure 2 displays the marginal prices, i. e. the partial derivatives of the hedonic price function with respect to characteristic z_1. The function is also called the implicit function of the characteristic i. It reveals indirectly, through the price of the whole property, the amount to which a household is willing to pay for one characteristic.[12]

$$p_{z_i}(z;\mathbf{Z}_{-i}) = \frac{\delta P(\mathbf{Z})}{\delta z_i}$$

The hedonic price function is the result of the interaction of supply and demand on the property market. Rosen[13] derives this equilibrium under the following assumptions:

(1) Individual households are price takers.

(2) Households only purchase one property.

Households choose the characteristics of the property and a composite good or *numeraire* (x) to maximize their utility function

$$U(\mathbf{Z}, x; \mathbf{s})$$

where **s** represents the characteristics of the household, under the budget constraint

$$y = x + P(\mathbf{Z})$$

where y is the income of the household.

Maximizing the utility function with respect to z_i, i = 1,..., k and x gives the conditions for optimal household choice of the preferred location.

$$\frac{U_{z_i}}{U_x} = p_{z_i}(z_i, \mathbf{Z}_{-\mathbf{i}})$$

The partial derivative of the hedonic price function with respect to characteristic z_i is the

[12] Cf. Day, B. (1999)
[13] Cf. Rosen, S. (1974)

ratio of marginal utilities, which is called bid function by Rosen[14]. One can interpret it as a marginal rate of substitution, so it is the slope of the indifference curve of a household. It represents the rate at which households give up money in order to get more of a specific properties attribute.

Taking the budget constraint into account explicitly, we can write the hedonic price function as

$$\theta = y - x(\mathbf{Z};\mathbf{s},u)$$

where y is the income of the household and θ is the bid function, the total amount a household could pay on a property given the choice of x. The bid function can be interpreted as

> "the maximum amount that a household would pay for a property with attributes Z such that they could achieve the given level of utility, U, with their income, y."[15]

The right panel of Figure 3 illustrates such bid curves. Bid curves can be represented as indifference curves by just flipping the vertical axis (see the left panel of this figure), so they express indifference relationships.

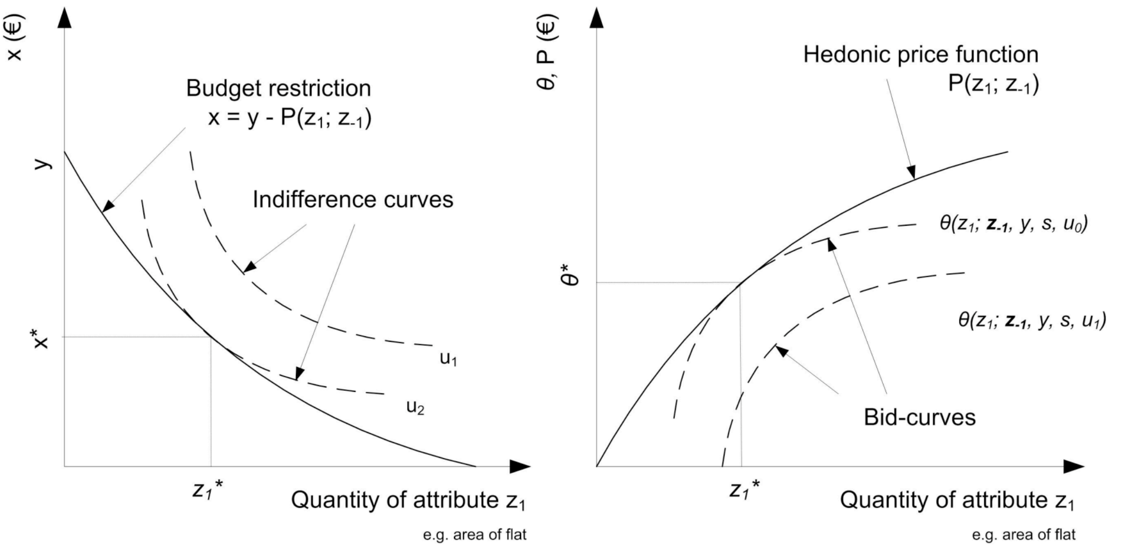

Figure 3: Indifference curves vs. bid-curves.

However, notice that the budget constraint is not linear. The optimal choice for each household is therefore the point of tangency between the highest bid curve and the budget constraint, resulting in the optimal bundle of flat characteristics composite goods for every household. Therefore, as discussed above, marginal prices are not constant. As households do not have the same income and preferences, the optimal choice "moves" along the budget constraint (of course achieving different utilities), which makes the bid curve identifiable.

Similarly, we can derive what Rosen[16] calls the offer function for the supply side. We now deal with profit instead of utility. Otherwise said, "the offer function describes the rent the landlord would need to receive in order to achieve a profit of π." [17] Again different suppliers will provide different bundles of characteristics, which makes the offer curve identifiable.

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[14] Cf. Rosen, S. (1974)

[15] Day, B. (1999).

[16] Cf. Rosen, S. (1974)

[17] Day, B. (1999).

If we bring the choices of consumers and of suppliers together in the property market, we can derive market equilibrium: The market clears in the hedonic price function, where demand equals supply (see Figure 4). The hedonic price function is therefore called a joint envelope function of all individual optimal bid and offer functions.

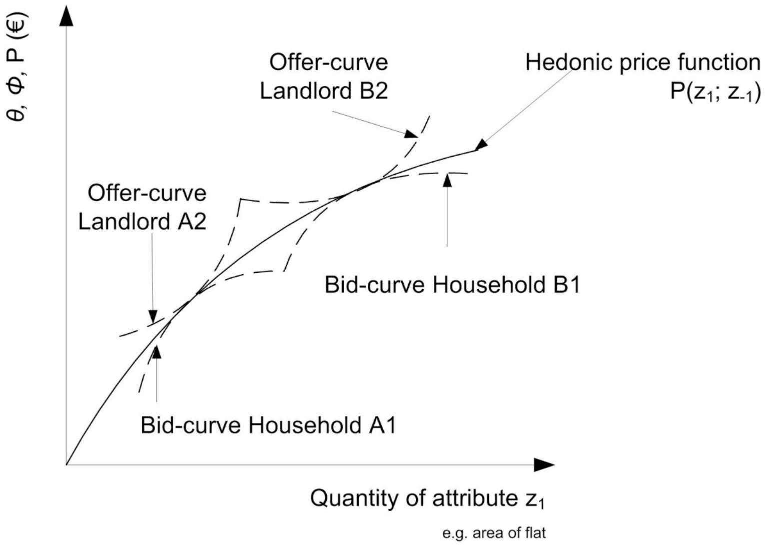

Figure 4: Hedonic price function.

However, although bid and offer functions are theoretically identifiable under certain assumptions, the complexity of hedonic markets and the unavailability of supply and demand shifters usually make it necessary to concentrate on a reduced form of the hedonic price function in empirical analysis.

3.2 Regression Analysis

3.2.1 Basics

Regression models consist of a deterministic and a stochastic component. The deterministic component describes the influence of the explanatory variable(s), also called the regressor, on the explained variable, the regressand. The explanatory variables can be denoted as vectors x_0, x_1 ... x_k or as matrix X. In general the dependent variable is denoted as y and the stochastic component as ε. While the deterministic part displays the notion of a causal effect with an additional amount of random noise, the stochastic component, also called error term, represents factors, which are not captured in the design of the study. To catch the causal effect of a characteristic, e. g. energy efficiency on rents per square meter other factors have to be held fixed. The regression model can be written as

$$\mathbf{y} = \mathbf{X}\hat{a} + \varepsilon$$

The influence on y is determined by x added by an individual error ε, while $\beta_{1\ldots k}$ denote the slope parameters of the function. To show up a single observation, the functional relationship can be written as

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} + u_i \,.$$ [18]

When only having the intercept and one explanatory variable, the model is called a

[18] In this case, of course we can omit x_{i0}.

simple or bivariate regression model.

3.2.2 Ordinary Least Squares

To find the best fitting function the error term has to be minimized. There are several possible approaches. The method of ordinary least squares (OLS) minimizes the squares of the individual error term, which can be described like

$$\min_{\beta_0,\beta_2} \sum_{i=1}^{n} \left(y_i - \beta_0 - \beta_1 \cdot x_i\right)^2 \quad for\ i = 1 \ldots n$$

According to the following conditions, referring to the Gauss-Markov-Assumptions, the OLS is the best linear unbiased estimator (BLUE):

(1) Linearity of Parameters - seems restrictive, but appropriate transformation allows nonlinear modeling.

(2) Random Sampling - random sample of size n.

(3) Sample variation in the explanatory variable - generating the dependent variable x is independent from generating y. This implies that the explanatory value is zero.

(4) Zero Conditional Mean.

(5) Homoscedasticity - all errors have the same variance.

A common model specification designed to address the nonlinearity in hedonic price functions takes the log or semi-log form, which furthermore mitigates the problem of heteroscedasticity. [19] A (semi-)log model is a model with a logarithmic variable and logarithmic or non-linear explanatory variables. The following example demonstrates this model:

$$\ln(rent\_psqm) = \beta_0 + \beta_1 \ln(energy\_psqm) + \beta_2 age + \varepsilon$$

This functional relation can be interpreted as: the dependent variable rent per square meter (rent_psqm) is dependent on the energy costs per square meter (energy_psqm) and the age of the building, while the independent variables rent_psqm and energy_psqm are natural logarithmic variables. β_1 is the elasticity of rent per square meter with respect to energy costs per square meter. If the coefficient β_1 is -0.1, then an increase in energy costs per square meter of 100% reduces rent by 10%. The coefficient β_2 is sometimes called a semi-elasticity, meaning that if it is multiplied by 100, it gives an estimate for the percentage change in rent per square meter if age is increased by one unit. For example, if this coefficient is 0.01, then one year of further age results in 1% of rent decrease.

Nevertheless, as stated by Martins-Filho and Bin[20], a frequent concern in hedonic price literature is the adequacy of parametric specifications. This specification problem arises because economic theory does not provide clear guidance concerning the functional form of the dependence of price on quality.[21] As explained in Wallace[22], this suggests that functional forms used to estimate hedonic prices should allow for the possibility of nonlinearity in the hedonic price functions.

In light of the potentially serious consequences of functional misspecification, there have been some attempts to estimate hedonic price models using semi- or nonparametric methods. The fundamental goal of these approaches is a flexible modeling of the influence of continuous covariates on the dependent variable. Semiparametric and

[19] Cf. Malpezzi, S. (2002)

[20] Cf. Martins-Filho, C., Bin, O. (2005)

[21] Cf. Anglin, P.M., Gencay, R. (1996)

[22] Cf. Wallace, N. (1996)

nonparametric approaches for real estate can be found e.g. in Pace23, or Clapp24 and will be used within the following case study analysis.

4 Case Study

The following case study is based on a real dataset, using empirical data on office buildings collected for benchmarking purposes. The database consists of various building attributes and service charges[25] as well as average rents per square meter.

The attributes and costs were collected on the basis of legal requirements (e.g. BetrKV, 2004; DIN 277, 2005; DIN 18960, 1999; DIN 31051, 2003 etc.), which makes the results traceable and convertible.

As the data was originally collected by a questionnaire, in the first step the original data was changed into a dataset that could be statistically investigated. For this purpose, all labels of categorical variables that were alphabetic characters were transformed into numbers. Therefore, the dummy variable elevator (existence of an elevator), originally labeled yes-no was changed to 1-0. Covariates air and quality were also encoded by dummy variables. The variable describing the city where the building is located was also encoded by numbers in alphabetical order. Furthermore, there were two ordinal variables with three categories, each also labeled by characters: Air condition (air) and building quality (quality). The first variable describes whether a building is equipped with full air condition (i.e., if air condition comprises heating, cooling, humidification and dehumidification), partial air condition (compared to full air condition, at least one of the functions is not contained) or no air condition.

The original sample consists of 1,578 observations, collected from 2000 to 2005 in 94 German cities. As the response variable was only collected from 2002 onwards and still not mandatory, the sample size was reduced to 532 observations in 57 cities. The following Table 1 describes the variables used for the regression analysis.

[23] Cf. Pace, R. (1998)

[24] Cf. Clapp, J.M. (2004)

[25] Service charges may be defined as the costs of area provision and management allocable to the tenant (see Jones Lang LaSalle, 2000 - 2005).

Variable	Description	Mean/ frequency	Std.-Dev.	Min	Max
rent_psqm	Average rent per sq.m. (NGF) per month	13.72	5.81	2.56	38.73
ngf	Netto Grundfläche (NGF), net floor space of all floors of a building	14,037.05	13,310.16	370.53	115,278.00
age	Age of the building, duration since the last redevelopment	14.37	13.39	0.00	113.00
quality	Quality of the building	1.17	0.59	0	2
quality_h	Dummy for high quality of the building	28%		0	1
quality_m	Dummy for medium quality of the building	62%		0	1
quality_l	Dummy for low quality of the building (reference)	11%		0	1
elev	Dummy for the existence of an elevator	99%		0	1
air	Air condition of the building	0.56	0.70	0	2
full_air	Dummy for full air condition	12%		0	1
part_air	Dummy for partial air condition	31%		0	1
no_air	Dummy for no air condition (reference)	56%		0	1
maint_psqm	maintenance costs per sq.m. per month	0.427	0.504	0.004	4.827
energy_psqm	energy costs (heating, electricity) per sq.m. per month	0.839	0.624	0.104	5.510
other_psqm	other service charges per sq.m. per month	1.700	0.667	0.316	4.373
year	Year of entry into the database	2,003.63	1.16	2,002.00	2,005.00
city_no	No of the city the building is located in			1	57

Table 1: Description of key variables used for regression.

A further explanation of the variable quality seems meaningful. The case study catagorizes the quality into several groups: “basic/low”, “fair/medium” and “high”. These categories depend on various items (see Table 2). Further, the reader should be aware that the description of this variable partly overlaps with other variables (elevator and air). This is likely to cause multicollinearity and therefore reduces the expressiveness and significance of these variables. Furthermore, one may recommend collecting each item of this variable separately, as that may lead to different effects on different cost categories. For example, a structured body shell may lead to higher heating energy consumption, while a curtain wall façade may have contrary effect. As both express high quality, the total effect of this category is blurred.

	Basic	Fair	High
Body Shell, Space Concept	Simple body shell structure, fixed space concept	Simple or structured body shell, flexible space concept	Structured body shell, flexible space concept
Façade	Perforated façade, ribbon windows, basic materials (e.g. plaster finish)	Ribbon windows, curtain wall façade, medium quality materials	Curtain wall façade, high-quality materials (e.g. glass)
Floor, Electricity supply	Solid floors, single sockets or dedo trunking	Dedo trunking or integrated floor ducts	Double-bottomed floors, hollow floors, ducts or floor containers
Ceiling, Lightning	Solid ceilings, suspended ceilings with integrated lights	Suspended ceilings with integrated high-quality lights	Suspended ceilings with direct as well as indirect lighting
Heating energy supply	Stationary heating, natural ventilation	Stationary heating, some air conditioning in special areas	Innovative heating system, partial or full air conditioning
Other equipment	Data transmission network, access control, smoke detectors	As before, in addition: lifts, emergency power generator	As before, in addition: central building control and video-based security systems

Table 2: Categories for building quality.

Additionally, the variable age (difference between the year of data collection and year of construction/redevelopment) was introduced in order to make the effects of the age of the building comparable across the whole sample and get a “cross section view”. If the building has been redeveloped, the year of redevelopment was used for the calculation of the age of the building, otherwise the year of construction. With respect to a possible time trend concerning the general cost level, dummies for the year of entry were introduced as control variables.

We first established a theoretical (“deterministic”) relationship for the regression analysis. Theoretical considerations tell us which functional form should be applied (a log- or semi-log specification, see chapter 3). This yields a model, where all metric variables except age are transformed logarithmically. Furthermore, we control for a time effect (year) and the city the building is located in. Specifically, we generate dummy variables if more than 4 observations are in the respective city.

$$\begin{aligned}\ln(rent\_psqm) &= \beta_0 + \beta_1 quality\_h + \beta_2 quality\_m + \beta_3 elev + \beta_4 full\_air \\ &+ \beta_5 part\_air + \beta_6 age + \sum_{i=7}^{10} \beta_i year_i + \sum_{j=11}^{31} \beta_j city\_no_j \\ &+ \beta_{32} \ln(ngf)) + \beta_{33} \ln(maint\_psqm) + \beta_{34} \ln(energy\_psqm) + \beta_{35} \ln(other\_psqm) + \varepsilon\end{aligned}$$

The results of this linear regression analysis can be seen in Table 3 (the dummy variable coefficients capturing locational heterogeneity are not shown in the table).

Linear Model

Number of obs	532
F(33, 498)	10.58
Prob > F	0.0000
R-squared	0.4121
Adj R-squared	0.3732
Root MSE	0.3115

logrent_psqm	Coef.	Std. Err.	t	P>|t|
_cons	2.615	0.210	12.43	0.000
logngf	-0.058	0.018	-3.19	0.002
age	-0.002	0.001	-2.09	0.038
logmaint_psqm	-0.020	0.018	-1.07	0.285
logenergy_psqm	**-0.095**	**0.035**	**-2.73**	**0.007**
logother_psqm	0.270	0.042	6.38	0.000
year_2003	0.044	0.043	1.03	0.304
year_2004	-0.023	0.041	-0.57	0.569
year_2005	-0.107	0.040	-2.67	0.008
quality_h	0.357	0.064	5.62	0.000
quality_m	0.125	0.053	2.34	0.019
elev	-0.142	0.145	-0.98	0.326
full_air	0.104	0.057	1.82	0.069
part_air	0.093	0.036	2.58	0.010

Table 3: Results of linear regression analysis.

The F-statistics show that the model is highly significant. With an adjusted R^2 of 37%, it gives a reasonable fit to the data. Furthermore, energy costs indeed seem to have a significant effect on rents per square meter: Ceteris paribus, 100% higher energy costs per square meter reduce rent per square meter by 9.5%. This result holds on a 5%-significance level.

Although we have a rough idea of which functional form to apply in the hedonic regression model from theoretical considerations, it seems fruitful to apply the additive mixed regression model AMM as described in Fahrmeir, et al.[26]. We use a semiparametric approach in order to deal with nonlinearity in regression parameters and a random city effect term to incorporate spatial heterogeneity.

Therefore, we estimate the model

$$\begin{aligned} \ln(rent\_psqm) &= \beta_0 + \beta_1 quality\_h + \beta_2 quality\_m + \beta_3 elev + \beta_4 full\_air \\ &+ \beta_5 part\_air + \beta_6 age + \sum_{i=7}^{10} \beta_i year_i + \sum_{j=11}^{31} \beta_j city\_no_j \\ &+ f(\ln(ngf)) + f(\ln(maint\_psqm)) + f(\ln(energy\_psqm)) \\ &+ f(\ln(other\_psqm)) + \varepsilon \end{aligned}$$

Taking a closer look at the semiparametric effect of energy costs per square meter, we find a rather pronounced nonlinearity. The following Figure 5 evaluates the effect of monthly energy costs per square meter at the sample mean rent per square meter (which is approximately 13.72 Euro).

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[26] Cf. Fahrmeir, L., Kneib, T., Lang, S. (2004)

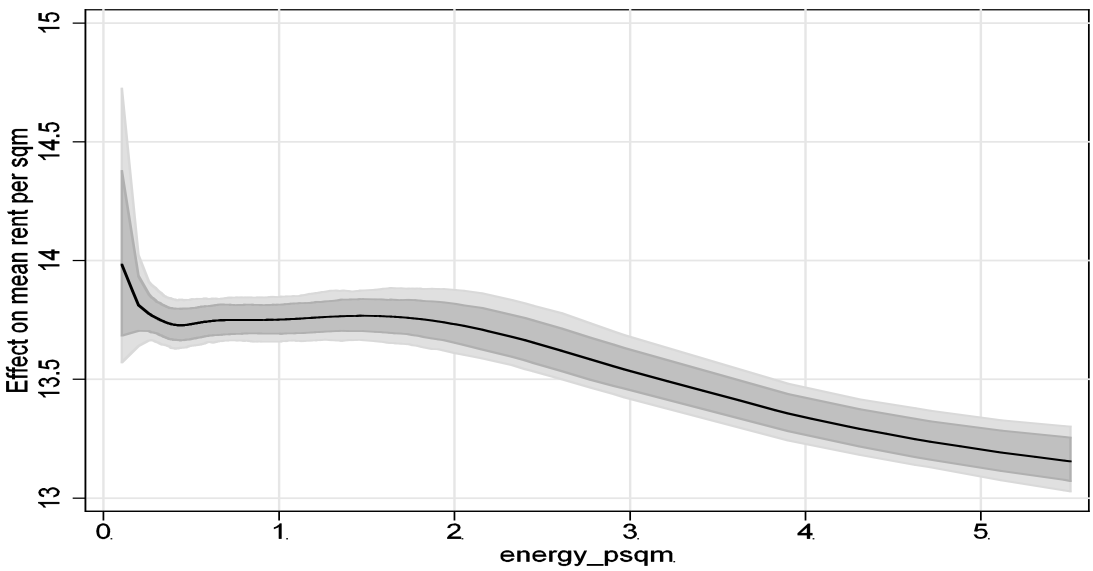

Figure 5: Effects of energy costs on monthly rent per square meter.

Interestingly, in the domain of 0.2 to 2 Euro per sqm, there seems to be a "zone of indifference", meaning that an increase in energy costs does not seem to have any effect on rents per sqm. However, as energy costs increase further, there is a noticeable effect on rents per square meter – a decrease from 14.0 Euro to 13.2 Euro per sqm (~5.8% of the mean).

Summarizing Figure 5 demonstrates that the market did not recognize energy efficiency as a special feature of a property so far. The range of indifference between 0.20 Euro per sqm and 2.00 Euro per sqm suggests that incentives for landlords to improve the energy efficiency of a building did not exist. The question, which arises is if positive effects on rents or further value influencing parameters due to a better energy efficiency changed in the meantime.

5 Conclusion

One should note when examining the analysis illustrated and explained above that such advanced interpretation methods to derive valuation input parameters fall well beyond the scope of standard valuation practices as (1) it requires a huge sample of totally transparent and comparable property information not usually available to valuers and (2) can only be performed with advanced statistical knowledge and ability.

Therefore, it is unreasonable to expect valuers to extract statistical significant results even if they could carry out such analysis in practice. As such we cannot claim that it is the valuers' task to perform such detailed analysis within the valuation process.

Instead, a sensible solution to this obstacle could come in the form of an analysis carried out and contributed by national committees of valuation experts or other real estate associations who have an access to large market information and related datasets. Such results would be of high interest and value if such organizations assured access to such regression results for specific markets and different property types. The German local "Gutachterausschüsse" is an example of a possible organization that would be capable of performing such calculations.

Thereafter, property valuers could use this quantified and specific evidence about the relation between energy performance/efficiency and its impact on market rents theoretically as a direct adjustment parameter for the valuation of the subject property.

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