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HOW DO DIFFERENT NOISE POLLUTION SOURCES AFFECT APARTMENT PRICES?

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Abstract. The paper analysed the impact of different noise sources on the residential market. This research used the hedonic method in OLS, SAR and SEM models based on the data set containing geocoded 16,247 apartments in Poznan. Strong evidence was found that noise is negatively linked with apartment prices. The apartment prices were the most significantly influenced by railway noise – an increase of 1 dB above 55 dB causes a 1.79% decrease in the value of an apartment. For other noise sources, aviation noise had the most significant impact with a 0.59% decrease in value per dB, tram noise with a 0.32% decrease and road noise with a 0.12% decrease. The influence of different noise levels on apartments is not constant and does not assume a linear relationship. For road noise, noise below 60 dB and tram noise below 65 dB were statistically insignificant. This may indicate that these noise levels are acceptable and are compensated by better access to public roads or urban transport.

Keywords: noise pollution, housing prices, housing market.

Introduction

Undoubtedly, the place of residence affects people's quality of life. Silence, clean air, and greenery positively affect everyone's mental health. It is not surprising that positive and negative environmental factors affect the value of housing. This impact is significant as housing is essential for any social unit. It is a well-known fact that the value of real estate depends not only on its physical characteristics (such as standard, technical condition, functionality, type of construction, etc.) but also on location and other factors forming the broader environment of the property.

Among these external factors, proximity to natural amenities like beaches, lakes, mountains, and parks can positively affect housing prices. Properties with scenic views and access to green spaces are often more attractive to buyers, leading to higher demand and, consequently, higher prices (Chen et al., 2022; Dell'Anna et al., 2022; Trojanek et al., 2018). Conversely, one can indicate examples of negatively influencing housing prices. High levels of noise pollution from sources like traffic, airports, or industrial activities can adversely affect housing prices (Breidenbach et al., 2022; Chen et al., 2017; Cohen et al., 2023; Gu et al., 2020; Ngo et al., 2023; Szopińska et al., 2022). Properties located in quieter, more serene areas are often valued more by buyers.

Noise is one of the most severe pollutants and one of the leading causes of deterioration in the quality of life in urban areas (European Environment Agency, 2014; Zambrano-Monserrate & Ruano, 2019). Sounds that negatively impact one's bodily or emotional well-being due to their persistence or strength are referred to as noise. The societal costs of using air transportation infrastructure are known as welfare losses.

Noise and pollution from air transportation services are responsible for generating the most severe local consequences regarding health effects and other complaints (Postorino & Mantecchini, 2016; Schipper et al., 2001). Humans are impacted by noise in many ways–unwanted social disruption by noise damages one's quality of life and overall well-being (Lawton & Fujiwara, 2016). Furthermore, noise can harm one's physical health by causing blood pressure to rise, heart disease, and sleep disturbances (Jones & Rhodes, 2013). Urban growth is influenced by noise from the use of transport structures, and it can hurt land use planning and property prices (Ferreira, 2016).

In the article, an examination of the impact of noise from various sources on Poznan house prices was

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conducted. The findings are consistent with past research on the detrimental effects of this factor on house prices. A thorough analysis, however, demonstrates that effects differ depending on the kind of noise (aircraft, railway, road, and tram) and emphasises its nonlinear nature.

The remainder of the paper is structured as follows. Section 1 covers the current empirical investigation of how noise affects housing prices. Section 2 discusses data issues. In Section 3, the methodology of the study is explained. Section 4 presents the findings together with a comparison to previous studies in the relevant literature. After that, last section assesses the results and offers suggestions for additional research.

1. Literature review

There are numerous papers on the topic, and the literature clearly shows that noise affects home prices. However, it can be difficult and sometimes impossible to compare the results of the studies directly, not least because of the locality of real estate markets. Firstly, different research methods are used – some studies are based on stated preference surveys – surveys are conducted where respondents are asked about their WTP for noise reduction (Dave et al., 2018); however, the predominant approach employed in the majority of studies is the utilisation of hedonic approaches, which are based on revealed preferences. Secondly, in most cases, an index that measures noise is frequently included in the list of explanatory variables in the numerous research studies that have employed hedonic regression to examine noise's impact on housing prices. The NDI – Noise Depreciation Index is employed in the vast majority of published studies. This index estimates how much a property's price will change if noise levels increase by one decibel. It is used to measure the depreciation of the price of properties exposed to noise. As the interpretation of the NDI index is straightforward, the crucial turns out to be the method incorporated to assess noise (NEF – noise exposure forecast, which gives an estimate of the total amount of aircraft-generated noise energy received at sites close to airports throughout a normal 24-hour period with a nighttime noise penalty factored in after 10 PM (Nelson, 1979); Ldn – annual average noise level (Wen et al., 2020; Zheng et al., 2020) NNI – like NEF, NNI creates a single cumulative index by combining measures of loudness and the number of events (Espey & Lopez, 2000). Another indicator used, for example, in Poland to designate limited-use areas around airports is LAeq (Bełej et al., 2023; Cellmer et al., 2019). Thirdly, various property types and rights with different potential noise vulnerabilities were analysed: single-houses (Cellmer et al., 2019; Wilhelmsson, 2000), land (Łowicki & Piotrowska, 2015), rents (Egbenta et al., 2021). With these limitations in mind, an attempt was made to summarise the results of recent studies (in case it was possible to determine NDI) on the impact of different noise sources on residential real estate prices.

Table 1 presents a comprehensive overview of recent scholarly works on aircraft noise's influence on housing prices.

Traffic noise is also a common problem (Blanco & Flindell, 2011; Lindgren, 2021). Due to the increasing number of cars in recent years and the expanding road network, it is becoming increasingly troublesome. For

Table 1. Recent studies on aircraft noise impact on the value of properties (source: own research)

Id	Author(s)	Location	Noise measure	Threshold Db	NDI	Research
1	Lavandier et al. (2016)	France, Paris	Lden	50 Db	mean value 1.08%	19891 sales, single-family houses, 2002–2008
					mean value 1.51%	23264 sales, apartments, 2002–2008
2	Winke (2016)	Germany, Frankfurt	Lden	55 dB	1.70%	19148 listings, apartments, 2006–2014
3	Le Boennec and Salladarré (2017)	France, Nantes	Lden	55 dB	0.35%	2969 observations, sales, houses, 2002–2008
4	Trojanek et al. (2017)	Poland, Poznan	Lden	55 dB	0.87%	438 observations, sales, and houses, 2010–2015
					0.57%	1328 observations, sales, apartments, 2010–2015
5	Beimer and Maennig (2017)	Germany, Berlin	Lden	55 dB	1.19%	27000 observations, sales, houses, 1990–2002
6	Trojanek and Huderek-Glapska (2018)	Poland, Warsaw	Laeq (OOU)	55 dB	0.8%	15572 observations, sales, apartments, 2009–2016
7	Batóg et al. (2019)	Poland, Poznan	Laeq (OOU)	55 dB	1.7%	313 sales, houses, 2012–2017

Table 2. Recent studies on road noise impact on the value of properties (source: own research)

Id	Author(s)	Location	Noise measure	Threshold Db	NDI	Research
1	Brandt and Maennig (2011)	Germany, Hamburg	Lden	55 dB	0.23%	4722 observations for sales, apartments, 2002–2008
2	Cellmer (2011)	Olsztyn, Poland	Lden	55 dB	0.36%	1100 observations, sales, apartments, 2008–2010
3	Gnat and Bas (2014)	Szczecin, Poland	Lden	55 dB	0.8%	420 observations, sales, apartments, 2009–2010
4	Franck et al. (2015)	Alter, Belgium	Lden	55 dB	0.75%	1171 observations, sales, houses, 2004-2009
		Brecht, Belgium			0.86%	945 observations, sales, houses, 2004–2009
5	Łowicki and Piotrowska (2015)	Poznan County, Poland	Lden, Lnight	55 dB	plots in the area with nighttime noise excess were roughly 57% less expensive than those outside of this area	prices of 56 undeveloped properties, 2011–2012
	Szczepańska et al. (2015)	Olsztyn, Poland	Lden	55 dB	from 0.70% to 0.94%	118 apartments, sales, 2013
6	Kuehnel and Moeckel (2020)	Munich, Germany	Lden	40 dB	0.4%	3,540 geocoded records of apartments and rent prices, 2016–2018
7	Morano et al. (2021)	Bari, Italy	Lden	40 dB	from 2.47% to 3.46%	200 residential properties, 2017–2019

this reason, studies on the impact of road noise on property prices are probably being carried out worldwide (von Graevenitz, 2018). Table 2 summarises recent publications on the effects of road noise on property prices.

In conclusion, a substantial body of literature exists about the influence of aviation and traffic noise on property values throughout many global regions. The estimated ratios of the Noise Discount Index (NDI) exhibit a range of 0.13 to 2.3 per cent drop in property prices per decibel (dB) for aviation noise and a range from no discernible effect to 2.22 per cent decrease per dB for road noise (Kopsch, 2016).

2. Data

Poznan is located in the central-western region of Poland in Wielkopolskie Province. It is the eighth largest city in Poland by area (262 sq km) and ranks fifth in terms of population (541.6 thousand residents). Poznan's administrative boundaries include two airports: the Poznan Lawica International Airport and the Poznan – Krzesiny military airport, both of which are affiliated with NATO. The Board of Geodesy and Municipal Cadastre in Poznan provided information on apartment sales between 2010 and 2015. The dataset needed some pre-processing steps. The collected data encompassed transactions about both residential and non-residential properties, including commercial properties and garages. Purchases of multiple residential units and non-free market transactions (such as sales to debt collectors) were eliminated throughout the data purification process. The following information about residences is included in notarial contracts: the date of transaction, the price, the size of a dwelling, the location of the apartment in the building, and information on additional premises. Notarial contracts lack crucial details regarding substantial pricing elements, such as the building construction method. The presence of these particular features has the potential to introduce bias into the research outcomes. Subsequently, a substantial amount of data about years of construction was completed through cadastre data. The height, year of construction, and unavailable technology-related details were acquired using the Street View feature on maps.google.com. The addresses of the transactions were subsequently geocoded by utilising the GoogleMaps API. We excluded from the dataset by restricting apartment size to between 20 and 200 square meters. Identifying atypical observations is crucial and necessary to properly carry out further stages of analysis (Su & Tsai, 2011). Outliers may lead to biased results and inappropriate interpretations (Rousseeuw & Hubert, 2011; Winson-Geideman & Krause, 2016). Given the above, we address this issue in our research based on Cook's distance. After these procedures, the dataset amount decreased to 16247 observations. The data is presented in Figure 1.

Among the property characteristics included in the research were the following: year of the transaction, area of the dwelling, time of construction, construction technology, floor, the height of the building, garage, distance to the nearest park, forest and primary school, distance to

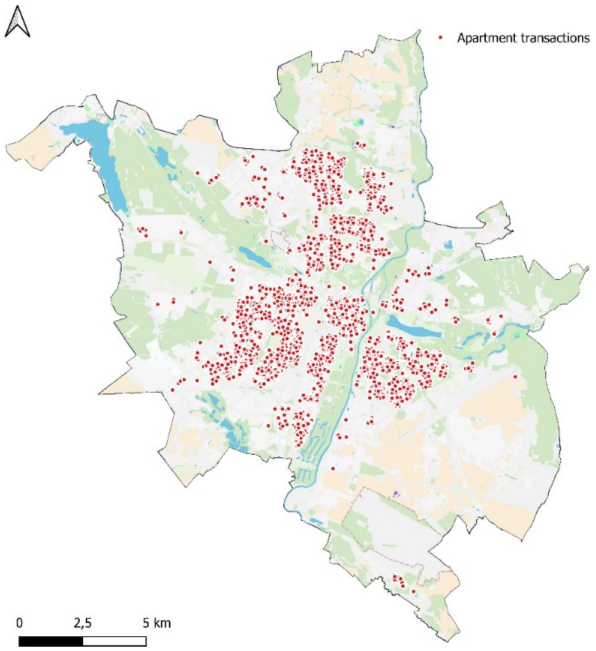

Figure 1. Apartments transactions included in the analysis in Poznan in the years 2010–2015
(source: based on the Board of Geodesy and Municipal Cadastre in Poznan and own research)

the city centre and aircraft, railway, road and tram noise levels. The choice of qualitative and quantitative data was limited by the availability of information in the database. Table 3 presents the variables used in the study.

Noise map

The 2012 acoustic map was used to extract data on noise zones for Poznan (Figure 2). Implementing a long-term strategy for noise environment protection throughout the nations of the European Union is mandated by Directive 2002/49/EC of the European Parliament. Determining long-term noise indicators LDEN and LN in protected areas is the foundation for its implementation. In this study, a threshold of 55 dB was chosen.

This act, among other things, normalises the idea of environmental noise, which refers to undesirable or damaging sounds produced by human activity outside, including noise from vehicles, rail traffic, aviation traffic, and industrial regions. A long-term environmental policy against noise is also mandated under the directive in the EU member states. On estimating long-term noise indicators LDEN and LN in protected areas, it is implemented. To assess the acoustic state of the environment, an acoustic map of the city is drawn up every five years. Its purpose is to indicate the places and areas threatened by an above-normal level of each type of noise, i.e. road, tram, rail, air and industrial noise. Considering the results of the Acoustic Map of the City of Poznan 2012, it can be seen that the most important noise sources for the city are road and aviation noise,

Table 3. Variables used in the estimations (source: own research)

Variable	Description
Price	Apartment price (in PLN)
Year	Time dummy variables, the base year 2010
City centre	Distance to the city centre (m)
Urban green area	Distance to the urban green area (m)
Primary school	Distance to primary school (m)
Area	Area of dwelling m^2
Construction technology	1 in the case of traditional technology, 0 in others
Age	Age of the building in years
Floor	3 dummy variables. If the dwelling is located on a given floor, it takes the value 1; otherwise, it takes 0
Height	2 dummy variables. If the building has a given height, it takes the value 1; otherwise, it takes 0
Garage	If a dwelling is associated with a garage, it takes value 1; otherwise, it takes value 0
Aircraft noise	1 – Ldwn 55–60 dB 2 – Ldwn 60–65 dB
Rail noise	1 – Ldwn 55–60 dB
Road noise	1 – Ldwn 55–60 dB 2 – Ldwn 60–65 dB 3 – Ldwn 65–70 dB 4 – Ldwn 70–75 dB 5 – Ldwn over 75 dB
Tram noise	1 – Ldwn 55–60 dB 2 – Ldwn 60–65 dB 3 – Ldwn 65–70 dB 4 – Ldwn 70–75 dB

Figure 2. Noise boundaries based on acoustic map of the city of Poznan 2012 (source: Poznan, 2012)

with road noise dominating. The remaining noise sources represent relatively minor noise pollution.

Road noise is the greatest threat to residents of the city. More than 30% of residents are exposed to above-standard road noise (over 55 dB) during the daytime and more than 19% at night. Another source of noise causing exceedances of acceptable noise levels is aviation noise, to which approx. 3.5% of residents and 0.2% of residents at night. On the other hand, tramway noise is exposed to approx. 2.9% of residents and 1.8% at night.

3. Methodology

The study's foundation is a hedonic regression model. Lancaster (1966) and Rosen (1974) created the theoretical foundation for the hedonic technique. The hedonic method's fundamental premise is that the qualities of heterogeneous items can be used to describe their pricing. In other words, this method can estimate the worth of specific product qualities. Using econometric equations, it is possible to determine how various characteristics affect an item's worth. The explanatory factors are the item's quantitative and qualitative characteristics, and the response variable is the item's price. The formula for the Equation (1) is:

$$y = X\beta + \varepsilon. \tag{1}$$

The dependent variable, denoted as y, represents the price, such as the price of a residential property. The independent variables, collectively referred to as X, encompass a set of factors that elucidate the determinants of the price. The vector β represents a set of parameters that require estimation, explicitly denoting the implicit willingness to pay for an additional unit of a particular feature. Meanwhile, the vector ε represents a set of error terms.

The primary difficulty with hedonic techniques is selecting the regression function's form. The literature has a division over the functional form utilised in hedonic regression models. The log-linear variant of the regression function is commonly employed in empirical research to analyse price changes in the real estate market.

$$\ln y = \beta_0 + \sum_{i=1}^{K} \beta_i X_i + \varepsilon. \tag{2}$$

Several criteria contribute to selecting this particular function (Malpezzi, 2008). The log-linear methodology enables proportional adjustments of the added value based on variations in size and other housing factors. Second, it is simple to interpret the calculated regression coefficients. For instance, the percentage change in a home's value brought on by a value driver's unit change can be used to determine the coefficient of a particular variable. Thirdly, the log-linear function often eases problems connected with heteroscedasticity and a random component's variability.

In traditional econometric models, explanatory variables may consider spatial effects in a form: dummy variables corresponding to the delimited areas (e.g. voivodeship) or distance variables indicating the distance to other objects. However, none of the above enables spatial interactions between individual objects to be taken into account directly in the model (Can, 1992). According to the First Law of Geography by Tobler (1970), "Everything is related to everything else, but near things are more related than distant things".

Due to spatial effects, such as spatial autocorrelation and spatial heterogeneity, established methods for analysing and modelling spatially connected data might produce biased conclusions (Anselin, 1998). According to Manski (1993), three different interaction effects may clarify why an observation specific to one site could depend on observations made at other locations. The presence of an endogenous interaction implies that the value of variable Y at one location can influence the value of Y at another location. Conversely, an exogenous interaction suggests that the values of Y in one location are dependent on the independent variable X, which in turn impacts Y in another location. Furthermore, a spatial relationship can arise from certain latent features that are not observable.

Spatially dependent errors can occur when objects nearby exhibit similar socioeconomic and community characteristics, leading to the spatial transmission of disturbances. Consequently, the residuals of a regression model may contain systematic spatial information not accounted for by the model (Gillen et al., 2001; Tu et al., 2007). Spatial correlation refers to the mutual relationship between spatially defined data regarding their relative location (Bowen et al., 2001).

Model residuals are often spatially correlated, meaning standard error estimates are biased. Therefore, it is only possible to observe and measure some locational aspects and other related spatial variables, which contributes to an issue with missing variables. The underlying framework addressing these concerns can be described as follows (the Manski model):

$$Y = \rho WY + X\beta + WX\theta + \varepsilon; \tag{3}$$

$$\varepsilon = \lambda W\varepsilon + \xi, \tag{4}$$

where Y is a vector of data on the dependent variable, which has dimensions $n \times 1$. W, on the other hand, is an exogenous spatial matrix with dimensions $n \times n$. Additionally, X is a $n \times k$ matrix that contains observations on the explanatory variables. The vector β represents the regression coefficients for a $k \times 1$ model. The parameter ρ captures the endogenous interaction effect, while θ captures the exogenous interaction effects. The vector ε represents the error terms in the model. Wy denotes the spatially lagged dependent variable, and $W\varepsilon$ represents the spatially weighted vector of error terms. The parameter λ represents the spatial autoregressive parameter, and ξ represents a vector of uncorrelated error terms.

Based on the specified constraint, it is possible to derive three primary categories of models from the version proposed by Manski (INSEE, 2018). The assumption of $\rho = 0$, which corresponds to the Spatial Durbin Error Model (SDEM), is applicable when there is no endogenous interaction and a dependence on the externalities of the neighbouring region. In the context of the Spatial Autoregressive Confused (SAC) model proposed by Kelejian and Prucha (2010), the parameter θ is set to zero when assuming no exogenous interactions. Similarly, in the Spatial Durbin Model (SDM), the parameter λ is set to zero when assuming no spatial connection. The SAC (Spatial Autocorrelation) and SDM (Spatial Durbin Model) frameworks can derive two distinct submodels, namely the SAR (Spatial Autoregressive) and SEM (Spatial Error Model) submodels.

There are two main approaches for evaluating model selection: the bottom-up method (Florax et al., 2003) and the top-down strategy (LeSage & Kelley Pace, 2009). The methodologies employed in this study are predicated on the underlying assumption that the neighbourhood matrix is treated as exogenous, as stated by INSEE (2018). The model's selection is determined by identifying spatial patterns through applying statistical techniques such as Moran's I, simple LM, simple LM spatial-lag test, and robust LM spatial-lag test.

4. Results

Two kinds of regression models were estimated in the study. The initial set of models considers the noise variables as continuous. The subsequent set of models was derived from the same sample. However, dummy noise variables were implemented to distinguish the impact on various isolines. In order to test for the presence of spatial effects in the data, spatial weights between observations were calculated with a 200 m threshold distance as it had the highest value of I-Moran statistics (taking into account 100 m, 300 m, 400 m and 500 m). As the nature of spatial dependence can take the form of a spatial lag, it was tested for the presence of spatial effect (both spatial autocorrelation and spatial lag dependence) with the use of Moran's I, simple LM, simple LM spatial lag test and a robust LM spatial lag test. The null hypothesis of no spatial lag dependence and no spatial autocorrelation was rejected in each case. The results of the estimation are displayed in Tables 4 and 5.

Table 4. Estimation results – Noise variable as continuous (dependent variable is the natural logarithm of the sale price) (source: own research)

	OLS		SAR		SEM	
Variable	coeff.	*p*-value	coeff.	*p*-value	coeff.	*p*-value
constant	11,86764	0,00000	11,79138	0,00000	11,81506	0,00000
year2011	0,00343	0,32397	0,00342	0,32348	–0,00076	0,81366
year2012	–0,05633	0,00000	–0,05624	0,00000	–0,05911	0,00000
year2013	–0,07045	0,00000	–0,07038	0,00000	–0,07460	0,00000
year2014	–0,03428	0,00000	–0,03433	0,00000	–0,03782	0,00000
year2015	–0,01802	0,00000	–0,01799	0,00000	–0,02483	0,00000
age	–0,00374	0,00000	–0,00372	0,00000	–0,00315	0,00000
area	0,02694	0,00000	0,02692	0,00000	0,02744	0,00000
area2	–0,00011	0,00000	–0,00011	0,00000	–0,00011	0,00000
floor2	0,00258	0,44991	0,00264	0,44010	0,00591	0,06634
floor3	0,01878	0,00000	0,01889	0,00000	0,01976	0,00000
technology	0,06746	0,00000	0,06720	0,00000	0,06359	0,00000
height	–0,03622	0,00000	–0,03602	0,00000	–0,03510	0,00000
garage	0,07622	0,00000	0,07626	0,00000	0,06597	0,00000
lncc	–0,06551	0,00000	–0,06530	0,00000	–0,05674	0,00000
lngreen	–0,00410	0,00450	–0,00408	0,00464	–0,00336	0,22324
lnschool	0,02273	0,00000	0,02232	0,00000	0,01316	0,00067
airnoise	–0,05244	0,00000	–0,05188	0,00000	**–0,03009**	0,00527
railnoise	–0,09276	0,00025	–0,09318	0,00023	**–0,09367**	0,00112
Road noise	–0,01142	0,00000	–0,01128	0,00000	**–0,00595**	0,00000
tramnoise	–0,01215	0,00003	–0,01228	0,00002	**–0,01603**	0,00000
W_lnprice			0,00626	0,01841		
lambda					0,72563	0,00000
N	16247		16247		16247	
R-squared	0,8143					
Pseudo *R*-squared			0,8149		0,811	

Table 5. Estimation results – Noise variable as a dummy (dependent variable is the natural logarithm of the sale price) (source: own research)

	OLS		SAR		SEM	
Variable	coeff.	p-value	coeff.	p-value	coeff.	p-value
constant	11,86839	0,00000	11,78679	0,00000	11,81490	0,00000
year2011	0,00345	0,32119	0,00344	0,32113	–0,00082	0,79901
year2012	–0,05656	0,00000	–0,05646	0,00000	–0,05917	0,00000
year2013	–0,07063	0,00000	–0,07056	0,00000	–0,07465	0,00000
year2014	–0,03438	0,00000	–0,03443	0,00000	–0,03784	0,00000
year2015	–0,01805	0,00000	–0,01802	0,00000	–0,02461	0,00000
age	–0,00373	0,00000	–0,00371	0,00000	–0,00315	0,00000
area	0,02697	0,00000	0,02694	0,00000	0,02745	0,00000
area2	–0,00011	0,00000	–0,00011	0,00000	–0,00011	0,00000
floor2	0,00262	0,44342	0,00268	0,43291	0,00589	0,06705
floor3	0,01887	0,00000	0,01899	0,00000	0,01973	0,00000
technology	0,06745	0,00000	0,06717	0,00000	0,06351	0,00000
height	–0,03616	0,00000	–0,03597	0,00000	–0,03522	0,00000
garage	0,07651	0,00000	0,07657	0,00000	0,06655	0,00000
lncc	–0,06553	0,00000	–0,06531	0,00000	–0,05661	0,00000

End of Table 5

	OLS		SAR		SEM	
lngreen	−0,00431	0,00285	−0,00429	0,00293	−0,00332	0,22936
lnschool	0,02256	0,00000	0,02211	0,00000	0,01278	0,00099
air55	−0,04659	0,00000	−0,04598	0,00000	**−0,03032**	0,01327
air60	−0,13323	0,00000	−0,13207	0,00000	**−0,05712**	0,03887
rail55	−0,09378	0,00021	−0,09421	0,00019	**−0,09499**	0,00096
road55	−0,00777	0,00367	−0,00760	0,00443	−0,00166	0,55905
road60	−0,02559	0,00000	−0,02518	0,00000	**−0,01306**	0,00021
road65	−0,03443	0,00000	−0,03392	0,00000	**−0,01590**	0,00026
road70	−0,04558	0,00000	−0,04516	0,00000	**−0,02629**	0,00003
road75	−0,06015	0,00001	−0,05993	0,00001	**−0,04742**	0,00108
tram55	−0,00960	0,18802	−0,00979	0,17889	−0,00547	0,47503
tram60	−0,00806	0,38622	−0,00795	0,39129	−0,01236	0,24187
tram65	−0,04476	0,00182	−0,04526	0,00158	**−0,06223**	0,00002
tram70	−0,11302	0,00010	−0,11344	0,00009	**−0,08888**	0,00332
W_lnprice			0,00670	0,01161		
lambda					0,72627	0,00000
N	16247		16247		16247	
R-squared	0,8143					
Pseudo *R*-squared			0,8147		0,8111	

The SAR and SEM regression were implemented alongside the baseline OLS model as a robustness check. The results are relatively similar, albeit several differences were found regarding statistical significance for selected parameters. Therefore, the estimates discussed below are based on the SEM regression model.

Based on the acquired findings, it can be inferred that the independent variables employed in the equation explain more than 80% of the variability observed in the pricing of apartments in Poznan. Furthermore, many of the variables employed in the models exhibited statistical significance. The regression coefficients about the explanatory variables exhibited consistency and stability across all models. By predetermined hypotheses, the coefficients of the explanatory variables exhibit the anticipated signs. Furthermore, a considerable proportion of the explanatory factors with quantitative characteristics exhibit statistical significance. The spatial error parameter λ is statistically significant, and the spatial lag parameter σ. The results suggest that spatial effects are present in the data, which can be attributed to unobserved variables and substantial spatial processes.

During the designated research timeframe spanning from 2010 to 2015, it was observed that the time variable exerted a noteworthy impact on transaction pricing. According to Trojanek (2021), there was a significant rise of around 100 per cent in house prices in Poland's major urban areas from 2006 to 2007. The commencement of the drop phase of the home price cycle occurred in late 2007 as a result of the unexpected surge in prices and the accompanying financial crisis.

Based on the presence of statistically significant negative regression coefficients associated with distance to the city centre, it can be inferred that customers are more willing to pay a higher price for apartments located closer to the city centre. In general, the relationships between the tangible characteristics of apartments and their selling prices were as anticipated. The inverse relationship between distance and home value was also noted in urban green spaces (Hill & Trojanek, 2022).

In light of the aims of this paper, it is crucial to assess the statistical significance of the noise factors. The initial set of models revealed that all noise-related variables negatively affected home prices in Poznan. However, their impact varied depending on the source of the noise. NDI indices were calculated to compare the results obtained, which show the change in the price of dwellings due to a 1 dB increase in noise. The apartment prices were the most significant influenced by railway noise – an increase of 1 dB above 55 dB causes a 1.79% decrease in the value of an apartment. Aviation noise had the most significant impact on other noise sources, with a 0.59% decrease in value per dB, tram noise had a 0.32% decrease, and road noise had a 0.12% decrease.

The results of the second group of models provide interesting insights. The dummy noise variable indicates the influence of different noise levels on apartments and does not assume a linear relationship. As in the first group of models, all binary variables relating to noise had negative signs, but not all proved statistically significant. For road noise, noise below 60 dB and tram noise below 65 dB were statistically insignificant. This may indicate that these noise levels are acceptable and are compensated by better access to public roads or urban transport. The values obtained for air and rail noise coincide when compared to the first group of models.

Conclusions

Environmental noise pollution significantly contributes to declining quality of life in urban settings. The phenomenon is attributed to various sources of discordance. The primary contributor to environmental noise pollution is road traffic, which has a widespread impact on more than 100 million individuals residing in member states of the European Environment Agency (EEA). Nevertheless, it is essential to acknowledge that rail and aviation traffic and industrial activities constitute substantial contributors to environmental pollution.

This research examines the effects of noise pollution originating from four distinct sources, namely road, aviation, train, and tram, on apartment prices in Poznan. The research employed the hedonic approach inside the Ordinary Least Squares (OLS), Spatial Error Model (SEM), and Spatial Autoregressive (SAR) frameworks. The research shows that railway noise negatively impacted housing prices, for which the NDI was 1.79%. Aviation noise had a more significant impact than the other noise sources, causing a decrease of 0.59% per dB, followed by tram noise with a decline of 0.32% and road noise with a decrease of 0.12%. The influence of different noise levels on apartments is not constant and does not assume a linear relationship. For road noise, noise below 60 dB and tram noise below 65 dB were statistically insignificant. This may indicate that these noise levels are acceptable and are compensated by better access to public roads or urban transport.

Most publications examined the effects of a single specific noise source, typically focusing on aviation or traffic noise. The findings derived from this investigation align with the spectrum of NDI values encompassing the minimum and maximum thresholds. Railway noise is a topic that receives relatively less attention. In contrast to the findings of Andersson et al. (2010), it is noteworthy that railway noise exerts a more pronounced influence on property prices within the investigated market when compared to road noise. Nevertheless, it is essential to consider that a direct comparison of these conclusions is not feasible due to variations in the underlying assumptions and methodologies employed throughout the many investigations.

The study does not fill the research gap related to the impact of noise on real estate prices. It could be interesting to study the noise sensitivity of different real estate types, such as undeveloped land, single-family houses or apartments, based on a single real estate market. This would undoubtedly provide exciting insights into how buyers of different real estate types respond to noise pollution. In addition, seeing if the age or gender of buyers has an impact on noise perceptions would seem to be tempting.

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