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Noise effects and real estate prices: A simultaneous analysis of different noise sources

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ABSTRACT

We simultaneously analyze the effects of alternative noise sources to isolate their relative harms. This research adds to the literature, which has only analyzed one noise source or has aggregated the noise levels of different sources. Flight noise had the most negative effect on housing prices, and road and train noises had similar but smaller effects.

1. Introduction

The effects of noise on housing prices have been analyzed since long (for an overview, see Brambor et al. (2006) and Nelson (2008)). However, to our knowledge, all publications on this topic concentrate on one noise source, such as road, train, or air traffic noises. No study has simultaneously analyzed the effects of different noise sources. In addition, studies that include several noise sources either aggregate the noise levels (Baranzini and Ramirez, 2005) or use dummy variables for noise levels, but they do not differentiate the noise sources (Theebe, 2004). This study aimed to close this gap and isolate the potentially differing effects of alternative noise sources on housing prices.

2. Data

The study analyzes all single-family home transactions in Berlin, the capital of Germany, as reported by the Kaufpreissammlung (statistics of real estate transactions provided by the Committee of Valuation Experts) between 1990 and 2012. The statistics also included characteristics, such as floor space, surface area, age of the building, number of floors, and (good and bad) condition (for a detailed description of the data, see Ahlfeldt and Maennig (2015)). The statistical data set included approximately 27,000 transactions.

Noise data were taken from the Department for Urban Development and the Environment. These data included information about the noise levels for every source of transportation noise based on 10 × 10-m grid cells. The noise levels were quantified by using a long-term sound pressure index (Lden). Although Lden has the same scale as the log-decibel scale (dB), Lden accepts that humans may perceive night noise to be more annoying than day noise. Lden adds 5 dB for the time period between 6 pm and 10 pm and 10 dB for the time period between 10 pm and 6 am. Following WHO recommendations, a Lden score over 55 is a serious annoyance (den Boer and Schroten, 2007). Therefore, we set noise values below 55 Lden as zero and subtracted 55 from all other actual noise levels (Ahlfeldt and Maennig, 2015).

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The selection of variables of socioeconomic and locational characteristics refers to one of the most referred noise studies by Sirmans et al. (2005), to Chang and Kim (2013), who analyzed an area similar to Berlin, to Swoboda et al. (2015), who provided one of the most recent publications on noise effects, and to Ahlfeldt et al. (2016), who provided the most recent hedonic model on real estate prices in Berlin.

The locational GIS control variables included the distances to the Central Business District (CBD), the nearest green space, the nearest body of water, the nearest metro rail station, the nearest playground, the nearest main street, and the nearest landmark. Sociodemographic characteristics included the population density, population share over 55 years old, cars per capita, non-German individuals (for 15.937 blocks), and unemployment rate (for 338 traffic cells). These sociodemographic characteristics were provided by the statistical office in Berlin. Data on income and income distribution were available for the Bezirk (district) area; as a proxy, we used the percentage of the high-income population (>3200 €/month), which is the most relevant income class in the real estate market. All data were provided by the Statistisches Landesamt Berlin (Statistical Office Berlin). We used a set of dummy variables for the years (Hiller, 2015). Due to the historic particularity of Berlin, we also added a dummy variable for properties located in the former East Berlin area.

3. Methods

The current study followed most studies that tested the noise effects (Sirmans et al., 2005) and used a semi-log hedonic model, which allows a direct interpretation of the coefficients of the noise variables in terms of the Noise Depreciation Index (NDI):

$$\ln(p) = \alpha_i * Year_i + \beta_j * NOISE_j + \gamma * SpatLag + \delta_k * X_k + \theta_l * Y_l$$

where p is the price, $Year_i$ is the year dummies, $NOISE_j$ is the noise sources, X_k is the house's characteristics, and Y_l is the socioeconomic and locational characteristics. Following Can and Megbolugbe (1997), a spatial lag variable (SpatLag) was included which allows to control for potential effects of price changes of other real estates in the surrounding. Our SpatLag includes properties at a range of up to 3000 m. It was generated using weighted matrixes ($W_{i,j,t}$) that account for the inverse distance between the block centroids using the following equation:

$$W_{i,j,t} = \frac{\frac{1}{d_{i,j}}}{\sum_i \left(\frac{1}{d_{i,j}}\right)}$$

where $d_{i,j}$ is the value of the Euclidian distance between two weighted centroids in meters. The block centroids were defined by the observations within each block, so the distributional information within each block could be used. Using all observations would make a weighted matrix that is too large to compute. We avoid an endogeneity problem by considering only transactions for the spatial lag parameter of an observation that occurred before the transaction. The actual SpatLag variable was calculated by multiplying every weighting matrix by the logarithm of the mean prices of the blocks used for the matrix. To test for robustness, the model was re-estimated without the SpatLag variable; in addition, a more general model was run by using a Box-Cox-Transformation (Mok et al., 1995).

4. Results

As a point of reference, Models A, B, and C in Tab. 1 depict the estimates if only one noise source is analyzed at a time, following the majority of the publications on this topic. Model A focused on road noise exclusively and found an NDI of 0.611, which is in line with the results of Swoboda et al. (2015), whose study found an NDI range of 0.25–0.5 for road noise. Model B analyzed air traffic noise exclusively and found an NDI of 1.27, which is in line with the results of Nelson (2008), whose meta study reported an average of 0.92 for air traffic noise. Model C analyzed train noise exclusively and found an NDI of 0.648, which is in line with Andersson et al. (2015), whose study found an NDI of 0.681 for train noise.

The coefficients for the control variables generally confirmed the findings in the referential studies on housing price determinants. The current study found that the distance to the next green space in models A to C had an insignificant effect on housing price, which may have been because the vast majority of single-family houses in Berlin are located in green areas. The study found a significantly positive coefficient for the share of foreigners, which may be because internationals who can afford to live in areas with single-family houses (SFH) may have different impacts on real estate prices than do internationals who (are forced to) live in denser areas of Berlin. The SpatLag coefficient is significantly positive, confirming the usual finding in real estate economics that increasing prices in the neighbourhood have a positive effect on properties.

Model D simultaneously analyzed all noise sources. The coefficients for all noise sources were (insignificantly) lower for every noise source than they were for the estimates in Models A, B, and C. Air traffic noise had the greatest negative effect. Upon comparing the AIC values, model D has the best fit compared to models A, B and C. The coefficients in model D can be translated into a reduced willingness to pay of −3118.3 € (±402.7) per dB for flight noise, −1530.6 € (±130.4) per dB for road noise, and −1494.2 € (±288.4) per dB for train noise.

Several explanations are at hand. Noise has direct and indirect health impacts on humans, ranging from annoyance to hypertension. An overview of the evidence-based impact was provided by Passchier-Vermeer and Passchier (2000). Miedema and Vos (1998) showed that at the same exposure level, as measured in dB, the effect of air noise is most annoying, followed by road noise and train noise, thus supporting our results.[1] The different effects on health may be due to the unsteady nature of air traffic noise; the different effects on the willingness to pay may be connected to the fact that it is difficult for humans to block this type of noise (Nelson, 2008).

Model E extends model D by using interactions terms between the noise variables.[2,3] There is no significant change in either the coefficients of the noise variables or the order of the impacts. We conclude that the results of model D are unbiased for houses that are only affected by one noise source (Brambor et al., 2006). However, three of the four interactives are significant, which implies that model D will be biased in cases of houses that are affected by more than one noise source. The mostly positive coefficients indicate that noise may have a decreasing disutility; the reduction of the willingness to pay for a house affected by more than one noise source cannot be estimated by simply adding the effects from the individual noise sources.[4]

As a robustness check, model F does not include the SpatLag variable. Air traffic and rail noises had (insignificantly) larger negative impacts in this model. According to the AIC and adj R^2, this model has the worst fit of the data. Model G uses a Box-Cox model without the SpatLag variable, which implies that the left-hand side variable must be transformed, with no assumptions needed for the transformation of the mean block prices. Note that the Box-Cox specification does not require the inclusion of interaction terms (Cassel and Mendelsohn, 1985). The order of the relative noise impacts remained stable with this model. Flight noise again had the greatest negative impact on housing prices (per Lden), followed by road and train noises, which had similar but smaller impacts. The results of this study are thus robust to alternative specifications with and without spatial lag variable inclusion or to estimations with a semi-log model or a Box-Cox model.

	Model A	Model B	Model C	Model D	Model E	Model F	Model G
SpatLag	0.195***	0.196***	0.194***	0.191***	0.190***		
	(0.0118)	(0.0117)	(0.0118)	(0.0117)	(0.0117)		
Road Noise	−0.00611***			−0.00589***	−0.00652***	−0.00732***	−0.0126***
	(0.000500)			(0.000502)	(0.000526)	(0.000531)	
Air Traffic Noise			−0.0127***	−0.0120***	−0.0120***	−0.0166***	−0.0319***
			(0.00154)	(0.00155)	(0.00162)	(0.00173)	
Train Noise		−0.00648***		−0.00575***	−0.00594***	−0.00701***	−0.0144***
		(0.00111)		(0.00111)	(0.00130)	(0.00136)	
Interact all Noise					0.000589**	0.000839***	
					(0.000183)	(0.000197)	
Interact Train & Road Noise					0.000747***	0.000758***	
					(0.000207)	(0.000221)	
Interact Train & Flight Noise					−0.00423***	−0.00675***	
					(0.00112)	(0.00119)	
Interact Flight & Road Noise					0.000513	0.000635	
					(0.000504)	(0.000533)	
Floor Space	0.00306***	0.00306***	0.00306***	0.00306***	0.00306***	0.00343***	0.00657***
	(0.000298)	(0.000297)	(0.000297)	(0.000297)	(0.000297)	(0.000320)	
Floors	0.0754***	0.0776***	0.0774***	0.0776***	0.0769***	0.0777***	0.146***
	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0113)	
Attic Apartment	0.0555***	0.0561***	0.0563***	0.0565***	0.0563***	0.0523***	0.0957***
	(0.00845)	(0.00846)	(0.00845)	(0.00845)	(0.00845)	(0.00909)	
Building Age	−0.00540***	−0.00521***	−0.00514***	−0.00532***	−0.00532***	−0.00632***	−0.0116***
	(0.000508)	(0.000515)	(0.000513)	(0.000508)	(0.000507)	(0.000543)	
(Building Age)^2/1000	0.0261***	0.0245***	0.0239***	0.0254***	0.0256***	0.0316***	0.0581***
	(0.00554)	(0.00562)	(0.00559)	(0.00553)	(0.00553)	(0.00597)	

[1] Basner et al. (2011) focus on the effects of noise on sleep also support differences in the effect of the three noise sources but find road noise to be the most annoying.

[2] We thank an anonymous referee for suggesting to include interaction terms to control for potential biases.

[3] We checked for multicollinearity but did not find any linear correlation higher than 0.5.

[4] Cf. Ai and Norton (2003) for a discussion of the interpretation of interaction effects.

(*continued*)

	Model A	Model B	Model C	Model D	Model E	Model F	Model G
Good Condition	0.169***	0.172***	0.172***	0.171***	0.171***	0.178***	0.340***
	(0.00710)	(0.00712)	(0.00712)	(0.00710)	(0.00711)	(0.00770)	
Bad Condition	−0.277***	−0.276***	−0.276***	−0.274***	−0.274***	−0.274***	−0.505***
	(0.0106)	(0.0107)	(0.0107)	(0.0106)	(0.0106)	(0.0109)	
Basement	0.0715***	0.0738***	0.0713***	0.0681***	0.0673***	0.0696***	0.131***
	(0.00644)	(0.00644)	(0.00649)	(0.00646)	(0.00646)	(0.00662)	
East Berlin	−0.120***	−0.122***	−0.130***	−0.126***	−0.128***	−0.184***	−0.337***
	(0.00682)	(0.00680)	(0.00689)	(0.00688)	(0.00697)	(0.00818)	
Floor Space Index	−0.608***	−0.618***	−0.615***	−0.613***	−0.614***	−0.677***	−1.277***
	(0.0264)	(0.0266)	(0.0264)	(0.0266)	(0.0266)	(0.0290)	
Dist. to CBD	−0.0171***	−0.0165***	−0.0170***	−0.0174***	−0.0174***	−0.0214***	−0.0412***
	(0.000889)	(0.000889)	(0.000890)	(0.000889)	(0.000889)	(0.00102)	
Dist. to Greenspace	−0.000674	−0.000833	−0.00282	−0.00382*	−0.00349	−0.00717***	−0.0146***
	(0.00177)	(0.00179)	(0.00181)	(0.00182)	(0.00182)	(0.00197)	
Dist. to Street	0.0296**	0.0709***	0.0803***	0.0446***	0.0497***	0.0481***	0.0809***
	(0.0101)	(0.00960)	(0.00977)	(0.0102)	(0.0102)	(0.0105)	
Dist. to Monument	−0.0731***	−0.0782***	−0.0826***	−0.0779***	−0.0806***	−0.0914***	−0.168***
	(0.00733)	(0.00734)	(0.00739)	(0.00735)	(0.00736)	(0.00757)	
Dist. to Playground	0.0253***	0.0239***	0.0233***	0.0261***	0.0237***	0.0298***	0.0650***
	(0.00704)	(0.00706)	(0.00705)	(0.00702)	(0.00705)	(0.00739)	
Dist. to Station	−0.0243***	−0.0257***	−0.0234***	−0.0242***	−0.0227***	−0.0243***	−0.0501***
	(0.00240)	(0.00240)	(0.00241)	(0.00240)	(0.00244)	(0.00249)	
Unemployed Share	−0.0203***	−0.0202***	−0.0189***	−0.0189***	−0.0190***	−0.0231***	−0.0440***
	(0.000724)	(0.000727)	(0.000744)	(0.000744)	(0.000745)	(0.000869)	
Income Share >3200 €	1.240***	1.246***	1.195***	1.180***	1.181***	1.555***	2.935***
	(0.0640)	(0.0642)	(0.0646)	(0.0645)	(0.0645)	(0.0682)	
Population Density	−5.250***	−4.955***	−4.873***	−5.622***	−5.680***	−6.336***	−12.07***
	−1.023	−1.031	−1.027	−1.027	−1.027	(1.125)	
Foreigners Share	0.442***	0.417***	0.445***	0.463***	0.467***	0.674***	1.312***
	(0.0482)	(0.0480)	(0.0484)	(0.0485)	(0.0484)	(0.0588)	
Population Share >55years	0.0856***	0.0833***	0.0976***	0.0852***	0.0825***	0.0966***	0.205***
	(0.0169)	(0.0170)	(0.0171)	(0.0171)	(0.0172)	(0.0176)	
Cars Per Capita	−0.0413**	−0.0411**	−0.0467**	−0.0408**	−0.0439**	−0.0277	−0.0457**
	(0.0146)	(0.0145)	(0.0146)	(0.0146)	(0.0148)	(0.0143)	
Constant	10.07***	10.03***	10.05***	10.12***	10.14***	12.51***	17.10172
	(0.130)	(0.130)	(0.130)	(0.129)	(0.129)	(0.0483)	
Theta Constant							0.0513**
							(0.00555)
Sigma Constant							0.665
Spatial Lag	YES	YES	YES	YES	YES	–	–
Year FE	YES	YES	YES	YES	YES	YES	YES
Interactions	–	–	–	–	YES	YES	–
Zip code FE	YES	YES	YES	YES	YES	YES	YES
Semi-Log	YES	YES	YES	YES	YES	YES	–
Box-Cox	–	–	–	–	–	–	YES
Observations	27,756	27,754	27,756	27,754	27,754	27,754	27,754
Adjusted R^2	0.609	0.608	0.608	0.610	0.611	0.586	
AIC	19,074.7	19,177.6	19,147.9	18,988.7	18,958.5	20,710.4	703,787.5

t Statistics in parentheses.

* $p < 0.05$.

** $p < 0.01$.

*** $p < 0.001$.

5. Summary

We simultaneously analyze the effects of alternative noise sources on the prices of single-family homes in Berlin, Germany. We analyze more than 25,000 observations and control for price determinants, which were found to be significant in earlier studies on house values, including socio-economic data and spatial amenities, as GIS-denominated data. We find that the effect of flight noise, compared to road or train noises, has a significantly higher negative impact per Lden. The effect of an increase of one Lden of flight noise decreases the price of a house by approximately 3,000 €. The price effect of road or train noise is approximately 1,500 € per Lden.

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