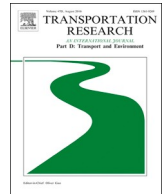


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Impact of simulation-based traffic noise on rent prices

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ABSTRACT

This paper is part of ongoing research on incorporating environmental aspects in microscopic integrated land use/transport models. The long-term goal is to add scenario sensitivity for noise emissions in a new modeling suite. Therefore, as a first step, the influence of simulated car traffic noise on real rent prices in the study area in question is analyzed and compared to existing studies. It is shown that modeled noise values from the transportation model are able to explain significant impacts on rent prices when using a hedonic pricing regression. When using noise as a continuous variable, price discounts of 0.4% per dB(A) are found. A discount of up to 9.6% for particularly loud locations is estimated when noise is used as a categorical variable. Care should be taken when controlling for accessibilities that may correlate with noise. The results are in line with results of previous studies and confirm that environmental aspects can and should be considered in integrated models.

1. Introduction

Environmental conditions such as noise can play a significant role in reducing the quality of life and therefore the value of real estate properties in neighborhoods. This problem arises especially in dense cities with high levels of traffic congestion, where local emissions are perceived by many people over long periods of time. Noise can impair the health of affected people. According to the WHO (2009), noise can lead to sleep disturbances, tinnitus and cardiovascular diseases (WHO, 2009). Transport related emissions can influence residential location choices as residents derive lower satisfaction from living at exposed locations (Maloir et al., 2009). This potentially triggers changes in traffic demand and emissions because location choice of households affect travel demand and travel demand affects emissions. It is difficult to assess whether traffic infrastructure has a positive or negative impact on residents and real estate values. While traffic emissions are clearly undesirable on a microscopic level, proximity to roads usually increase accessibility on a macroscopic level (Maloir et al., 2009; Allen et al., 2015).

A typical way of modeling a feedback between traffic and land use is to use integrated land use/transport (ILUT) models. ILUT models run over multiple years and capture the interaction between transport system and land use: location choices are influenced by accessibilities that depend on travel times. Travel times in turn are determined by travel demand derived from the location of people. In their review of ILUT models and recommendations for future research, Acheampong and Silva (2015) identified that new ILUT models should incorporate environmental impacts, as they are still very limited in current models. They claim that most existing models cannot describe the (long-term) impact of climate related policies like promotion of alternative fuel types, road pricing and others. Wegener (2004) pointed out that ILUT models should account for environmental issues as they become more important in the future but that most models lack the spatial resolution to do so. He also raised the issue of spatial equity. In large cities, people who suffer from negative externalities can be very different from those who cause them. To address issues of equity it will be beneficial to

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utilize microscopic, agent-based models, in which single individuals can be distinguished by socioeconomic characteristics.

This paper is a first step towards incorporating environmental impacts in an ILUT model. A new microscopic ILUT modeling suite will be used to simulate traffic that is derived from demand of a representation of real-world population (synthetic population). Following the assignment of the demand in the transport model, vehicle noise emissions will be modeled. To include the impacts of noise on real estate values in a future step, price discounts on rent prices are estimated based on observed real estate data. Monthly rent instead of buying prices will be assessed, as those are a factor in the relocation choice model. In addition, most of the mobile, moving people in a European urban environment rent apartments instead of buying them. By using modeled emissions of the traffic assignment, it will be plausible to transfer the impact on prices into the land-use model. This will introduce a new feedback between land-use and traffic model.

2. Literature review

There have been multiple studies that analyze the impact of traffic noise on real estate prices. In general, a significant negative relationship can be found (Bateman et al., 2001). A widely used measure for noise impacts on housing prices is the noise sensitivity depreciation index (NSDI) which can be used to compare results between studies. The NSDI is the percentage change in housing prices caused by an increase of one dB in noise level exposure:

$$NSDI = \frac{\text{percentage change of housing price}}{\text{increase of noise}} \quad (1)$$

In an overview of previous studies, Bateman et al. (2001) report NSDI values between 0.08% and 2.22%, with an average of 0.4%. Nelson (1982) found NSDI values between 0.17 and 0.63, with 0.4 being the average.

Two basic approaches for evaluating noise impacts on real estate prices can be identified. Surveys and stated preferences can be used to identify willingness-to-pay for reduction in noise (Theebe, 2004). An advantage of this method is the low amount of required data. However, survey data can be biased and might not reflect true values. The more common approach is to use the hedonic pricing method (see respective section in chapter 4), which allows to estimate the impact of different goods on prices based on observed transactions. The downside of observed transactions is that in very tight housing markets, in which people have to take what they can get, the costs might reflect compromises that underestimate true valuations.

Most studies in the literature focus on the total price of buying a house or an apartment. Theebe (2004) estimated NSDI values between 0.3% and 0.5% with the help of hedonic pricing applied on a rich dataset in the Netherlands. In his estimation, he included accessibility values to control for positive aspects of infrastructure and to prevent underestimation of noise impacts. However, he did not use noise as a continuous variable but ranges of noise as dummy variables to allow for nonlinear relationship between noise and price. Noise impacts varied across sub-markets and did not significantly change throughout different years. Szczepańska et al. (2014) conducted a study on traffic noise impacts on urban apartment prices. The data consisted of 215 apartments in multi-family houses in the city of Olsztyn in Poland. They found NSDI values between 0.74% and 0.83%. Another study by Allen et al. (2015) used distance to highway as a proxy for traffic noise in a spatial regression. Based on a sample of 1,025 single-family detached house transactions in Orange County, they found a price discount of 4% for houses adjacent to highways, while also controlling for accessibility impacts. Wilhelmsson (2000) conducted a study on the impact of noise on the values of single-family houses in Sweden using the hedonic pricing approach. Loud properties sold with a discount of up to 30% compared to more quiet houses. Using a double-log form regression, Kim et al. (2007) found a relation in which a 1% increase in traffic noise leads to a decrease of 1.3% in land price per square meter in an urban area. In a cost-benefit analysis by Becker and Lavee (2002) in Israel, the reported NSDI values are 1.2% and 2.2% for urban and rural areas, respectively. The application of hedonic pricing on property prices in Sweden by Andersson et al. (2010) included a concave function to reflect noise impact on prices and was compared to a traditional semi-log regression model. While the traditional model resulted in NSDI values between 1.15% and 1.17%, the concave specification resulted in values between 1.35% and 2.9%, depending on base noise level. When comparing NSDI between traditional OLS and a spatial lag model, the difference was negligible.

To analyze the impact of noise, one has to obtain data on sound levels at buildings. One possible approach to retrieve the data is to physically measure noise. As a more flexible and less expensive alternative, noise can be modeled by using traffic noise models (Quartieri et al., 2009) of which many have been developed over the years. The first models go back into the 1950s and modeled the 50th percentile of traffic noise based on distances and traffic volume. Later models also included the mean speed of vehicles and the share of heavy vehicles. Today, noise models are an important tool to generate noise maps that are required by the environmental noise directive 2002/49/EC of the European council (Directive 2002/49/EC, 2002). In Germany, the standard for modeling noise is defined in the Richtlinien für den Lärmschutz an Straßen (RLS 90) (FGSV, 1990). The standard is capable of taking into account many variables, such as noise propagation and reflection, sound barriers, traffic flow, road dimension and geometry, among others. The base of the calculation is a function that takes into account vehicles per hour and the percentage of heavy vehicles measured at a distance of 25 m from the center of the road. Based on this, various correction terms are added, such as corrections for speed limit, road surfaces and absorption characteristics of buildings (Quartieri et al., 2009). In this study, a traffic noise model based on the RLS 90, which is available for the transport model of the ILUT system, will be used. An example of a noise *immission* model, which takes building structures into account, is the TRANEX model (Gulliver et al., 2015).

Modeling and integrating environmental stressors in integrated land use/ transport models has been attempted as part of the ILUMASS project (Moeckel et al., 2003). Even though submodules for environmental emissions were developed and tested, the full integration never became operational. One of the reasons was the complexity of the model and its data based information exchange

between submodules (Wagner and Wegener, 2012). Other approaches modeled emissions resulting from land-use and transportation, but did not close the feedback loop to the land-use side, for example see Bandeira et al. (2011).

3. Microscopic integrated land-use/transport model

The framework for this study is to integrate environmental aspects into an ILUT model. Therefore, a new modeling suite currently under development will be used (Ziemke et al., 2016; Moeckel and Nagel, 2016). The model couples the land use model SILO (simple integrated land use orchestrator, (Moeckel, 2016) and the transport simulation MATSim (Horni et al., 2016). Both are microscopic models based on individual agents that can capture behavioral decision-making. SILO and MATSim are open-source and written in Java, which allows a tight integration.

SILO is a zone based microscopic land use model currently developed at the Technical University of Munich. Based on a synthetic population, SILO models long- and short-term decisions over multiple years in a one year time step resolution. The population consists of households and their members. Each household lives in a synthesized dwelling and persons can take individual jobs. The spatial level of resolution of dwellings and jobs are either zones or microscopic coordinates, depending on implementation. Spatial decisions like relocation and dwelling development are modeled with Logit models (Domencich and Mcfadden, 1975). Markov models with applied transition probabilities simulate other decisions like marriage, dwelling renovation, giving birth, etc. (Moeckel, 2016). Currently, demographic changes, household relocation and real estate changes are covered within SILO. The model has been successfully implemented and integrated for the Maryland statewide transportation model (MSTM) and Munich. SILO can optionally run with a transport model to update travel times and, thus, accessibilities, which in turn influence location choices.

MATSim is an activity-based transport model framework in which each traveler is represented as a synthetic agent. Every agent follows a scheduled plan for a given day. Plans consist of activities (e.g. “being at home”, “shop”) and their locations. MATSim uses an iterative approach called co-evolutionary algorithm. In each iteration, agents execute their plan in the mobility simulation and, afterwards, evaluate their performance using a utility-based score. They obtain positive scores for performing their activities and penalties for traveling and being late. Agents that spent their day in congestion will likely have a poor score. After scoring their plans, some of the agents learn by replanning their schedule, e.g. by choosing a different mode or departing earlier. During the simulation, many iterations of the same day are run, until a stochastic user equilibrium is reached. In this equilibrium, agents do not gain any significant improvements in score through re-planning anymore.

For the ILUT modeling suite, the initial demand for MATSim is derived from the land use population. For this, a third module called MITO (microscopic travel demand orchestrator) converts the SILO population into MATSim agents (Moeckel et al., 2019). MITO is a modified four step demand model that creates trips on a household/person level. It takes into account different purposes that include mandatory (work, education) and non-mandatory trips (shop, other). A drawback is that trip chains of a person are not necessarily consistent (e.g. implausible mode combinations). Thus, every trip will be converted to its own MATSim agent for assignment. By representing full day travel demand and assignment, noise levels can be calculated for a whole day.

4. Data and methods

4.1. Study area and modeling suite application

The study area for this paper is the city of Munich which is located in the southern part of Germany (see Fig. 1). However, to include commute flows and other trips that cross the city boundary, the greater Munich metropolitan region with a population of 4.5 million is used to model traffic flows and noise generation. The synthetic population for the agent-based transport model was created using an improved iterative proportional updating procedure (Moreno and Moeckel, 2018).

Starting from 2011, the land use model has been run until the year 2016, which will serve as the reference year for this paper. Subsequently, travel demand is generated using MITO. In total, around 8.8 million trips were created in MITO of which around 3.5 million trips were done by car. A five percent sample of all car trips was assigned in MATSim to get a trade-off between computational run time and reasonable results. The network capacities were scaled down accordingly. In total, 175,340 car trips were assigned. The MATSim network for the study was derived from OpenStreetMap (OpenStreetMap Contributors, 2018). Since the travel demand provided by MITO is already a good starting solution, only 50 iterations of MATSim were run. A previous study for the same study region confirmed the efficiency of this combination of sample size and number of iterations (Llorca and Moeckel, 2019). Fig. 2 shows the leg histogram for the simulated car users in the last iteration. It represents the number of agents that arrive, depart and are en route over the course of the day. One can identify a morning peak at 8 AM and an afternoon peak at around 4 PM. As it is shown, the assignment not only covers the peak hours but also gives reasonable traffic flows throughout the day, which is important for averaged daily noise levels.

A simple representation of heavy duty vehicles is included and has been disaggregated from German-wide aggregated commercial flows.

For the remainder of this paper, only the city of Munich itself will be analyzed. The simulation of the greater study area was still required to capture in- and outbound traffic. The focus on a single city for noise impact evaluation is necessary to get a more homogeneous dataset, which inherits a more or less homogenous housing market. Rural areas around Munich feature different housing markets in which the share of property owners is much higher compared to the share of tenants.

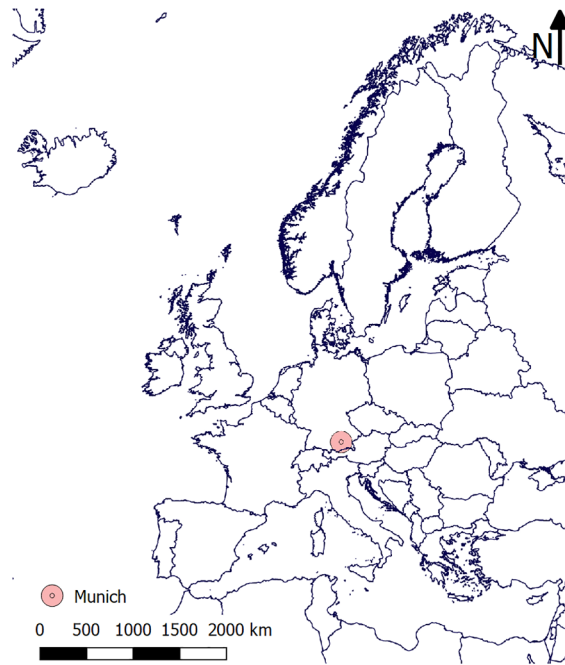


Fig. 1. The location of the study area within Europe.

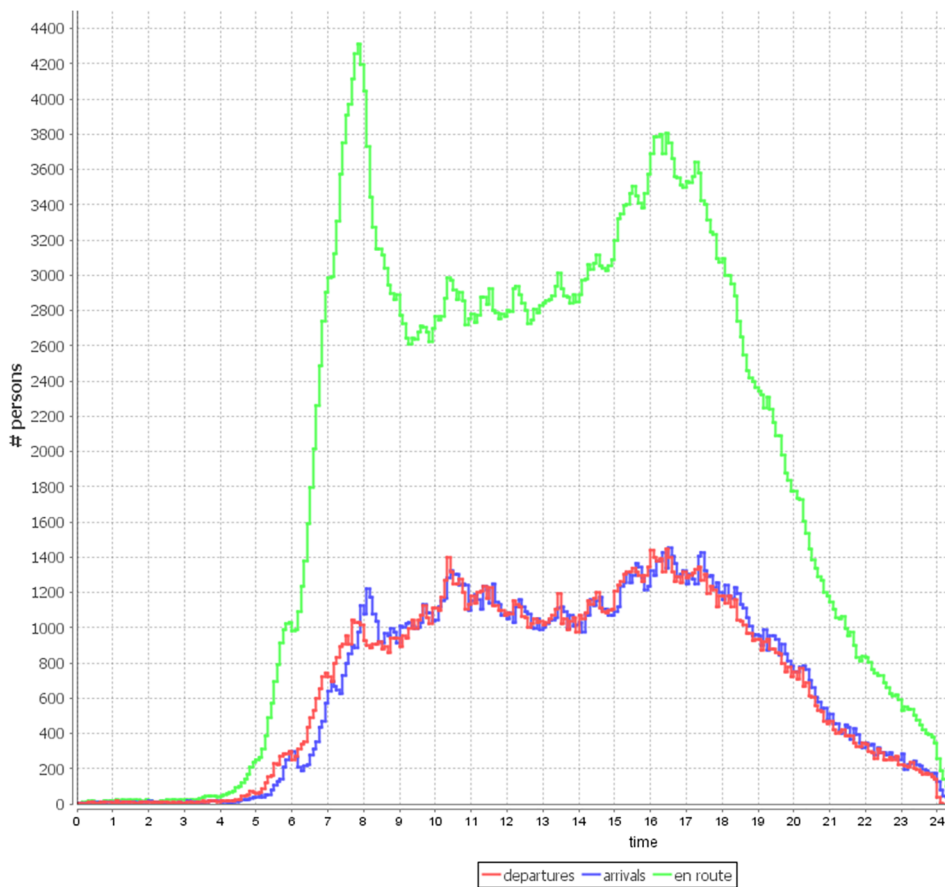


Fig. 2. Leg Histogram of car users in the last MATSim iteration. red: departures, blue: arrivals, green: en route. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

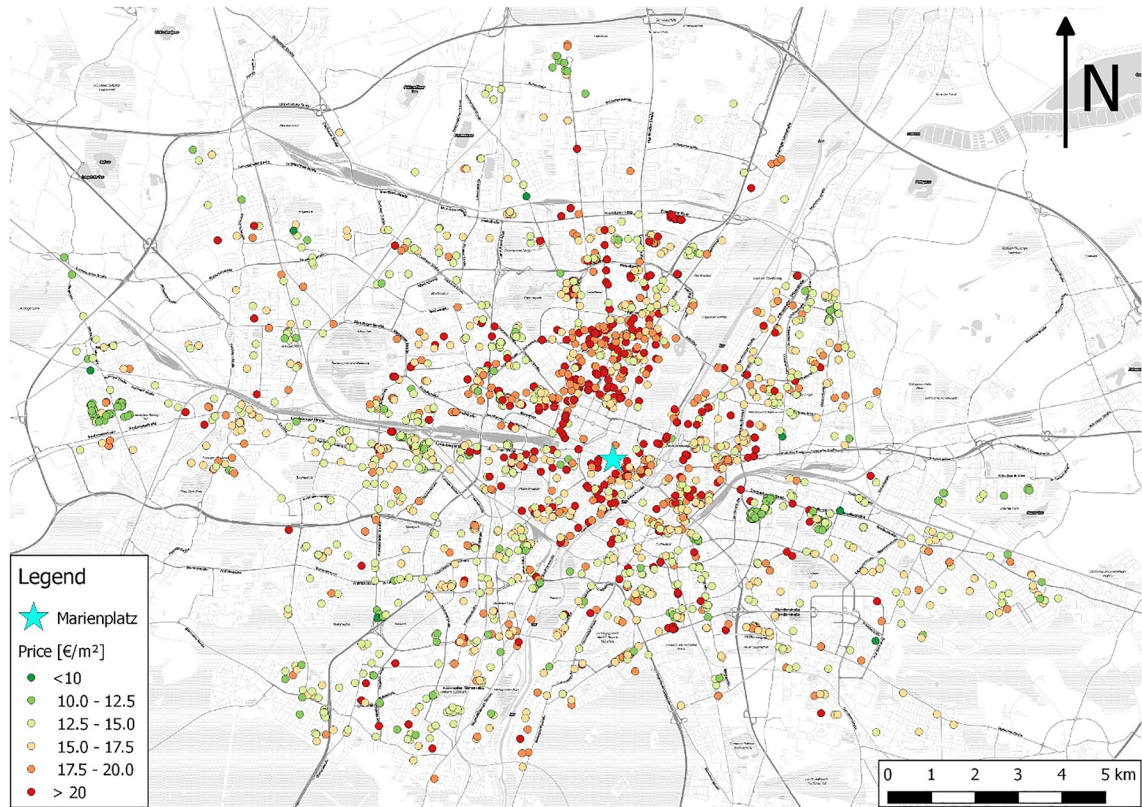


Fig. 3. Apartment locations and price per m^2 . Background image © Stamen Design (Stamen, 2018).

4.2. Accessibilities and prices of dwellings

In contrast to most other studies that focus on the total value of real estate properties, this paper analyzes rent prices of individual apartments. This will allow a better integration with the land use model, as agents in SILO relocate based on – among other location factors – rent prices of dwellings. Data on rent prices for the city of Munich were collected by observing advertisements on immobilienscout24.de (Immobilienscout24, 2018), one of the largest online platforms for real estate properties in Germany. In total, the collected database contains 3,540 geocoded records of apartments from the years 2016 to mid of 2018. The mean rent per square meter over these three years was 17.27€, 17.90€ and 18.03€, respectively. For the estimation, the rent prices were scaled to the base year of 2016 to correct for this gradual increase. The locations of the objects and their respective price per square meter can be seen in Fig. 3. As expected, the price increases towards the city center. The corrected data show a mean total rent of 1,209€ and a mean rent per square meter of 18.04€/m² for Munich, which is considered to be the most expensive housing market in Germany (official data for newly rented apartments: 18€/m² (Abendzeitung München, 2018). In addition to monthly rent and size, the collected records include information on number of rooms, construction year, level and quality (“Average dwelling quality”, “Superior dwelling quality” and “Luxury dwelling quality”) as reported by the property owner or estate agent. The reported quality of an apartment is subjective. However, it is assumed that the three classes exhibit an ordinal scale and represent, on average, differences in quality levels reasonably well. Other information, such as rent and area, are assumed to be correct, as there is no incentive provide wrong information, as long as the advertisement is not fake. Suspicious outliers with unrealistic rent prices per m² were excluded from the final dataset.

To account for higher prices closer to the city center, accessibilities measures are commonly used (Xiao, 2017). Accessibility can be understood as the potential for interaction (Hansen, 1959). Various accessibility measures were tested, including distance to the Munich city center, potential accessibilities (Hansen, 1959) and microscopic accessibilities (Ziemke et al., 2018). Based on model fit and reasonability of parameters, the latter was selected for this research. Ziemke et al. presented this microscopic accessibility measure, which is integrated in the MATSim framework and defined by the following logsum (Ziemke et al., 2018):

$$A_i = \frac{1}{\mu} \sum_j e^{\mu V_{ij}^{trav}} \quad (2)$$

where A_i is the accessibility at location i , μ is a scale parameter and V_{ij}^{trav} is the (negative) utility of traveling from i to opportunity j . Note that i and j are microscopic places with x/y coordinates. The microscopic accessibility can be directly calculated within MATSim for either a grid or for defined points i . Ziemke et al. (2018) showed that opportunities j can be identified with data from

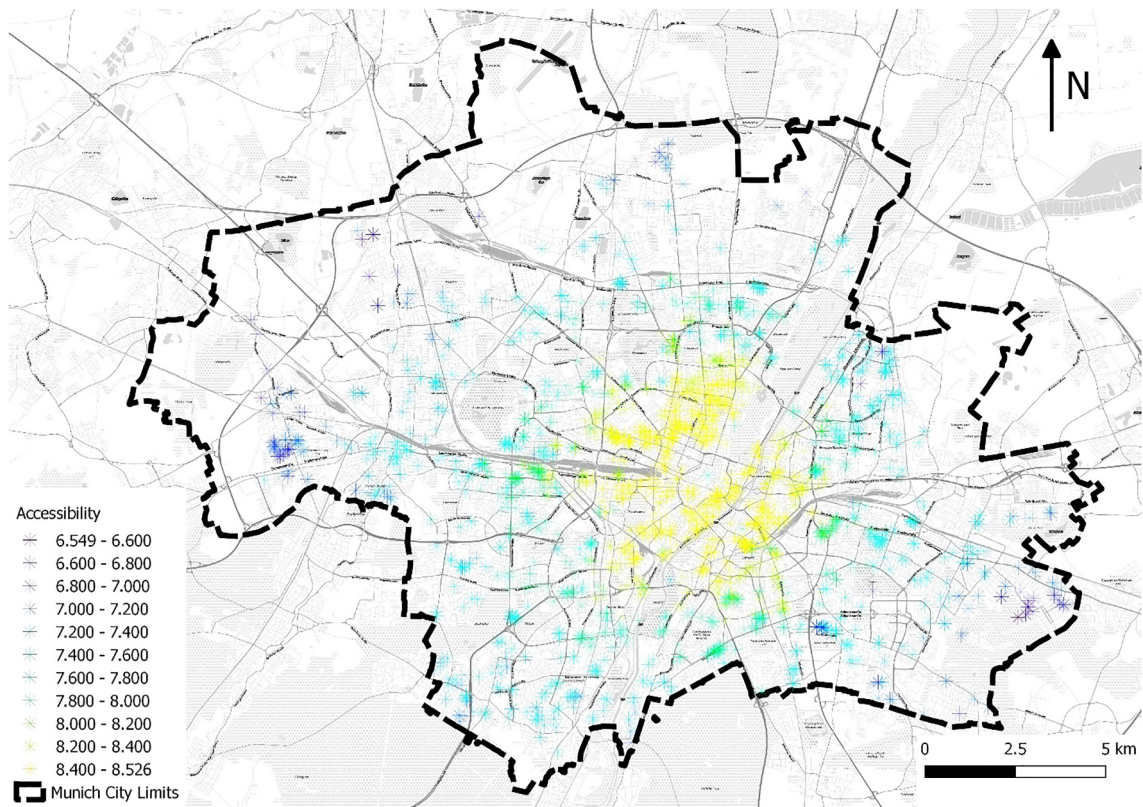


Fig. 4. Microscopic accessibilities as calculated by MATSim. Background image © Stamen Design (Stamen, 2018).

OpenStreetMap, which makes accessibility measure easy to calculate and the method transferable to other study areas. Results suggest that this measure yields to intuitive patterns of accessibility. In this study, the microscopic accessibility indicator is used as the centrality measure. A dataset of all amenities that would typically be identified as activity locations (e.g. bars, shops, doctors, banks, etc.) was retrieved from OpenStreetMap for the whole study area and used for the accessibility calculation in MATSim.

Fig. 4 shows computed microscopic MATSim accessibilities of recorded apartments in Munich for the car mode. Obviously, accessibility is the highest in the city center. However, the figure shows that accessibilities do not linearly decrease with increasing distance to the center.

4.3. Simulated noise levels

Noise levels of car traffic were obtained using the noise contribution of MATSim which was described by Kaddoura et al. (2017). This extension models noise emission values based on link volumes, heavy good vehicles share and average speeds. The calculation follows a simplified version of the German RLS-90 approach (FGSV, 1990). Emissions are corrected for actual speeds, while additional correction factors like road surface are ignored. Emissions are calculated for each link in one-hour time bins, where the resulting value is the average noise emission level in dB(A). Immissions of noise are calculated using receiver points that are defined either by specifying a grid or by providing individual coordinates. For each receiver point, the immission is calculated based on distance to the nearest links and their respective emissions. Additionally, the shielding effect of building structures that are obtained from OpenStreetMap are considered, which is novel in comparison to most other similar studies. In a previous study, it was found that neglecting shielding effects of building structures in dense areas can lead to overestimations of noise damages of up to 20% (Kuehnel et al., 2019). Building reflections and insulation are not considered. Reflection is supposed to only have a small impact compared to the shielding of buildings. Insulation is hard to measure and not available in the dataset of apartments. Most buildings in this area are built out of stone and have at least double-glazed windows, leading to comparable insulation level, anyway. To get an average noise level for a whole day, immissions are expressed in weighted average L_{DEN} values. L_{DEN} stands for day-evening-night-level. It is based on energy equivalent noise levels over a whole day, including a penalty of 10 dB(A) for night time noise and 5 dB(A) for evening noise (European Environment Agency, 2018). Fig. 5 shows computed noise emission values for links in Munich during the eight AM peak hour. The maximum emission is 77 dB(A) and was observed on the outer motorway ring. The points in Fig. 5 represent the obtained apartment records. Their color is graduated based on L_{DEN} immission values.



Fig. 5. Calculated network emissions for 8 AM peak hour and averaged daily immissions for apartments.

4.4. Hedonic pricing

To estimate the impact of simulated traffic noise on rent prices, hedonic pricing is used. The theory was first described by Rosen (1974). The idea is, that in a competitive market, the value of a composite good can be decomposed such that every component can be attributed an individual implicit value as a contribution to the total value. In the case of real estate properties, differences in price can therefore be explained by different attributes of each property. In the overview of Bateman et al. (2001), four groups of explanatory variables are identified:

- Structural variables (level, number of rooms)
- Accessibility variables (distance to city center, travel time to various points of interest)
- Neighborhood variables (crime/ unemployment rates)
- Environmental variables (noise, pollution)

To infer the value of each component, multiple linear regression can be used:

$$y = \alpha + \beta_1 * x_1 + \beta_2 * x_2 + \dots + \beta_n * x_n + \varepsilon \tag{3}$$

where y is the response variable or composite good. The parameter α is a constant term and $\beta_{1..n}$ are estimated parameters for the predictor variables $x_{1..n}$. The error term ε accounts for variation that cannot be explained by the included predictor variables and follows an independently identically distributed normal distribution with mean 0. In this simple linear form, the change of one unit of x_k would lead to a change of β_k units of y, all else held constant. In cases where a simple linear relationship is not justified, transformations to either response or predictor variable can be applied. Two commonly used transformed models are the log-log-model and the semi-log model (Xiao, 2017). In a log-log-model, predictor and response are transformed by taking the logarithm:

$$\ln(y) = \alpha + \beta_1 * \ln(x_1) + \beta_2 * \ln(x_2) + \dots + \beta_n * \ln(x_n) + \varepsilon \tag{4}$$

In a log-log formulation, the impact of a predictor can be interpreted as a (price) elasticity (von Auer, 2016):

$$\text{percentage change of response} = \beta * \text{percentage change of predictor} \tag{5}$$

Log-log relations can only be applied to positive continuous variables. In the semi-log model, only the response variable is transformed by the logarithm:

$$\ln(y) = \alpha + \beta_1 * x_1 + \beta_2 * x_2 + \dots + \beta_n * x_n + \varepsilon \tag{6}$$

The semi-log model thus allows to incorporate dummy variables. For small β , the relation between response and predictor is a semi-elasticity (von Auer, 2016):

$$\text{percentage change of response} = \beta * 100 * \text{change in predictor} \tag{7}$$

This makes the semi-log relation very convenient to infer the NSDI when noise is used as a continuous variable:

$$NSDI = \beta_{\text{noise}} * 100 \tag{8}$$

where β_{noise} is the noise estimate.

Additionally to using noise as a continuous variable, the impact of a categorical classification of noise was evaluated. As Theebe (2004) pointed out, a noise level of 55 dB(A) can be identified as the ambient noise level from which housing prices start to decrease. This was confirmed when plotting rent prices against noise. Multiple re-classifications and re-estimations of the models led to the three noise categories low, moderate and loud noise. Low noise is used for immission values below the 55 dB(A) threshold. The moderate noise category describes values from 55 to 65 dB(A) and loud noise is defined as everything above 65 dB(A) A more fine-grained classification above 65 dB(A) led to inconsistent estimation results, which is likely caused by the small number of samples in this range. Only about 5% of all apartments in the dataset have a noise level above 65 dB(A). The calculated accessibility measure shows a moderate correlation with noise with a correlation coefficient of $R = 0.46$. While correlation between independent variables is undesired in regression analyses, this fairly moderate correlation is accepted to represent the positive impacts of road infrastructure. The variables level and construction year turned out to be not significant. Number of rooms and the area of the apartment provided similar explanatory power and could be used interchangeably. However, those two variables were highly correlated, and the more significant variable, namely area, was chosen. Obviously, the dataset does not include all variables that influence the rent price. It is assumed that those unincluded variables distribute randomly across all observations, and thus, are absorbed by the error term.

Two different models are presented. Both of them include the log transformed area, the accessibility and the quality of the apartment as dummy variables. The difference between both models is that one uses noise as a continuous variable while the other one makes use of the categorical classification.

Table 1 shows the selected variables and their usage in the models. Area is log transformed, while the other variables form a semi-log relation with the response variable. Multiple combinations by trial and error led to the decisions of which transformations were applied. The response variable in this paper is total monthly rent for an apartment.

5. Results

The results of the two specified models are shown in Table 2. All variables are significant at least at the 99.9% level. Robust standard errors were used to account for heteroscedasticity in higher rent price ranges. Variance inflation factors between 1.06 and 1.28 indicate that multicollinearity is not a problem. Both models show similar and reasonable estimates for area and quality. The area of an apartment has a positive impact on total rent price. Because of the log–log relation between predictor and response variable the estimator cannot be directly interpreted as price per square meter. Following Eq. (4) and using estimates of Table 2, a 1% change in area is thus reflected in a change in rent price between 0.769% and 0.778%, depending on the selected model. This non-linear relationship means that prices per m^2 are not constant and decrease at higher levels of area. This finding was verified by plotting rent price against area. The estimates for quality show expected signs for “Luxury dwelling quality” and “Average dwelling quality”, with “Superior dwelling quality” being the baseline. According to Eq. (6), a luxury apartment is rented for a roughly 21% higher price compared to superior apartments. Average apartments are rented for 19% less. The adjusted R^2 of both models are similarly high with a value of about 0.84.

Microscopic accessibility shows stable estimates across both model formulations. For each unit increase of the microscopic accessibility, prices increase by 20%. The model that uses noise as a continuous variable shows a noise estimate of -0.004 . Eq. (8) leads to an NSDI of 0.4. An increase of 1 dB(A) thus refers to a discount of 0.4% in rent prices. The minimum modeled noise level for an apartment is around 38 dB(A), while the maximum is at 88 dB(A). The maximum implicated price difference between the loudest and

Table 1
Variables used in the regression models.

Variable	Unit	Min	Max	Mean	n (N = 3,540)	Used in model
Area	m^2	14.00	278.00	70.10		all (log transformed)
Noise (L_{DEN})	dB(A)	37.97	88.09	57.24		1
Low noise	Dummy				1,202	2 (baseline category)
Moderate noise	Dummy				2,149	2
Loud Noise	Dummy				199	2
Microscopic accessibility	–	6.54	8.52	7.91		all
Average dwelling quality	Dummy				1,063	all
Superior dwelling quality	Dummy				2,178	all (baseline category)
Luxury dwelling quality	Dummy				289	all

Table 2
Regression model results.

		Dependent variable:	
		log(rent)	
		Model (1)	Model (2)
Log(area)		0.769***(0.0066)	0.778***(0.0066)
Noise		-0.004***(0.0006)	
Low noise			0 (Base)
Moderate noise			-0.058***(0.0068)
Loud noise			-0.096***(0.0138)
microscopic accessibilities		0.204***(0.0085)	0.210***(0.0081)
Luxury dwelling quality		0.213***(0.0112)	0.211***(0.0110)
Superior dwelling quality		0 (Base)	0 (Base)
Average dwelling quality		-0.197***(0.0067)	-0.197***(0.0066)
constant		2.433***(0.0718)	2.196***(0.0738)
Observations		3,540	3,540
R ²		0.838	0.842
Adjusted R ²		0.838	0.842
Residual Std. Error		0.1783	0.1757
F Statistic		3,657	3,147
Note:		Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 robust SE in (brackets)	

the quietest apartment is $(88 \text{ dB} - 38 \text{ dB}) \cdot 0.4 = 20\%$. When noise is used as a categorical variable, a price discount of 9.6% for loud apartments can be found. For apartments with moderate noise, the discount is 5.8%.

Fig. 6 shows a plot of predicted against actual values of the model that uses noise as a categorical variable (model 6 in Table 2). It can be seen that the linear fit matches well, although the variance of residuals increases with rent level, especially for prices above

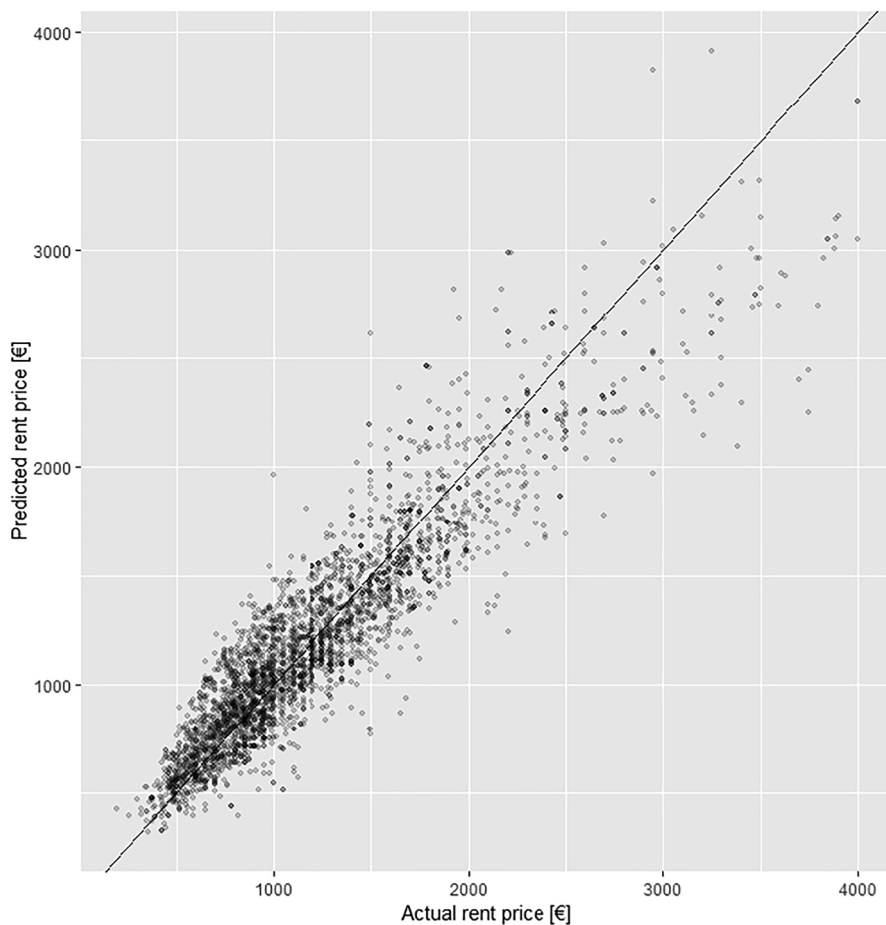


Fig. 6. Predicted vs actual plot for total rent price.

Table 3
Variance inflation factors for model (6).

	log(area)	moderate noise	loud noise	microscopic accessibilities	Luxury dwelling quality	Average dwelling quality
VIF	1.11	1.28	1.15	1.23	1.07	1.06

2.000€. This can be explained by the fact that exclusive, high quality apartments feature a higher variance in rent prices, caused by unobserved variables. The model gives a reasonable linear fit for the majority of apartments with a price below 2.000€.

6. Discussion

The two estimated models show reasonable and significant estimates and have a high and similar R^2 value around 0.84. The authors tend to favor the second model, which uses noise as a categorical variable. It is more reasonable that noise levels below the 55 dB(A) threshold do not have an impact on price. Also, having noise as a continuous variable pretends an accuracy that is not reflected in the simplified calculation of emission and immission values. The microscopic accessibility measure is assumed to be more accurate than a zonal accessibility that has been used initially for this study, especially for larger zones. In an earlier estimation, the noise estimates had a significant higher p-value and were less significant when a zonal accessibility was used. In fact, microscopic accessibility overcomes the issues that results are influenced by zone size. As the required input data is solely dependent on open source data from OpenStreetMap, it is easy to transfer this approach to different study areas.

The accessibility measure can be seen as a confounding variable that avoids biases for the estimates of noise. Accessibility is positively correlated with noise and price and noise is negatively correlated with price. Omitting the accessibility measure, therefore, leads to an underestimation of the negative impact of noise. When omitting any accessibility measure from the estimation, the noise estimate yields a positive change of 0.2% in rent prices per decibel, which shows the positive bias. When including the confounding variable, possible issues of multicollinearity that reduce the precision of estimates need to be analyzed. A common measure for this is the variance inflation factor (VIF) which can be used to detect collinearity among predictor variables in multiple linear regression models (Belsley et al., 1980). It is calculated by running a regression on each predictor against all other predictors and should ideally have a value of 1 in the case of no multicollinearity. A typical cutoff point for problematic cases is a VIF greater than 5 (Craney and Surles, 2002). Table 3 shows VIFs for the used predictors in model 2. All values are close to 1, which suggests that multicollinearity is not a problem in the fitted model.

The estimated NSDI value of 0.4% for noise as a continuous variable is in line with previous studies, with the value of 0.4% matching the reported average values of Bateman and Nelson (Bateman et al., 2001; Nelson, 1982). However, many other recent studies in cities found higher NSDI values (Szczepańska et al., 2014; Becker and Lavee, 2002; Andersson et al., 2010). A reason for this could be the tight housing market in Munich, which leads to high market prices. The price discounts of the categorical noise values are in plausible ranges when compared to Allen et al. (Allen et al., 2015) who found a discount of 4% for properties close to the street. In model 6, for example, the difference in discount between loud and moderate objects is 3.8%, which is about the range of the moderate noise category, 10 dB(A), multiplied by the NSDI of 0.4%, which is 4%.

A limitation of the current implementation is that freight transport and heavy-duty vehicles are only modeled in a simplistic way and might not be very accurate. Another limitation is that immissions could be calculated in a more sophisticated way by also accounting for tunnels and the height or level of the apartment. Official traffic noise models also take reflection of building facades into account (Bayerisches Landesamt für Umwelt, 2018).

The estimation applies to the city of Munich only. The impact of noise cannot be transferred easily to other cities (Xiao, 2017).

Accessibilities by other modes such as public transport, walk or bicycle should be evaluated in a future application. Previous studies confirmed a positive correlations of non-motorized accessibility with housing values (Cortright, 2009; Guo et al., 2017). Microscopic accessibilities provided by MATSim were not obtainable in a feasible way for modes other than car and should be investigated in the future. However, the main aim of this study was not to get the best fitting model for prediction of housing prices but rather to understand the impact of road traffic noise. It was shown that car accessibility is a variable that must be controlled for, as higher car accessibility will lead to higher road traffic noise. In the case of walk or bike accessibility, the correlation to road traffic noise will be less pronounced than for car accessibility. Therefore, omitting non-motorized accessibilities is expected to introduce a small bias at most.

Based on these estimations, it will be possible to account for the feedback of noise on price in the land use model. In the integrated modeling suite, noise will be accounted for as an additional variable in the relocation choice model. The price differences in rent prices should then be the outcome of reduced demand due to noise. The values estimated here will then serve for calibration and validation.

Fig. 3 shows a pattern of prices per m^2 that cannot fully be explained by distance to the city center. Different neighborhoods could form their own housing submarkets. One way of accounting for this could be to incorporate different residential neighborhoods into the model, as classified in official rent level reports (Landeshauptstadt München, 2018).

7. Conclusions

The results in this paper support the idea of integrating environmental aspects in an ILUT model as traffic noise has a significant

impact on rent prices. Two models were estimated, differing in the usage of noise as a continuous and a categorical variable. The models show reasonable results in terms of NSDI as compared to existing studies. An important finding of this study is that it is important to control as well as possible for the positive aspects of accessibility. Otherwise, the noise estimate will be severely biased. It was shown that modeled noise emissions as part of an ILUT model can be used to identify price discounts in rent prices when evaluated against real-world real estate data. This justifies a future implementation of noise exposure into the pricing model of a land use component to create this feedback cycle. In a next step, the presented models will be applied for buying prices of real estate properties in Munich. Based on a literature review, the impact of noise on household relocation as a negative aspect will be assessed. By incorporating environmental aspects into the ILUT model, policy studies that target noise and pollution abatement (e.g. road pricing) can be conducted over the course of multiple years. Currently, the authors know of no fully integrated and operational microscopic ILUT model that accounts for environmental aspects. It is expected that model sensitivities for noise abatement scenarios will be increased. Relocation should be affected significantly by decreased prices. The microscopic setup of the modeling suite will allow to identify issues of spatial equity related to traffic emissions.

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Declaration of Competing Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.trd.2019.11.020>.

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