

Urban, Planning and Transport Research >

An Open Access Journal

Volume 8, 2020 - Issue 1



Open access

3,413 5

Views

0

CrossRef citations to date: Altmetric



Research Article

Residential housing prices: impact of housing characteristics, accessibility and neighbouring apartments – a case study of Dortmund, Germany

Dirk Wittowsky [✉](#), Josje Hoekveld, Janina Welsch [ORCID](#) & Michael Steier

Pages 44-70 | Received 17 Dec 2018, Accepted 09 Dec 2019, Published online: 08 Jan 2020

[Download citation](#) <https://doi.org/10.1080/21650020.2019.1704429>

ABSTRACT

Formulae display: [MathJax](#) ?

In this research we analyse the most important factors that determine housing prices. On the one hand, we test whether neighbourhoods with a good accessibility are more attractive and consequently show higher housing prices. For this purpose, we introduce an adapted Walk Score as part of the accessibility indicators. On the other hand, we compare an ordinary-least-squares regression (OLS) and a spatial lag model and test which model better explains residential housing prices. The regression models show the importance of classical factors such as dwelling characteristics or the types of neighbours. In addition, they also reveal that a differentiated approach is needed for analysing the accessibility, the location and the environment of a dwelling. The mere presence of a single amenity, a public transport stop or a motorway access is not a sufficient explanatory factor. Information such as density of supply, walking distances or public transport service quality needs to be taken into account as well as. The test of the spatial lag model reveals that prices of the most proximate dwellings can be taken into account as a relevant factor in explaining residential housing prices and should therefore be included in research on residential housing prices.

Q KEYWORDS: Hedonic price model housing prices accessibility Walk Score public transport[Previous article](#)[View issue table of contents](#)[Next article](#) >


In this article



insights have been gained into which characteristics determine housing prices. These characteristics reflect two different aspects: those which are correlated with the dwelling itself and those which are correlated with the location and the surrounding area. The latter are also referred to as neighbourhood related aspects. For example, dwelling related aspects are the type and size of the dwelling, the number of rooms or the amount of land that goes with it. Among others, neighbourhood related aspects are the walkability of the surrounding, the level of crime, the quality of proximate schools, the racial or ethnic population composition, green spaces or parks, the effects of investments in amenities, or the presence or absence and the quality of sidewalks in walkable and in car-dependent residential areas (Anderson & West, 2006; Boyle, Barrilleaux, & Scheller, 2014; Cervero & Duncan, 2004; Li et al., 2015; Lynch & Rasmussen, 2001; Song & Knaap, 2004). Accessibility variables such as distances to the central business district (CBD), motorways and public transport are also described to correlate with housing prices (Hess & Almeida, 2007).

However, continents, countries and cities differ in the factors that determine residential housing prices. In this research, the main goal is to identify and analyse the most important factors that determine housing prices in Dortmund, a former industrial city in the Western part of Germany. To this end, we compare two different statistical methods to determine a stable method with valid results. In addition, we also aim to cover two issues in the housing prices debate that have not as yet received much attention. The first issue is content-related: Americans, in particular, are avidly debating the creating of pedestrian-friendly residential areas and how they are more attractive to house-buyers and tenants. They are supposed to induce walking and to be beneficial to inhabitants' health (Frank et al., 2006). Generally, the debate on accessibility refers to design urban spaces and nodes (Rode & Floater 2014). Several widely known indices are used to indicate whether the surrounding environment of a dwellings location is pedestrian-friendly or not: the Walk Score®, Walkability, the Neighbourhood Destination Accessibility Index (NDAI) or the Land Use Public Transportation Accessibility Index (LUPTAI) (Bucksch & Schneider, 2014; Gilderbloom, Riggs, & Meares, 2015; Yigitcanlar, Sipe, Evans, & Pitot, 2007; Walk Score® Website; Witten, Pearce, & Day, 2011). Perhaps the most well-known is the Walk Score®, which calculates the walkability of any given address on the basis of its accessibility to a set of amenities (grocery stores, restaurants, shops, coffee corners, banks and cash machines, parks, schools, bookstores and entertainment) within walking distance of the address. The commercial website of Walk Score® advertises with the slogan 'Walk Score helps you find a walkable place to live'. We adapted the Walk Score® for our analysis, e.g. we test single Walk Scores for different amenities and, as Dortmund provides a very dense pedestrian network, we didn't use a penalty as it is calculated for North American cities due to their grid pattern or block length. We test whether dwellings with high adapted Walk Scores are more attractive and consequently have higher residential housing prices than low ones.

The second issue is method-related. In traditional hedonic house price modelling, little attention is paid to spatial dependence. All things being equal, housing prices may also be affected by the prices of proximate

In this article  district. In addition, a bias reflects the price differences between districts. In such a
 it independent of the neighbouring ones and a spatial autocorrelation – also

coefficients (standard errors of β), which in turn affects the correctness of the hypothesis tests (Ward & Gleditsch, 2008). There is growing interest in spatial econometric techniques dealing with this issue (de Meulen & Mitze, 2014). For example, a spatial lag model explicitly includes spatial dependency by adding a spatially lagged dependent variable in the regression equation that represents the mean value of housing prices in the adjacent dwellings. Therefore, in our analysis, we use both an OLS model and a spatial lag model to identify the most important factors that influence housing prices in Dortmund, and to test which model is better at explaining residential housing prices.

The paper has six main sections. Following the introduction, the next section sets out the study's conceptual background. This is followed by a brief introduction of the study area, Dortmund. Subsequently, the methodology and the data for the regression analysis are described, while the next section presents the empirical results. The discussion and conclusion section sets forth the key findings and presents further research questions.


2. Conceptual background

2.1. Hedonic price models

Hedonic price modelling is based mainly on Lancaster's consumer behaviour theory, which argues that it is not the good itself that creates utility but its individual characteristics (Lancaster, 1966). Hedonic price modelling estimates the demand for a good by considering the revealed preferences. Housing in particular is a multidimensional heterogeneous good (Bourne, 1981). Housing characteristics can be divided into three sets: the dwelling's characteristics, the neighbourhood characteristics and the accessibility characteristics. The last two may also be combined as locational characteristics. Due to the spatial immobility of dwellings, locational characteristics are highly important.

The price of a dwelling is determined by the sum of these individual characteristics. Via a regression model that uses residential housing prices as a dependent variable and individual housing characteristics as independent variables, it is possible to decompose property prices into their price-determining components. Formalized by Rosen (1974), this approach allows to measure the marginal effects of the decomposed individual characteristics on the corresponding residential housing price.

Traditionally, hedonic price modelling uses OLS models. However, recent work in urban economics has criticized the commonly used techniques of hedonic analysis, most notably the assumption of constant model parameters across the geographical study area. Homoscedasticity and normality of the error distribution (two requirements for an OLS model) are often not fulfilled because adjacent dwellings might have similar observable and unobservable characteristics (Basu & Thibodeau, 1998). As a consequence, differences of residential housing prices per square metre tend to be spatially auto-correlated with

In this article  dwellings located near each other often have similar prices, while price similarities
 These spatial effects should be taken into account when estimating hedonic price

accessibility characteristics (Anselin, 1988; Dubin, 1992). Formally, the OLS model in matrix notation is:

$$Y = X\beta + \varepsilon \quad (1)$$

Where Y is a $(n \times 1)$ vector of the prices for individual dwellings, X is a $(n \times k)$ matrix of the independent variables subdivided into different characteristics, β is a k vector of the estimated coefficients and ε is a $(n \times 1)$ error term (Li et al., 2015). A SAR model is also referred to as a spatial lag model and acknowledges the possibility of spatial autocorrelation and therefore includes a lag term. In our case, the lag term specifies adjacent housing prices and has coefficient and significance level as the other independent variables:

$$Y = \beta_0 + \beta x + \rho w y + \varepsilon \quad (2)$$

Where Y is the house price, x is a matrix of observations on the explanatory variables and pwy is the spatial lag variable. ρ measures the degree of spatial correlation and w is the spatial weights matrix. The value ρ ranges between -1 and 1 . A ρ of zero means there is no spatial correlation. A positive ρ means that housing prices are expected to be higher if spatially proximate housing prices are higher. ε is a vector of the independent and identically distributed error terms (Ward & Gleditsch, 2008).

2.2. Accessibility, walkability and residential housing prices

Accessibility as a concept that is used in different contexts and research fields and thus is defined numerous different ways. According to Geurs and van Wee (2004), accessibility is based on a structure of effects whose components consist of land use, the transport system, the time resources and the individual resources of a particular person. Accessibility therefore links a dwelling to the surrounding or city-/region-wide land-uses, the transport systems and the locations for different activities. Thus, giving individuals the opportunity to participate in activities in different locations (Geurs & van Wee, 2004; van der Vlugt, Curl, & Wittowsky, 2019; Weibull, 1980). In this research we focus on the accessibility of the dwellings as a location, as these are the most important starting points for most of the everyday trips. In order to estimate the quality of the accessibility of the dwelling, we use different accessibility indicators. On the one hand, we calculate the walking time on the pedestrian network to the nearest facilities, such as daily needs, shopping, park/green space or restaurants. In addition, we calculate the accessibility of the dwelling to public transport stops and the travel time to the city centre as well as the connection to the motorway.

In Alonso's (1964) famous access-space-trade-off model, the main accessibility variable contributing to housing price is the distance to a CBD. That model has been criticized as it does not work in a polycentric spatial structure and it is also problematic in this day and age where several individuals in a household often work in multiple locations (Heikkila et al., 1989). Thus, it could be argued that accessibility to

In this article e or even to hubs (from which one can travel easily to multiple destinations) is nt. However. studies into the importance of accessibility to public transport facilities

specific location and contextual characteristics within the city. Whether or not the system translates into property values depends on a city's character, the type of railway services and the spatial extensiveness of the system. Debrezion, Pels, and Rietveld (2006) found a significant correlation between housing prices and railway station accessibility: Houses that are located closer to a railway station show higher property prices. But they also found, that very close proximity is correlated with lower prices, probably due to noise pollution. In addition, service levels (train frequency, railway network connectivity and service coverage) prove to have a significant positive effect on housing prices.

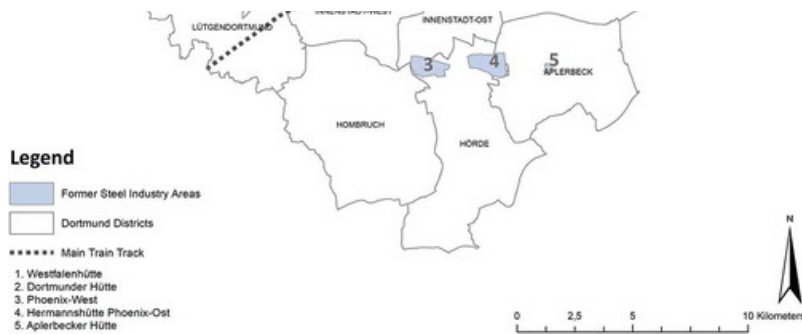
Further research into accessibility has shown that the effect of accessibility on housing prices differs according to the surrounding environment and type of the residential area: the effect of proximity to a railway station is higher in low-income neighbourhoods than in high-income neighbourhoods (Bowes & Ihlanfeldt, 2001). This intra-urban differentiated effect is also seen by Adair, McGreal, Smyth, Cooper, and Ryley (2010). They argue that accessibility hardly matters for housing prices on a city-wide level, whereas it has a significant effect on a sub-market level. As mentioned in the introduction, walkability, i.e. pedestrian access to different amenities, is also discussed as an important factor that influences a residential area's attractiveness and consequently variability in housing prices. Albrecht (2010) and Stieringer (2014) found that the rental prices are significantly higher if the dwellings are located within walking distance of a railway station. In contrast, when Boyle, Barrilleaux, and Scheller (2014) examined the effects of walkability on house values, they found that its impact becomes statistically insignificant, especially after controlling for heteroscedasticity and neighbourhood fixed effects.

3. Case study area: Dortmund and its residential housing market

Dortmund, a former industrial city, is located in the Ruhr area, a former highly industrialised and densely populated polycentric agglomeration within the Western part of Germany. The city grew rapidly during industrialisation period and main industrial areas were built in close proximity to residential and commercial areas (Figure 1). In 2015 it had a population of 596,575 and is therefore the largest city within the Ruhr area (City of Dortmund, 2016). Dortmund has a heterogeneous social structure and can be described as a rather polycentric city due to its historically grown sub centres. It constitutes an interesting case study not only but also due to the major structural changes and consequent transformations in the job market as well as due to its heterogeneous population and consequently diverse housing market.

Figure 1. Former steel industry areas in Dortmund (Source: own illustration based on OSM)






Display full size

During the period of industrialization, Dortmund's coal-mining and steel industry and also the brewing sector boomed. Up to the 1960s, industrial employment attracted large numbers of workers, both within Germany and from abroad. But Dortmund lost over 80.000 jobs in the last third of the 20th century and the city experienced mass unemployment, out-migration and a declining population as a result of the collapse of the coal-mining and steel industry. Nowadays some three-quarters of all jobs in the city are in the tertiary sector (Irle & Röllinghoff, 2008).

In general, Dortmund has managed to slowly but steadily recover from the economic downturn, and its population has recently started growing again. Large brownfield sites with high economic potential have been redeveloped. For example, the Phoenix area within the district 'Hörde' is well-known as a case study. Built on the site of two former steel and ironworks in the southern part of Dortmund, its western part contains a high-quality technology location focused on micro- and nano-technologies, engineering and software development. Its eastern part features a new artificial lake called 'Phoenixsee' and surrounding residential and recreational areas (City of Dortmund, 2015; Connective Cities, 2018). Between 2014 and 2015, the main residence population in Dortmund rose by 1.2 % (7.292 inhabitants). In the same year, the number of foreigners has risen by 10 % (8.687 inhabitants), mainly due to international immigration. It should be noted that this figure is influenced by the influx of refugees as well as of EU citizens (City of Dortmund, 2016).

Dortmund's residential housing market can be described as dynamic and reflects the many changes in the city's social and economic structures. In the previous century, many rather low-standard dwellings were built in close proximity to the (former) industrial areas. These were located predominately in the northern part of the city. The inner city is generally dominated by apartment buildings, while the majority of owner-occupied houses are located in the outskirts. House prices have increased sharply between 2012 and 2016, both for detached houses (+25 %; median: 375 700 €; 390 000 € in 2017), semi-detached new-builds (+19 %; median: 286 000 €; 284 200 € in 2017) and older semi-detached houses (+25%; median: 275 000 €, 295 000 € in 2017). The average value of an owner-occupied apartment is 2 800 €/m² (2 680 €/m² in 2017). The increasing number of building permits (+33 % between 2012 and 2016, -9.5 % between 2016 and 2017) can be seen as a positive sign for the investment market, and the city of Dortmund claims that it has

In this article  : stock of building land. For example, the land-use plan includes more than
 : ential use (either approved or in the process of being approved). expectedlv about 8

(median 2016: 10.16 €/m² 2017: 10.50 €/m²). Nevertheless, when compared to other German cities such as Frankfurt am Main, Cologne or Munich, prices on Dortmund's real estate and rental market remains still reasonably affordable (City of Dortmund, 2017, 2018a).

4. Data and methodology

4.1. Description of data sources and variables

The analysis consists of spatial regression analyses on dwelling and housing environment characteristics, with a special focus on accessibility variables. The dependent variable is the price for owner-occupied and rental dwellings in Dortmund in 2013. Information on housing prices and on dwelling characteristics are received from immobilienscout24. It is the largest real estate website for sales and rentals in Germany ([Immobilienscout24 Website](#)). On this platform, owner can put in their offers for buying or renting residential housing in Germany. It should be noted that both rental and selling prices on immobilienscout24 do not reflect transaction prices per se, though they are often similar to contract prices (Thomschke, 2015).

There are some limitations for this type of data source. The immobilienscout24 data is dependent on the accuracy and honesty of the owner's portrayal and description of the dwellings. For example, not all possible features are included in the registration form. It is not known whether such missing values actually reflect a situation (e.g. no balcony), or whether the owner just did not want to or simply forgot to tick that box while filling in the immobilienscout24 registration form. In addition, the dataset included duplicates, as some owners and landlords register their dwelling more than once, possibly in order to get to the top of the hitlist. These duplicates were removed, as were implausible cases (e.g. small homes with 9 bathrooms). There might exist a self-selecting bias with regard to private providers or to younger user, as older people are sometimes not familiar with Internet platforms.

Based on the final dataset, we executed three separate regression analyses with housing prices as the dependent variable: one for owner-occupied houses, one for owner-occupied apartments and one for rental apartments (our sample did not include rental houses). The independent variables included dwelling characteristics, neighbourhood characteristics, location and accessibility characteristics (see [Table 1](#)).

Table 1. Dependent and independent variables for housing price analysis

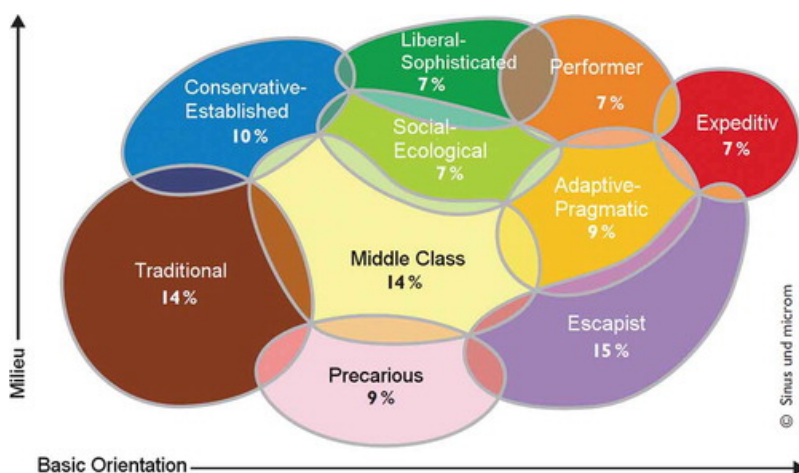


CSV Display Table

4.2.1. Calculation of the Geo-Milieu indicators

Data on socio-demographic and socio-economic characteristics of the inhabitants in combination with information on attitudes are combined to build different milieu characteristics. These can be used as an additional indicator for the neighbourhood characteristics. In this research we use the Sinus-Geo-Milieus® (Microm Website). These milieus are offered as a (marketing) tool for companies in order to identify different milieus, target groups or types of potential customers. Geomilieus provide an additional spatial information on where the milieu groups are located within a city or a region. They can also be used to characterize the types of neighbours within a residential area. The data consists of ten milieus, differentiated by a combination of socio-economic status and of attitudes/norms. These milieus represent groups of people who differ with regards to social status, family structure, age, house type, housing environment, car usage, consumption and purchasing power. However, one drawback of this data source is the lack of information on the exact procedures of data collection and of algorithms that form the basis of the ten geomilieu groups, as this is intellectual property of Microm. Figure 2 shows the location and relative size of the ten milieus. The milieus differ in terms of socio-economic status, ranging from low to high social/economic situation (social location on the vertical axis) and in terms of attitudes/norm (basic orientation on the horizontal axis). Attitudes range from traditional to modern. Appendix 1 offers a detailed description of the milieus.

Figure 2. Graphical representation of the ten Sinus-Geo-Milieus® (Source: adapted illustration based on Microm)



Display full size

Microm calculated the representation of these ten milieus for 6818 streets in Dortmund. In order to reduce complexity within the analysis, we regrouped the ten milieus (Figure 2) into five. Four milieus remained untouched: Traditional (Traditionelle), Precarious (Prekäre), Escapist (Hedonistische), Established Conservative (Konservativ-Etablierte). A new group ('Modern milieus group') was defined by combining the

based on all streets in the Microm sample within 400 m buffer of the dwelling.

4.2.2. Calculation of the adapted Walk Scores

The original Walk Score®⁶ measures the distance from a dwelling to the nearest amenity (park, bank, school etc.). The distance is entered into a polynomial distance decay function. Distances that are shorter than a quarter of a mile (approx. 400 m or a 5-minute walk) receive the highest possible score of 100. Distances, that are one-and-a-half miles or further (approx. 2.4 km or a 30-minute walk) receive the lowest possible score of zero. The score for each amenity type is weighted in a specific manner and all individual scores are summarized in the total Walk Score®. For example, restaurants and shopping locations have a higher weight as they are deemed to be more important than book stores or banks. In addition, variety and choice are important with regard to restaurants, shopping locations and coffee shops. Therefore, for these types of amenities multiple facilities are taken into account and the weight declines for every facility that is further away. For the total Walk Score®, street connectivity is also included, here a low intersection density and a high average block length are penalized at max. 5 % of the total Walk Score®.

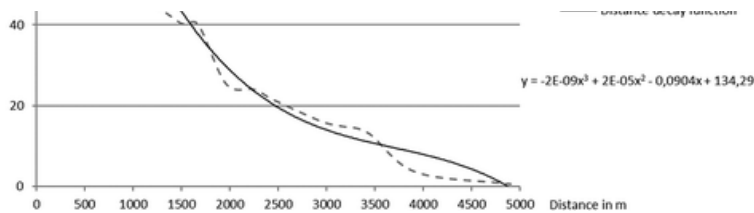
To a large extent, our own adapted Walk Score calculations resemble the original Walk Score® calculation, though with three modifications: first, we calculated separate adapted Walk Scores for the various amenity types, unlike the original one that bundles them into one final score. This allows to distinguish the influence of different types of amenities on housing prices. Second, we calculated a separate distance decay function for each amenity, as people are willing to walk for example further distances in order to access restaurants than for bakeries or kindergartens. Third, we calculated the adapted Walk Scores for a slightly different set of amenities due to data availability (see Table 1).

The separate distance decay functions are calculated based on empirical data that show the maximum walking distances for inhabitants of German cities. The underlying distances are derived from the dataset 'Mobility in Germany' (MiD, 2008). It contains one-week trip diaries of all household members of approx. 50 000 German households in 2008. In order to use data from cities that are similar to Dortmund, we only included those households that are located in West German cities with more than 100 000 inhabitants. For those household members we analysed the length of walking trips between the dwellings and different types of amenities. The accumulated trips were sorted by distance and formed the basis for the polynomial function. For every amenity a separate distance decay function was constructed. This analysis of actual walking behaviour revealed substantial differences in maximum walking distances for many types of amenities. Figure 3 shows an example of the cumulative values of the walking distances and the distance decay function for the amenity type restaurant.

Figure 3. Example of a polynomial distance decay function for walking distances to restaurants (Source: own calculation based on MiD, 2008)

Reprints & Permissions

PDF



Display full size

Next, we calculated the distance between every immobilienscout dwelling and the amenities using ArcGIS network analysis, based on the street network with sidewalks and footpaths of Dortmund (excluding motorways, trunk roads and similar ones that are restricted to motorized vehicles only).

The adapted Walk Score uses different search radiuses for different amenity types⁷ in accordance to the empirically derived walking distances. If amenities were present within the search radius, the walking distance to the closest facility was calculated by routing within Dortmund's pedestrian network. When the amenity was within a 400 m walking distance of the dwelling, the dwelling scored 100 points in the adapted Walk Score for that specific amenity. When it was further away, the distance decay function was used, with the adapted Walk Score diminishing accordingly (example see Figure 3). The adapted Walk Score is calculated as follows:

$$\text{Adapted Walk Score}_i = d_{ij} * f \quad (3)$$

where d_{ij} is the distance between the dwelling_i and the amenity_j and f the distance decay function. For restaurants, daily errands shops and other shops, the calculation of the adapted Walk Score differs, as we included the variety of restaurants and shops (in line with the original Walk Score®). Therefore, the adapted Walk Scores for these amenities are based on the ten closest facilities around the dwelling:

$$\text{Adapted Walk Score}_i = \sum_n^a \text{weight}_n (d_{ij} * f) \quad (4)$$

Each adapted Walk Score of the ten amenities was weighted⁸ according to distance, with amenities further away assigned lower weights. These weighted values were then summarised.

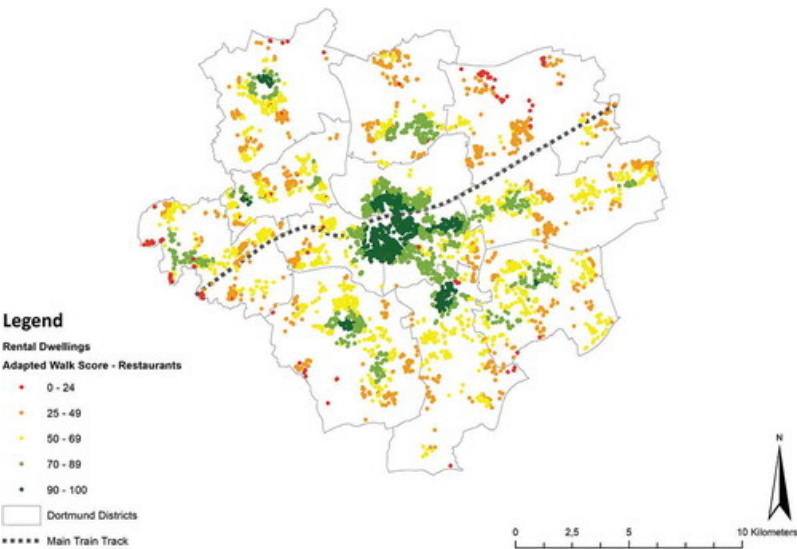
Finally, for both types of adapted Walk Scores, they are standardized into values from 0 (low adapted Walk Score) to 100 (high adapted Walk Score). We did not calculate a penalty for the variables 'block length' and 'intersection density' as it is done for North American cities, as Dortmund has a dense pedestrian network (Figure 4) and similar to other analyses in Germany a penalty is considered not to be necessary under these circumstances (Reyer, Fina, Siedentop, and Schlicht 2014; Siedentop, Roos, and Fina 2013). Also, no grid pattern exists and therefore average block length is not a suitable measure. For map representation

Figure 4. Pedestrian network in Dortmund (Source: own illustration based on OSM)



Display full size

Figure 5. Adapted Walk Score for restaurants (example: rental dwellings) (Source: own calculation)



Display full size

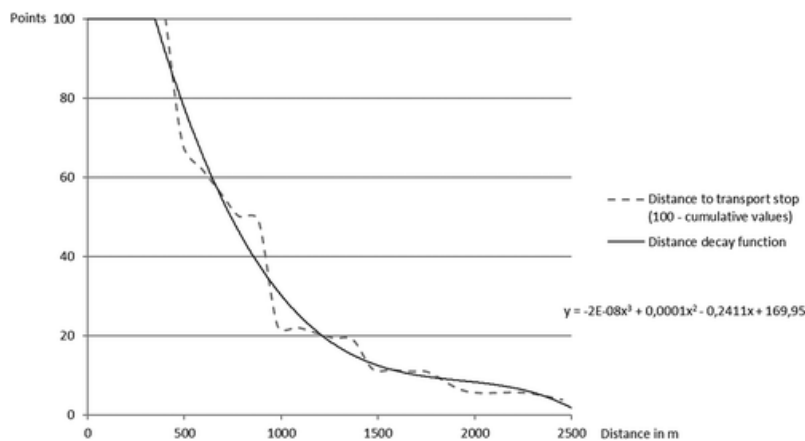
4.2.3. Calculation of the public transport indicators

In order to include the quality of services and the accessibility of public transport in relation to the dwelling, we used three different types of public transport indicators. Dortmund has a dense public transport network, in the analysis we distinguish between bus, underground/tram⁹, suburban/regional

In this article port hubs. The latter are transport stops that are served by two or more of the public transport.

to walk to a stop further away. For example, only 2.8 % of people were willing to walk to a stop 800 m away (Kickner, 1998). Similar to the adapted Walk Scores we base the distance decay function for public transport stops on empirical data derived from MiD 2008 (Figure 6).

Figure 6. Example of a polynomial distance decay function for walking distances to public transport stops (Source: own calculation based on MiD, 2008)



Display full size

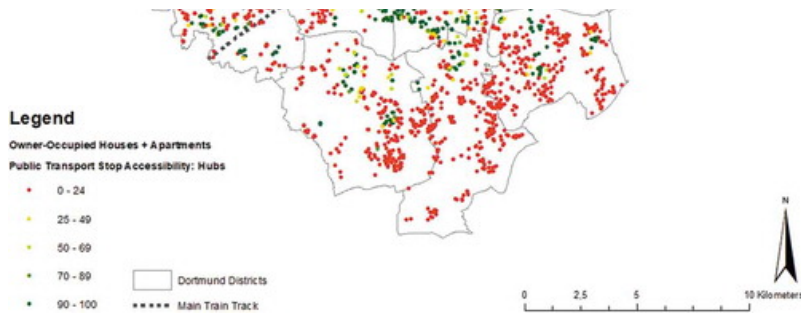
The indicator Public Transport Stop Accessibility is calculated separately for each of the closest stops of the four transport types. It indicates the distance from dwelling_i to the closest public transport stop_j of a specific type and uses the distance decay function f that is derived from MID data as described above:

$$\text{Public Transport Stop Accessibility}_i = d_{ij} * f \quad (5)$$

These results were standardized into values between 0 (low accessibility) and 100 (high accessibility). See as an example of the public transport stop accessibility for public transport hubs (Figure 7), where it is easy to switch between different public transport types. Here, the index values are classified into similar categories as the adapted Walk Scores. They represent situations between perfect accessibility or riders' paradise and no or minimal transport stop accessibility.

Figure 7. Public Transport Stop Accessibility for hubs (example: owner-occupied houses and apartments) (Source: own calculation)





Display full size

The indicator Public Transport Score incorporates the quality characteristics of the stop by including not only the distance to a specific stop but also the average departures per hour and the travel time to Dortmund city centre. It takes into account all stops of a specific type within an 800 m radius of the dwelling. In case several stops are served by the same line within this radius, only the nearest stop is included in the calculation.

$$Public\ Transport\ Score_i = \sum \left(\frac{departures\ per\ hour}{travel\ time\ to\ city\ centre} \right) * \frac{(d_{ij} * f)}{100} \quad (6)$$

The number of departures is the average number per hour between 08:00 am and 19:00 pm on weekdays. Travel time expresses the total travel time from this stop to one of the four stops demarcating the city centre¹⁰ and includes transfers. These public transport scores are standardized to obtain a value between 0 and 100. The function f is calculated the same way as for the other accessibility variables: distances below 400 m were assigned a value of 100, while between 400 m and 800 m the value is calculated with a distance decay function based on the probability of a person's willingness to walk to a stop (Kickner, 1998; MiD, 2008).

The accessibility of the motorway and trunk road network was included as an additional accessibility indicator. It was calculated as the travel time by car on the road network from dwelling to the closest access point. Dortmund has a dense motorway network (Figure 8) and in addition some main roads are included, as they are restricted to motorized vehicles only and are built in an almost motorway-like layout.

Figure 8. Motorway network and its access points (Source: own illustration based on OSM-data)





Display full size

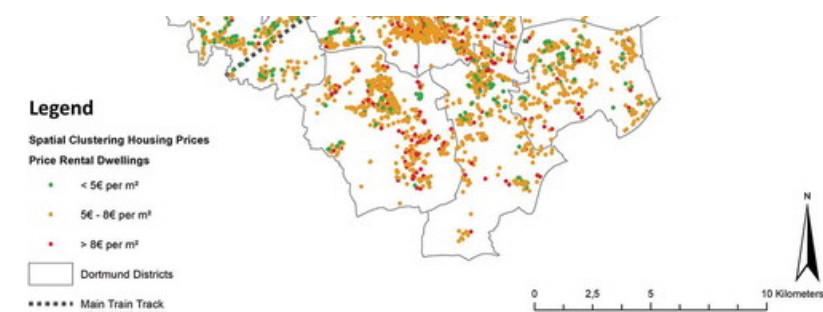
4.3. Indicators for spatial location and spatial cluster

4.3.1. Relative location variables

Two variables are used to describe the dwelling's relative location within the city (dummies for the administrative districts and a dummy for the broader area north of the main railway line). This decision is spurred by the fact that the dataset exhibits a spatial clustering of housing prices in specific areas. As Figure 9 shows, there is a marked cluster of low prices north of the main railway line. Such a division between north and south is quite common in many cities in the Ruhr area and reflects the history of settlement developments. Most of the old town centres are located to the south of the main train stations, while many industrial areas and their related housing developments are located to the north. Nowadays, many of these former working-class residential areas have a rather negative image, as is true for Dortmund and its 'Nordstadt' (Borstel & Fischer, 2016, City of Dortmund, 2018b; Peters, 2017). Therefore, we include the information whether the dwelling is located in this area, reflecting the widespread opinion in Dortmund that, when looking for a new place to live, the northern part of the city is only an option for those who can't afford to live in the southern part and that one 'doesn't want to live in the North'.

Figure 9. Spatial clustering of rental prices per m² in Dortmund (Source: own calculation based on immobilien Scout24-data)



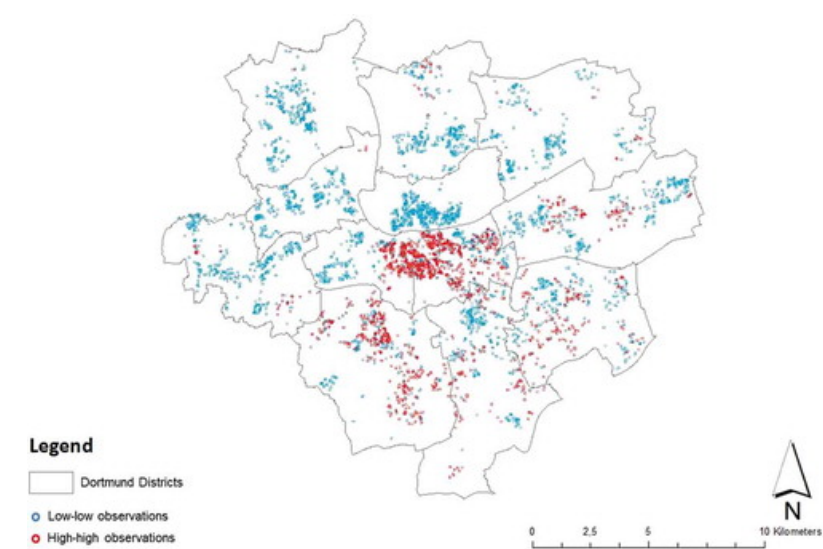


Display full size

4.3.2. Spatial cluster of auto-correlated dwellings

A first inspection of the data revealed that housing prices were indeed very much clustered and that residuals were spatially auto-correlated. We calculated average housing prices per square metre, comparing the value of a single dwelling with that at all other locations. Figure 10 shows two of the components of the spatial auto-correlation analyses for rental dwellings. The blue dots portray dwellings with below-average prices and with neighbours also with below-average prices (low-low observations). The red dots indicate above-average dwellings with above-average neighbours as well (high-high observations).

Figure 10. Spatial distribution of rental housing price observations (Moran's I) (Source: own calculation based on immobilien Scout24-data)



Display full size

These results indicate clusters of similar housing prices within Dortmund, but also differences. We therefore used spatial regression modelling to further analyse explanatory variables and their influence on housing prices within the city and present the results in the next section.

occupied apartments and rental apartments). When a spatial lag model is significant, the observations of the dependent variable – housing prices – are affected by nearby housing prices. The distance weight determines which dwellings are considered as neighbours, thus possibly influencing a dwelling’s price. In our analysis we used a distance band of 500 m, which is the distance that ensures that each dwelling has at least one neighbour.

To identify the most important and also the most suitable independent variables for the final models, we first checked the data for multicollinearity and removed one of the partners of highly-correlated variables. Secondly, only those variables with a significance level of <0.1 were included in the models. For example, public transport indicators showing the mere presence of a transport stop or the accessibility of different stops were therefore not included in the analysis. Table 2 shows the regression results of both the OLS models and the spatial lag models separately for owner-occupied houses, owner-occupied apartments and rental apartments. The coefficient, t-values and z-values respectively and significance are presented for each independent variable, but the input variables differ to some extent between the models. Due to the different types of regression calculation, it is not possible to directly compare the explained variation of the models by using adjusted R-squares, as the R² of the spatial lag model is a pseudo-R². In addition, we used the log likelihoods, Akaike info criterion and Schwarz criterion to compare the two models.

Table 2. Parameter estimation for residential housing prices


CSV

Display Table



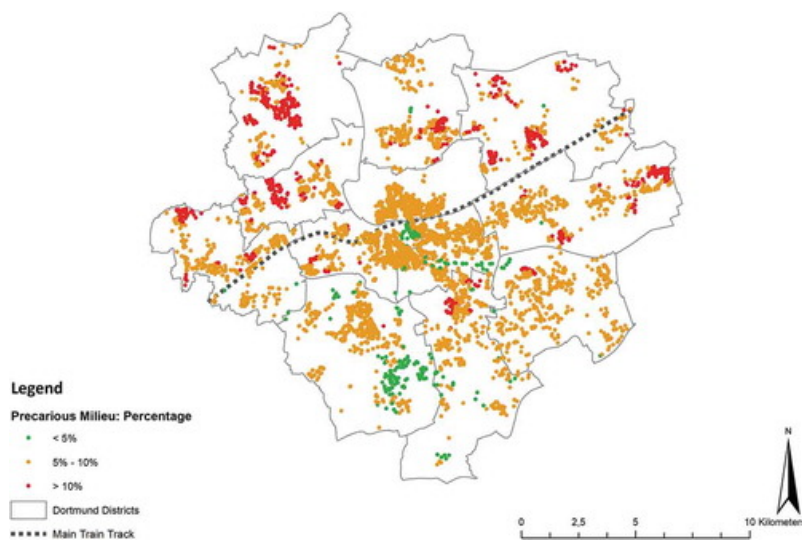
The OLS regression analyses revealed several major factors determining housing prices in Dortmund for the three types of dwellings. The model fits are acceptable, with owner-occupied apartments showing the highest values. In addition to the variables that were included in the OLS models we introduced the spatial lag term into the spatial lag model to test whether house prices were also affected by the price of neighbouring dwellings. The inclusion of the spatial lag term improved the model fit for all three types of dwellings, as it is shown by changes of the log likelihoods, the Akaike info criterion and Schwarz criterion. For all three types of dwellings we found a significant effect. For example, prices of owner-occupied houses could be expected to increase by approximately 0.2 € per m² when prices of neighbouring houses increase by 1 € per m². As expected, the inclusion of the prices of neighbouring dwellings also changed the coefficients (mostly decreasing) and some variables show a slight reduction of significance levels.

In both regression types, the variables are significant and the effects point in the expected direction. The condition of dwellings shows comparatively high coefficients compared with the other independent variables. For example, a newly built or recently renovated apartment had a m² price tag 443 € higher (OLS model; 412 € spatial lag model). The number of rooms was also important, though the relation was

In this article pes: the more rooms, the lower the price. The size of the living area was positively using price, but proved to be relevant only for owner-occupied apartments.

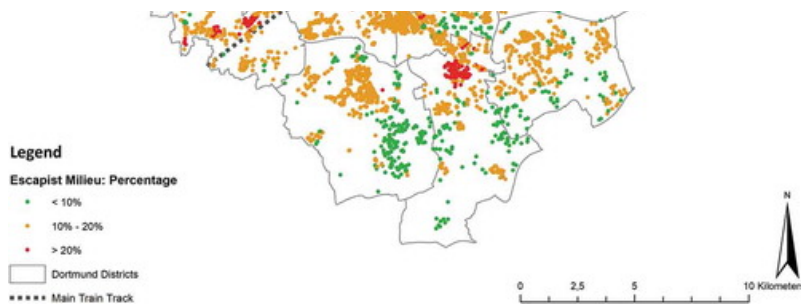
neighbours who belong to the Modern milieus group correlated with higher housing prices, whereas higher percentages of Precarious milieus correlated with lower housing prices (the latter is described as fun-oriented low class and lower middle class). In addition, for owner-occupied apartments the level of Escapist milieus was also important: one additional standard deviation of the percentage of Escapist milieus lowered the m^2 price for owner-occupied dwellings by 150 € (OLS model; –120 € spatial lag model). Figures 11 and 12 show the spatial distribution of different levels of Precarious and Escapist milieus, with low levels of Precarious and Escapist milieus in the southern part of the city, but higher levels in the northern part. There is also a spatial concentration of these two milieus in a more densely populated subcentre located in the northern part of Hörde (one of the administrative districts, located in the southern part of Dortmund).

Figure 11. Percentage of Precarious milieu (Source: own calculation based on Microm)



[Display full size](#)

Figure 12. Percentage of Escapist milieu (Source: own calculation based on Microm)


[Display full size](#)

The relative location of the dwelling within the city can be characterised by its associated administrative district. Of the 12 Dortmund districts, only Hombruch in the south-western part of the city had a relevant influence, but only for prices of owner-occupied houses. Here, m² prices increase by 254 € (OLS model) compared to the rest of the city (spatial lag model: 212 €). The rather broad relative location variable describing whether the dwelling was located in the northern part of the city had a strong but negative influence on the prices of both owner-occupied houses and rental dwellings.

Accessibility indicators are relevant in all three dwelling type models and they correlate to residential housing prices. Here, adapted Walk Scores, public transport indicators and drive time to motorway access points varied in importance depending on the types of dwelling. Travel minutes to the next motorway access point were significantly correlated only to the prices of owner-occupied houses, where higher prices were found for houses located further away from the motorway (OLS: 54 €, spatial lag 45 €). Of the various public transport indicators, accessibility to and quality of bus stops and public transportation hubs were factors positively correlated in explaining housing prices, but to a lesser extent. Higher public transport scores for hubs positively affected prices for both owner-occupied apartments and rental apartments, but not for owner-occupied houses. For those dwellings, public transport scores for buses were also relevant. For all three types of dwellings, one or more of the adapted Walk Score variables turned out to be significantly correlated to housing prices, namely those for parks/green spaces, for kindergartens and for restaurants. Good adapted Walk Scores for restaurants had a positive effect on both types of apartments, while good adapted Walk Scores for parks/green spaces positively affected owner-occupied houses. By contrast, adapted Walk Scores for kindergartens had negative correlations but only for owner-occupied houses and rental apartments.

6. Discussion and conclusion

The classical estate agent phrase 'location, location, location' has once again proved to be a key factor explaining residential property prices. However, our research showed that 'location' encompasses not only the environment of the dwelling in the classical sense, i.e. class of neighbours, presence and accessibility

to transport and motorway accessibility. In addition, the price of neighbouring apartments was a significant determinant of housing prices. This finding calls for the use of a spatial lag term denoting the importance of

apartment models. One explanation might be that such apartments in Dortmund are concentrated in areas with rather homogenous building structures. Apartment buildings with several apartments of the same size and with the same layout are quite easy to compare. Renters would possibly not accept a substantially higher rent for an apartment that is no different from neighbouring ones in size, layout, condition and level of luxury.

As expected, the most important factors are directly related to the dwellings condition, irrespectively of the type. A somewhat unexpected result is the negative effect of additional rooms. Possibly, fewer but larger rooms – a trend that can be observed for newly built and modern dwellings, are more attractive to owners and tenants. Also, kitchen and bathroom need to be provided anyway and these rather expensive parts of a dwelling represent a smaller percentage when it comes to large dwellings. Unfortunately, data on the presence and size of a garden/balcony – features also expected to have an effect on housing prices – could not be included in our analyses due to the large number of missing values in these data categories.

The accessibility of the dwelling is also a relevant factor, the inclusion of accessibility indicators complements the discussion on residential housing prices. Moreover, our research shows that a specific type of accessibility is related to housing prices, at least in Dortmund: not the mere presence of a public transport stop in the vicinity of a dwelling, but a combination of accessibility and quality of the service seems to be relevant when public transport indicators are to be included in similar analyses. Furthermore, it is not just any kind of public transportation that matters but rather the multimodal hubs, at least for centrally located dwellings. As houses are less often located close to the city centre and are therefore often served only by bus with often longer travel times, these findings are not unexpected. For owner occupied houses, further distances to motorways seem to increase the prices. This might indicate that people prefer a quiet residential area over motorway accessibility. This would be not surprising, given the fact that Dortmund has a dense network of arterial roads and motorways, meaning that a motorway access point is never far away.

Our research also shows that services within walking distance of the dwelling are important. However only two amenities correlate in a positive way with housing prices: restaurants and parks. Clustering all amenities into one comprehensive Walk Score, as done by the original Walk Score®, may lead to information loss and thus mask the true relationships between walkable amenities and housing prices. When we tested these aggregated Score, i.e. the average of all ten individual Scores, this variable was negatively related to housing prices, meaning that higher housing prices were found in areas with lower accessibility. These findings might also correlate with the above mentioned densely populated low-price areas that are located close to the city centre and some sub-centres in Dortmund, where accessibility is rather high. The adapted Walk Scores deviate from the original in not using a penalty for large block length. A dense pedestrian network is vital for a good connectivity and greatly increases walkability of an area. In Dortmund, almost every street is accompanied by pedestrian sidewalks. There are plenty of small

In this research, we could show the effect of the neighbours on residential housing prices by including levels of certain geo-milieu groups who live in close proximity of the dwellings. But the question remains whether housing prices are low because of the Precarious and Escapist milieus (both lower-class) or whether the low prices attract more people who belong to milieus not richly endowed with financial resources. As mentioned above, the city's historical development and the image of these areas could indicate a possible answer. Most of the former steel industry areas were located in the northern part of the city and in Hörde. There, low standard houses were built for workers and their families, many of whom came from abroad. Nowadays, low-income, partly ethnic households can still be found in those rather low-maintained and unattractive housing areas. They correlate with the spatial concentrations of Precarious and Escapist milieus, partly due to historical developments and path dependency, and partly as a result of the negative image accompanying such a socio-demographic concentration of lower income groups and thus probably reinforcing this pattern. The relative location northern city also reduces prices for owner-occupied houses (as well as rental apartments). We assume that bad image plays an important role in addition to the condition of the dwelling itself. People, who buy a house, are often going to invest in it. If they intend to upgrade the house anyway, other variables – such as image of the neighbourhood – could become more important than the condition the house is currently in.

The variable indicating the location of the dwelling in the northern part of the city turned out to be an important variable and these findings can only be understood by considering the city's historical development. It would be interesting to see whether a similar variable co-explains differences in housing prices in other former industrial cities as well. This relationship would have been overlooked, had we not taken a look at the spatial distribution of the residuals of our original OLS regression model. It is therefore advisable to plot the residuals in spatial analysis software to see whether they are spatially clustered. To summarize we set out to test two different aspects found to be relevant for explaining differences in housing prices in addition to classic location and dwelling related variables. The results show, that in order to explain residential house prices, accessibility should be included in a differentiated way. Simple presence or absence e.g. of transport stops or aggregate amenities are not sufficient. Also, the spatial lag model and the consideration of neighbouring house prices leads to a more precise understanding of the effects and a better model fit.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

In this article



◻ zirk: Smallest statistical/administrative unit, there are 170 sub-districts in
 ◻ rage surface area of 1.65km².

3. Including shops for clothing, shoes, electronics, photo equipment, home utensils and decoration, furniture, orthopedic/medical needs, toys and hobby products, sport and recreational products.

4. Kassenärztliche Vereinigung Westfalen-Lippe.

5. Apothekerkammer Westfalen-Lippe.

6. The Walk Score® Methodology is described in a white paper (Walk Score® Methodology, [2011](#)).

7. 1000 m: Playgrounds, 1500 m: Kindergarten, 2000 m: General practitioner (GP), 2500 m: Daily needs, 3000 m: Elementary school; Banks and cash machines, 4000 m: Pharmacy/Shopping, 5000 m: Restaurants, 6000 m Park/Green space.

8. Weights of 0.25; 0.15; 0.083; 0.083; 0.075; 0.075; 0.075; 0.075; 0.067; 0.067.

9. Dortmund is served by a light rail system, where underground stations exist in the city centre. The network continues and is served outside the centre as a tram. Above ground, tracks and stops differ (separated tracks/stops vs. street-level tracks/stops, depending on the available space and layout).

10. m

ain station/Hauptbahnhof, Kampstrasse, Reinoldikirche, and Stadtgarten.

References

1. Adair, A. , McGreal, S. , Smyth, A. , Cooper, J. , & Ryley, T. (2010). House prices and accessibility: The testing of relationships within the Belfast urban area. *Housing Studies* , 15(5), 699–716. [\[Taylor & Francis Online\]](#), [\[Google Scholar\]](#)
2. Albrecht, V. (2010). *Auswirkungen von urbanen Schieneninvestitionen auf den Wohnungsmarkt* . (Dissertation an der Bergischen Universität Wuppertal), Solingen. [\[Google Scholar\]](#)
3. Alonso, W. (1964). *Location and land use. Toward a general theory of land rent* . Cambridge, London: Harvard University Press (Publications of the Joint Center for Urban Studies of the Massachusetts Institute of Technology and Harvard University). doi:10.4159/harvard.9780674730854 [\[Crossref\]](#), [\[Google Scholar\]](#)
4. Anderson, S. T. , & West, S. E. (2006). Open space, residential property values, and spatial context. *Regional Science and Urban Economics* , 36(6), 773–789. [\[Crossref\]](#), [\[Web of Science ®\]](#), [\[Google Scholar\]](#)

In this article *patial econometrics: Methods and models* . Dordrecht: Springer. doi:10.1007/978-94-
 :fl. [\[Google Scholar\]](#)

7. Borstel, D. , & Fischer, U. L. (ed.). (2016). *Stadtgeschichten - Soziales Dortmund im Spiegel von Biografien* . Wiesbaden: Springer VS. doi:10.1007/978-3-658-11498-5 [\[Crossref\]](#), [\[Google Scholar\]](#)
8. Bourne, L. (1981). *The geography of housing* . New York: Halsted Press. doi:10.1111/1540-6229.00380 [\[Crossref\]](#), [\[Google Scholar\]](#)
9. Bowes, D. R. , & Ihlanfeldt, K. R. (2001). Identifying the impacts of rail transit stations on residential property values. *Journal of Urban Economics* , 50(1), 1–25. [\[Crossref\]](#), [\[Web of Science ®\]](#), [\[Google Scholar\]](#)
10. Boyle, A. , Barrilleaux, C. , & Scheller, D. (2014). Does walkability influence housing prices? *Social Science Quarterly* , 95(3), 852–867. [\[Crossref\]](#), [\[Web of Science ®\]](#), [\[Google Scholar\]](#)
11. Bucksch, J. , & Schneider, S. (ed). (2014). *Walkability - Das Handbuch zur Bewegungsförderung in der Kommune* . Bern: Huber. [\[Google Scholar\]](#)
12. Cervero, R. , & Landis, J. (1995). Development impacts of urban transport: A US perspective. In D.Banister (Ed.), *Transport and urban development* (pp. 136–156). London: E & FN Spon. [\[Crossref\]](#), [\[Google Scholar\]](#)
13. Cervero, R. , & Duncan, M. (2004). Neighbourhood composition and residential land prices: Does exclusion raise or lower values? *Urban Studies* , 41(2), 299–315. [\[Crossref\]](#), [\[Web of Science ®\]](#), [\[Google Scholar\]](#)
14. City of Dortmund . (2015). Phoenix Dortmund – Der Zukunft einen Standort geben. Retrieved from <http://www.phoenixdortmund.de/de/home/index.html> [\[Google Scholar\]](#)
15. City of Dortmund . (2016). *Jahresbericht dortmunderstatistik 2016* . Stadt Dortmund. [\[Google Scholar\]](#)
16. City of Dortmund . (2017). *Wohnungsmarktbericht 2017 – Ergebnisse des Wohnungsmarktbeobachtungssystems 2016* . Dortmund: Stadt Dortmund, Amt für Wohnungswesen. [\[Google Scholar\]](#)
17. City of Dortmund . (2018a). *Wohnungsmarktbericht 2018 – Ergebnisse des Wohnungsmarktbeobachtungssystems 2017* . Dortmund: Stadt Dortmund, Amt für Wohnungswesen. [\[Google Scholar\]](#)

19. Cohen, J. P. , & Coughlin, C. C. (2008). Spatial hedonic models of airport noise, proximity, and housing prices. *Journal of Regional Science* , 48(5), 859–878. [\[Crossref\]](#), [\[Web of Science ®\]](#), [\[Google Scholar\]](#)
20. Connective Cities . (2018). Revitalising a steel production site - The Phoenix Mega-Project in the City of Dortmund. Retrieved from <https://www.connective-cities.net/en/good-practice-details/gutepraktik/revitalisierung-eines-stahlstandortes> [\[Google Scholar\]](#)
21. de Meulen, A. , & Mitze, T. (2014). Exploring the spatial variation in quality-adjusted rental prices and identifying hot spots in Berlin ´s residential property market. *Regional Studies, Regional Science* , 1(1), 310–328. [\[Taylor & Francis Online\]](#), [\[Google Scholar\]](#)
22. Debrezion, G. , Pels, E. , & Rietveld, P. (2006). The impact of rail transport on real estate prices: An empirical analysis of the Dutch housing market. Tinbergen Institute Discussion Paper, No. 06-031/3. doi:10.2139/ssrn.895270 [\[Crossref\]](#), [\[Google Scholar\]](#)
23. Dubin, R. A. (1992). Spatial autocorrelation and neighborhood quality. *Regional Science and Urban Economics* , 22(3), 433–452. [\[Crossref\]](#), [\[Web of Science ®\]](#), [\[Google Scholar\]](#)
24. Frank, L. D. , Sallis, J. F. , Conway, T. L. , Chapman, J. E. , Saelens, B. E. , & Bachman, W. (2006). Many pathways from land use to health: Associations between neighborhood walkability and active transportation, body mass index, and air quality. *Journal of the American Planning Association* , 72(1), 75–87. [\[Taylor & Francis Online\]](#), [\[Web of Science ®\]](#), [\[Google Scholar\]](#)
25. Geurs, K. T. , & van Wee, B. (2004). Accessibility evaluation of land-use and transport strategies: Review and research directions. *Journal of Transport Geography* , 12(2), 127–140. [\[Crossref\]](#), [\[Google Scholar\]](#)
26. Gilderbloom, J. I. , Riggs, W. , & Meares, W. L. (2015). Does walkability matter? An examination of walkability's impact on housing values, foreclosures and crime. *Cities* , 42(Part A), 13–24. [\[Crossref\]](#), [\[Google Scholar\]](#)
27. Heikkila, E. , Gordon, P. , Kim, J. I. , Peiser, R. B. , Richardson, H. W. , & Dale-Johnson, D. (1989). What happened to the CBD-distance gradient? Land values in a policentric City. *Environment & Planning A* , 21(2), 221–232. [\[Crossref\]](#), [\[Web of Science ®\]](#), [\[Google Scholar\]](#)
28. Henneberry, J. (1998). Transport investment and house prices. *Journal of Property, Valuation and Investment* , 16(2), 144–158. [\[Crossref\]](#), [\[Google Scholar\]](#)

37. MiD . (2008). Website. Retrieved from <http://www.mobilitaet-in-deutschland.de/mid2008-publikationen.html> [Google Scholar]

42. Rosen, S . (1974). Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of Political Economy* , 82(1), 34—55. doi:10.1086/260169 [Crossref], [Web of Science ®], [Google Scholar]
43. Siedentop, S. , Roos, S. , & Fina, S . (2013). *Ist Die „Autoabhängigkeit“ Von Bewohnern Städtischer Und Ländlicher Siedlungsgebiete Messbar? Raumforschung Und Raumordnung* , 71(4), 329–341. doi:10.1007/s13147-013-0240-0 [Crossref], [Google Scholar]
44. Song, Y. , & Knaap, G.-J. (2004). Measuring the effects of mixed land uses on housing values. *Regional Science and Urban Economics* , 34(6), 663–680. [Crossref], [Web of Science ®], [Google Scholar]
45. Stieringer, K. (2014). *Der SPNV als Erfolgsfaktor bürogenutzter Immobilien? Wechselwirkung zwischen der Anbindung an den schienengebundenen öffentlichen Nahverkehr (SPNV) und dem Mietpreis von Büroimmobilien – Eine hedonische Analyse* . (Dissertation an der Bergischen Universität Wuppertal), Karlsfeld. [Google Scholar]
46. Thomschke, L. (2015). Changes in the distribution of rental prices in Berlin. *Regional Science and Urban Economics* , 51, 88–100. [Crossref], [Web of Science ®], [Google Scholar]
47. van der Vlugt, A.-L. , Curl, A. , & Wittowsky, D. (2019). What about the people? Developing measures of perceived accessibility from case studies in Germany and the UK. *Applied Mobilities* , 4(2), 142–162. [Taylor & Francis Online], [Google Scholar]
48. Walk Score® Methodology . (2011, July 15). Walk Score Methodology, White Paper. Retrieved from <http://pubs.cedeus.cl/omeka/files/original/b6fa690993d59007784a7a26804d42be.pdf> [Google Scholar]
49. Walk Score® Website . Walk Score Methodology with Walk/Bike/Transit Score descriptions. Retrieved from <https://www.walkscore.com/methodology.shtml> [Google Scholar]
50. Ward, M. D. , & Gleditsch, K. S. (2008). *Spatial regression models. Series: Quantitative applications in the social sciences* (pp. 155). Thousand Oaks, California: Sage. doi:10.4135/9781412985888 [Crossref], [Google Scholar]
51. Weibull, J. W. (1980). On the numerical measurement of accessibility. *Environment & Planning A* , 12(1), 53–67. [Crossref], [Web of Science ®], [Google Scholar]

accessibility indexing model. *Australian Planner* , 44(3), 30–37. [Taylor & Francis Online], [Google Scholar]

Appendix 1. Description of Sinus- Milieus®

Table

CSV Display Table



Related articles

People also read Recommended articles Cited by 5

Developing a tool for assessing park-and-ride facilities in a sustainable mobility perspective >

Aud Tennøy et al.
Urban, Planning and Transport Research
Published online: 26 Nov 2019



In support of sustainable densification in urban planning: a proposed framework for utilising CCTV for propagation of human energy from movement within urban s ... >

Emil Jonescu et al.
Urban, Planning and Transport Research
Published online: 18 Dec 2019



Urban structure and its influence on trip chaining complexity in the Mexico City Metropolitan Area >

Dorian Bautista-Hernández
Urban, Planning and Transport Research
Published online: 30 Dec 2019



View more

Reprints & Permissions PDF

Editors

Librarians

Societies

Help and info

Help & contact

Newsroom

Commercial services

Advertising information

All journals

Books

Open journals

Open Select

Cogent OA

Dove Medical Press

F1000Research

Keep up to date

Register to receive personalised research and resources by email

Sign me up

Facebook

Twitter

LinkedIn

YouTube

ResearchGate

Settings