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What Would Households Pay for a Reduction of Automobile Traffic? Evidence From Nine German Cities

Nicolas Wellmann* Daniel Czarnowske †

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Abstract

This paper quantifies the marginal willingness to pay for a reduction of automobile traffic. By using a new structural approach in a hedonic framework by Bishop and Timmins 2019 we are able to avoid common issues in hedonic studies using instrumental variables. Our analysis is based on data from nine large cities in Germany between 2016 and 2019 and includes 533,402 detailed observations at the apartment level as well as for various points of interest. To the best of our knowledge this is the first paper to conduct this analysis for Germany. We estimate that the average willingness to pay for a reduction of traffic by city and per year ranges between €30.3–59.2 for a 10% reduction, €93.8–158.3 for a 20% reduction and €190.6–252 for a 30% reduction. The highest willingness to pay for a reduction of traffic is observed in Frankfurt am Main, the lowest in Leipzig. Further, we compute the expected gains for a reduction of traffic at the city level. In addition to the willingness to pay for a reduction of traffic, this considers the composition of the road network as well as for the number of households. Accordingly, these expected gains amount to €163,970–1,019,454€ for a 10% reduction, €484,023–3,261,837 for a 20% reduction, and €1,018,240–6,727,148 for a 30% reduction. The highest expected gains for a reduction of traffic is observed in Munich, the lowest in Leipzig.

JEL Classification: O18, Q51, R48
keywords: willingness to pay, traffic, air pollution, hedonic price models, rent prices, environmental policy

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1 Introduction

The past century can be seen as the golden age for automobiles. By offering consumers the option to travel anywhere, any time, automobiles quickly became not only a symbol of freedom but also a status symbol in society (Gartman 2004). Today, the automobile is a mass produced product. In Europe an average of five out of 10 persons own an automobile (Eurostat 2019) while in the US around eight out of 10 people are automobile owners (Davis and Boundy 2019). However, traveling by car is not only convenient, it is also important for economic reasons. For example, 86% of the US workforce use their automobile to commute to work (United States Census Bureau 2017). The popularity of automobiles is also reflected in the infrastructure of many cities in the US and Europe, which are adapted to the needs of automobile drivers: On streets, typically a major share of the lanes is dedicated to automobiles, while only a minor share of the space is allocated to pedestrians and cyclists. The timing of traffic signals is optimized for a continuous flow of automobiles, also known as the 'green wave.' In Germany construction law contributes to a continuous growth of parking lots, by regulating the minimum number of parking lots for residential buildings and other facilities (e.g., LBO Baden Württemberg 2019).

Over the course of time the positive image of automobiles has faded and automobiles are looked at more critically in society. Their emissions are known to cause significant harm to human health but also to the environment. This includes air pollution like particulate matter, nitrogen dioxide, carbon dioxide, black smoke, benzene, ozone, polycyclic aromatic hydrocarbons or lead. Evidence suggests that air pollution raises the risk of cardiopulmonary causes, heart attacks, cancer, allergies, asthma attacks (WHO 2005, p. 125, 126), and infant mortality (Knittel et al. 2016), and also lowers cognitive performance (Shehab and Pope 2019). For example, in the US, the UK, and Germany emissions from land traffic account for around 20% of the mortality by ambient particulate matter and ozones.[1] Carbon dioxide emissions from automobiles contribute to global warming and climate change (Houghton 1996). In the EU 21% of total carbon dioxide emissions originate from automobiles (Commission 2019b). Estimates suggest that damages from climate change will amount to at least €190 billion in the EU if no further

[1]Number refers to particular matter smaller than 2.5 micrometers.

actions are taken (Carlos et al. 2014). Finally, noise emissions are not only found to increase the occurrence of stress and depression but they also lower well-being in general (Gee and Takeuchi 2004).

Besides air pollution, automobile traffic is associated with various effects which harm public health. Road crashes kill 94,500 people in high income countries every year.[2] Approximately 50% of these crashes affect vulnerable road users like cyclists or pedestrians. For children and young people road crashes are particularly an issue, as this is the leading cause of death of those aged between five to 29 (WHO 2018). Delays by traffic jams are not only costly (EU: nearly € 100 billion annually), there is also evidence that extreme congestions may increase domestic violence (Beland and Brent 2018). Using an automobile instead of other more active transportation alternatives bears significant opportunity costs as it raises obesity. In the OECD, overweight and related diseases reduce the GDP, on average, by 3,3%, cost 92 million lives, and will lower life expectancy by nearly three years by 2050 (OECD 2019).

To reduce damages to health and the environment from automobiles in Europe, different regulations have been put in place in Europe. This includes taxes on CO2-based motor vehicles, gasoline, and various restrictions to reduce inner-city traffic at the local level. For example, various metropolis like London, Oslo, Stockholm or Mailand, which have been naturally plagued by excessive traffic, have introduced congestion prices. These prices typically range between €5 and €10 per day and are usually differentiated by criteria such as vehicle size, time or engine type (Urban Access Regulation 2019). With the EU directive for clean air, air pollution has become a much discussed topic also beyond the metropolis. This EU directive aims to reduce air pollution by 2020 below the threshold where it significantly affects human health and the environment. Today, 227 cities in seven European countries have created low emission zones to restrict access to cities for automobiles above a certain emission threshold.[3] In Italy, 306 cities have restricted traffic in various districts to residents only. Other regulations include the ban of lorries in the city or prohibited access for all automobiles (Urban Access Regulation 2019).

[2] Countries are classified as high-income countries in this study if their gross national income per capita exceeds US $12,235.

[3] Namely these countries are: Germany, Italy, Netherlands, Belgium, Denmark, Norway and the UK.

However, despite the measures taken by various cities a number of countries in the EU have failed to comply with the EU directive for clean air. As a consequence, the European Commission has taken these countries to the EU court of justice (Commission 2019a, Commission 2018). Among those countries which have violated the EU directive for clean air is Germany. Despite an emergency program[4] by the German government, 57 cities exceeded the critical value for nitrogen oxide in 2018 (Umweltbundesamt 2019).

The aforementioned damages can be considered as externalities from automobile traffic and thus it is important to address these in regulation policy. Since their actual costs from consumption are not incorporated in prices for consumers, there will be excess consumption absent regulation. However, addressing this topic appropriately in regulation policy is a challenging task as it is closely linked to questions of social justice. Ignoring the social implications of environmental policies can lead to a strong public backlash, as recently observed in France. As part of its environmental policy to reach carbon neutrality by 2050, the French government had planned to raise fuel taxes in 2018 by €7.6 cents per litre diesel and €3.9 cents per litre petrol (Republique Français 2018 Republique Français 2017). However, given that fuel prices at that time period were already on a high level, this lead to protests by more than 280,000 people and gave rise to the 'yellow-vest' protest movement. In consequence, the French government had to postpone the increase of fuel taxes and promised various tax reliefs worth more than €10 billion in order to tame the tensions (Economist 2019, Economist 2018).

This paper estimates the marginal and non-marginal willingness to pay for a reduction of traffic. Using a novel estimation approach and a very detailed dataset, it contributes to the political debate by indicating to what extend consumers value political efforts for traffic reductions. In detail, we make use of 533,402 observations which were collected between October 2016 and December 2019 in nine German cities and match these with data from Openstreetmap on street characteristics. For the estimation, we use a novel approach by Bishop and Timmins (2019) which allows us to determine the marginal and non-marginal willingness to pay without instrumental variables and their associated estimation biases, while making use of only moderate econometric assumptions. In our analysis we are able to control for

[4]Among others, this program includes subsidies for cars and electric bikes and the expansion of cycle networks.

a number of apartment characteristics as well as various location-specific variables. Specifically, we consider for each apartment the minimum distance to various shops, amenities and to the city center.

Our findings suggest that, after controlling for rich apartment characteristics, traffic from automobiles significantly affects apartment prices in cities and that consumers have a positive willingness to pay to reduce traffic from automobiles. We estimate that the non-marginal willingness to pay for a reduction of traffic per household and year ranges by city between €30.3–59.2 for a 10% reduction, €93.8–158.3 for a 20% reduction, and €190.6–252€ for a 30% reduction. The highest non-marginal willingness to pay for a reduction of traffic is observed in Frankfurt am Main, the lowest in Leipzig. Moreover, we compute the expected gains for a reduction of traffic at the city level. In addition to the non-marginal willingness to pay for a reduction of traffic, this considers for the composition of the road network as well as for the number of households. Accordingly, these expected gains amount between €163,970–1,019,454 for a 10% reduction, €484,023–3,261,837 for a 20% reduction and €1,018,240–6,727,148 for a 30% reduction. The highest expected gains for a reduction of traffic is observed in Munich, the lowest in Leipzig. This is also relevant for the current debate of regulation is able to meet the environmental goals which are currently discussed.

The remainder of the paper is organized as follows: Section 2 introduces our econometric model, describes the necessary assumptions which have been made and the estimation procedure. Section 3 gives an overview of our data set and provides various descriptive statistics of the variables which are used in the further analysis. Section 4 presents our estimates for the marginal and non-marginal willingness to pay as well as the expected gains for exemplary traffic reductions. Section 5 discusses the allocative and distributive effects of a policy intervention. Section 6 concludes.

2 Econometric Model

Estimating the willingness to pay to reduce traffic is not straightforward, as traffic is not a good which is publicly traded in the market. One opportunity to address this issue are hedonic price models which determine the implicit price of a product based on product characteristics. Compared to other valuation methods hedonic price models have several advantages as their analysis is typically based on observed rather than stated preferences. First, this means that data is gathered from actual consumption decisions as observed in the market and not a hypothetical setting (e.g., in surveys). Second, it allows us to study the consumption decision in the context of other variables, which typically confound the decision making e.g. apartment characteristics. Third, the number of observations can be easily scaled in the analysis, while this can become fairly costly in surveys (Baranzini et al. 2008, p. 4).

Rosen (1974) proposed a structural framework for hedonic price models to estimate the marginal willingness to pay of consumers for a differentiated good.[5] His approach consists of a two-step procedure in which the price of a good is first regressed on its characteristics. Then the marginal price of the characteristic of interest is computed for each unit of observation and then regressed against a set of supply and demand shifters, respectively, to infer the marginal willingness to pay. A particular strength of the model is that it allows us to compute the effect of a non-marginal policy change on consumers' marginal willingness to pay (Bishop and Timmins 2019).

A well-known drawback of the approach from Rosen (1974) is that the estimation gives rise to multiple endogeneity problems. One source may originate from the classical endogeneity problem in markets: The marginal hedonic price for a product characteristic is determined by the interaction of supply and demand. Bartik (1987) and Epple (1987) stress another source of endogeneity which may arise from the non-linear hedonic price function. This allows consumers to endogenously choose the prices and quantities of a characteristic. In consequence, the choice of both price and quantity of a product characteristic is influenced by unobserved taste preferences. For example, consumers with a higher preference for a specific characteristic will also consume more of it. Different suggestions have been made to address the endogeneity problems in Rosen's model with instrumental variables. But given that the variables of interests are determined in an equilibrium model, it is far from trivial to find valid instruments.

For example Kahn and Lang (1988) suggest exploiting variations in the distribution

[5] Previous work on hedonic price models has been done, for example, by Lancaster (1966) or Griliches (1961).

of firms and consumers between markets as these are likely to be independent of supply and demand equations. Though this does not only require homogeneity of preferences across markets, it is also questionable whether the variation between markets affects the endogenous variable sufficiently (Bishop and Timmins 2019). Eventually, this boils down to a common issue with instrumental variables: their application is widespread in the econometric literature, but their choice and the analysis based on them are typically subject to intensive debate.

For the analysis, this paper makes use of a new approach by Bishop and Timmins (2019) to determine the marginal and non-marginal willingness to pay in a likelihood estimation. Their work entails several benefits for the further analysis. First, it requires no instrumental variables. Second, the data requirements are fairly modest, as it requires no information on income or other such demographic information of households to estimate the marginal and non-marginal willingness to pay. Third, the framework relies only on fairly modest econometric assumptions. Fourth, the approach is computationally simple and straightforward.

Following Bishop and Timmins (2019) and adapting their framework to our setting we observe $i = 1, \ldots, N$ households in $j = 1, \ldots, J$ markets. For the moment assume that each city is considered as a separate market. Household i in market j pays a monthly rental price for its apartment which is determined by the following function:

$$p = p(z_{ij}, \mathbf{x}_{ij}, \xi_{ij}) \tag{1}$$

where z_{ij} denotes the amenity of interest, $\mathbf{x}_{ij}$ are additional control characteristics which might be either apartment or neighborhood-specific, while ξ_{ij} refers to other unobserved apartment characteristics. Further, we assume that the utility function of household i in market j is defined as follows:

$$u = u(z_{ij}, \mathbf{x}_{ij}, \xi_{ij}, c_{ij}, \nu_{ij}) \tag{2}$$

and depends on the amenities (z_{ij}, $\mathbf{x}_{ij}$), a numeraire consumption c_{ij}, unobserved household attributes ν_{ij}, and household income y_{ij}. Assuming that household i in market j maximizes utility, subject to its budget constraint, and normalizing the price of numeraire consumption to one allows us to rewrite the household's problem as

$$\max_{i,j} \; u_j(z_{ij}, \mathbf{x}_{ij}, \xi_{ij}, c_{ij}, \nu_{ij}) \tag{3}$$
$$\text{subject to} \quad p(z_{ij}, \mathbf{x}_{ij}, \xi_{ij}) + c_{ij} \leq y_{ij} \, .$$

Under the assumption that the household's optimum lies on the budget line, we can reformulate utility as

$$u = u(z_{ij}, \mathbf{x}_{ij}, \xi_{ij}, y_{ij} - p(z_{ij}, \mathbf{x}_{ij}, \xi_{ij}), \nu_{ij}) \, . \tag{4}$$

Assuming quasi-linear utility in y_{ij} allows us to relax the data requirements so that we are able to estimate the parameters of the marginal willingness to pay function without household-specific income information. Following Bishop and Timmins (2019) we specify a quadratic utility function:

$$u = \alpha_{1j} z_{ij} + \frac{1}{2}\alpha_2 z_{ij}^2 + \nu_{ij} z_{ij} + g_j(\mathbf{x}_{ij}, \xi_{ij}) + y_{ij} - p_j(z_{ij}, \mathbf{x}_{ij}, \xi_{ij}) \, , \tag{5}$$

which yields the following household optimal consumption of z_{ij}:

$$p'(z_{ij}) = \alpha_{1j} + \alpha_2 z_{ij} + \nu_{ij} \, , \tag{6}$$

where $p'(z_{ij}) = \partial p_j(z_{ij}, \mathbf{x}_{ij}, \xi_{ij})/\partial z_{ij}$, α_{1j} is a market-specific intercept, and α_2 is the slope of the marginal willingness to pay function.

Obviously, we are not able to fully isolate z_{ij} on the left-hand side of (6) without restricting the functional form of $p'(z_{ij})$. However, there is usually no theoretical justification for arbitrary parametric assumptions about the functional form. The traditional approach of Rosen (1974) leaves $p'(z_{ij})$ unrestricted and uses a two-step approach, where $p'(z_{ij})$ in (6) is replaced by an estimate from the hedonic regression (Bishop and Timmins 2019). It is well known that this approach leads to an endogeneity problem, so it is common practice to use instrumental variables for z_{ij}. Instead, Bishop and Timmins (2019) suggest an alternative approach where they first isolate ν_{ij} on the left-hand side:

$$\nu_{ij} = p'(z_{ij}) - \alpha_{1j} - \alpha_2 z_{ij} \, . \tag{7}$$

Under the assumption that ν_{ij} is normally distributed with variance σ_ν^2, they employ a change of variables such that the parameters $(\boldsymbol{\alpha}_1, \alpha_2, \sigma_\nu)$ can be estimated by maximum likelihood.[6] The corresponding log-likelihood function is

$$L\left(\boldsymbol{\alpha}_1, \alpha_2, \sigma_\nu\right) = \sum_{i=1}^{N}\sum_{j=1}^{J} \log\left(\sigma_\nu \phi\left(\hat{\nu}_{ij}(\boldsymbol{\alpha}_1, \alpha_2)\right) \widehat{J}(\alpha_2)\right) , \tag{8}$$

where $\phi(\cdot)$ is the probability density function of the standard normal distribution, $\hat{\nu}(\boldsymbol{\alpha}_1, \alpha_2)$ is (7) with $p'(z_{ij})$ replaced by an estimate from the hedonic regression, $\widehat{J}(\alpha_2) = |\hat{p}''(z_{ij}) - \alpha_2|$ is the Jacobian that stems from the application of the change of variables, and $\hat{p}''(z_{ij}) = \partial^2 \hat{p}_j(z_{ij}, \mathbf{x}_{ij}, \xi_{ij})/\partial z_{ij}^2$. Instead of maximizing (8) directly, Bishop and Timmins (2019) suggest using the following profile log-likelihood function:

$$\mathcal{L}\left(\alpha_2\right) = \sum_{i=1}^{N}\sum_{j=1}^{J} \log\left(\tilde{\sigma}_\nu(\alpha_2) \phi\left(\tilde{\nu}_{ij}(\alpha_2)\right) \widehat{J}(\alpha_2)\right) , \tag{9}$$

where $\tilde{\nu}_{ij}(\alpha_2)$ are the residuals of a regression of $\hat{p}'(z_{ij}) - \alpha_2 z_{ij}$ on market identifiers and $\tilde{\sigma}_\nu(\alpha_2) = \frac{1}{NJ}\sum_{i=1}^{N}\sum_{j=1}^{J} \tilde{\nu}_{ij}(\alpha_2)$. Thus, $(\boldsymbol{\alpha}_1, \alpha_2, \sigma_\nu)$ can be estimated from a simple univariate optimization problem. The corresponding standard errors can be obtained by a non-parametric bootstrap.[7]

Further, Bishop and Timmins (2019) show that their suggested approach is able to identify the parameters of the marginal willingness to pay function. More precisely, $\boldsymbol{\alpha}_1$ is identified from the average consumption of z_{ij}, σ_ν is identified from the variance of z_{ij}, and α_2 is identified from the nonlinearity of $p'(z_{ij})$. Intuitively, the nonlinearity of $p'(z_{ij})$ leads to differences in the level of consumption for different types of households, where the extent of these differences influences α_2. The availability of data on multiple markets provides additional sources of identification. For instance, the variation of z_{ij} and $p'(z_{ij})$ across markets (for a detailed treatment on different sources of identification see Bishop and Timmins

[6] Note that the distributional assumption about the true unobserved household attributes ν_{ij}^0 is not overly restrictive. If it does not hold, the estimator simply becomes a pseudo-maximum likelihood estimator and is still consistent (See Greene (2012) chapter 14.8). Alternatively, the authors propose a generalized method of moments estimator that can be used to estimate the parameters of (6) and σ_ν.

[7] Alternatively, we could estimate the parameters of the hedonic price function and (6) simultaneously.

2019, section 2.2).

3 Data

A particular strength of this paper is that we unite detailed information on rental apartments with various location-specific variables. In total, our analysis is based on 533,402 observations from the seven largest cities in Germany (Berlin, Hamburg, Munich, Frankfurt, Düsseldorf, Cologne, Stuttgart) and the two major cities in eastern Germany (Leipzig and Dresden). We focus the analysis on the largest cities in Germany as excessive traffic and related externalities such as air pollution and noise are a particular issue there. We also consider two cities from eastern Germany, as even today, 30 years after the German reunification, various differences in the social and economic development can still be observed between East and West Germany (BMWi 2019). Against this background it will be interesting to see whether these differences can also be observed for the willingness to pay to reduce automobile traffic.

Data on the real estate market is scraped daily from the two major real estate portals for apartment rentals in Germany and was collected between October 2016 and December 2019. The data include very detailed information on prices, characteristics, and features of the apartment as well as the exact geographic coordinates.[8] For the analysis, we assume that the posted rental price for the apartment, exclusive of heating and other additional costs, corresponds to the actual rent paid by the tenant for the apartment. Given the high demand for rental apartments in German cities, this does not seem to be a strong assumption. For one, housing prices in the seven largest cities in Germany nearly doubled between 2010 and 2018 (Bundesbank 2019). For another, the duration of an advertisement in our data set is, with a median of 12 days, fairly short. Thus, it is unlikely that posted prices for apartments are renegotiated afterwards with the landlord. Finally, given that we consider a period of three years and three months in the analysis, we deflate the apartment prices with the consumer price index for rental housing at the state level.

[8]This is not possible for apartments where the postal code is the only geographic information. Thus, these apartments are excluded from the analysis, as it remains unknown how their rental price is affected by location-specific confounders.

Given that the willingness to pay for traffic reductions is determined from rental prices in the real estate market, one important consideration is their regulation. Principally, the regulation of rental prices may distort the willingness to pay as it potentially limits rents to a lower bound than in a unregulated market. This may distort the consumption decisions of consumers and lead to a misallocation in the market (Glaeser and Luttmer 2003). Thus it may also potentially bias the estimation of the willingness to pay.

Rent prices in Germany are regulated, but we argue that this regulation does not interfere with the analysis of this paper. First, the regulation of rental prices is not that restrictive with regard to the magnitude. Every three years it allows an increases in rental prices of up 20%. In cities, where housing prices have been particular excessive, these still amount to 15% within three years. In our data set rental price increases are restricted to 20% in Leipzig and 15% in Berlin, Hamburg, Munich, Frankfurt am Main, Düsseldorf, Cologne, Stuttgart, and Dresden (Haufe 2019). Second, the regulation of rental prices is also less restrictive as it is based on relative increases. Thus, prices can still be adjusted in accordance with the overall development of the market. This is a significant difference to a regulation which would enforce an absolute limit of rental prices. Third, there are important exceptions. Rental controls do not apply to newly built apartments or significantly refurbished apartments. Further, if the previous tenant has profited from refurbishment but was not charged a higher rental price, the landlord may increase the rental price for the next tenant beyond the restrictions of the rental control (§ 556e, BGB). Third, the rent regulation is not enforced by the state. Instead, the tenant has the right to request information on the previous rent from the landlord and then has to prove that the rent is excessive (§ 556g, BGB). Finally, and most importantly, the overall trend in rental prices is fairly constant and is seen to be upward sloping constant between 2010 and 2018, despite the introduction of rental price controls in 2013 and a further extension in 2015 (See for example (Bundesbank 2019). Thus, it is also not surprising that a study confirms that these regulations of rental prices have only a minor impact on the future rental income of investors (Kholodilin et al. 2016).

Data on the geolocations of various kinds of shops and amenities (e.g., cafés, bars, restaurants, supermarkets, banks, doctors) as well as street characteristics (speed, lanes) is gathered from Openstreetmap. Based on the latter information we also calculate for each street the mean capacity of automobiles per hour. To be more precise, we calculate for each street s in city c a physical upper bound for automobile traffic per hour:

$$\mathsf{traffic}_{\mathsf{cs}} = \frac{\mathsf{speed}_{\mathsf{cs}} \times \mathsf{lanes}_{\mathsf{cs}}}{\mathsf{automobile} + \mathsf{buffer}} \tag{10}$$

where we assume that the maximum capacity of a street s depends on the product of the maximum speed (in k.p.h) and the number of lanes, which is then divided by the average length of an automobile in Germany and a safety margin of one meter. We interpret this quantity as an indicator for potential traffic. For instance, if a household visits an apartment, it only has limited information about the true traffic per hour on the street of this apartment. However, this household can form some expectations about the potential traffic based on the number of lanes and the maximum speed. Afterwards, we match this quantity with the respective apartments which are located on that street. Apart from that, we compute for each apartment individually various linear distance measures to points of interest. For one, this includes the distance to the city center. For the analysis we assume that this corresponds to the location of the town hall, as cities in Germany are historically expanded around this center. For another, we calculate for each apartment the minimum distance to various groups of shops, amenities, public services, the next stop position for public transport, and to the next motorway junction.[9]

Figure 1 displays with black dots the location of the apartments in our data set by city. It can be seen that our samples are fairly representative, as the apartments in our data set are equally distributed across cities and match the general outline of the respective cities fairly well. Remaining inner-city blank spaces can be typically explained with waterways (e.g., the river Elbe in Hamburg) or green areas (e.g., the forest Dresdner Heide in Dresden).

The main variables, which are used in our econometric model, are shown in Figure 2. The distribution of deflated rent prices differs significantly across cities in our data set. In Berlin, Düsseldorf, Cologne, Hamburg, Stuttgart, and Frankfurt am Main rent prices are centered around modes between €468 and €678. In contrast, the rent price distribution in Munich is much more platykurtic and is centered

[9] For details see also Figure 4.

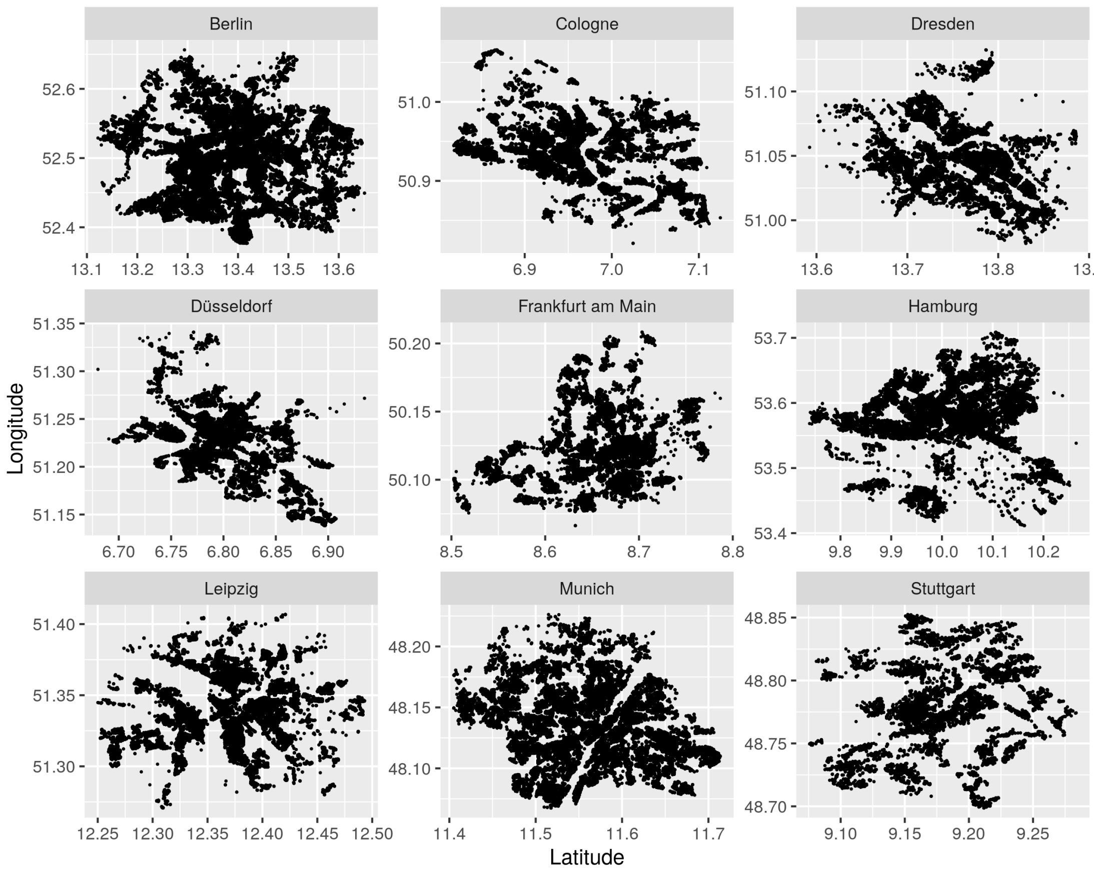

Figure 1: *Location of Apartments in Our Dataset by City. Own illustration. Data: Own data set*

around a mode of €1,136 per month. This indicates that excess demand for apartments is much higher in Munich. At the same time the opposite is true for Dresden and Leipzig where the distribution of rent prices is much more leptokurtic and centered around a mode of €331 and €354 respectively. However, these price differences have been not put in context with apartment characteristics, which may also vary by city.

The variation of street capacity is fairly similar in Hamburg, Munich, Frankfurt, Düsseldorf, Cologne and Leipzig. This includes both the total distribution and the distribution of street traffic between the 25th and 75th percentile, A similar distribution can be observed for both Berlin and Dresden, though at a lower magnitude. A notable exception is the distribution of street capacity in Stuttgart, as the variation is much smaller and fewer outliers can be observed here. Among those cities considered for the analysis, Stuttgart is among the smallest cities. At

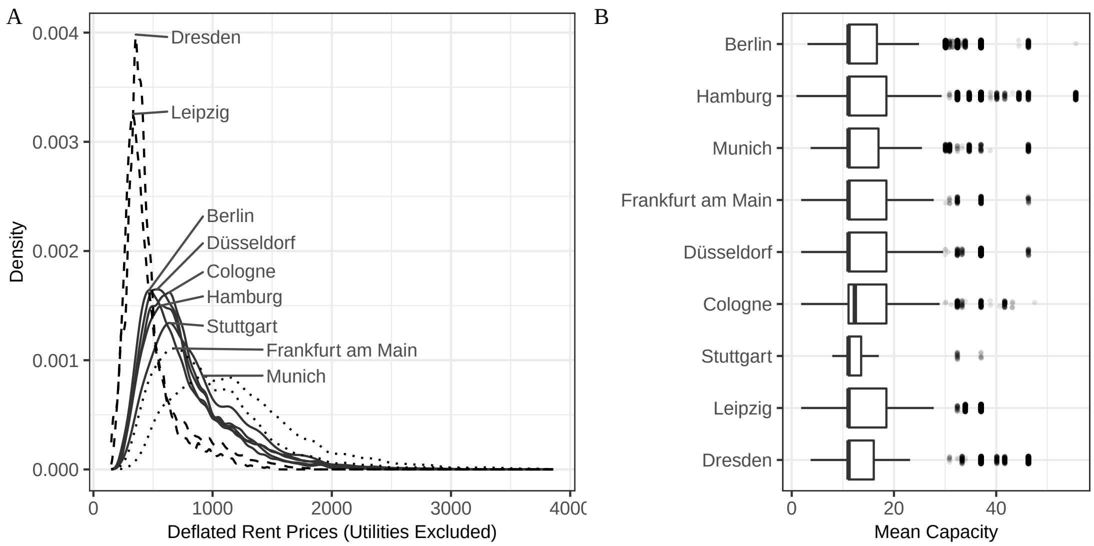

Figure 2: *Distribution of Rent Prices and Traffic in Different German Cities. Own illustration. Data: Own data set*

the same time, the distribution of rent prices in Stuttgart indicates a notable shortage in apartment supply. Given that we match the apartments with the street in front of their house, it is not too surprising that fewer listings also imply less variation in street characteristics.

Figure 3 displays the size of the apartments in our data set. It can be observed in plots A and B that the number of rooms as well as the size of the apartments varies significantly between different cities. In particular the share of apartments with either one-room or apartments that are under 40 sqm is substantially higher in Munich. This corresponds to the former observation that the price level for apartments in Munich is significantly higher compared to other cities (see also Figure 2). This can also be observed in Figure 4 which displays the rent prices per square meter in the different cities. Similar to Figure 2 the density distribution of rent prices per square meter is centered around the lowest rent prices per square meter in Dresden and Leipzig. The distribution of rent prices per square meter in Düsseldorf, Cologne, Berlin, Hamburg, and Stuttgart are centered fairly in the middle among the cities in our dataset. Frankfurt am Main and Munich have not only the highest rent prices per square meter but also the highest variation across these prices.

Figure 5 gives an overview of the observed apartment characteristics in our data

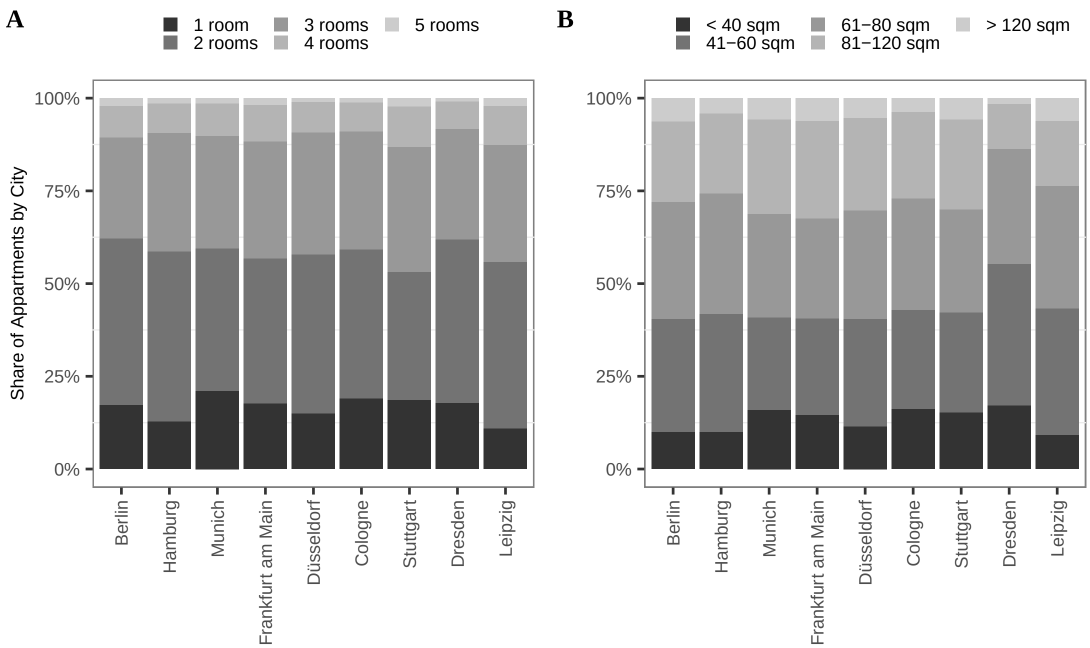

Figure 3: *Distribution of the Number of Rooms and Apartment Sizes. Own illustration. Data: Own data set*

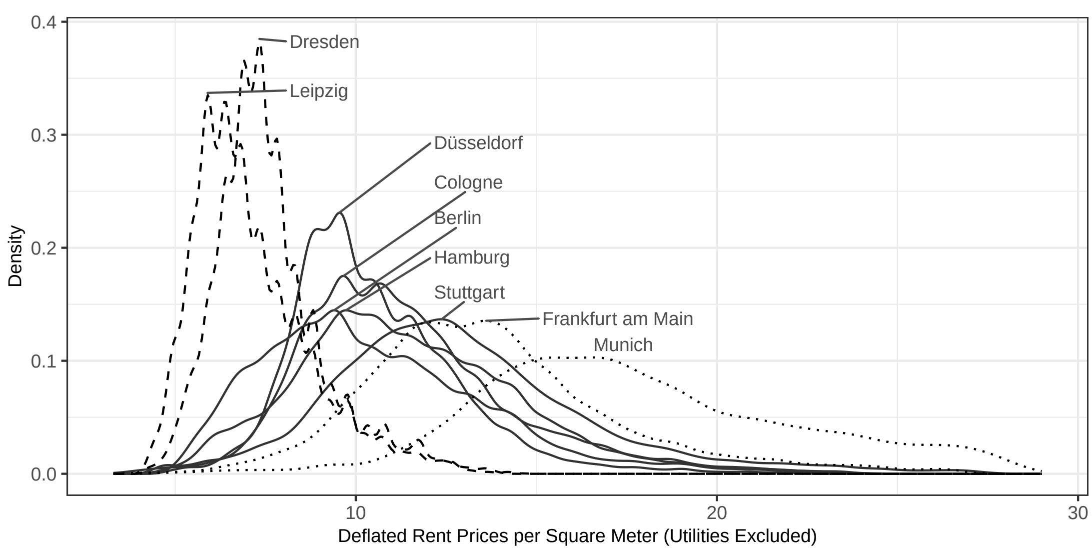

Figure 4: *Distribution of Rent Prices per Square Meter in Different German Cities. Own illustration. Data: Own data set*

set. This extensive list is gathered from a predefined list of features (e.g., balcony, new) and the description text (e.g. bright, panoramic view) of the advertisements. It can be observed that this encompasses an extensive list of features. However, in

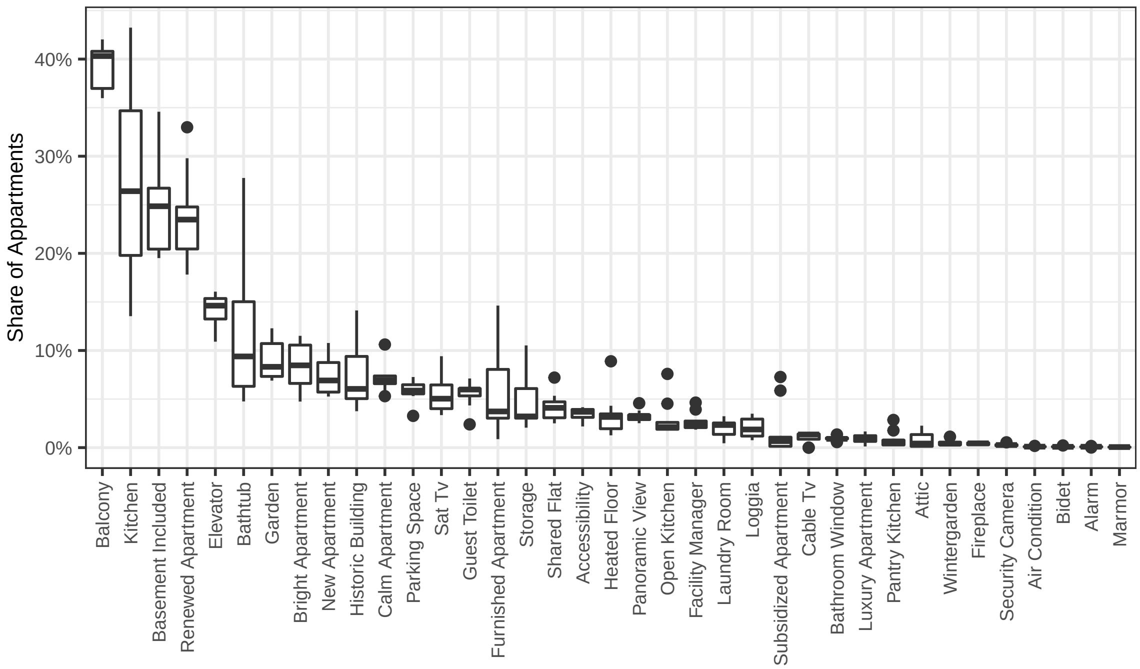

Figure 5: *Apartment Characteristics. Own illustration. Data: Own data set*

most cases a characteristic occurs from the top 10 list (e.g., balcony, basement, kitchen), while other characteristics are only of minor importance. Interestingly, we also observe a notable variation in the occurrence of the top 10 features between different cities. These systematic differences might indicate that the market for rental apartments is also driven by confounders at a local level, such as regulations or path dependencies.

Figure 6 gives an overview of how the distance to the next shop (A) or amenity or public services (B) varies for tenants across different cities. It becomes apparent that everyday commodities (e.g., groceries, recycling) can be typically found nearby. In contrast, less frequently visited shops such as electronics or finance are located at further distances. For these types of categories the variation of the average distance is much larger across different cities.

All in all, it can be noticed in the previous figures that a significant heterogeneity is present across cities in our data set. For one, this is important for the identification of the marginal willingness to pay in our econometric model, as this is also identified by the differences between markets. For another, it is important for the external validity of our estimation results, as the marginal willingness to pay is calculated

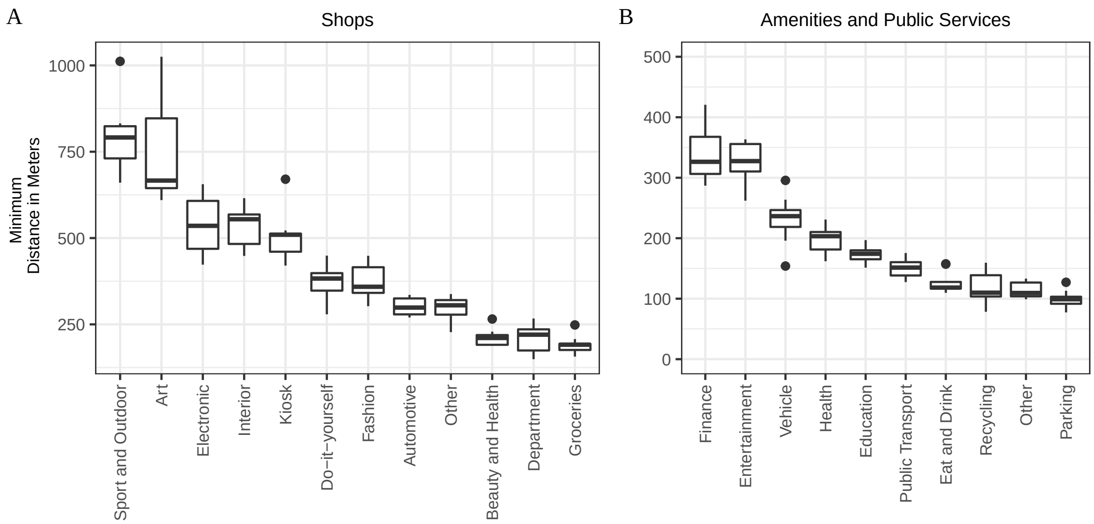

Figure 6: *Variation of Minimal Distance from Apartments to Shops as well as Amenities and Public Services between Different Cities. Own illustration. Data: Own data set*

for a varying set of market conditions.

4 Econometric Specification and Results

Based on the aforementioned theoretical framework,[10] the first stage of the estimation is specified by the following hedonic price function:

$$\text{price}_{ijt} = \gamma_j \; f\left(\text{traffic}_{ij},\, \lambda\right) + \mathbf{x}'_{ijt}\boldsymbol{\beta}_j + \mathbf{d}'_{ijt}\boldsymbol{\delta}_j + \xi_{ijt} \tag{11}$$

where price_{ijt} denotes the deflated price for apartment i in market j at time t, traffic_{ij} denotes our measure for potential traffic on the apartment's road, $\mathbf{x}_{ijt}$ includes a set of apartment-specific characteristics and different location- and time-specific fixed effects, $\mathbf{d}_{ijt}$ includes distance measures for various types of shops, amenities, and public services as well as to the city center and the next motorway junction, ξ_{ijt} are other unobserved apartment characteristics, and $f(\cdot,\, \lambda)$ is a non-linear transformation that we explain later.[11] In our baseline specification,

[10]See also Section 2.

[11]For details of the apartment characteristics as well as the calculated distances to shops, amenities and public services see also the data description in Section 3.

$\mathbf{x}_{ijt}$ includes a full set of zipcode-year fixed effects.

In our baseline analysis we treat each city as a separate market. For one, they are geographically separated, given that the minimal distance between two cities is 45 km in our data set. For another, we also observe significant differences in various parameters across cities in the descriptive analysis. In an alternative specification we also test the hypothesis that East Germany (Leipzig, Dresden) and West Germany (Berlin, Hamburg, Munich, Frankfurt am Main, Düsseldorf, Cologne, Stuttgart) still constitute separate markets.

Following Bishop and Timmins (2019) and Ekeland et al. (2004) we model the relationship between our variable of interest and the dependent variable in a non-linear fashion. However, economic theory does not suggest a specific functional form which is best suited to model this non-linear relationship. Thus, hedonic models are frequently estimated with a Box-Cox transformation for the amenity of interest. Next to transforming a variable into a normal distribution, it allows us to test for various functional relationships between a variable of interest and the dependent variable (Cropper et al. 1988). More precisely, we define

$$f\left(\text{traffic}_{ij},\, \lambda\right) = \begin{cases} \frac{\mathsf{traffic}_{ij}^{\lambda}-1}{\lambda} & \text{if} \quad \lambda \neq 0 \\ \log\left(\mathsf{traffic}_{ij}\right) & \text{otherwise} \end{cases} . \tag{12}$$

Among others, the considered transformation includes commonly used functional forms such as the square-root-, quadratic-, or logarithmic transformation. We try different values for $\lambda \in \{-3, -2.95, ..., 3\} \setminus 1$ and choose the value that maximizes the value of the profile log-likelihood in the second stage.[12] We achieve the maximum value of the profile log-likelihood function for $\lambda = 1.05$.[13]

Given that the value of an apartment in our econometric model is derived from its intrinsic value, information on apartment characteristics is particularly important

[12]The corresponding first- and second order derivatives of the hedonic price function are

$$\hat{p}'\left(\text{traffic}_{ij}\right) = \begin{cases} \hat{\gamma}_j \ \text{traffic}_{ij}^{\lambda-1} & \text{if} \quad \lambda \neq 0 \\ \hat{\gamma}_j \ \text{traffic}_{ij}^{-1} & \text{otherwise} \end{cases} ,$$

$$\hat{p}''\left(\text{traffic}_{ij}\right) = \begin{cases} \hat{\gamma}_j \ \left(\lambda-1\right) \ \text{traffic}_{ij}^{\lambda-2} & \text{if} \quad \lambda \neq 0 \\ -\hat{\gamma}_j \ \text{traffic}_{ij}^{-2} & \text{otherwise} \end{cases} .$$

[13]A plot of the negative profile log-likelihood function for different values of λ can be found in the Appendix.

for the analysis. Consequently, 37 apartment characteristics are considered in the regression.[14] Alongside the apartment characteristics, the rent of an apartment is significantly affected by its location. Other papers in the literature on hedonic models typically employ fixed effects at various levels e.g., city, district or zipcode, to account for location-specific differences in the housing market (See also Baranzini et al. 2008). For example, crime rates, distances to shops, amenities or public services may vary significantly between districts and thus affect rent prices. However, it is not unlikely that the value of a location also differs significantly within districts, particular in larger districts. Thus, it is also a contribution of this paper that we account for this by including apartment-specific distance measures to shops, amenities or public services in the analysis. Further, we control for different sets of location and time fixed effects as the development of rent prices and thus the housing market has been undergoing substantial changes in the past years.

In the second stage we estimate the parameters of the marginal willingness to pay by maximizing (9). In principle, the approach of Bishop and Timmins (2019) allows us to control for household-specific characteristics in the estimation of the willingness to pay in the second stage of the regression. For example, for our research question it would be interesting to explore how the estimated marginal willingness to pay is affected by household demographics like age, income, or voting behavior. However, apartment-specific household information is generally not available, for instance, due to data protection reasons.

Table 1 displays the regression results for the first stage of the estimation based on 533,402 observations and with heteroskedasticity robust standard errors. Consistent with economic theory the relationship between inner-city traffic and the derivative of rental prices is negative in all cities. Overall, it can be observed that the coefficients are estimated fairly precisely, which is important for the identification of the marginal willingness to pay in the second stage. One slight exception is Stuttgart, where the standard error is relatively larger. Given that the fewest observations (n = 12,676) in our data set are from Stuttgart, this may serve as an explanation.

[14]In detail, this includes the following list of apartment characteristics and features: facility manager, storage, balcony, basement, elevator, open kitchen, pantry kitchen, kitchen, barrier free, bathtub, guest toilet, apartment share, garden, historic, new, renewed, furnished, parking, heated floor, subsidized, level, heating, floor, laundry room, sat, bathroom window, luxury, loggia, attic, camera, alarm, winter garden, fireplace, bidet, air condition, marmor, view, calm and bright.

	Coef.	Std. Error	CI 95%
		γ_j	
Berlin	-0.717	0.080	[-0.873; -0.561]
Dresden	-0.752	0.050	[-0.85; -0.655]
Düsseldorf	-0.809	0.127	[-1.057; -0.561]
Frankfurt Am Main	-2.092	0.244	[-2.571; -1.613]
Hamburg	-0.435	0.083	[-0.597; -0.272]
Cologne	-0.581	0.117	[-0.81; -0.352]
Leipzig	-0.525	0.059	[-0.64; -0.41]
Munich	-0.708	0.237	[-1.173; -0.244]
Stuttgart	-0.804	0.396	[-1.58; -0.027]
Markets:		Cities	
Apartment Characteristics:		All	
Shops, Amenities & Public Services:		Minimal Distance	
Fixed Effects:		Zipcode × Year	
Observations:		533,402	

Note: Standard errors are robust to heteroscedasticity.

Table 1: *Estimation Results of the Hedonic Price Function (1st Stage) with the Baseline Setup*

Table 2 shows the regression results for the second stage of our estimation. Given that our results are obtained from a two-step estimation procedure, the reported standard errors are computed based on a non-parametric bootstrap with 200 replications. All our coefficients are highly significant at the 1% level. We observe a very negative city-specific intercept and a substantially smaller but positive slope. Consequently, reductions of the average street capacity have a positive but a decreasing effect on the marginal willingness to pay of a household. Further, the observed city-specific intercepts have a fairly similar magnitude ranging from -20,619 (Stuttgart) to -24.353 (Hamburg).

A strength of the structural model by Bishop and Timmins (2019) is that it also allows us to compute the willingness to pay for non-marginal policy changes. Given that streets can be described as an interconnected network, the effects of a policy intervention cannot be evaluated in isolation. Thus, limiting traffic on a street or even shutting it down is likely to diverge traffic and increase traffic on other streets nearby. Therefore, we evaluate exemplary traffic reductions of 10%, 20%,

	Coef.	Std. Error	CI 95%
Traffic Capacity	1.584	0.471	[0.662; 2.507]
Sigma	8.768	2.599	[3.673; 13.863]
Berlin	-21.805	6.234	[-34.023; -9.587]
Dresden	-22.350	6.415	[-34.922; -9.777]
Düsseldorf	-22.742	6.513	[-35.508; -9.977]
Frankfurt am Main	-22.513	6.445	[-35.146; -9.88]
Hamburg	-24.353	6.992	[-38.057; -10.649]
Cologne	-23.127	6.630	[-36.122; -10.132]
Leipzig	-22.883	6.568	[-35.755; -10.01]
Munich	-22.506	6.449	[-35.146; -9.866]
Stuttgart	-20.619	6.578	[-33.512; -7.727]
Markets:			Cities
Apartment Characteristics:			All
Shops, Amenities & Public Services:			Minimal Distance
Fixed Effects:			Zipcode × Year
Observations:			533,402

Note: Estimation results with city specific intercept. Standard errors are obtained by a non-parametric bootstrap with 200 replications.

Table 2: *Estimation Results of the Marginal Willingness to Pay Function (2nd Stage) with the Baseline Setup*

and 30% for all streets in the city. However, it is acknowledged that for some very small streets, further gains can hardly be realized with further reductions of traffic. Figure 7 presents the willingness to pay various exemplary non-marginal traffic reductions. As the values are calculated based on data from the city-specific road network, the values of the x-axis vary to some extent by city. Nonetheless, it can be overall observed that the shape of the functions is fairly similar across cities.

Figure 3 displays the expected gains for different exemplary traffic reductions for an average household on a yearly basis. Generally, the magnitude of the expected gains is in a fairly similar range, while being smallest for Stuttgart and highest for Frankfurt am Main. Interestingly, the expected gains are already quite significant for small reductions of traffic.

Additionally, we calculate the total average expected gains for different exemplary traffic reductions by city on a yearly basis (Figure 4). For this purpose we first

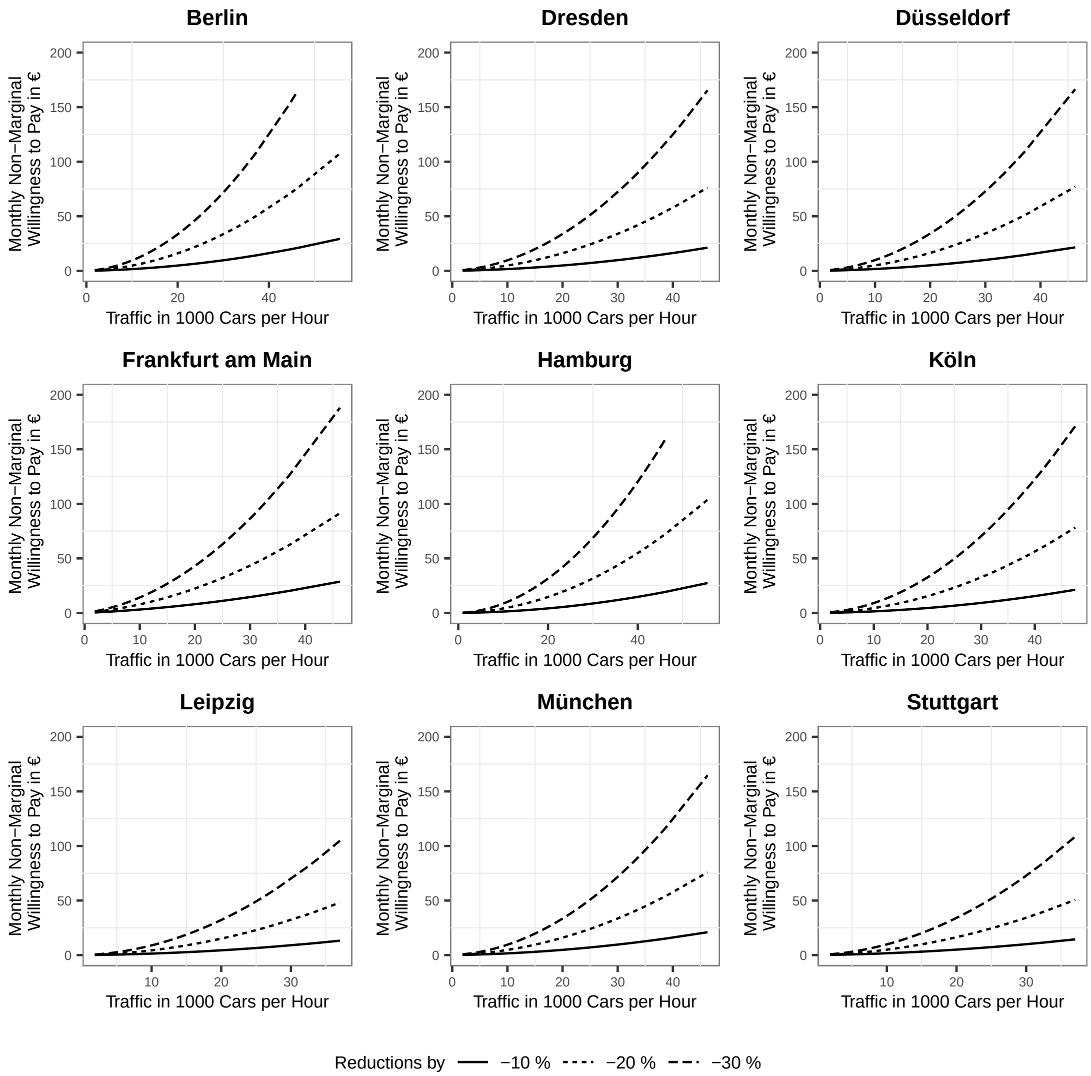

Figure 7: *Relationship Between the Monthly Non-Marginal Willingness to Pay per Household and Different Traffic Reductions*

Traffic Reduction	-10 %	-20 %	-30 %
Berlin	32.6	104.4	215.5
Dresden	34.7	110.5	227.6
Düsseldorf	36.6	115.9	237.6
Frankfurt am Main	59.2	158.3	297.4
Hamburg	33.9	118.0	252.0
Köln	33.0	109.6	229.7
Leipzig	30.9	103.5	217.8
München	33.4	107.0	220.8
Stuttgart	30.3	93.8	190.6

Table 3: *Non-marginal Willingness to Pay for Different Exemplary Traffic Reductions per Household and Year in Euros.*

calculate the average expected gain for exemplary traffic reductions for each quarter. Then, we assume that the average number of members in a household is two in our data. Thus, the number of households can be derived from the population in each quarter. Finally, the average expected gain in each city can be gleaned by computing the mean expected gain across all quarters and weighting it with the number of households in each quarter. The expected gains by households differ from the total expected gains by city as these account for the capacity of the street network as well as the number of households in each city. Overall, it can be noted that the total average expected gains by city are more heterogeneous than the average expected gains by household. For example, the expected gains are the highest for Munich, despite being only the 3rd largest city in Germany. Similarly, the expected gains for Stuttgart are fairly large, although the city ranges among the smallest cities in the analysis.

In order to ensure the robustness of the results several checks have been conducted. One important element for the estimation of the willingness to pay is the non-linear relationship between the amenity of interest and the dependent variable. As noted previously, various parameters of λ have been considered in the Box-Cox transformation and thus also different functional forms (see also Figure 8 in the Appendix).

Another important element in the estimation of the willingness to pay is the market definition. In the default setup each city is defined as a separate market. Given that all cities vary substantially by size and geographic location it can be argued

Traffic Reduction	-10 %	-20 %	-30 %
Berlin	634 035	2 029 263	4 185 684
Dresden	163 970	524 672	1 082 107
Düsseldorf	229 919	723 694	1 481 325
Frankfurt am Main	459 525	1 223 798	2 292 818
Hamburg	316 951	1 100 094	2 349 430
Köln	209 467	694 436	1 454 908
Leipzig	144 610	484 023	1 018 240
München	1 019 454	3 261 837	6 727 148
Stuttgart	398 046	1 230 718	2 498 014

Table 4: *Total Average Expected Yearly Gains in Euros for Different Exemplary Traffic Reductions by City.*

that this is the most plausible approach. Nonetheless, two alternative market definitions have been considered: In one case each city and year combination is treated as a separate market. It can be observed in Table 8 in the Appendix that the magnitude of both the slope and intercept are larger. However, also σ, the variance of the marginal willingness to pay, increases significantly too. This indicates that the marginal willingness to pay is estimated less precisely. Hence, the city-year market definition does not seem to be superior to the default market definition. In another case East and West Germany are defined as separate markets, as 30 years after the German reunification still several differences between the two still persist (BMWi 2019). However, this does not seem to be a useful market definition as the magnitude of the coefficients barely differs between East and West (see Table 9 in the Appendix). Consequently, it seems unlikely that this market definition is a better contribution to the model identification than the default market definition.

Further robustness checks include different fixed effects in the hedonic estimation in the first stage of the structural model (tables 10 and 11). But this changes the results only slightly and in particular raises the standard error of the marginal willingness to pay function. Finally, we consider the mean instead of the minimum as a measure of distances to points of interest. The latter has the advantage because it accounts not only for the distance to the next pub but also from this pub to the pub after that. In that sense this metric can be considered as more precise. Though neither case substantially alters the regression results.

This paper answers an important question, namely what would households pay for a reduction of automobile traffic. Indeed, we also argue that this is the most relevant question for an evaluation of policy measures. What is beyond the scope of this paper is to answer what motivates the individual willingness to pay for a traffic reduction. Are families that are concerned about road safety willing to pay a higher price? Do consumers prefer quiet apartments or cleaner air? What is the role of health concerns related to the externalities of traffic? As the mentioned variables are not modelled explicitly in the estimation it remains unknown what the exact driver for the estimation results is. But answering these questions in a robust empirical framework is far from trivial while the gains for policy-makers may in some cases be limited. For one, prospective tenants typically make their decision based on a bundle of externalities and can hardly distinguish if e.g., more traffic implies more nitrogen dioxide or particulate matter. Second, isolating the causal effect of various externalities which are mutually dependent is empirically challenging. Finally, trying to isolate separate effects of externalities may raise the risk of an omitted variable bias, as all externalities which have an effect on the pricing decision need to be quantified and considered in the analysis.

5 Discussion

Our results suggest that households in cities gain from a reduction of automobile traffic. This section discusses possible policy implications and their allocative and distributive effects. Generally, the effects of a policy which aims to reduce traffic are ambilateral.

On the one hand, reducing inner-city traffic raises the utility of residents as it lowers ceteris paribus their exposition to a negative externality. This renders apartments of residents more valuable on the real estate market. For example, families who currently live in the suburb might prefer to live downtown if inner-city automobile traffic is lower. In turn, this utility gain for tenants allows landlords to charge higher rents from their tenants or to sell their property at higher prices on the real estate market. As a consequence, tenants have to pay higher rental prices in exchange for their reduced exposure to automobile traffic and its externalities. Similarly, buyers of property on the real estate market have to pay higher housing prices but gain a more valuable property in exchange. Given that air pollution is particularly an topic in larger cities, where rents have dramatically increased over the past years, this may further ignite housing prices. Further, cities may benefit from higher taxes if the tax yield of property taxes depends on the value of the real estate property (e.g., Germany). If the reduction of automobile traffic raises the utility of tenants, cities may profit from higher rents as this leads to a higher tax income from property taxes.

On the other hand, reducing the street capacity for automobiles also raises ceteris paribus transportation cost for automobiles. This does not only affect the allocation choice of commuters, consumers, and firms. Reducing the street capacity for automobiles renders automobile driving more costly, as it raises ceteris paribus the likelihood of traffic jams. Thus, automobile drivers either have to bear the higher time cost or substitute with another mode of transportation which was previously considered as less attractive relative to automobiles by a rational consumer. In turn, this may also increase the travel costs for other modes of transportation. For one, these costs may be monetary as providers of alternative transportation modes may raise their prices in response to an increasing demand. For another, these costs may also be non-monetary, for example, if traveling on public transport becomes more crowded and thus less comfortable or if increased demand leads to more delays. As a consequence, reducing the street capacity of automobiles may raise inner-city travel costs independent of the mode of transportation.

Commuters would be among the first ones to be affected by higher travel costs. In Germany 68% of the working population commute to their workplace by automobile (Bundesamt für Statistik 2017). In those cities considered for the analysis, on average 46% of a city's working population commutes from the urban hinterland to work. Correspondingly, on average, 27% of the city's working population commute to the urban hinterland.[15] Hence, limiting inner-city mobility affects a significant share of the working population and thus their income opportunities. In addition, it might also be a locational disadvantage for inner-city firms if their candidates of interest typically commute to their workplace. This is an important issue as, for example, 49% of the medium-sized firms in Germany have stated that they have recruiting problems due to a lack of labor supply (DIHK 2019).

[15] In detail, the rounded share of the working population which commutes to and from the city are respectively: Berlin (22%, 14%), Hamburg (36%, 17%), Munich (45%, 28%), Frankfurt am Main (64%, 32%), Cologne (49%, 30%), Düsseldorf (62%, 35%), Stuttgart (60%, 37%), Leipzig (36%, 27%), and Dresden (36%, 25%) Bundesagentur für Arbeit 2019.

Firms and in particular retail stores may face losses, as these may, depending on the scope of the traffic restrictions, bear higher travel costs for transportation. Indeed, firms may try to pass these higher transportation costs on to consumers if demand for their products is rather inelastic. However, consumers may then prefer to buy their goods for a cheaper price in a local market or the Internet rather than traveling downtown. Thus, besides rendering cities less attractive for commuting workers with lower incomes, raising inner-city travel costs may also render cities less attractive for purchases.

All in all, reducing inner-city traffic from automobiles may involve ceteris paribus noticeable costs and gains. Linking a policy to reduce inner-city traffic from automobiles with other measures to reduce the cost of alternative modes of transportation may help to balance these costs and gains. The results of this paper show that there is a significant and positive willingness to pay for a reduction of traffic. Thus, the externalities from automobile traffic are not only well understood but it is also in the interest of residents. Answering which mode of transportation suits the requirements of a modern city best depends on the individual city-specific context and is beyond the scope of this paper. Finally, cities like Copenhagen or Amsterdam demonstrate how life in cities can be organized with alternative modes of transportation. In both cities more than two thirds of the traffic is conducted with alternative modes of transportation (City of Copenhagen and Administration 2019, van Infrastructuur en Waterstaat 2019).

6 Conclusion

In this paper we have estimated the willingness to pay of residents for a reduction of inner-city traffic from automobiles. For this purpose we make use of a novel approach by Bishop and Timmins (2019) which allows us to estimate the willingness to pay without instrumental variables using only moderate econometric assumptions. Our analysis is based on data from nine large cities in Germany between 2016 and 2019 and includes 533,402 detailed observations at the apartment level as well as for various points of interest. Therefore, in the analysis we are able to control for various apartment characteristics and distances measures at a very fine-grained level. To the best of our knowledge this is the first paper which to conduct this analysis for Germany. We estimate that the non-marginal willingness to pay for a reduction of traffic per household and year ranges by city between €30.3–59.2 for a 10% reduction, €93.8–158.3 for a 20% reduction and €190.6–252 for a 30% reduction. The highest non-marginal willingness to pay for a reduction of traffic is observed in Frankfurt am Main, the lowest in Leipzig. Further, we compute the expected gains for a reduction of traffic at the city level. In addition to the non-marginal willingness to pay for a reduction of traffic, this considers the composition of the road network as well as for the number of households. Accordingly, these expected gains amount between €163,970-1,019,454 for a 10% reduction, €484,023-3,261,837 for a 20% reduction and €1,018,240-6,727,148 for a 30% reduction. The highest expected gains for a reduction of traffic is observed in Munich, the lowest in Leipzig. To ensure the robustness of the results various tests have been conducted. This includes variations of the functional form, the market definition, the control variables, and fixed effects.

Though we observe a significant willingness to pay for a reduction of traffic, the effects of such a policy are ambilateral and its allocative and distributive effects need to be carefully balanced. On the one hand, a reduction of traffic reduces the exposition of apartments to negative externalities and raises the value of these apartments for tenants and owners. But this may also lead to price increases in an already heated housing market. On the other hand, a traffic reduction in cities may ceteris paribus raise the transportation costs of commuters, consumers, and firms. This may render it less attractive to drive to cities for work and purchases and may thus also affect the tax income of cities. Therefore, it might help to link such a policy with other measures which aim to maintain inner-city mobility.

Further research on the willingness to pay for traffic reductions may focus on two topics: To start with, an analysis may complement the results from this study, by broadening the range of different cities in the analysis. This includes nine of the most largest cities in Germany, but currently 57 cities exceed the critical value for air pollution. So the topic of this paper is also an issue that goes beyond the largest cities in Germany. Then, further research may include more detailed information on households, such as demographic information or voting behavior as this may allow us to target policies more precisely to the preferences of consumers and voters.

References

Baranzini, A., Ramirez, J., Schaerer, C., & Thalmann, P. (2008). *Hedonic Methods in Housing Markets - pricing environmental amenities and segregation*. Springer Science; Business Media.

Bartik, T. J. (1987). The Estimation of Demand Parameters in Hedonic Price Models. *Journal of Political Economy*, *95*(1), 81–88.

Beland, L.-P., & Brent, D. A. (2018). Traffic and crime. *Journal of Public Economics*, *160*, 96–116.

Bishop, K. C., & Timmins, C. (2019). Estimating the marginal willingness to pay function without instrumental variables. *Journal of Urban Economics*, *109*, 66–83.

BMWi. (2019). *Jahresbericht der bundesregierung zum stand der deutschen einheit 2019*. Retrieved June 30, 2020, from https://www.bmwi.de/Redaktion/DE/Publikationen/Neue-Laender/jahresbericht-zum-stand-der-deutschen-einheit-2019.html

Bundesagentur für Arbeit. (2019). Pendleratlas. Retrieved June 30, 2020, from https://statistik.arbeitsagentur.de/DE/Navigation/Statistiken/Interaktive-Angebote/Pendleratlas/Pendleratlas-Nav.html

Bundesamt für Statistik. (2017). Berufspendler. Retrieved June 30, 2020, from https://www.destatis.de/DE/Themen/Arbeit/Arbeitsmarkt/Erwerbstaetigkeit/Tabellen/pendler1.html;jsessionid=ED439C0B4D26A0DF98303DCBD2726BD3.internet712?nn=206552

Bundesbank. (2019). *Monatsbericht februar 2019* (Vol. 71. Jahrgang). Retrieved June 30, 2020, from https://www.bundesbank.de/de/aufgaben/themen/preise-fuer-wohnimmobilien-sind-2018-kraeftig-gestiegen-778630

Carlos, C. M. J., Luc, F., Antonio, S. R., Carlo, L., Miles, P., Frank, R., Francoise, N., Hande, D., Mátè, R., Alessandro, D., Marcello, D., & SRI. (2014). *Climate Impacts in Europe. The JRC PESETA II Project*. Retrieved June 30, 2020, from https://ideas.repec.org/p/ipt/iptwpa/jrc87011.html

City of Copenhagen, T., & Administration, E. (2019). The bicycle account 2018 - copenhagen city of cyclists. Retrieved June 30, 2020, from https://kk.sites.itera.dk/apps/kk_pub2/index.asp?mode=detalje&id=1962

Commission, E. (2018). Eu-kommission verklagt deutschland und fünf weitere mitgliedsstaaten wegen luftverschmutzung. Retrieved June 30, 2020, from https://ec.europa.eu/germany/news/20180517-luftverschmutzung-klage_de

Commission, E. (2019a). Commission takes italy to court over air pollution and failure to properly treat urban waste water. Retrieved June 30, 2020, from https://ec.europa.eu/commission/presscorner/detail/en/IP_19_1475

Commission, E. (2019b). Road transport: Reducing co2 emissions from vehicles. Retrieved June 30, 2020, from https://ec.europa.eu/clima/policies/transport/vehicles_en

Cropper, M. L., Deck, L. B., & McConnell, K. E. (1988). A new approach to consumer theory. *The Review of Economics and Statistics*, *70*(4), 668–675.

Davis, S. C., & Boundy, R. G. (2019). *Transportation energy data book: Edition 37.2*. Retrieved June 30, 2020, from https://tedb.ornl.gov/wp-content/uploads/2019/03/TEDB_37-2.pdf

DIHK. (2019). Arbeitsmarktreport 2019. Retrieved June 30, 2020, from https://www.dihk.de/de/themen-und-positionen/fachkraefte/beschaeftigung/fachkraefteengpaesse-gross-trotz-schwaecherer-konjunktur-5906%22

Economist. (2018). What, and who, are france's "gilets jaunes"? Retrieved June 30, 2020, from https://www.economist.com/the-economist-explains/2018/11/27/what-and-who-are-frances-gilets-jaunes

Economist. (2019). The french president responds to the gilets jaunes. Retrieved June 30, 2020, from https://www.economist.com/europe/2019/04/26/the-french-president-responds-to-the-gilets-jaunes

Ekeland, I., Heckman, J. J., & Nesheim, L. (2004). Identification and estimation of hedonic models. *Journal of political economy*, *112*(S1), S60–S109.

Epple, D. (1987). Hedonic prices and implicit markets: Estimating demand and supply functions for differentiated products. *Journal of Political Economy*, *95*(1), 59–80.

Eurostat. (2019). Passenger cars per 1 000 inhabitants, keyword: Road_eqs_carhab. Retrieved June 30, 2020, from https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=road_eqs_carhab&lang=en

Gartman, D. (2004). Three ages of the automobile: The cultural logics of the car. *Theory, Culture & Society*, *21*(4-5), 169–195. https://doi.org/10.1177/0263276404046066

Gee, G. C., & Takeuchi, D. T. (2004). Traffic stress, vehicular burden and well-being: A multilevel analysis. *Social Science & Medicine*, *59*(2), 405–414. https://doi.org/https://doi.org/10.1016/j.socscimed.2003.10.027

Glaeser, E. L., & Luttmer, E. F. P. (2003). The misallocation of housing under rent control. *American Economic Review*, *93*(4), 1027–1046.

Greene, W. H. (2012). *Econometric analysis, 7th edition*. Pearson.

Griliches, Z. (1961). Hedonic price indexes for automobiles: An econometric of quality change, 173–196. Retrieved June 30, 2020, from https://www.nber.org/chapters/c6492

Haufe. (2019). Kappungsgrenze für mieterhöhung. Retrieved June 30, 2020, from https://www.haufe.de/immobilien/verwaltung/mietpreisdeckel-regelungen-der-bundeslaender-zur-kappungsgrenze/mietrechtsaenderung-ermoeglicht-laendern-senkung-der-kappungsgrenze_258_275652.html

Houghton, E. (1996). *Climate change 1995: The science of climate change: Contribution of working group i to the second assessment report of the intergovernmental panel on climate change* (Vol. 2). Cambridge University Press.

Kahn, S., & Lang, K. (1988). Efficient estimation of structural hedonic systems. *International Economic Review*, *29*(1), 157–166.

Kholodilin, K. A., Mense, A., & Michelsen, C. (2016). Market Break or Simply Fake? Empirics on the Causal Effects of Rent Controls in Germany, (1584). Retrieved June 30, 2020, from https://ideas.repec.org/p/diw/diwwpp/dp1584.html

Knittel, C. R., Miller, D. L., & Sanders, N. J. (2016). Caution, drivers! Children present: Traffic, pollution, and infant health. *The Review of Economics and Statistics*, *98*(2), 350–366.

Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of Political Economy*, *74*(2), 132–157.

LBO Baden Württemberg. (2019). Landesbauordnung 6. teil - Einzelne Räume, Wohnungen und besondere Anlagen (§§ 34 - 40).

OECD. (2019). The heavy burden of obesity, 240. Retrieved June 30, 2020, from https://www.oecd-ilibrary.org/content/publication/67450d67-en

Republique Français. (2017). 2018: Tout ce qui va changer. Retrieved June 30, 2020, from https://www.gouvernement.fr/2018-tout-ce-qui-va-changer

Republique Français. (2018). The french president responds to the gilets jaunes. Retrieved June 30, 2020, from https://www.gouvernement.fr/action/plan-climat

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy*, *82*(1), 34–55.

Shehab, M., & Pope, F. (2019). Effects of short-term exposure to particulate matter air pollution on cognitive performance. *Scientific reports*, *9*(1), 8237.

Umweltbundesamt. (2019). Liste der städte mit no2-grenzwertüberschreitung. Retrieved June 30, 2020, from https://www.umweltbundesamt.de/dokument/liste-der-staedte-no2-grenzwertueberschreitung

United States Census Bureau. (2017). Sex of workers by means of transportation to work. Retrieved June 30, 2020, from https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=ACS_16_1YR_B08006&prodType=table

Urban Access Regulation. (2019). Urban access regulations in europe. Retrieved June 30, 2020, from https://urbanaccessregulations.eu/

van Infrastructuur en Waterstaat, M. (2019). Mobiliteitsbeeld 2019. Retrieved June 30, 2020, from https://www.kimnet.nl/publicaties/rapporten/2019/11/12/mobiliteitsbeeld-2019-vooral-het-gebruik-van-de-trein-neemt-toe

WHO. (2005). *Health effects of transport-related air pollution*. Retrieved June 30, 2020, from http://www.euro.who.int/en/publications/abstracts/health-effects-of-transport-related-air-pollution

WHO. (2018). *Global status report on road safety 2018*. Retrieved June 30, 2020, from https://www.who.int/violence_injury_prevention/road_safety_status/2018/en/

7 Appendix

Statistic	N	Mean	St. Dev.	Min	Max
Art	533,402	1,136.29	1,365.34	0.28	13,574.25
Automotive	533,402	519.37	824.48	0.21	8,836.44
Beauty And Health	533,402	449.43	815.41	0.13	8,001.08
Department	533,402	412.77	768.71	0.09	7,893.65
Do-It-Yourself	533,402	569.94	799.84	0.14	8,453.26
Electronic	533,402	859.67	1,043.52	0.26	12,029.39
Fashion	533,402	655.12	948.96	0.03	11,486.79
Groceries	533,402	408.93	811.55	0.12	8,083.71
Interior	533,402	852.27	1,088.67	0.12	11,282.01
Kiosk	533,402	821.68	1,084.02	0.35	12,145.19
Other	533,402	562.84	893.97	0.04	8,852.33
Sport And Outdoor	533,402	1,105.32	1,101.55	0.67	10,278.46

Table 5: *Summary Statistics of Shop Distances*

Statistic	N	Mean	St. Dev.	Min	Max
Townhall	533,402	5,605.75	3,741.04	4.09	19,751.06
Motorway	533,402	3,526.91	2,221.30	1.27	13,856.14
Public Transport	533,402	264.89	540.55	0.21	6,973.58
Eat And Drink	533,402	323.53	749.52	0.08	7,484.79
Education	533,402	357.21	741.61	0.13	7,486.89
Entertainment	533,402	566.29	808.71	0.12	7,610.56
Finance	533,402	574.16	824.10	0.04	7,904.98
Health	533,402	400.15	780.17	0.05	7,817.80
Other	533,402	285.63	721.47	0.05	7,331.73
Parking	533,402	272.89	716.45	0.21	7,319.02
Recycling	533,402	310.36	748.90	0.32	7,564.13
Vehicle	533,402	452.12	765.50	0.93	7,599.45

Table 6: *Summary Statistics of Amenity Distances*

Statistic	N	Mean	St. Dev.	Min	Max
Price	533,402	725.53	423.22	150	3,857
Size	533,402	68.42	27.01	17	214
Number of Rooms	533,402	2.37	0.92	1	8
Number of Lanes	533,402	1.93	0.45	1	6
Maxspeed in Street	533,402	37.77	9.91	5	100
Facility Manager	533,402	0.03	0.17	0	1
Storage	533,402	0.05	0.22	0	1
Balcony	533,402	0.39	0.49	0	1
Basement included	533,402	0.25	0.43	0	1
Elevator	533,402	0.15	0.36	0	1
Open Kitchen	533,402	0.03	0.18	0	1
Pantry Kitchen	533,402	0.01	0.10	0	1
Kitchen	533,402	0.25	0.44	0	1
Accessibility	533,402	0.03	0.18	0	1
Bathtub	533,402	0.15	0.36	0	1
Guest Toilet	533,402	0.05	0.22	0	1
Shared Flat	533,402	0.05	0.21	0	1
Garden	533,402	0.09	0.29	0	1
Historic Building	533,402	0.09	0.29	0	1
New Apartment	533,402	0.07	0.26	0	1
Renewed Apartment	533,402	0.27	0.44	0	1
Furnished Apartment	533,402	0.04	0.20	0	1
Parking Space	533,402	0.05	0.23	0	1
Heated Floor	533,402	0.04	0.19	0	1
Subsidized Apartment	533,402	0.03	0.17	0	1
Laundry Room	533,402	0.02	0.13	0	1
Sat TV	533,402	0.06	0.24	0	1
Cable TV	533,402	0.01	0.09	0	1
Bathroom Window	533,402	0.01	0.10	0	1
Luxury Apartment	533,402	0.01	0.09	0	1
Loggia	533,402	0.02	0.14	0	1
Attic	533,402	0.01	0.08	0	1
Security Camera	533,402	0.003	0.05	0	1
Alarm	533,402	0.001	0.03	0	1
Wintergarden	533,402	0.01	0.08	0	1
Fireplace	533,402	0.004	0.06	0	1
Bidet	533,402	0.001	0.03	0	1
Air condition	533,402	0.001	0.03	0	1
Marmor	533,402	0.0005	0.02	0	1
Panoramic View	533,402	0.03	0.18	0	1
Calm Apartment	533,402	0.07	0.25	0	1
Bright Apartment	533,402	0.07	0.26	0	1

Table 7: *Summary Statistics of Appartment Characteristics (See also Section 3 for their origin)*

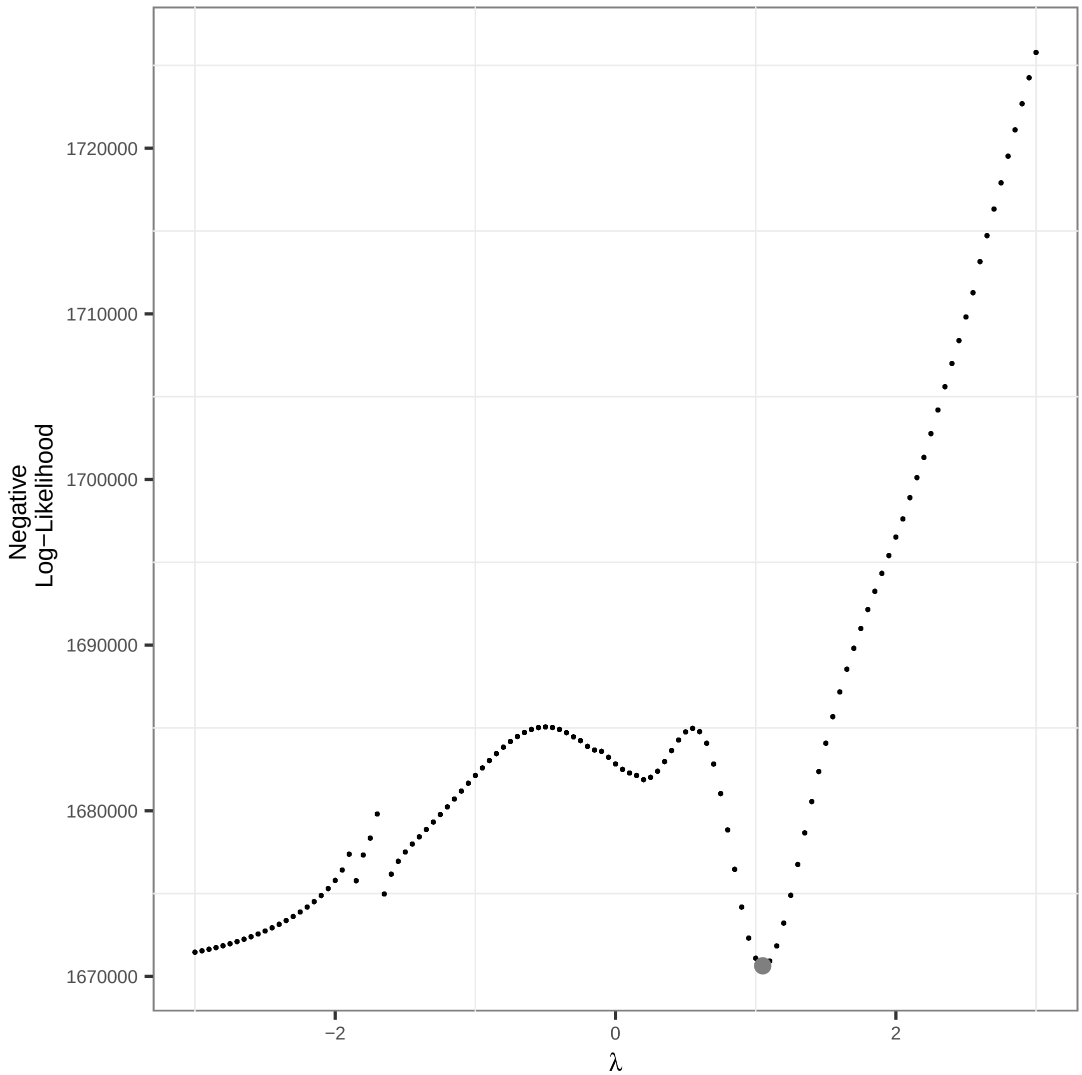

Figure 8: *Relationship between the λ-Value in the Box-Cox Transformation and the Negative Log-Likelihood in the Maximum-Likelihood Estimation in the Second Stage of the Estimation with the Baseline Setup as reported in Tables 1 and 2.*

	Coef.	Std. Error	CI 95%
Traffic Capacity	2.224	0.082	[2.064; 2.384]
Sigma	12.300	0.437	[11.442; 13.157]
Berlin2016	-30.462	1.412	[-33.229; -27.695]
Berlin2017	-30.113	1.698	[-33.441; -26.786]
Berlin2018	-30.696	1.617	[-33.865; -27.527]
Berlin2019	-29.955	1.587	[-33.065; -26.844]
Dresden2017	-31.320	1.660	[-34.573; -28.066]
Dresden2018	-31.369	1.485	[-34.28; -28.459]
Dresden2019	-30.828	1.631	[-34.024; -27.631]
Düsseldorf2016	-33.429	2.385	[-38.104; -28.754]
Düsseldorf2017	-31.307	1.554	[-34.352; -28.261]
Düsseldorf2018	-31.690	1.615	[-34.856; -28.524]
Düsseldorf2019	-31.481	1.481	[-34.383; -28.578]
Frankfurt Am Main2016	-31.290	1.674	[-34.571; -28.009]
Frankfurt Am Main2017	-31.255	1.958	[-35.093; -27.417]
Frankfurt Am Main2018	-31.601	1.423	[-34.389; -28.812]
Frankfurt Am Main2019	-31.093	1.738	[-34.5; -27.686]
Hamburg2016	-34.017	2.206	[-38.341; -29.693]
Hamburg2017	-33.889	1.937	[-37.685; -30.094]
Hamburg2018	-34.228	1.575	[-37.315; -31.141]
Hamburg2019	-33.568	1.621	[-36.746; -30.391]
Cologne2016	-32.511	2.019	[-36.468; -28.553]
Cologne2017	-32.106	1.563	[-35.169; -29.043]
Cologne2018	-32.292	1.821	[-35.86; -28.723]
Cologne2019	-32.085	1.460	[-34.945; -29.224]
Leipzig2017	-31.769	1.675	[-35.052; -28.487]
Leipzig2018	-32.191	1.735	[-35.592; -28.791]
Leipzig2019	-31.418	1.640	[-34.632; -28.204]
Munich2016	-31.244	1.903	[-34.973; -27.514]
Munich2017	-30.964	1.485	[-33.874; -28.054]
Munich2018	-31.673	1.531	[-34.673; -28.673]
Munich2019	-31.198	1.562	[-34.259; -28.137]
Stuttgart2016	-29.699	1.718	[-33.067; -26.332]
Stuttgart2017	-28.821	1.973	[-32.689; -24.953]
Stuttgart2018	-28.583	1.715	[-31.945; -25.221]
Stuttgart2019	-28.301	1.756	[-31.742; -24.859]
Markets:		City × Year	
Apartment Characteristics:		All	
Shops, Amenities & Public Services:		Minimal Distance	
Fixed Effects:		Zipcode × Year	
Observations:		533,402	

Note: Estimation results with city-year specific intercept. Standard errors are obtained by a non-parametric bootstrap with 200 replications.

Table 8: *Estimation Results of the Marginal Willingness to Pay Function (2nd Stage) with City and Year as Markets.*

	Coef.	Std. Error	CI 95%
Traffic Capacity	0.065	0.044	[-0.022; 0.152]
Sigma	0.372	0.247	[-0.112; 0.857]
West	-1.745	0.632	[-2.985; -0.506]
East	-1.736	0.637	[-2.983; -0.488]
Markets:		East and West Germany	
Apartment Characteristics:		All	
Shops, Amenities & Public Services:		Minimal Distance	
Fixed Effects:		Zipcode $\times$ Year	
Observations:		533,402	

Note: Estimation results with region specific intercept. Standard errors are obtained by a non-parametric bootstrap with 200 replications.

Table 9: *Estimation Results of the Marginal Willingness to Pay Function (2nd Stage) with East and West Germany as Markets.*

	Coef.	Std. Error	CI 95%
Traffic Capacity	1.955	0.570	[0.838; 3.073]
Sigma	10.817	3.151	[4.64; 16.993]
Berlin	-26.647	7.538	[-41.421; -11.872]
Dresden	-27.347	7.756	[-42.549; -12.145]
Düsseldorf	-27.806	7.878	[-43.246; -12.365]
Frankfurt am Main	-27.520	7.799	[-42.806; -12.235]
Hamburg	-29.782	8.457	[-46.357; -13.207]
Cologne	-28.273	8.002	[-43.957; -12.589]
Leipzig	-27.992	7.940	[-43.555; -12.429]
Munich	-27.505	7.805	[-42.802; -12.209]
Stuttgart	-25.170	7.953	[-40.758; -9.582]
Markets:		City	
Apartment Characteristics:		All	
Shops, Amenities & Public Services:		Minimal Distance	
Fixed Effects:		Zipcode + Year	
Observations:		533,402	

Note: Estimation results with city specific intercept. Standard errors are obtained by a non-parametric bootstrap with 200 replications.

Table 10: *Estimation Results of the Marginal Willingness to Pay Function (2nd Stage) with Zipcode and Year Fixed Effects.*

	Coef.	Std. Error	CI 95%
Traffic Capacity	1.951	0.581	[0.811; 3.09]
Sigma	10.791	3.215	[4.491; 17.092]
Berlin	-26.570	7.690	[-41.641; -11.498]
Dresden	-27.280	7.910	[-42.784; -11.777]
Düsseldorf	-27.728	8.034	[-43.476; -11.981]
Frankfurt am Main	-27.443	7.955	[-43.034; -11.852]
Hamburg	-29.695	8.624	[-46.598; -12.791]
Cologne	-28.192	8.159	[-44.183; -12.2]
Leipzig	-27.918	8.097	[-43.789; -12.048]
Munich	-27.421	7.959	[-43.02; -11.822]
Stuttgart	-25.089	8.114	[-40.991; -9.186]
Markets:		City	
Apartment Characteristics:		All	
Shops, Amenities & Public Services:		Minimal Distance	
Fixed Effects:		Zipcode	
Observations:		533,402	

Note: Estimation results with city specific intercept. Standard errors are obtained by a non-parametric bootstrap with 200 replications.

Table 11: *Estimation Results of the Marginal Willingness to Pay Function (2nd Stage) with Zipcode Fixed Effects.*

	Coef.	Std. Error	CI 95%
Traffic Capacity	1.545	0.426	[0.711; 2.38]
Sigma	8.552	2.354	[3.938; 13.165]
Berlin	-21.250	5.647	[-32.317; -10.182]
Dresden	-21.802	5.814	[-33.196; -10.407]
Düsseldorf	-22.182	5.903	[-33.752; -10.612]
Frankfurt am Main	-21.964	5.842	[-33.413; -10.515]
Hamburg	-23.767	6.334	[-36.181; -11.352]
Cologne	-22.554	6.006	[-34.327; -10.782]
Leipzig	-22.333	5.951	[-33.998; -10.669]
Munich	-21.945	5.843	[-33.396; -10.493]
Stuttgart	-20.121	5.954	[-31.79; -8.452]
Markets:		City	
Apartment Characteristics:		All	
Shops, Amenities & Public Services:		Mean Distance	
Fixed Effects:		Zipcode × Year	
Observations:		533,402	

Note: Estimation results with city specific intercept. Standard errors are obtained by a non-parametric bootstrap with 200 replications.

Table 12: *Estimation Results of the Marginal Willingness to Pay Function (2nd Stage) and Mean Distances to Shops, Amenities and Public Services.*

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