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Master Thesis

Modelling Off-Street Parking Supply at the Parcel Level: A Regression-Based Case Study in two German Cities

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Abstract

Data on off-street parking supply is poorly documented, although highly needed for effective parking policies. To address this gap, this study models off-street parking supply in the German cities Hamburg and Munich. Parking capacities are derived using aerial imagery-based surface parking segments, cadastral data, and OpenStreetMap features, yielding over 1.3 million off-street parking spaces in Hamburg and over 600,000 in Munich. Negative binomial count regression is conducted to model parking supply and its determinants on parcel level. Ground floor area and open space ratio show strong positive relationships with the residential parking supply density, while the latter is decreased with rising standard land values and higher household purchasing power. Non-residential coefficients are less stable throughout the three investigated samples. Parking supply prediction using cross-validation reveals moderate errors for residential models driven by outliers and substantially higher errors for non-residential uses. Transferring the Hamburg model to Munich data suggests that model specification is a greater challenge than spatial disparities between cities. This study provides a replicable approach for off-street parking supply modelling that future research can build upon, with particular need for further investigation into non-residential parking provision and the spatial transferability of model results across diverse urban contexts.

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List of abbreviations

MPR	Minimum Parking Requirement
OSM	OpenStreetMap
MBO	Musterbauordnung
LBO	Landesbauordnung
DOP	Digital Orthophoto
GFA	Ground Floor Area
SLV	Standard Land Value
PT	Public Transport
GTFS	Generalised Transit Feed Specification
GLM	Generalised Linear Models
NB	Negative Binomial
ZINB	Zero Inflation Negative Binomial
OLS	Ordinary Least Squares
VIF	Variance Inflation Factor
GAM	Generalised Additive Model
IRR	Incidence Rate Ratio
CI	Confidence Interval
CV	Cross Validation
LOOCV	Leave-One-Out Cross Validation
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
IDW	Inverse Distance Weighting

1. Introduction

Motorised individual transport remains the predominant mode of travel in Germany, reflecting its central importance for daily mobility across urban and rural areas (Follmer, 2025). On average, a private car requires four parking spaces: one at the place of residence and three others at destinations such as workplaces, shopping facilities, or recreational areas (Marsden, 2014; Shoup, 2021). This demand for space illustrates the high land consumption of car traffic, particularly in urban areas, where land use competition is high.

Effective parking management requires knowledge of existing parking supply. However, information on off-street parking is scarce, as it is usually kept in building files of authorities or surveyed only prior to the introduction of a parking permit zone (Bauer et al., 2024; FGSV, 2023). The city of Hamburg, Germany has recently addressed this gap, as the total number of parking spaces was recorded by the local geoinformation agency (Freie und Hansestadt Hamburg, Landesbetrieb Geoinformation und Vermessung, 2025a). While this procedure yields accurate ground-truth data on parking capacities, it is time-consuming, resource-intensive, and does not yet offer insights into the underlying factors influencing off-street parking supply.

This study presents a data-driven approach to derive and model off-street parking supply as well as its determinants. Using aerial imagery, cadastral data, and OpenStreetMap features, parking spaces are extracted for the study areas Hamburg and Munich to build comprehensive off-street parking datasets. After comparing the derived datasets with surveyed data, residential and non-residential parking supply as well as their determinants are investigated at the parcel level using count regression. The models are evaluated regarding their ability to predict off-street parking both within the study area and in an unknown spatial context.

Chapter 2 reviews the research on parking supply modelling and derives the research questions of this study. Chapter 3 describes data preparation and the parking supply derivation framework, followed by Chapter 4, which motivates the use of count regression as the analytical framework. Regression results and the transferability of the model are presented in Chapter 5. Finally, Chapter 6 discusses the findings and their implications.

2. Literature Review

Parking spaces can be divided into three main categories: (1) public parking, (2) semi-public parking, and (3) private parking (FGSV, 2023). Public (or on-street) parking is located in public space and accessible to everyone. Municipalities are able to manage parking spaces with regulations regarding prices and user groups. In zones with high parking demand, residential parking zones may restrict the (cost-free) accessibility of public parking spaces to a certain user group. Semi-public parking includes off-street parking facilities on private ground, which are usually accessible to the public upon payment or when consuming goods of the adjacent facility (e.g. supermarkets, retail). These parking facilities can be owned by municipalities as well as private persons or institutions. Private parking spaces are also located off-street and only available to a restricted user group (e.g. residents parking on their property).

Following this categorisation, this study focuses on modelling semi-public and private parking spaces, in the following referred to as off-street parking. The German cities Hamburg and Munich are chosen as study areas, as ground-truth data on off-street parking supply are available for both cities, providing the necessary basis for model evaluation. Section 2.1 gives an overview of the legal requirements regulating off-street parking in Germany. Literature on the supply and usage of off-street parking is analysed in Section 2.2. An analysis of current research on parking space quantification is provided in Section 2.3, which then leads to the motivation of this study's research objective in Section 2.4.

2.1. Parking requirements in Germany

The first legal framework regulating the parking of cars on private premises goes back to 1939, when the first Minimum Parking Requirement (MPR) in the form of a garage regulation (*Reichsgaragenordnung*) was established. The goal was to ensure that traffic flow was not blocked by parking cars and, at the same time, make sure that there was at least one parking space per residential unit as part of the ambition to reach mass motorisation with the new *Volkswagen* (Weidner, 2012; Zukunftsnetz Mobilität NRW, 2023).

With the introduction of a new German building regulation (Musterbauordnung (MBO)) and its implementation on federal state level (Landesbauordnung (LBO)) at the beginning of the 1960s, MPRs shifted the focus away from subsidising car ownership towards regulating and decreasing car parking in public space (Weidner, 2012). Furthermore, the new law stated that parking spaces may not be used for purposes other than intended (MBO 1959: § 67 Abs. 11). Every LBO was supplemented by a garage ordinance, all of which were based on the MBO and its complementing garage ordinance (*Mustergaragenverordnung*). German federal states were given the freedom to regulate parking requirements on an individual level, but were all influenced by the MBO (Weidner, 2012).

At this time, on-street parking in Germany was prohibited unless a private parking space existed, until a mandate enforced the 1966 "street lamp parking" decision by the Federal Administrative Court. This ruling legitimised overnight parking on public streets and effectively granted cars a privileged status in the public realm (BVerfG, decision of 09 October 1984, 2 BvL 10/82). This legacy persists to this day and gives car holders the option to park their car outside of private premises.

As of the 1980s, the awareness of negative effects of high MPRs such as induced traffic demand rose and with it came an amendment to the MBO. Municipalities were granted the right to refuse or restrict the creation of parking spaces for traffic reasons (Weidner, 2012; Zukunftsnetz Mobilität NRW, 2023). However, municipalities were obliged to provide sufficient parking in public space and real estate developers needed to pay a redemption fee if they could not provide enough parking spaces. This trend was reinforced in the 1990s, as federal states started to differentiate their LBOs from the national MBO. As an example, several states implemented the possibility of a reduction of parking requirements if public transport accessibility was sufficient. Berlin even abolished the duty to provide private parking spaces for newly constructed buildings (Weidner, 2012). Furthermore, MPRs for bicycles were subsequently established during this period (Zukunftsnetz Mobilität NRW, 2023).

The fragmentation of MPRs throughout Germany was supported in the early 21th century, when another amendment of the MBO in 2002 explicitly gave municipalities freedom to design MPRs according to local conditions. It also stated that the function of parking requirements does not specifically aim to shift parking from public to private space, and instead could be understood as part of the local transport policy. A general deletion of MPRs for residential buildings was discussed, but discarded (Bauministerkonferenz (ARGEBAU), 2002). However, among other cities, Hamburg has meanwhile adopted a different approach and established a regulation where the MPR is replaced by a "proof of mobility". This regulation contains various modules that allow the number of parking spaces to be reduced on an individual basis (Freie und Hansestadt Hamburg, Behörde für Stadtentwicklung und Wohnen, 2022).

2.2. Usage and Determinants of Off-Street Parking

From a legal perspective, the German state has no control over how off-street parking is used (Zukunftsnetz Mobilität NRW, 2023). Hence, although regulations like parking requirements aim to reduce the number of cars parked in public space, car holders have the free choice to use and pay for a private parking space. According to relevant case law (OVG RLP, 27 November 2001 – 7 A 10728/01; VG München, May 19, 2017 – M 23 K 16.1536), an approval authority may reject an application for a residential parking permit if a private parking space is legally available on the property.

Instead of parking in a garage on their property, car holders could still choose to park their car in public parking spaces where a residential parking permit is not mandatory. An observational study of a temporary parking ban in a residential neighbourhood found that two thirds of vehicles which were parked in public parking spaces did not reappear within the surrounding district (Blees, 2021). This suggests a shift of vehicles parked on private parking spaces during the parking ban and, hence, a misuse of private parking spaces. Similar behaviour is also found in Dortmund and Melbourne (Scheiner et al., 2020; Taylor, 2020).

Meanwhile, semi-public parking belonging to service facilities and retail areas is generally used during business hours only. This creates the potential for shared use as residential parking during off-peak hours. Aichinger and Blees (2024) claim that the multiple use of semi-public and private facilities is cost-efficient and pragmatic, but requires coordination and regulation from municipalities to be successful. 11 supermarkets in the city of Düsseldorf currently provide their parking lots for overnight use in return for low fees (ampido, 2025b).

How off-street parking is used depends in part on how it is provided. Several structural, regulatory, and socio-economic factors have been identified in the literature as determinants of off-street parking supply. Parking requirements in Germany are primarily defined as a function of usable floor area and use category, with the required number of spaces scaling proportionally with Ground Floor Area (GFA) (Freie und Hansestadt Hamburg, Behörde für Stadtentwicklung und Wohnen, 2022; Landeshauptstadt München, 2025). Required parking rates vary considerably across use categories, with higher rates typically prescribed for industrial, retail, and workplace uses, and comparably lower rates for educational, leisure, and hospitality facilities (Freie und Hansestadt Hamburg, Behörde für Stadtentwicklung und Wohnen, 2022; Landeshauptstadt München, 2025). Empirical evidence from Bangkok confirms a positive relationship between total floor area and parking supply in condominium developments (Chullabodhi et al., 2020).

Public transport accessibility is intended to reduce parking supply through regulatory provisions that allow requirement reductions in well-connected locations (Weidner, 2012). Current regulatory frameworks confirms this, as the city of Munich reduces the amount of required parking for non-residential uses if the property is located in a zone with sufficient public transport access. The city of Hamburg goes one step further, as parking requirements can be replaced if it can be proven that other mobility options such as public transport are easily accessible. Evidence from other contexts confirm the regulatory expectation, as parking supply levels are lower for condominiums with public transport adjacency (Chullabodhi et al., 2020). In Shenzhen, the sign and strength of transport accessibility vary across space in office parking provision (Liu et al., 2019).

The building density is generally positively associated with parking supply, though evidence remains limited. When measured through the floor area ratio, Liu et al. (2019) find a positive correlation with parking supply. Li et al. (2022) report increased parking density for high-rise buildings in the US cities San Francisco, Oakland, and San Jose. An off-street parking inventory for 15 US cities reveals that central business districts show the highest percentage of land denoted to parking (Qiam & Lehe, 2025).

The effect of financial characteristics varies depending on the considered indicator. Higher land values increase the economic incentive to maximise built area and relocate parking to costly underground garages (Derschmeier et al., 2023). Chullabodhi et al. (2020) find that higher condominium unit prices are associated with greater parking provision, suggesting that wealthier developments tend to offer more parking. This aligns with evidence that car ownership potential is positively correlated with income (Ritter & Vance, 2012), which in turn increases the demand for parking.

To compare MPRs with the demand for off-street parking, a cross-national study contrasts the number of required parking spaces with the number of registered cars in twelve mid-sized cities across Germany, the Netherlands, and Switzerland. The study finds that MPRs often exceed actual vehicle ownership in central urban areas, whereas in suburban single-family housing areas, the ratio is closer to one or below (Merten & Kuhnimhof, 2024). However, the study does not account for historical urban areas where parking minimums are not applicable. The authors therefore recommend that future research should focus on the number of implemented rather than required parking spaces to more accurately capture existing supply conditions.

Despite the obligation to provide parking according to regulatory frameworks, the effects of MPRs on parking supply are discussed in the literature. Evidence from the United States shows that the increase in parking supply between 1960 and 2000 is mainly driven by MPRs and perceived market demand (McCahill & Garrick, 2014). Jung (2011) and Derschmeier et al. (2023) argue that MPRs often lead to an oversupply of parking spaces in multifamily residential developments. This oversupply effectively acts as a subsidy, discouraging efficient land use and resulting in fewer housing units reaching the market. Consequently, this raises market-clearing prices. In Berlin, however, the deletion of MPRs in the 1990s did not reduce the ratio of demanded parking according to regulations versus actually built parking spaces (44.1 % with, 45.3 % without MPRs) (Kaden & Thiel, 2002).

The discrepancy between required parking according to regulations and actually built parking spaces shows that apart from parking regulations, other factors influence the parking supply. These factors are, however, barely investigated in the literature. Even if parking requirements were the same throughout Germany, property owners could still decide to construct more parking spaces than the minimum required. Fragmented parking requirements as well as the possibility of paying a redemption fee make quantifying parking spaces based on regulatory frameworks practically impossible. Thus, the factors driving off-street parking supply beyond minimum requirements remain poorly understood.

2.3. Quantification and Modelling of Parking Supply

According to German law discussed in Section 2.1, the obligation to provide parking spaces is derived from the building regulations of the federal states, for example Section 48 of the North Rhine-Westphalia Building Code. The corresponding parking space verification (*Stellplatznachweis*) must be submitted as part of the building application and is subsequently documented in the building file maintained by the building supervisory authority (cf. Section 29 VwVfG – Administrative Procedure Act). Consequently, the most reliable method of quantifying parking supply consists of collecting data from building files. Although this information is available to German municipalities, the total number of existing parking spaces is not systematically recorded and therefore remains largely unknown to municipal authorities (Bauer et al., 2024; Merten & Kuhnimhof, 2024). One reason is the time-consuming process of scanning thousands of documents, motivating the use of data-driven approaches to estimate parking supply.

Quantifying the number of both public and private parking spaces requires either direct collection or estimation. Three quantification approaches can be identified: (1) pedestrian-, camera- or sensor-based counting, (2) manual or computer-automated segmentation of traffic areas using aerial imagery, or (3) household and facility surveys. While (1) is primarily used to measure public parking, (2) and (3) are commonly used methods for semi-public and private parking spaces. Where data are not fully available, approximations derived from partial inspections are used to quantify the number of parking spaces. In addition, crowdsourced data collection (e.g., via OpenStreetMap) and land registers available at open data platforms of municipalities provide additional sources of parking data.

In recent years, municipalities have started gathering information on their public parking supply. Hamburg publishes public parking data on its open data portal (Freie und Hansestadt Hamburg, Landesbetrieb Verkehr, 2025). Berlin conducted sensor- and camera-based surveys across the entire city as well as measuring parking demand in parking management zones (Senatsverwaltung für Mobilität, Verkehr, Klimaschutz und Umwelt Berlin, 2025). Basel additionally reports on the development of private parking based on direct measurement for new constructions and estimates for supply in the existing building stock (Kanton Basel-Stadt, 2025).

The quality and completeness of OpenStreetMap (OSM) data largely depend on the extent to which users actively maintain and update the mapping base and thus vary locally (Retat & Schaffert, 2018). In Germany, OSM provides relatively comprehensive coverage of semi-public parking facilities, however, OSM contains only limited information on public and private parking. Seidel and OpenStreetMap Contributors (2021) address this gap by analysing all types of parking in Berlin-Neukölln. Their methodology consists of on-street and web-based inspection as well as post-processing of collected data, analysis of the land register, and further web research of missing data. As a continuation of this project, OSM contributors gathered data, resulting in a comprehensive database, although the focus of the project is primarily on public parking (FixMyCity, 2022). Using OSM data, Szell (2018) developed a comparative visualisation of urban space allocated to cars, bicycles, and rail infrastructure, including information on public and commercial parking facilities. Similarly, Czeh (2024) analysed land use of motorised vehicles based on OSM and land register data and reported that approximately 22 km^2 of Berlin (the area of the city's district Friedrichshain-Kreuzberg) are covered by off-street car infrastructure, primarily parking facilities.

Quantifying private parking spaces remains particularly challenging, as these facilities are located on private property and are often concealed in underground garages or courtyards, which restricts visibility. To address this issue, the state of Luxembourg applies a mixed-methods approach that uses evaluation of OSM data as well as web-based and on-street inspections in sample areas with varying land-use characteristics. The resulting data are used to develop coefficients for estimating the parking supply across the entire country (Ministère de la Mobilité et des Travaux publics, 2021). This methodology was adapted and applied in Mainz (Müller, 2025). While the Luxembourg approach produces reliable estimates for public and commercial parking, invisible private parking facilities are approximated indirectly—typically by counting doorbells and assuming one parking space per household. A similar procedure is adopted in Cologne, combining on-street and web-based inspection, surveys, and doorbell counting to estimate garage capacities (ampido, 2025a). The study aims to make underutilised private parking more available for public use.

The project *ACUP* investigates parking supply in the city of Aachen. With regard to private parking, the analysis is limited to two sample neighbourhoods, applying a combined approach of on-street and web-based inspection and household surveys (Louen et al., 2022). The results indicate that estimates based on official land register data capture less than half of the actual number of private parking spaces. The authors therefore emphasise the need for further research, particularly on estimating private parking supply through regression models that integrate census data and other spatially referenced variables (Louen et al., 2022, p. 12).

Another method for quantifying parking spaces is the use of remote-sensing technologies to automatically derive parking areas from aerial imagery. Hellekes et al. (2023) use traffic area segmentation to estimate on-street parking availability. Their methodology combines computer–based parking area detection from aerial imagery with road network and land use data. Thomas (2024) builds on this data, focusing on the actual number of parking spaces in Berlin. The use of parking space measures and cadastral data enables validation of public parking estimates and a first approximation of private parking spaces. While the first iteration still underestimates parking by around 17%, the approach of traffic area segmentation provides novel data on private parking. Recent work by Rauch et al. (2025) further develops the approach by including vehicle detection and cadastral data in order to distinguish the parking category (public, semi-public, private) as well as the parking type (parallel, diagonal, vertical). Results show that public parking data surveyed by the city of Berlin underestimate the total parking availability by around 40 %.

While parking data acquisition through traffic area segmentation provides an efficient and scalable approach that can be automated for entire regions thanks to the availability of aerial imagery, it lacks accuracy regarding invisible private parking spaces, for example those concealed by vegetation or located in (underground) garages. Thomas (2024) emphasises the insufficient validation of such results, particularly for private parking, where hidden spaces frequently occur.

Studies modelling off-street parking supply through regression approaches remain uncommon. Orquina et al. (2003) analyse residential condominium parking supply using linear regression on survey data. Chullabodhi et al. (2020) apply a similar approach in Bangkok, modelling structural and socio-economic determinants of condominium parking. Liu et al. (2019) model office parking provision in Shenzhen, China using geographically weighted regression. All three studies rely on small samples of fewer than 1,000 observations and focus on specific property types, limiting the generalisability of their results. Furthermore, none of the studies are conducted in a European context.

2.4. Research Objective

Research on parking quantification in German cities highlights both the difficulty of capturing off-street parking and the potential of combining spatial data sources to derive parking supply at scale. At the same time, the literature review reveals that empirical knowledge on the determinants of off-street parking supply remains scarce. The factors driving real-world parking supply within and beyond minimum requirements are therefore poorly understood. This motivates the first of two research questions of this study:

Research Question 1 *Which structural factors influence parking supply at the parcel level?*

This study aims to analyse how structural and economic characteristics affect parking supply, thereby filling the knowledge gap that remains after parking requirements are applied. To do this, count regression modelling is applied to measure the effect of parking supply determinants. The analysis is carried out at the parcel level, as this is the most detailed spatial unit at which geo-referenced parking spaces can be linked to the characteristics of the underlying property. Table 2.1 provides an overview of the determinants investigated in this study, along with their spatial granularity, their variable type and the expected relation with the number of parking spaces based on the reviewed literature in this chapter.

As off-street parking quantification remains a challenge for municipalities, it is desirable to develop a model capable of estimating parking supply where direct quantification is resource-intensive or not feasible. To assess whether a model trained on data from one study area is capable of predicting parking supply in similar or different environments, the second research question is formulated as follows:

Table 2.1.: Determinants of off-street parking spaces per parcel.

Independent variable	Spatial granularity	Variable type	Expected effect
Ground floor area [m²]	Building	Continuous	+
Use category	Building	Categorical	∘
Year of construction	Building	Categorical	∘
Public transport access	Parcel	Continuous	−
Building density (open space ratio)	Parcel	Continuous	+
Building type	Building	Categorical	∘
Standard land value [€]	Land value areas	Continuous	−
Household purchasing power [€]	Household	Continuous	−

Note. + positive effect; − negative effect; ∘ effect depends on category

Research Question 2 *How can the model be transferred to predict the parking supply of other cities?*

This work conducts regression analysis in two study areas, namely the German metropolises Hamburg and Munich. This allows model results to be cross-validated and compared across two distinct urban contexts. Three approaches are pursued to answer Research Question 2. First, the modelling outcomes for both study areas are compared to identify similarities and differences in estimated coefficients. Second, resampling methods are applied to assess model performance when trained within the same city. Third, the model fitted on Hamburg data is used to predict surveyed parking supply in Munich, providing a direct test of cross-city transferability.

By addressing both the quantification and the modelling of off-street parking supply, this work seeks to identify structural determinants of parking supply at the parcel level and to assess the transferability of the resulting model across urban contexts. Both research questions form the foundation for the data processing and the methodological approach outlined in the following chapters.

3. Data

This study uses both derived and surveyed parking supply data from two German cities as input for regression modelling of off-street parking supply. Raw data are spatially pre-processed to derive off-street parking supply as well as its determinants on a parcel level. Figure 3.1 provides an overview of the processing workflow, with each step explained in detail throughout this chapter. Section 3.1 describes the data sources of determinants in the regression model. Section 3.2 presents the derivation of off-street parking supply, demonstrating the potential of computational approaches for parking capacity estimation. Section 3.3 introduces the ground-truth data used for validating the derived parking supply and and to estimate an alternative model.

3.1. Parking supply determinants

The determinants of off-street parking supply are examined at the parcel level, which requires several pre-processing steps to prepare the data for regression analysis. Data on the chosen parking supply determinants are extracted from three types of sources: cadastral data, household data and public transport data. The spatial pre-processing—from raw input to variables ready for regression analysis—is described in the following.

3.1.1. Cadastral Data

Cadastral data in Germany are maintained by federal states in accordance with nationwide coding standards (Arbeitsgemeinschaft der Vermessungsverwaltungen der Länder der Bundesrepublik Deutschland, 2025) or the European *INSPIRE* directive (European Commission, 2025). In the scope of this study, cadastral data were obtained from geo portals or provided by authorities (Bayerische Vermessungsverwaltung, 2026; Freie und Hansestadt Hamburg, Landesbetrieb Geoinformation und Vermessung, 2024; Landeshauptstadt München - Kommunalreferat - Geodatenservice, 2026). The data contain different layers, ranging from aggregated district and land use layers to detailed polygons of parcels and buildings.

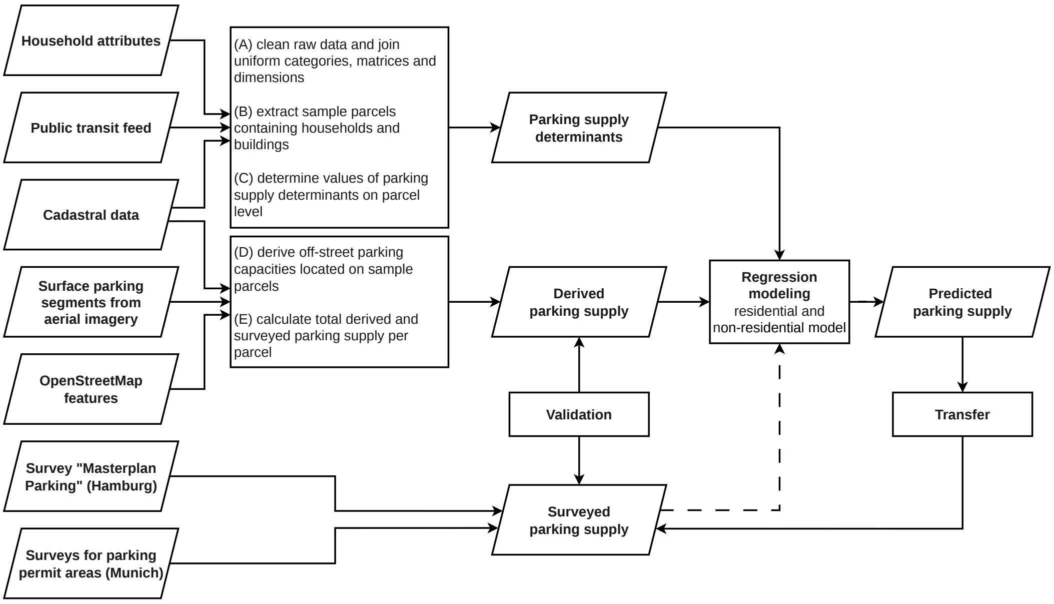

Figure 3.1.: Data processing flowchart. Dashed line: Only Hamburg surveyed supply serves as input for regression modelling.

Cadastral parcel polygons form the starting point of the analysis as this study examines parking at the parcel level. Parcels can represent private property or public land and are maintained in the German cadastral information system (Bayerische Vermessungsverwaltung, 2026; Freie und Hansestadt Hamburg, Landesbetrieb Geoinformation und Vermessung, 2024). As parking data and some determinants are not obtained at the address level, parcel-level analysis allows for a consistent spatial assignment of determinants and parking supply. Spatial joins and intersections using PostgreSQL with the PostGIS extension lead to the final parcel samples used in the analysis, covering wide parts of both investigated cities.

Land use information is relevant to distinguish on-street from off-street parcels. In addition to roads, land use types with a public character such as railways, squares, and woods are not considered as off-street due to the public usage or availability for citizens. The land use types and their mapping as on- or off-street areas are depicted in Table A.1.

To extract off-street parcels, a spatial join between parcels and the land use layer is performed. If a parcel intersects with more than one land use polygon, the land use polygon with the higher intersection share defines the land use of the parcel and thus decides whether a parcel is considered in the sample or not. However, the dominant land use does not yet define the use category of the parcel, since the coarser granularity of land use polygons compared to parcels may obscure heterogeneous use over multiple buildings located on parcels.

Building blocks have a finer granularity than land use polygons. Surveyed parking supply in Munich is available on block-level, which is why the connection of parcels and blocks is mandatory for later validation. Based on the same dominance threshold as with land use polygons, parcels are assigned to a block.

The cadastral information systems of Hamburg and Munich provide very detailed information on buildings and building parts. Most important for this analysis are (1) the building footprint, (2) the floor count, and (3) the use type of the building. The multiplication of (1) and (2) results in the GFA, which is one of the driving factors of off-street parking supply according to the regulatory framework of German municipalities (Weidner, 2012). In the case of Munich, additional building information is provided, from which the GFA by use can be extracted (Landeshauptstadt München - Planungsreferat, 2026).

In order to assign buildings and building parts to parcels, a spatial intersection is executed. Buildings and building parts intersecting more than one parcel are split at the parcel border, with the overlapping fragment assigned to the according parcel. The footprint of each building part is subtracted from the parent building footprint prior to GFA calculation, to avoid double-counting floor area. The GFA per parcel can then be calculated as the sum of GFA over all buildings and building parts on a parcel.

Similarly, the dominant use category of a building is defined. Use types are classified after 200 categories (Arbeitsgemeinschaft der Vermessungsverwaltungen der Länder der Bundesrepublik Deutschland, 2025), which is not suitable for later regression analysis. Thus, the granularity of use types is reduced by aggregating them to a group of 6 categories, which are aligned with the use categories defined in the German recommendations for parking facilities (FGSV, 2023). Several building use types such as pump stations, sheds, and transformer stations are omitted from GFA calculation as these uses are not found to require parking according to legal framework (Freie und Hansestadt Hamburg, Behörde für Stadtentwicklung und Wohnen, 2022; Landeshauptstadt München, 2025). The mapping of use types to use categories is depicted in Table A.2.

The dominant use category is determined by the highest accumulated GFA share across all buildings on a parcel. Residential uses show an exception as they receive a "mixed" flag as soon as residential use is below 80 %. Table 3.1 provides an overview of the aggregated use categories used for the regression analysis and their distribution among the parcels of both cities' samples. Given that residential parcels account for almost 90 % of observations in both samples, a regres-

Table 3.1.: Distribution of use categories.

	Hamburg		Munich	
Use Category	n	Share (%)	n	Share (%)
Residential	153961	89.1	90057	83.9
Residential, Mixed	9735	5.6	11960	11.1
Retail	2326	1.3	524	0.5
Industry	2307	1.3	1121	1.0
Workplace	2010	1.2	1934	1.8
Education	884	0.5	1322	1.2
Gastronomy, Accommodation	876	0.5	434	0.4
Leisure, Assembly	668	0.4	-	-
Total	172767	100.0	107352	100.0

sion model containing both residential and non-residential parcels would be dominated by residential patterns and fail to capture the distinct factors of non-residential parcels. For this reason, separate models for residential and non-residential parcels are estimated in this study.

To obtain the building density of a parcel, the combined footprint of all above-ground buildings excluding garages is subtracted from the parcel area and the remainder divided by the total parcel area. The resulting open space ratio represents the share of uncovered land within a parcel.

The Standard Land Value (SLV) captures the capitalised expectation of future land rents and is available on block level. The city of Hamburg provides SLVs on their open data portal (Freie und Hansestadt Hamburg, Landesbetrieb Geoinformation und Vermessung, 2026). SLVs for multi-residential homes were chosen, since they are available for the majority of parcels in the sample. SLV data for Munich were excluded from the analysis as they are only available commercially. Figure 3.2 depicts the obtained SLVs of building blocks for Hamburg. SLVs are increasing towards the city centre, reflecting spatial differences between central and suburban parcels.

3.1.2. Household Data

Household data are provided by the German Federal Office of Cartography and Geodesy and available on address level (Bundesamt für Kartographie und Geodäsie, 2022). The dataset contains nationwide information on household and population counts, income, number of companies as well as building data such as use category, construction year classes, and building type. The latter two are used in this work, with the construction year reflecting trends and regulations of pro-

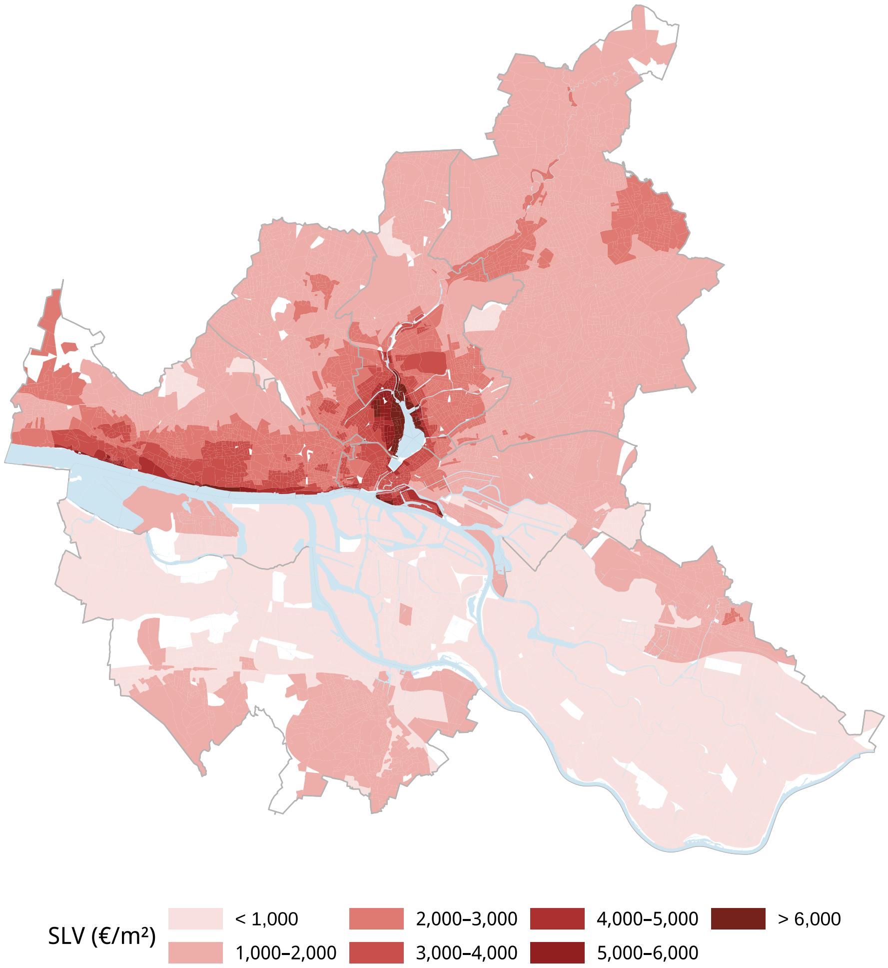

Figure 3.2.: Standard land values in Hamburg.

viding parking on private ground. The building type reflects the characteristics of a building and is aggregated to three classes: (1) small residential, (2) multi-residential and (3) large-residential.

Since the household dataset contains geo-located point data, the values of used attributes are aggregated on a parcel level. Address data may yield different construction year classes and building characteristics within one parcel, which requires a dominance determination on a parcel level. Therefore, data points are assigned to the underlying building from the cadastral building data set, which allows to obtain the GFA value. The dominance of a construction year class or a building characteristic is then equally determined by the highest GFA share of an attribute over the whole parcel.

3.1.3. Public Transport Data

To measure the influence of public transport on parking availability, the public transport access from any point can be classified using quality grades originally developed by the Swiss Federal Office for Spatial Development (Ministerium für Verkehr Baden-Württemberg, 2025). The quality grade is evaluated in two steps. First, the quality class of public transport stops is evaluated from a matrix of stop frequencies between 6.00 am and 8.00 pm on a work day and mode of transport. Second, the resulting stop class is blended with walking times to the stop, which results in the final public transport quality class. The classes range from 1 to 9 and follow roughly a linear increase in accessibility.

Public Transport (PT) data for Germany are obtained in Generalised Transit Feed Specification (GTFS) format via *gtfs.de* (Brosi, 2026). The dataset contains information on stop locations, routes, trips and stop times. Following the quality classification undertaken in the public transport report of the German federal state of Baden-Wuerttemberg, this study uses 9 classes to define the public transport quality (see Tables A.3 and A.4). The distance from parcels to their closest public transport stop is collected as the crow flies. The walking distance classes are thus converted into linear distance classes using a correction factor of 1.5, which is obtained as average detour factor for walking distances in the Swiss Microcensus of 2015 (Danalet, 2020).

3.2. Derivation of Off-Street Parking Supply

As discussed in Chapter 2, data on off-street parking is sparsely available and the process of surveying off-street parking data is resource intensive. Hence, finding a way to approximate parking capacities with computational means can be useful for municipalities. This study introduces a combined approach for deriving parking capacities in off-street areas using three data sources: (1) aerial imagery, (2) cadastral data, and (3) OSM features. Each of these sources has different processing requirements for providing an estimate of off-street parking capacity, which are explained in the following.

3.2.1. Surface Parking Segments

Aerial imagery allows to observe surface parking spaces from a bird's-eye perspective. Several studies use manual counting, making use of parking capacities visible from above (Louen et al., 2022; Ministère de la Mobilité et des Travaux publics, 2021; Müller, 2025). However, this process

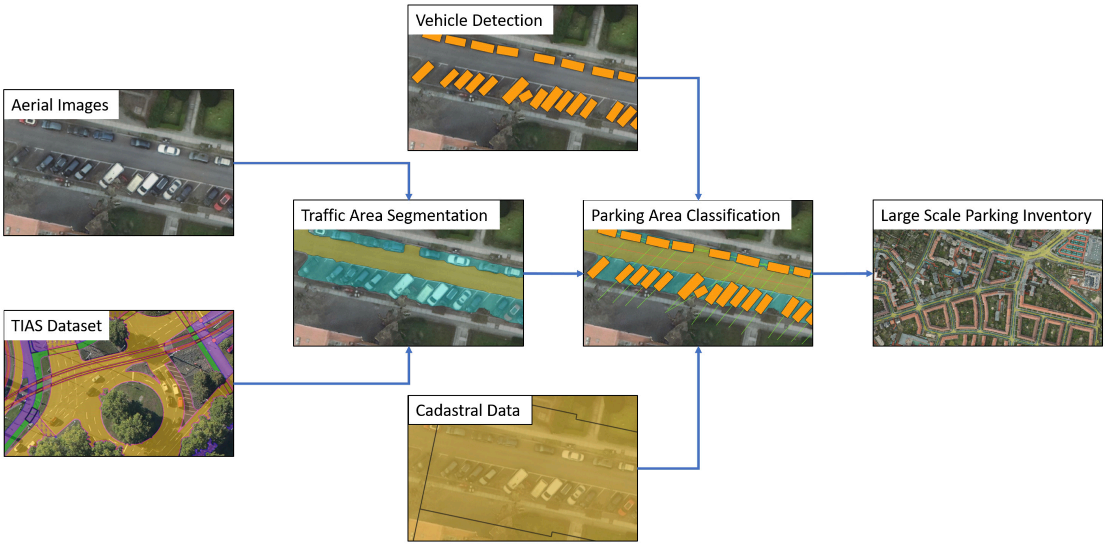

Figure 3.3.: Workflow for the creation of large-scale parking area inventories. Source: Rauch et al. (2025).

is time-consuming when applied at large scale. This study therefore employs a computer-driven approach to extract surface parking segments combining AI-based traffic area segmentation with DINO-based vehicle detection to generate a surface parking inventory. Figure 3.3 depicts the approach following several steps to extract parking polygons from aerial imagery and derive capacity estimates based on vehicle detection. Components of this pipeline have been applied in prior work on on- and off-street parking supply estimation (Hellekes et al., 2023; Thomas, 2024), the full pipeline including vehicle detection is applied by Rauch et al. (2025).

Initially, high resolution aerial imagery serves as the input for traffic area segmentation. Since each pixel is assigned a traffic area value, it is advantageous to use high-resolution aerial imagery. Most German federal states provide Digital Orthophoto (DOP) with a resolution of 20 x 20 cm per pixel (Bayerische Vermessungsverwaltung, 2025; Freie und Hansestadt Hamburg, Landesbetrieb Geoinformation und Vermessung, 2025b). Next, aerial imagery is segmented to traffic areas using a segmentation model based on U-Net and DenseNet architectures (Henry et al., 2021). The segmentation algorithm is trained using a dataset of 51 manually annotated aerial images, which are classified into nine distinct properties: roads, access ways, bike paths, footways, keep-out areas, parking areas, railroad bed, road shoulder, and water (Merkle et al., 2024).

To extract parking polygons, the properties parking areas, access ways and roads are used for further analysis. After segmentation, the resulting raster map is converted into vector polygons with smoothed edges and intersected with cadastral data, classifying the accessibility of parking spaces into public, semi-public, and private parking (Rauch et al., 2025). As this study is investigating off-street parking in general, the accessibility classes of parking spaces are defined by the cadastral land use classification explained in Section 3.1.1.

To estimate the orientation for each parking polygon (parallel, diagonal or perpendicular), a three step process is applied: (1) the extraction of centerlines from road and access way polygons using PostGIS's ST_VoronoiLines function, (2) a vehicle detection framework to extract the orientation of bounding boxes, and (3) the determination of the intersection angle of road/access way centerlines with the longitudinal axis of the detected vehicle (Rauch et al., 2025). The parking orientation is then used for a capacity calculation of the parking polygon using the German guideline framework (FGSV, 2023): 5.5 by 2.15 meters for parallel parking, 5.42 by 2.7 meters for diagonal parking, and 5.14 by 2.7 meters for perpendicular parking. If the orientation of the parking polygon is not known after this process, the capacity is estimated using a default size of 5.2 by 2.4 meters (Rauch et al., 2025).

Segmenting parking areas from aerial imagery provides an automated approach to identify parking polygons on a large scale that is far more efficient than manual parking capacity annotation of aerial imagery. However, it comes with some challenges as it may not always estimate the correct amount of parking spaces. First, the calculation of parking capacities may differ from the actual parking area capacities, as special cases such as disabled parking are not yet accounted for in the analysis (Rauch et al., 2025). Second, leafy trees, shadows, carports or overhanging building parts may conceal surface parking areas, while parking capacities inside buildings or (underground) garages are not captured either (Hellekes et al., 2023; Thomas, 2024). To minimize the occlusion of vegetation, aerial imagery from winter months is preferred for traffic area segmentation. Third, the size of parking areas is often underestimated due to the occlusion, which may underestimate parking capacities of a polygon (Hellekes et al., 2023). Fourth, if an unmarked parking area is located on another property such as access ways or streets, a parking polygon is only marked as one if a car is detected on it. Upon visual inspection, it is noticeable that off-street parking spaces are often only recognized if there is a car parked there.

This study uses a fused product with aerial imagery from several years. Detected parking segments from all years are fused, with the capacity being again calculated based on vehicle detection data from the same years. This approach improves the parking inventory, as vehicles are detected over several timestamps and occlusion effects by leafy trees can be compensated with DOPs from the winter (Hellekes et al., 2023). In the case of Hamburg, 5 DOPs from the years 2020 to 2025 (except 2023) are used (Freie und Hansestadt Hamburg, Landesbetrieb Geoinformation und Vermessung, 2025b), yielding a total of 1,586,563 surface parking spaces of which 970,883 are classified as off-street. For Munich, aerial imagery from the years 2019 and 2024 is utilized (Bayerische Vermessungsverwaltung, 2025; Landeshauptstadt München, 2019), yielding 801,106 surface parking spaces of which 255,754 are classified as off-street. A more detailed analysis of parking space distribution and a validation with observed parking is provided in Section 3.3.

3.2.2. Cadastral Buildings and Building Parts

As mentioned in Section 3.1, cadastral data include building datasets that contain information on their usage, allowing buildings and building parts to be identified as parking amenities. The six use classes referring to parking amenities according to Arbeitsgemeinschaft der Vermessungsverwaltungen der Länder der Bundesrepublik Deutschland (2025) are aggregated to three classes: (1) garages, (2) underground garages, and (3) park decks (see Table A.5 for the aggregation of classes). All of the cadastral parking facilities are usually covered by a roof and thus not visible via aerial imagery which is why cadastral data provide a necessary complement for surface parking segments derived from aerial imagery.

As cadastral parking facilities do not provide information on their capacity, it is necessary to approximate parking supply based on the floor area of the obtained cadastral parking polygons. Table 3.2 displays the measures per parking space depending on the parking type, with the conservative value chosen to not overestimate parking capacities. Following the German Guidelines for Parking Facilities (FGSV, 2023), the footprint of a garage is 15.86 m^2 without walls, which is conservatively increased to 20 m^2 in the scope of this study. The average area of a parking space located on a parking lot or inside a park deck ranges between 25 and 35 m^2 due to additional required space for access ways and landscaping (Litman, 2025). Following the German Guidelines for Parking Facilities (FGSV, 2023), parking lot spaces consume between 25 and 30 m^2 and park decks between 30 and 40 m^2 per parking space.

Using pre-processed building fragments from Step B of Figure 3.1, parking capacities are summed over all parking facilities on a parcel. This means that if an underground garage spans over multiple parcels, its capacity is distributed among the intersecting parcels and calculated depending on the intersection area of parcel and garage.

3.2.3. OpenStreetMap features

OSM provides collaboratively generated, openly licensed geospatial features that include detailed representations of real world objects like buildings, streets, and points of interest. Among those,

Table 3.2.: Reference values for parking space dimensions.

Parking type	Parking space dimension (m^2)	Source
Surface parking	35	Litman (2025)
Covered parking	20	FGSV (2023)
Garage	20	FGSV (2023)
Underground garage	40	FGSV (2023)
Park deck	40	FGSV (2023)

Note. Surface parking space dimensions are applied to OSM surface parking segments only. For surface parking segments, capacity is calculated directly as part of the data processing pipeline.

parking infrastructure is mapped too and is incorporated as additional source of off-street parking facilities. OSM parking features are extracted using the Overpass API (OpenStreetMap contributors, 2025), (see Figure A.1 for the Overpass query). They are marked as polygon or point layer with the attribute *amenity* containing the classes *parking* or *parking_entrance*. The attribute *parking* holds information about the parking type, such as surface, underground, or carport. The parking types are aggregated to the categories used in Table 3.2 (see Table A.5 for the mapping of categories).

The *capacity* attribute contains the number of parking spaces of a feature, however, this is not always filled out. If the capacity is not stored in the *capacity* attribute of the feature, parking spaces per polygon are derived by dividing the polygon area by the parking space dimensions of Table 3.2 depending on the parking type of the polygon. For parking entrances, the capacity is calculated by dividing the footprint of an intersecting building by the parking space dimension.

3.2.4. Combined Parking Supply Derivation

After processing all three data sources on the parcel level, the final parking supply estimation is a result of combining the capacities of all sources. Since parking spaces from cadastral data are located in buildings, they add up to the surface parking areas detected by traffic area segmentation, which are located outside of buildings due to their visibility on aerial imagery[1].

Figure 3.4 depicts an example of the three parking sources, on the basis of which the process of combined parking supply derivation can be explained. Surface parking segments and cadastral parking always contribute to the capacity per parcel. OSM parking acts as an additional source

[1]It may happen that parking detected by traffic area segmentation is in fact the top level of a car park. This appearance is omitted in this analysis.

Figure 3.4.: Example of parking space derivation.

in two cases. First, OSM adds to the capacity when its polygon is classified as surface parking and does not intersect any aerial imagery surface parking polygon (see the left green polygon)[2]. Vice versa, an OSM feature is additive when its polygon is classified as underground parking and does not intersect any cadastral parking polygon. Second, OSM capacities are considered for parcels where OSM polygons or entrances are found and neither surface parking segments from aerial imagery nor cadastral parking facilities are detected (see the right purple triangle)[3]. The surveyed parking points indicate that there is a deviation in derived and surveyed parking (more on that in Section 3.3).

Table 3.3 depicts the total derived parking supply by source in the whole city area before intersected with parcels. OSM entrances are not considered in this statistic as they are only evaluated on a parcel level. Hamburg reveals more than double the amount of off-street parking spaces, which can be explained by the larger city area and population (Hamburg: 755 km^2 and 1.49 million inhabitants; Munich: 311 km^2 and 1.85 million inhabitants (Bayerische Vermessungsverwal-

[2]Thus, the right OSM polygon in Figure 3.4 is not considered, as it intersects surface parking segments.
[3]Thus, the left OSM entrance is not considered since cadastral parking is already identified on this parcel.

Table 3.3.: Parking supply derivation and descriptive statistics by source and city.

Source	Hamburg	Munich
Surface parking segment	968,252	254,147
Cadastral building	246,947	146,809
Cadastral building part	84,126	155,773
Cadastral building point	-	3,753
OSM Polygon	31,929	73,073
Total	1,331,254	633,555

tung, 2026; Bundesamt für Kartographie und Geodäsie, 2022; Freie und Hansestadt Hamburg, Landesbetrieb Geoinformation und Vermessung, 2024)) as well as the large harbour area close to the river Elbe. Among all parking sources, surface parking segments show the largest discrepancy, with Hamburg yielding nearly four times as many spaces as Munich. This may partly be explained by the aerial imagery used for surface parking detection, which is based on a fused product spanning five different acquisition years in Hamburg compared to only two in Munich. In contrast, cadastral data yield almost the same parking capacity for both cities, indicating that in the case of Munich more parking spaces are located in buildings and cadastral data are better mapped. At the same time, capacities from OSM are more than double in Munich, which might be due to parking spaces not discovered by aerial and cadastral data or due to a more active mapping community.

Following the workflow of Figure 3.1, the derived parking capacities are assigned to parcels to allow for further analysis. This also means that from the derived parking spaces in Table 3.3, only those which are located on a sample parcel are used for the regression model.

3.3. Validation with Parking Supply Surveys

The derived off-street parking supply is validated against surveyed values to assess the accuracy of the derivation approach. Following its plan to create a *Master Plan Parking*, policymakers in Hamburg agreed on collecting off-street parking capacities with a property owner survey as part of the coalition agreement of 2025 (SPD & Bündnis 90/Die Grünen, 2025). As a survey turned out to be too ineffective, private parking data were instead collected by manual evaluation of aerial imagery, vehicle data, and cadastral data. The dataset is provided by the city of Hamburg in the scope of this study (Freie und Hansestadt Hamburg, Landesbetrieb Geoinformation und Vermes-

Table 3.4.: Derived vs. surveyed parking capacity by category.

	Hamburg			Munich		
Category	Derived	Surveyed	Δ	Derived	Surveyed	Δ
Underground	145,367	293,228	-147,861	55,633	147,024	-91,391
Garage	132,588	227,223	-94,635	26,345	30,461	-4,116
Park deck	57,165	24,937	32,228	0	23,307	-23,307
Surface	846,655	405,433	441,222	61,425	64,448	-3,023
Covered	348	45,350	-45,002	0	-	-
Total	1,182,809	996,171	186,638	143,403	265,240	-121,837

sung, 2025a). To the best knowledge of the author, Hamburg is the only German metropolis to have carried out a data survey on off-street parking for the whole city area. The surveyed parking data from Hamburg contain geo-located parking spaces by type, which makes it possible to assign and compare them on a parcel level.

Additionally, surveyed ground truth data on off-street parking in parts of the city area are provided by the city of Munich (Landeshauptstadt München - Mobilitätsreferat, 2026). The dataset contains off-street parking facilities that were surveyed throughout the years 1999 to 2019, in which Munich introduced residential parking permit areas. In contrast to Hamburg, the dataset contains parking data aggregated to block-side level. As parcels cannot always be clearly assigned to a block-side, the evaluation of derived and surveyed parking supply for Munich is undertaken on block level.

Table 3.4 depicts a comparison of derived and surveyed parking supply by category for areas where both derived and surveyed parking supply are present. In the case of Hamburg, this is almost the whole city area, excluding parts of the harbour territory and critical infrastructure premises. For Munich, this area contains blocks largely located around the city centre, with a few blocks located towards the suburbs. Figure 3.5 compares derived and surveyed parking supply on parcel level for Hamburg in a scatter plot. The darker the point, the more parcels are showing the displayed deviation.

Regarding parking located in buildings, derived supply for both Hamburg and Munich is underestimated. Especially underground capacities in Munich show that cadastral and OSM data do not yield a comprehensive picture of the present parking supply. An exception of this is parking in park decks, where derived supply shows double the capacity compared to the surveyed sup-

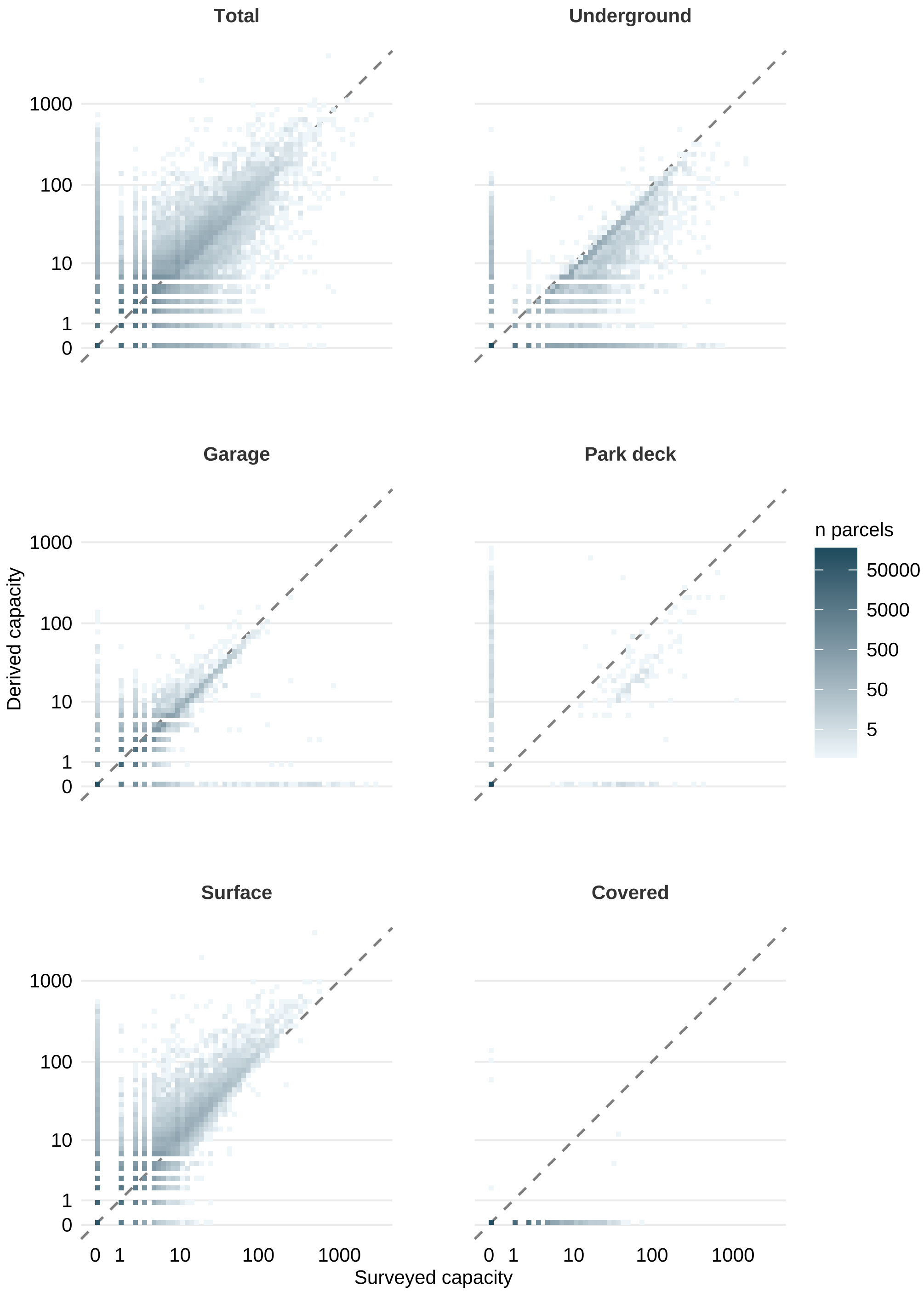

Figure 3.5.: Scatterplot of derived vs. surveyed parking supply (parcel-level) by parking category in Hamburg.

Table 3.5.: Surface parking – difference by use category (derived − surveyed).

Use Category	n (derived)	n (surveyed)	Ratio	Mean	Min	Max
Residential	194233	100091	1.94	1.5	-25	211
Mixed residential	34879	17296	2.02	3.0	-38	565
Workplace	50704	25354	2.00	15.9	-127	568
Industry	106431	31777	3.35	31.8	-159	1841
Retail	62846	25390	2.48	22.9	-25	3388
Education	17079	11194	1.53	7.8	-20	273
Gastronomy, Accommodation	12976	7357	1.76	10.3	-12	350
Leisure, Assembly	6628	3871	1.71	5.8	-34	186

ply. After visual data inspection, this difference can be attributed to deviating classification of parking capacities, with derived park decks often surveyed as garages. The vertical line of park deck points and the horizontal line of garage points in Figure 3.5 confirm this impression, as they can be partially substituted.

Cadastral and OSM data in Munich did not yield park deck polygons, which is why the derived value is zero. Covered parking such as carports is only derived by OSM. The covered parking capacities are highly underestimated in the case of Hamburg. Munich's surveyed parking does not classify covered parking, and no covered parking capacities are derived from OSM features in Munich either.

By far the highest deviation comes from surface parking in Hamburg. Derived parking yields 441,222 additional parking spaces compared to ground truth data. Looking at the surface parking plot on Figure 3.5, it becomes apparent that the deviation is spread among two phenomena: (1) parcels not yielding any surveyed supply, but mostly low values of derived supply, and (2) a slight overestimation of derived supply. The first case indicates that parking polygons were detected by the segmentation, where surveyed parking was not observed. In fact, around 380,000 derived surface parking spaces are not within a 2 meter boundary of a mapped surveyed parking space, which indicates that the majority of the deviation comes from additional polygons instead of false capacity estimation per surface parking segment. This may be the case if a car parks in front of a garage in a driveway. Additionally, polygons are misidentified and do not depict a parking space in real life, though this case was not systematically found upon visual inspection.

Table 3.5 displays the differences in surveyed parking by use category for parcels where at least one surface parking space was derived or surveyed. The average delta between derived and surveyed parking is the lowest for residential parcels with on average 1.5 additional parking spaces.

In contrast, industry and retail parcels show on average a difference of 31.8 and 22.9 parking spaces per parcel, respectively. The ratio of four categories is above 2, with residential parcels just below 2 and substantially higher ratios in case of industry and retail. A cluster of overestimation can be found close to the Hamburg harbour area (see Figure A.2).

As already displayed in Figure 3.5, the derived parking supply is further analysed at the parcel level. For this purpose, parking polygons are intersected with the parcels to obtain capacity values on the parcel level. In case of derived capacities, this means that overlapping polygons are split at the parcel border and every parcel is assigned the number of parking spaces located within its boundaries depending on the overlap share. This enables the regression analysis of determinants influencing off-street parking supply at the parcel level.

4. Methodology

A comprehensive dataset on private and semi-public parking supply on a property level is novel in the German context and enables an in-depth analysis of the factors influencing parking supply. Previous studies have primarily examined the effect of parking requirements, which have been shown to increase the number of parking spaces (McCahill & Garrick, 2014). However, to the best knowledge of the author, no study has systematically analysed the influence of various structural and socio-economic factors on parking supply. This study therefore employs a regression model to explore these relationships.

This chapter outlines the methodological framework used to analyse off-street parking supply in German cities. It describes the integration of the spatial datasets described in Chapter 3, the statistical modelling strategy, and the final model setup based on pre-estimation.

4.1. Theoretical Framework of Count Regression Models

To allow for an analysis of off-street parking supply and its determinants, data is analysed on parcel level, as this aggregation level is fine enough to yield data on individual attributes such as the construction year of a building. Each derived or surveyed parking space as well as determinants on a building or address level are thus assigned to a parcel. The analysis is conducted on derived parking supply in Hamburg and Munich as well as on surveyed supply in Hamburg.

Since parking spaces are an integer count variable which does not go below zero, linear regression models such as Ordinary Least Squares (OLS) are not suitable and instead, count regression from the family of Generalised Linear Models (GLM) have to be applied (Cameron & Trivedi, 2013).

The typical starting point of a count model is a Poisson regression. With the assumption that the dependent variable Y given its covariates $\mathbf{x}$ is Poisson distributed, the conditional density function can be denoted as

$$P(y_i \mid \mathbf{x}_i) = \frac{\mu_i^{y_i} e^{-\mu_i}}{y_i!}, \quad y_i = 0, 1, 2, \ldots \tag{4.1}$$

with μ_i as the conditional mean parameter. The Poisson regression model assumes that the conditional mean is linked to the covariates through an exponential mean function:

$$\mu_i = \exp(\mathbf{x}_i' \boldsymbol{\beta}) \tag{4.2}$$

where $\boldsymbol{\beta}$ is a vector of regression parameters of the covariates $\mathbf{x}$. As the Poisson distribution requires equidispersion of mean and variance, the variance can be expressed by the exponential mean function too:

$$\mathrm{Var}[y_i \mid \mathbf{x}_i] = \exp(\mathbf{x}_i' \boldsymbol{\beta}) \tag{4.3}$$

Equation 4.4 denotes the log-link transformation of the exponential mean function into a linear model, as known from ordinary least squares (OLS):

$$\log(\mu_i) = \mathbf{x}_i' \boldsymbol{\beta} \tag{4.4}$$

The log-link ensures that the predicted number of parking spaces is non-negative (Cameron & Trivedi, 2013).

Equation 4.1 imposes the assumption that the conditional mean and variance of y_i are equal. When looking at count data, this assumption is often rejected, since the variance is not constant over various values of $\mathbf{x}_i$. This is called overdispersion and requires a different model usage (Cameron & Trivedi, 2013), which is why a Negative Binomial (NB) regression model is introduced.

The advantage of a NB model is the introduction of θ, a parameter to describe the conditional variance-mean relation and thus accounting for overdispersion. There are different ways to describe the variance mean relationship, with the NB1 and NB2 among the most common variance functions. The NB1 derives its variance from the mean multiplied with the overdispersion factor θ:

$$\text{Var}[y_i \mid \mathbf{x}_i] = \theta \mu_i \tag{4.5}$$

Increasing values of θ thus reflect higher overdispersion. In case of the NB2, the variance follows a quadratic function of the mean, able to control a faster overdispersion increase over y_i:

$$\text{Var}[y_i \mid \mathbf{x}_i] = \mu_i + \frac{\mu_i^2}{\theta} \tag{4.6}$$

In contrast to the NB1 variance function, higher overdispersion is here reflected by lower values of θ.

Another model violation of count regression models is the occurrence of excess zeros, which is referred to as zero-inflation (Cameron & Trivedi, 2013). In the scope of this study, zero-inflation might appear if parcels systematically do not yield off-street parking, for example due to older building stock and high building density. To account for systematic zeros, the Zero Inflation Negative Binomial (ZINB) model can be utilized. It assumes that the regression is driven by a mixture of two processes: (1) a structural zero process, capturing properties that cannot realistically provide private parking, and (2) a count process following an NB distribution, which accounts for overdispersed positive counts as well as sampling zeros. Formally, the ZINB model defines the probability of observing y_i for parcel i as

$$\Pr(y_i \mid \mathbf{x}_i, \mathbf{z}_i) = \pi_i \, \mathbb{I}\{y_i = 0\} \; + \; (1 - \pi_i) \, f_{\text{NB}}(y_i \mid \mu_i, \theta) \tag{4.7}$$

where π_i denotes the probability that parcel i belongs to the structural-zero process, and $f_{\text{NB}}(y_i \mid \mu_i, \theta)$ is the Negative Binomial probability mass function with mean μ_i and dispersion parameter θ. In this formulation, structural zeros arise with probability π_i, while all remaining observations follow the Negative Binomial distribution, which accommodates both sampling zeros and overdispersed positive counts. The two model components are linked to covariates through

$$\log(\mu_i) = \mathbf{x}_i^\top \boldsymbol{\beta}, \qquad \text{logit}(\pi_i) = \mathbf{z}_i^\top \boldsymbol{\gamma} \tag{4.8}$$

The depicted model assumptions are tested on the dependent variable of the regression model: the parking capacity per parcel. The next section depicts various pre-estimation statistics and derives the final model setup.

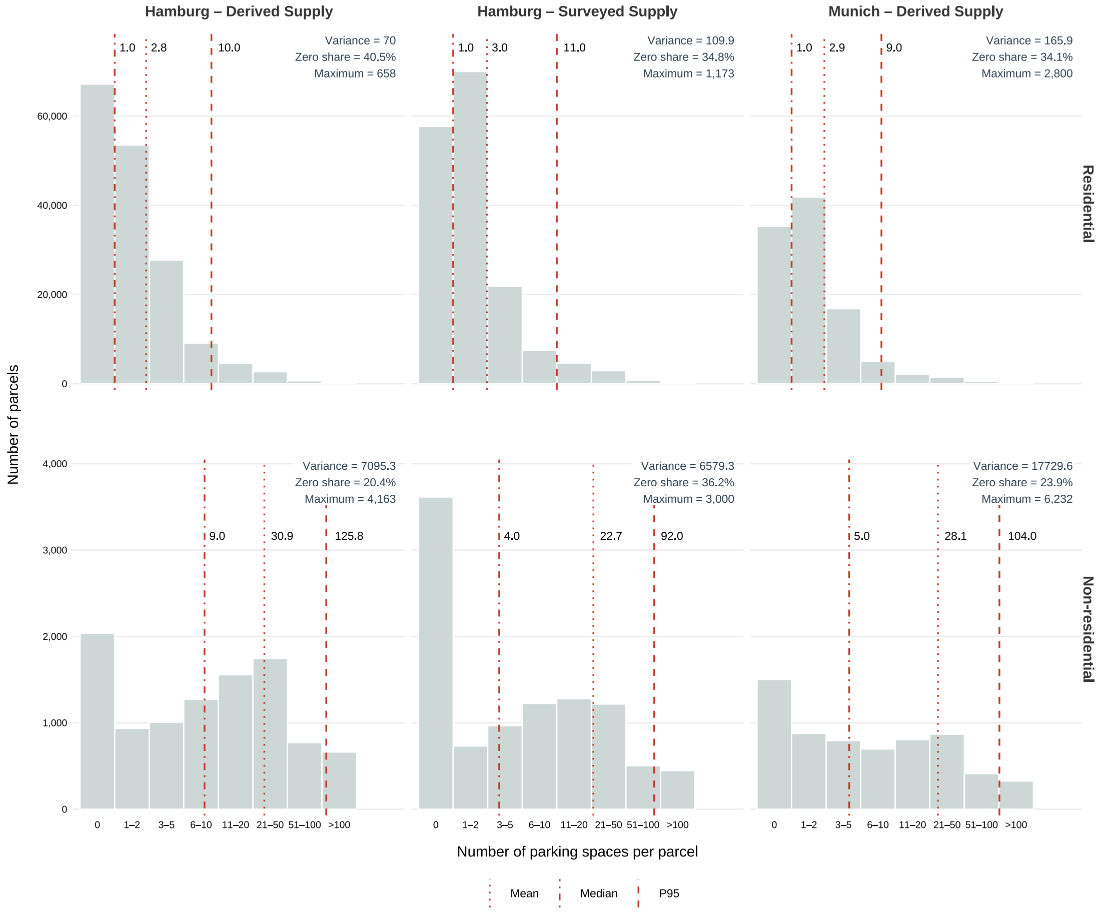

Figure 4.1.: Parking supply histogram on parcel level with logarithmic bins.

4.2. Model Setup and Pre-Estimation

The starting point for developing the final regression model is the descriptive analysis of the dependent model variable. The analysis of parking supply is split into a residential and a non-residential panel, as a combined model would highly over-represent residential parcels (see Section 3.1.1). Figure 4.1 shows the logarithmic histogram of parking capacities accompanied by key statistics for the derived and surveyed supply in Hamburg as well as for the derived supply in Munich. In case of the residential panel, low capacity values are clearly dominating all samples, as the median is 1 in all three cases. Furthermore, the high zero shares of 33.6 to 39.4% indicate a first sign of zero inflation. With 95% of capacity values within 9 to 11 parking spaces and maximum parking capacity of 658 to 2,800 parking spaces, the distributions show the high range of parking availability per parcel and the presence of outliers, which is confirmed by high variance values.

Table 4.1.: Descriptive statistics of continuous variables (Hamburg, derived supply).

Variable	Mean	SD	Min	P5	P95	Max	Skew
Residential (n = 163,695)							
Parcel area (m^2)	1,022	1,710	25	164	2,633	79,442	11.0
GFA (m^2)	601	1,748	3	76	2,359	143,977	15.2
Open space ratio	0.75	0.15	0.00	0.44	0.91	1.00	
PT accessibility rank	8.17	1	1	6	9	9	
SLV (€/m^2)	1,773	898	555	945	3,300	9,800	2.8
Purchasing power (€)	54,481	10,069	16,520	38,646	70,482	217,241	0.9
Non-residential (n = 9,068)							
Parcel area (m^2)	4,326	10,060	11	251	16,942	243,433	10.6
GFA (m^2)	4,274	9,740	3	165	16,679	177,590	7.4
Open space ratio	0.54	0.25	0.00	0.03	0.88	1.00	
PT accessibility rank	8.50	1	2	7	9	9	
SLV (€/m^2)	1,935	1,104	555	770	3,700	11,700	2.0
Purchasing power (€)	48,590	9,630	20,572	35,714	65,381	198,642	1.5

As the mean-variance ratio ranges from around 25 (Hamburg derived) to 57 (Munich derived), the dependent variable shows strong overdispersion indicating that, as expected, a Poisson model is not suitable in this context.

The non-residential panel exhibits a distinctly different distribution pattern. Zero parking parcels represent the largest bin across all three samples, with the Hamburg surveyed sample showing a zero share comparable to the residential panel. Among parcels with at least one parking space, the majority fall in the 21–50 space range for both Hamburg derived and Munich derived samples, while Hamburg surveyed parcels peak in the 11–20 range. All three distributions display substantial variance, with variance-mean ratios ranging from 230 (Hamburg derived) to 633 (Munich derived), indicating severe overdispersion. These figures are largely driven by extreme outliers, which surpass the 95th percentile. Given the overdispersion and zero inflation in both the residential and non-residential panels, a formal assessment of model fit requires pre-estimation analysis later conducted in this section.

As derived in Chapter 2.4, various factors are found influential for determining off-street parking supply. Data sources for parking supply determinants explained in Chapter 3 are now investigated for regarding their suitability for regression modelling. The model setup as well as pre-estimation statistics in this section are depicted for Hamburg, with the Munich statistics to

Table 4.2.: Categorical variables – residential sample (Hamburg)

Variable / Level	n	%
Construction year		
before 1945	43,860	27.0
1946-1960	39,190	24.1
1961-1980	49,583	30.5
1981-2005	26,738	16.5
2006-2021	3,041	1.9
Building type		
small residential	118,950	73.2
multi residential	42,516	26.2
large residential	946	0.6
Mixed-residential	9,286	5.7

Table 4.3.: Categorical variables – non-residential sample (Hamburg)

Variable / Level	n	%
Construction year		
before 1945	2,917	32.2
1946-1960	1,645	18.1
1961-1980	2,880	31.8
1981-2005	1,446	15.9
2006-2021	180	2.0
Use category		
retail	2,326	25.7
industry	2,306	25.4
workplace	2,010	22.2
education	884	9.7
gastronomy, accomm.	874	9.6
leisure, assembly	668	7.4

be found in Appendix B. As the values for Munich show similar effects, the derived model setup based on data for Hamburg is seen to be suitable for both cities.

Table 4.1 depicts the numeric determinants and their descriptive statistics as well as their skewness, with the latter calculated as the standardized third central moment. The average residential parcel has around 1,000 m^2 of parcel area with a usable ground floor area of 600 m^2. At the same time, the average non-residential parcel is about four times larger with an almost equal parcel area-GFA ratio. Both panels hold in common to have very high outliers, as their maximum values exceed the 95 percentile values by far. This is again confirmed by high skewness values. The open space ratio of residential parcels indicates that on average two thirds of the parcel are not built-up. Non-residential parcels are instead more dense. The mean public transport accessibility rank is in both cases close to the maximum, as the metropolitan area of Hamburg yields high quality transportation services. Average standard land values are similar and rather low compared to the maximum value, which in combination with the skewness reveals right-skewed distribution. Residential households yield an average income of around 54,000 € per year, which is slightly above the non-residential parcels.

The distribution of categorical variables among parcels are depicted in Tables 4.2 and 4.3. Construction year classes show high representations over both samples, except for newer building stock. The same can be said for parcels with large residential facilities, as those appear rarely

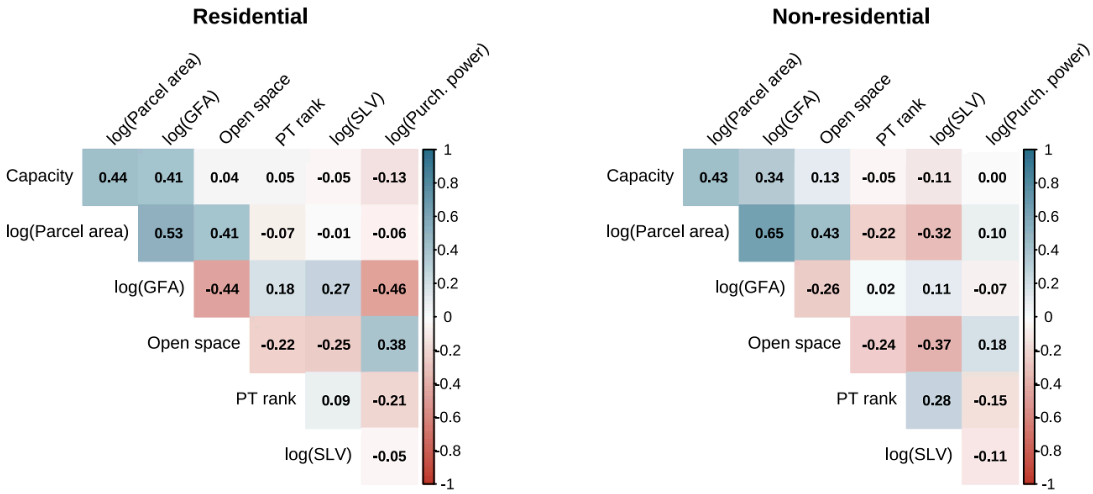

Figure 4.2.: Correlation matrix of the dependent variable and metric determinants (Hamburg).

compared to small and multi-residential buildings. After sample splitting, the distribution of use categories in the non-residential sample for Hamburg is more balanced, with no category highly under-represented.

Next, the inclusion of determinants and their form is discussed. Metric determinants are analysed on a logarithmic scale as their skewness (see Table 4.1) is reduced in all cases. Additionally, the log-log connection allows for an elasticity analysis of parking supply and its metric determinants. Figure 4.2 shows the correlation matrix of all variables considered for the regression model. The correlation coefficient for each variable pair is calculated using Pearson correlation coefficients from the `corrplot` package in R (Friendly, 2002). The first row depicts the Pearson coefficients of derived capacity with its determinants. The log parcel area and the log GFA show the highest values, yielding a pre-modelling indication of the factors highly correlated with parking capacities.

Looking at the correlation of independent variables, the parcel area shows medium to high positive correlation with the GFA and the open space ratio. At the same time, larger parcels reveal a higher open space share and thus a lower building density. The parcel area thus shows the highest collinearity values and is not found to be influential for the parking supply according to regulatory frameworks and literature, which is why it is not seen as a determinant of parking supply. At the same time, first undertaken estimation results show that excluding the parcel area leads to a substantially decreased model fit. This is not feasible in the context of a regression model aiming to provide parking predictions. Therefore, the log parcel area is instead introduced into the model as an offset, which changes the context of the dependent variable to be interpreted as capacity density per m^2 parcel area.

A noteworthy correlation of parking supply determinants is the negative link of open space ratio and log(GFA). Higher GFA values thus come with a lower open space ratio and thus a higher building density. While the Pearson coefficient is moderate at -0.44 and -0.26 respectively, the correlation yields the potential to suppress the influence of GFA on the parking supply. The same is valid for the correlation between the open space ratio and the public transport accessibility rank as well as the log standard land value, which yield moderate negative correlations throughout both samples. As multicollinearity yields a model violation (Cameron & Trivedi, 2013), the Variance Inflation Factor (VIF) for the final models is assessed for the final model setup.

To assess the functional form of each continuous predictor, a Generalised Additive Model (GAM) is fitted against the log-transformed outcome and compared to OLS fits using the `mgcv` package in R (Wood et al., 2016). Systematic deviations between GAM and OLS indicate nonlinearity on the log scale. The plots can be seen in Appendix B. While the logarithmic form provides a reasonable approximation for most variables, the GFA can be better suited by a quadratic term. Therefore, the GFA is introduced into the regression model as $\log(\mathrm{GFA}) + (\log(\mathrm{GFA}))^2$.

Pre-estimation contains fitting both samples with Poisson, NB and ZINB models to see which framework fits the data best. Following Equations 4.5 and 4.6, both a linear and a quadratic variance function are investigated for trying to control overdispersion by fitting an NB1 and NB2 model respectively. The package `glmmTMB` in R is utilized for modelling, as it is suitable to fit several GLMs (Brooks et al., 2017). Following the framework of Cameron and Trivedi (2013), this study carries out tests for overdispersion and zero inflation using the `DHARMa` package in R, which simulates residuals for GLMs and yields tests for the mentioned problems (Hartig, 2024). The overdispersion test is conducted by calculating the Pearson Chi-squared test with a value above 1 indicating overdispersion.

As for zero inflation, first, a logistic regression model is fitted to see which factors mainly drive the parking supply to be zero. The results are depicted in Tables B.4 and B.5 and show that for all three samples the open space ratio is the driving factor of zeros, as it shows the largest coefficient. Thus, the probability of observing structural zeros in the ZINB2 model is a function of the open space ratio. To test how the fitted models control zero inflation, the function `testZeroinflation` from the `DHARMa` package is utilised, checking how many zeros were predicted by the regression model (Hartig, 2024).

Table 4.4.: Goodness-of-fit diagnostics by panel for the Hamburg derived supply model.

		Overdispersion test		Zero-inflation test	
Panel	Model	Disp. ratio	p	ZI ratio	p
Residential	Poisson	4.08	<0.001	1.55	<0.001
	NB1	1.02	<0.001	0.92	<0.001
	NB2	1.02	<0.001	0.99	0.030
	ZINB2	1.14	<0.001	0.96	<0.001
Non-residential	Poisson	28.89	<0.001	4.90	<0.001
	NB1	0.99	0.836	0.80	<0.001
	NB2	1.29	<0.001	1.35	<0.001
	ZINB2	1.39	<0.001	1.13	<0.001

Note. Dispersion ratio relative to $(n-k)$; values > 1 indicate overdispersion. ZI ratio > 1 indicates excess zeros relative to model prediction. p-values from respective LM/score tests.

The results of the `DHARMa` tests conducted on the Hamburg derived model are depicted in Table 4.4, while the remaining results for Hamburg surveyed and Munich derived can be found in Table B.6. Starting with the residential sample and a Poisson regression as described in Section 4.1, the model reveals strong overdispersion in both samples, as could be expected with the observed mean-variance ratio in Figure 4.1. Fitting an NB1 variance function does not adequately solve the problem, with the overdispersion still exceeding 1. As the NB2 model is introduced, both the Pearson Chi-squared value as well as the zero inflation ratio reach close to perfect values, with 1.02 and 0.99 respectively. The ZINB2 does neither improve dispersion nor zero inflation ratio, which is why the NB2 model is chosen for the analysis. Goodness of fit diagnostics for the surveyed supply in Hamburg and the derived supply in Munich confirm NB2 as the best model fit, however, overdispersion cannot completely be accounted for in the case of surveyed supply in Hamburg.

Regarding the non-residential sample, the dispersion ratio in the Poisson model is even higher than in the residential sample. Introducing the NB1 model improves both dispersion ratio and zero inflation ratio directly, with the dispersion ratio close to 1 and not showing significant overdispersion. As the zero inflation ratio of NB1, NB2, and ZINB2 all do not come near zero, NB1 with the second best zero inflation ratio is seen as the best balance overall. For the derived model of Munich, results differ slightly, as the ZINB2 model would be preferred here. The Hamburg surveyed model shows best model fit when using NB1 or NB2, which is why overall the NB1 model is seen as most suitable.

```r
# residential model
glmmTMB(
    capacity_best_guess ~
    log_gfa_total_m2 + I(log_gfa_total_m2^2) +
    open_space_ratio + pt_access_rank +
    log_standard_land_value_eur_m2 +
    log_purchasing_power_mean +
    construction_year + building_type_mode +
    is_residential_mixed +
    offset(log(parcel_area_m2)),
 family = nbinom2,
 data = df_residential
)
```

```r
# non-residential model
glmmTMB(
    capacity_best_guess ~
    log_gfa_total_m2 + I(log_gfa_total_m2^2) +
    open_space_ratio + pt_access_rank +
    log_standard_land_value_eur_m2 +
    log_purchasing_power_mean +
    construction_year + use_category +
    offset(log(parcel_area_m2)),
 family = nbinom1,
 data = df_non_residential
)
```

Figure 4.3.: Final model setup in R.

Finally, the VIF is calculated for all chosen models package in R to assess if multicollinearity is appearing after regression modelling. The results can be found in Table B.7. All six models do not yield multicollinearity except for the GFA estimators, which is expected as multicollinearity between a linear term and its quadratic counterpart is an artifact of the model specification. The final residential and non-residential model setups for the samples of both study areas are depicted in Figure 4.3. As standard land values are not available for the Munich sample, they are omitted as a determinant in both Munich models.

5. Results

Building on the data preparation in Chapter 3 and the negative binomial regression framework established in Chapter 4, this chapter presents the regression results. Six regressions are carried out in total, one per panel and supply dataset. Section 5.1 discusses the regression coefficients and their effect on predicted parking supply across five common urban scenarios. Section 5.2 covers model diagnostics, including goodness of fit and spatial autocorrelation. Section 5.3 assesses how well the model predicts parking supply in similar and different urban environments.

5.1. Model Estimates

Regression coefficient estimates of fitted models are depicted in Tables 5.1 (residential panel) and 5.3 (non-residential panel) respectively. Several points have to be noted when observing model results:

1. For large samples p-values turn significant, even if the observed effect is tiny. As recommended by Wasserstein and Lazar (2016), this study uses the Confidence Interval (CI) to address the uncertainty of the observed effects.

2. The Incidence Rate Ratio (IRR) column contains exponentiated coefficients, which expresses the multiplicative change in the expected count per unit increase in the respective predictor. This makes interpretation easier compared to the raw coefficient in the case of categorical variables and numeric variables which are not log-transformed. Logarithmic determinants yield a log-log connection to the dependent variable, which means that the coefficient can approximately be interpreted as elasticity.

3. As the log of the parcel area is included in all regression models as offset, coefficients represent the influence of the respective determinant on the capacity per m^2 parcel area, in other words, the parking space density per m^2.

4. The intercept can be interpreted as the parking space density with all numeric variables set to 0. Thus, the expected IRR is 0, too.

5. The coefficients of categorical determinants can be seen as deviation of parking space density relative to the reference category.

5.1.1. Residential Panel

Starting with the residential panel, the intercept shows an IRR of almost zero with high z-values confirming high significance. This is in line with the expectation that a parcel with attributes set to zero practically does not have any parking.

The GFA is described by a linear and a squared regressor due to its quadratic relation with parking supply. The positive linear term indicates that additional GFA raises parking space density, the negative quadratic term shows that the effect declines with increasing GFA. To illustrate this: for a small residential house with a GFA of 150 m^2, a 1% increase in GFA leads to an increase of parking space density by 0.19, 0.24 and 0.2% in the case of Hamburg derived, Hamburg surveyed, and Munich derived, respectively. At the same time, if the GFA sits at 1,000 m^2, the increase is lower, with 0.16, 0.2 and 0.14%. Thus, the initial effect of GFA is strongest for derived supply in Munich, but it shows the highest decline too. The CI spans around 0.05 in both directions for the linear GFA term, which is higher than the observed CI for the quadratic term indicating greater uncertainty in the linear GFA estimate.

The open space ratio is measured in percentage points, meaning that the IRR reflects the change in parking space density if the absolute open space ratio is increased by 1 %. This is similar to the elasticity, albeit the open space ratio effect reflects an absolute rather than a relative increase. A one percentage point increase thus leads to a 1.1% higher parking space density for the derived model in Hamburg. The effect is half as strong for the Hamburg surveyed parking model. Munich's model reveals the highest percentage increase in parking supply density. Among all continuous determinants, the open space ratio is the strongest positive determinant across all three samples. Furthermore, the open space ratio is estimated with high precision, as the CI spans one percentage point around the coefficient.

PT access is measured in classes and fitted as a continuous numeric variable, as an increase to the next higher access class is assumed to be roughly linear (see Section 3.1.3). Better PT accessibility by one class increases the parking space density by 8.3 and 6.4% for the Hamburg derived and the Hamburg surveyed model, respectively. A two-class increment equals the squared IRR and

Table 5.1.: Regression results – residential panel (NB2).

	Hamburg derived		Hamburg surveyed		Munich derived	
	Coef. [95% CI]	IRR	Coef. [95% CI]	IRR	Coef. [95% CI]	IRR
Intercept	-4.287 [-4.763, -3.811]	0.014	-7.449 [-7.906, -6.992]	0.001	-7.195 [-7.733, -6.657]	0.001
log(GFA)	0.280 [0.230, 0.330]	1.323	0.347 [0.299, 0.395]	1.415	0.371 [0.311, 0.432]	1.450
$(\log(\text{GFA}))^2$	-0.009 [-0.013, -0.005]	0.991	-0.011 [-0.015, -0.008]	0.989	-0.017 [-0.021, -0.013]	0.983
Open space (%)	0.011 [0.010, 0.011]	1.011	0.005 [0.004, 0.006]	1.005	0.015 [0.015, 0.016]	1.015
PT access	0.080 [0.073, 0.086]	1.083	0.062 [0.056, 0.069]	1.064	0.004 [-0.004, 0.012]	1.004
log(SLV)	-0.368 [-0.384, -0.351]	0.692	-0.098 [-0.113, -0.082]	0.907	—	—
log(Purchasing power)	-0.183 [-0.224, -0.141]	0.833	-0.057 [-0.097, -0.018]	0.944	-0.151 [-0.195, -0.107]	0.859
Construction year						
1946–1960	0.086 [0.068, 0.103]	1.089	0.158 [0.141, 0.175]	1.171	0.219 [0.197, 0.240]	1.244
1961–1980	0.071 [0.055, 0.088]	1.074	0.188 [0.172, 0.204]	1.207	0.275 [0.257, 0.294]	1.317
1981–2005	0.198 [0.178, 0.218]	1.219	0.458 [0.439, 0.477]	1.581	0.493 [0.468, 0.518]	1.637
2006–2021	0.676 [0.633, 0.719]	1.966	0.727 [0.686, 0.767]	2.068	0.576 [0.544, 0.607]	1.779
Building type						
Multi-residential	0.221 [0.202, 0.240]	1.247	0.300 [0.282, 0.319]	1.350	0.108 [0.087, 0.128]	1.114
Large residential	0.508 [0.437, 0.580]	1.662	0.605 [0.539, 0.671]	1.832	0.177 [0.118, 0.236]	1.194
Mixed residential	0.238 [0.213, 0.263]	1.269	0.107 [0.083, 0.131]	1.113	0.220 [0.198, 0.242]	1.246
N parcels	162,412		162,412		101,619	
θ	1.09		1.25		1.86	

Note. Reference categories: construction year – ≤1945; building type – small residential.

thus leads to an increase of 13.2 and 17.3%, respectively. Estimates are precise given the narrow CI. The PT coefficient of the Munich derived model does not significantly differ from zero.

Standard land values are available for Hamburg only, as Munich SLV data are not publicly accessible. The SLV shows a negative effect on parking space density, with the derived supply model showing three times the elasticity of the surveyed model. The log(SLV) coefficient for Hamburg derived is both large in magnitude and precisely estimated with a narrow CI, indicating that the SLV is among the most reliably identified determinants of residential parking density in this sample.

Purchasing power shows a negative coefficient across all residential models, albeit with low effect strength. A 1% increase in purchasing power of households thus leads to a 0.18% decrease in parking supply for the Hamburg derived model. CIs span around 0.04 in both directions, indicating lower precision than the SLV estimate. At the same time, they overlap substantially across both derived supply samples, suggesting that the negative association is small but consistent.

Across all residential models, newer construction years are associated with higher parking space density. However, effect strengths differ, with the Hamburg derived model showing weaker effects for buildings constructed between 1946 and 2005. The surveyed model of Hamburg as well as the derived model of Munich indicate that buildings constructed after 1980 show on average at least 45 % more parking supply density than buildings constructed before 1945. All construction year categories show confidence intervals strictly above zero across all samples, confirming a positive association with parking density regardless of the sample.

The coefficients for the building type reveal that larger residential buildings lead to more parking spaces compared to small residential buildings. Among all samples, the model trained on surveyed data in Hamburg shows the highest effect strength. In both models of Hamburg, the effect of large residential buildings is around double that of multi-residential buildings. Large residential building estimates are considerably less precise than those for multi-residential buildings.

Finally, the observed coefficient on mixed residential use is positive, indicating that parcels that host other uses besides residential show on average a higher parking space density. While the derived models of Hamburg and Munich yield similar estimates, the surveyed model shows an effect roughly half that of the derived models. All calculated CIs span a maximum of 0.03, which is narrow relative to the effect strength, indicating precise estimates.

With the exception of PT access in Munich, all coefficients show consistent signs across the three samples, suggesting that the direction of effects is robust across samples. However, when comparing derived and surveyed data from Hamburg, the relative magnitude of coefficients is not consistent across data sources, with no consistent pattern of one data source yielding systematically larger effects. While the derived supply model shows stronger effects for open space ratio, SLV, purchasing power, and mixed-residential usage, the opposite holds for the estimates of GFA, PT access, construction year, and building type.

The dispersion parameter θ is estimated at 1.093 for Hamburg derived, indicating overdispersion in the residential sample as the conditional variance exceeds the conditional mean by a factor of approximately $1 + \frac{\mu}{1.093}$. As low values of θ yield high values of overdispersion in case of the NB2 variance function (see Equation 4.6), a value around 1 is considerable given the range of predicted counts in the data. The overdispersion of the Munich model is substantially lower, with the Hamburg surveyed model showing a similar value to the Hamburg derived model.

In order to transfer the parking space density to the predicted number of parking spaces of a parcel, three residential building archetypes are chosen from the Hamburg datasets to gain results on predicted parking spaces. Each archetype represents an example that can be found on a parcel in urban environments: (1) a mid-rise multi-residential building in a block structure, constructed prior to 1945, located in an established inner-city neighbourhood, (2) a detached single-family house in a peripheral urban location, and (3) a large-scale mixed-use residential building in a

Table 5.2.: Scenario analysis for residential archetypes in Hamburg.

	Multi-residential	Small residential	Large Residential
Determinants			
Parcel area (m^2)	751	1,406	1,836
GFA (m^2)	1,947	140	2,995
Open space ratio	0.48	0.90	0.51
PT access rank	9	9	8
SLV (€/m^2)	5,000	1,575	3,100
Purchasing power (€)	49,363	68,280	48,045
Construction year	<1945	1981-2005	1946-1960
Mixed residential	0	0	1
Derived supply model			
Predicted supply [95% CI]	0.8 [0.8, 0.8]	1.4 [1.3, 1.4]	4.3 [4.0, 4.7]
Derived supply	0	0	6
Surveyed supply model			
Predicted supply [95% CI]	1.7 [1.7, 1.8]	2.5 [2.4, 2.6]	8 [7.4, 8.6]
Surveyed supply	0	3	26

near-central urban location. The determinant values as well as the predicted supply accompanied by the derived and surveyed parking supply of the respective model are depicted in Table 5.2.

The multi-residential archetype modelled by the derived supply model yields a predicted supply of 0.8 parking spaces, half of the capacity predicted by the surveyed model. This shows that the parcel area as an offset is not the outstanding driver of parking supply and instead the combination of factors is contributing to the final product. At the same time, the surveyed supply model predicts an expected parking supply of 1.7 parking spaces, which is more than double compared to the derived supply model. As the CI has low spans for both predictions, the capacities are predicted with high precision. In the case of this parcel, the derived and surveyed supply from the original dataset is in both cases zero. Thus, both models overestimate the supply, albeit only for this observation which does not yet reveal systematic over- or underestimation (more on that in Sections 5.2 and 5.3).

The predicted supply for the detached single family home lies at 1.4 for the derived supply model and 2.5 for the surveyed supply model. In this specific example, the derived supply is zero, compared to a surveyed supply of 3 parking spaces. The prediction increase compared to the multi-residential archetype can mainly be attributed to double the parcel area and open space ratio, a newer construction year and a 70 % lower SLV. At the same time, the GFA is only one tenth of

Table 5.3.: Regression results – non-residential sample (NB1).

	Hamburg derived		Hamburg surveyed		Munich derived	
	Coef. [95% CI]	IRR	Coef. [95% CI]	IRR	Coef. [95% CI]	IRR
Intercept	-1.017 [-2.136, 0.101]	0.362	-5.655 [-7.161, -4.149]	0.004	-4.361 [-5.464, -3.258]	0.013
log(GFA)	-0.089 [-0.174, -0.003]	0.915	-0.125 [-0.248, -0.001]	0.883	-0.115 [-0.196, -0.034]	0.891
$(\log(\text{GFA}))^2$	-0.002 [-0.008, 0.003]	0.998	-0.006 [-0.013, 0.002]	0.994	0.000 [-0.004, 0.005]	1.000
Open space (%)	0.003 [0.002, 0.004]	1.003	-0.003 [-0.004, -0.001]	0.997	0.004 [0.003, 0.005]	1.004
PT access	0.187 [0.164, 0.209]	1.205	0.183 [0.152, 0.215]	1.201	0.090 [0.063, 0.117]	1.094
log(SLV)	-0.055 [-0.097, -0.012]	0.947	0.334 [0.278, 0.390]	1.397	—	—
log(Purchasing power)	-0.385 [-0.477, -0.293]	0.681	-0.149 [-0.273, -0.025]	0.862	-0.078 [-0.171, 0.015]	0.925
Construction year						
1946–1960	0.278 [0.225, 0.332]	1.321	0.100 [0.026, 0.174]	1.105	0.123 [0.035, 0.210]	1.131
1961–1980	0.252 [0.206, 0.299]	1.287	0.233 [0.170, 0.295]	1.262	0.244 [0.179, 0.310]	1.277
1981–2005	0.208 [0.155, 0.262]	1.232	0.322 [0.251, 0.393]	1.379	0.189 [0.114, 0.265]	1.208
2006–2021	0.328 [0.210, 0.446]	1.388	0.263 [0.098, 0.429]	1.301	0.192 [0.080, 0.305]	1.212
Use category						
Industry	-0.285 [-0.336, -0.233]	0.752	-0.665 [-0.735, -0.594]	0.514	0.122 [0.056, 0.188]	1.129
Retail	-0.076 [-0.129, -0.023]	0.927	-0.270 [-0.339, -0.201]	0.764	0.354 [0.269, 0.439]	1.424
Education	-1.562 [-1.635, -1.489]	0.210	-1.286 [-1.377, -1.194]	0.276	-0.950 [-1.020, -0.879]	0.387
Gastron./accomm.	-0.433 [-0.508, -0.358]	0.649	-0.262 [-0.355, -0.169]	0.770	0.032 [-0.077, 0.140]	1.032
Leisure/assembly	-1.530 [-1.622, -1.439]	0.216	-1.241 [-1.350, -1.132]	0.289	—	—
N parcels	9,068		9,068		5,335	
θ	29.65		59.36		26.06	

Note. Reference categories: construction year – ≤1945; building type – small residential.

the multi-residential home, and the purchasing power is higher, both reducing the increase of parking supply.

Finally, the mixed-residential parcel reveals the highest predictions at 4.3 parking spaces for the derived supply model and 8 parking spaces for the surveyed supply model. Again, the latter predicts around double the capacity as the former does. The higher predicted parking supply compared to the multi-residential archetype can mainly be attributed to the larger parcel area and GFA as well as a lower SLV and a newer construction year. The mixed-residential attribute contributes to the higher capacity too. The difference between derived capacity (6 parking spaces) and surveyed capacity (26 parking spaces) shows an example of higher observations in case of the surveyed supply model, which contributes to higher model predictions.

5.1.2. Non-residential Panel

The intercepts of the non-residential models show a similar pattern to those of the residential model, with an IRR around zero in the case of the Hamburg surveyed and Munich derived model. The IRR of the Hamburg derived model is slightly higher, however, the CI spans around zero meaning that the intercept does not significantly deviate from zero.

GFA values draw the opposite picture compared to the residential model. Coefficients show a negative sign, albeit with the upper CI border close to 0. The $\log(\mathrm{GFA})^2$ term yields confidence intervals spanning zero in all three samples, confirming that the quadratic term does not contribute meaningfully to the model fit in the non-residential context and that the GFA-parking density relationship is adequately described by the linear term alone. A 1% increase in GFA thus reduces the parking space density by around 0.1%.

The observed open space ratio effect is differing from residential parcels, as the observed IRR is a third or less. Both models fitted on derived parking supply show a low positive correlation of open space ratio and parking space density. This effect is still among the strongest, as an increase in open space ratio by 1 % increases parking supply density by 0.3 to 0.4 %. However, the effect is opposite for the surveyed model in Hamburg, yielding a significant deviation in effect direction between the non-residential models. Similar to the residential model, the CI shows a narrow span with a maximum of 0.003. In case of the Hamburg surveyed model, the CI comes closest to zero, albeit not overlapping the CI of derived models and thus indicating that the sign reversal is statistically robust.

PT access yields positive estimates for both models of Hamburg at a similar level, while Munich's model obtains an effect half of the Hamburg level. A step up by one PT access rank thus increases parking space density by 10 to 20 %, respectively. This rate is more than double the effect observed in the residential models of Hamburg, and a first significant coefficient for Munich. The range of coefficients within the CI is higher for the Hamburg surveyed and the Munich derived model, indicating that the Hamburg derived model yields more accurate estimates.

SLVs show diverging patterns for Hamburg, with Munich not providing an estimate due to missing data. While the SLV of the derived model reveals a negative pattern, surveyed data show a strong positive effect that contrasts the results obtained for the residential samples too. The city structure thus seems to show the opposite pattern: 1% higher land values increase the parking space density by 0.3% according to the surveyed model. The confidence intervals for the SLV do not overlap between the Hamburg derived and the Hamburg surveyed model, confirming that the sign reversal between data sources is significant.

Similar to the residential models, purchasing power for both Hamburg models reveals a negative coefficient, albeit with a CI close to zero in the case of surveyed parking. For the Hamburg derived model, the coefficient is more than double compared to the residential model. The purchasing power coefficient for Munich does not exclude zero, preventing a significant effect in contrast to Hamburg derived and surveyed, where the negative association is confirmed by the CI.

The construction year shows positive estimates similar to the residential samples. However, effect strength especially for newer buildings is reduced. A newer construction year class does not automatically increase the parking compared to the class below, as was mostly the case in the residential sample. Instead, coefficients show differing pattern, when taking 1946-1960 as a baseline: Newer construction years slightly decrease the parking supply density in the case of Hamburg derived, while showing the highest values again for the newest construction year class. The 2006–2021 construction year category yields substantially wider intervals across all samples, indicating limited statistical precision.

Looking at the use categories, the results diverge throughout the three samples. The Hamburg surveyed model yields stronger negative coefficients for industry and retail than Hamburg derived, while Munich shows opposite patterns with positive coefficients. Education facilities yield lower parking density rates compared to workplaces, with the lowest value found for the derived model in Hamburg, where parking density is on average 79% below baseline levels. Gastronomy and accommodation facilities as well as places for leisure and assembly are found to have less parking spaces compared to workplaces too, with slightly higher coefficients identified for the Hamburg derived model. In the case of Munich, gastronomy and accommodation are not found to significantly deviate from workplace parking density, while leisure and assembly could not be classified as the primary use category of parcels.

Overall, the results of non-residential models show a much more diverse pattern than the residential models. PT access and education facilities show consistent patterns across all samples, while construction year coefficients are uniformly positive but vary in magnitude between classes. Other variables show either signs reversal or low to no significance.

In the case of NB1 models, the overdispersion parameter θ increases with higher overdispersion in the model, as the conditional variance is linearly connected to the conditional mean (see Equation 4.5). The Hamburg surveyed model yields by far the highest θ, more than double compared to both derived supply models.

The results of the non-residential panel are further analysed for two archetypes: (1) a newly constructed office in a central high-density neighbourhood, and (2) an industry building with a large parcel area located towards the outskirts of the city. The determinant values of the archetypes are depicted in Table 5.4.

The predicted parking supply for the office archetype is characterised by a low open space ratio, a high SLV and a small parcel area for non-residential standards. The parcel reveals a predicted capacity of 11.2 and 19.7 parking spaces for the derived and surveyed supply model, re-

Table 5.4.: Scenario analysis – non-residential archetypes.

	Workplace	Industry
Determinants		
Parcel area (m^2)	1,180	27,526
GFA (m^2)	7,155	15,961
Open space ratio	0.24	0.65
PT access rank	9	9
SLV (€/m^2)	4,800	1,395
Purchasing power (€)	56,079	54,258
Construction year	2006-2021	1981-2005
Derived supply model		
Predicted supply [95% CI]	11.2 [9.7, 12.7]	169.9 [157.2, 182.6]
Derived supply	22	206
Surveyed supply model		
Predicted supply [95% CI]	19.7 [16.1, 23.2]	138 [124, 152.1]
Surveyed supply	32	188

spectively. Higher predictions for the surveyed supply model can thus also be observed for the non-residential panel in the case of this use category. Both derived and surveyed supply are underestimated for this observation.

The industrial archetype yields a large parcel area more than 20 times the size of the office parcel. GFA values and open space ratio are more than double too, while the SLV sits at only one third. The predicted parking supply is higher for the derived model, showing that the derived supply model does not always predict less parking compared to the surveyed supply model. The CI spans around 25 parking spaces, which reveals higher prediction insecurity for large capacities. Both models again underestimate the actual derived or surveyed parking supply.

The derived coefficients draw a picture of the effect of determinants on the parking supply density, with the applied context of the archetype analysis depicting real world parking supply predictions. These results contribute to finding answers to Research Question 1, which will further be discussed in Chapter 6. The archetype analysis revealed mostly underestimation of the regression models in the case of the chosen five parcels. To see if these prediction patterns appear systematically, the models are further analysed regarding their goodness of fit in the following section.

5.2. Model Diagnostics

In order to assess the model performance, it is crucial to compute post-regression tests. Cameron and Trivedi (2013) recommend "a cycle of model specification, estimation, testing, and evaluation", the first three of which have mainly been conducted in Section 4.2. Testing for overdispersion and zero inflation led to the choice of an NB2 model for the residential panel and the NB1 model for the non-residential panel. This section is devoted to the evaluation and diagnostics of the fitted model results.

5.2.1. Residual Analysis

The analysis of residuals is seen as important means for diagnosing count models, as it yields information on possible outliers, influential observations, or misspecification of the model (Cameron & Trivedi, 2013). Count models typically yield heteroscedastic residuals with inconstant mean and variance. This can be accounted for by using the Pearson residual p_i, which divides the standard residual by the estimated variance:

$$p_i = \frac{y_i - \hat{\mu}_i}{\sqrt{\hat{\omega}_i}} \tag{5.1}$$

with the observed count y_i, the expected count $\hat{\mu}_i$ predicted by the regression model, and the estimated variance $\hat{\omega}_i$. A positive Pearson residual thus reveals underestimated parking supply for observation i.

Throughout this section, Pearson residuals will be analysed. The starting point for residual analysis are descriptive statistics on their distribution, which are depicted in Table 5.5. Besides common descriptive statistics like mean, minimum, quantiles, and maximum, the skewness calculated as the third standardised moment serves as an indicator for outliers in the sample as the latter contribute disproportionately to a high skewness.

The mean Pearson residual of the residential fitted models is negative and close to zero, indicating that there is no systematic over- or underestimation of parking supply. Non-residential means are deviating more from zero, indicating that these models show on average slightly higher overestimation of parking supply in relation to the estimated variance at i. A standard deviation of around 1 indicates a correct specification of the variance function in the case of all derived models.

Table 5.5.: Descriptive statistics of Pearson residuals.

Model	Mean	SD	Skewness	Min	P10	P90	Max
Residential (NB2)							
Hamburg derived	-0.009	1.009	7.586	-1.042	-0.826	1.178	93.890
Hamburg surveyed	-0.007	1.129	21.643	-1.118	-0.846	1.023	125.947
Munich derived	-0.003	0.956	3.223	-1.362	-0.900	1.199	44.944
Non-residential (NB1)							
Hamburg derived	-0.070	0.989	6.025	-5.449	-0.763	0.729	26.191
Hamburg surveyed	-0.054	1.199	13.797	-2.917	-0.595	0.493	46.876
Munich derived	-0.105	1.079	14.573	-3.298	-0.718	0.589	39.822

However, the surveyed models for Hamburg still show overdispersion, which has already been observed in the pre-estimation conducted in Section 4.2.

A closer look at the 90th percentiles and maximum values of the Pearson residuals indicates the presence of strong outliers in the dataset, which were wrongly predicted by the model. In all cases, the maximum value is highly deviating from the P90 value, meaning that outliers interfere with an accurate prediction of parking supply. The effect is strongest for the surveyed dataset in Hamburg, as its values of the 90th percentile are the lowest of both panels, while the maximum Pearson residuals are the highest. High skewness value confirm this impression.

The minimum Pearson residuals of around -1 in the case of residential parcels is given by the NB2 overdispersion function, limiting the Pearson residual to a minimum of $-\sqrt{\theta}$. The linear overdispersion of the NB1 variance is not limited, which does not allow for a comparison of minimum Pearson residuals between the two models. Nonetheless, the minimum values of non-residential parking supply models are not as high as the maximum values, indicating that overestimation in the extreme cases is not as severe as underestimation.

Cameron and Trivedi (2013) and Hartig (2024) mention that statistical residual tests are limited for evaluating the fit of count models, as obtained test values remain a black box. To address this, they instead recommend visual analysis. As just discovered, parking supply is on average slightly overestimated in all six fitted models. To see where this pattern appears, the predicted parking supply is compared with the derived and surveyed supply of the capacity bins used in Figure 4.1.

Figure 5.1 depicts the capacity bins as well as the predicted supply for all six models. Thanks to the well controlled overdispersion ratio (see Table 4.4), the Hamburg derived residential model predicts similar quantities of each derived or surveyed bin. Underestimation is present for the

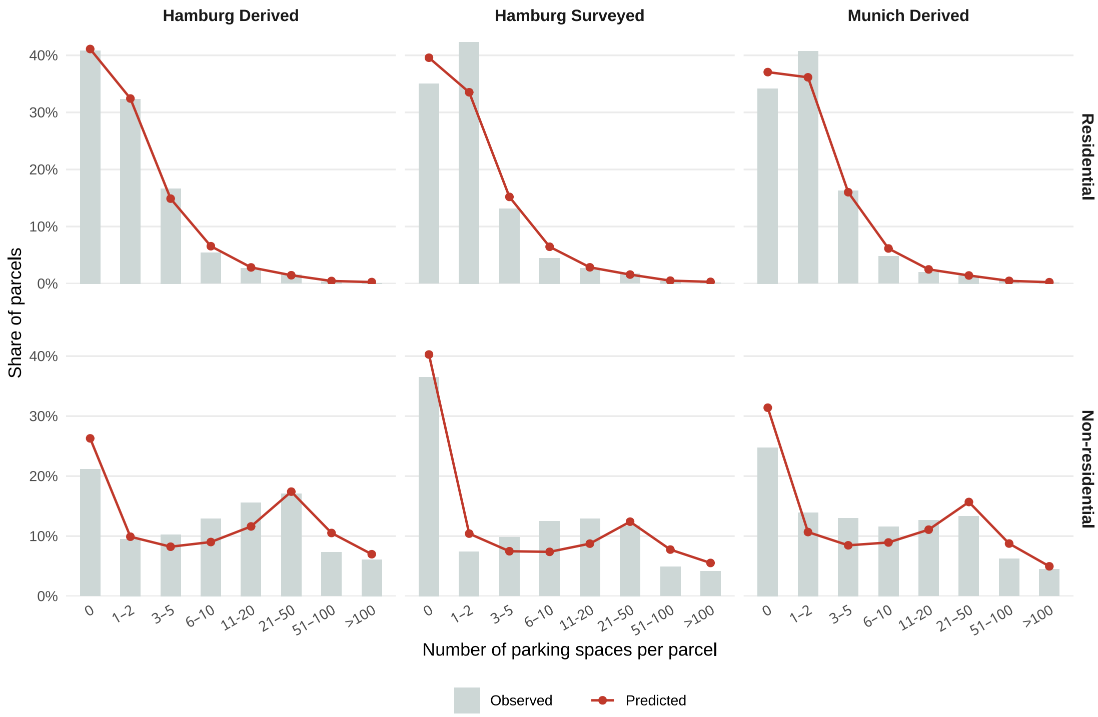

Figure 5.1.: Predicted and observed parking supply per frequency bin.

bin of 3-5 parking spaces, while the opposite is the case for the capacity range of 6 to 10 parking spaces per parcel. It can be noted that the zero inflation is well captured by the model. The surveyed model of Hamburg shows a different picture: The surveyed parking supply holds more observations in the bin of 1 to 2 parking spaces, while prediction values are similar to the derived model. This leads to an overestimation of zeros and middle range capacities of 3 to 10 parking spaces, while substantially underestimating the class of 1 to 2 parking spaces per parcel. Munich derived data show similar bin sizes to the surveyed parking supply, which is better fitted by the model. The same pattern of over- and underestimation as for the Hamburg surveyed model can be observed, albeit with less deviation from derived values.

The non-residential models show systematic overestimation of zero values and high capacities above 50 parking spaces. At the same time, capacities of 3 to 20 parking spaces are generally underestimated. Both Hamburg models show a spike for predicting the class of 21 to 50 parking spaces, which is in line with the derived and surveyed capacities and thus showing a good model fit. Munich reveals a similar prediction pattern, however, this class is overestimated by the model. Overestimation is continued for the highest capacity bins.

Overall, the residential model predictions are more accurate as they yield a lower span of residuals and model estimations closer to the actually derived and surveyed residuals. The overestimation of high capacity bins in the case of the non-residential model indicates that model estimates are driven by extreme values, which weaken the model performance.

5.2.2. Spatial Autocorrelation

The framework of parking supply prediction is carried out in a spatial context, which is subject to Waldo Tobler's First Law of Geography, defining that "near things are more related than distant things" (Tobler, 1970). This also applies to the built environment such as buildings, which show similarities in building structure such as that buildings within a block are often equally shaped. Thus, testing for spatial autocorrelation is crucial to discover if neighbourhood effects are present after model fitting.

Global spatial autocorrelation tests provide information if spatial autocorrelation is present in the residuals across the investigated area. The test is usually conducted by computing the Moran's I statistic on the residuals (Fischer & Getis, 2010). The package `spdep` in R provides the function `moran.test` calculating Moran's I given the residuals of the variable of interest and a predefined spatial weight matrix, which reflects the expected spatial relationship between an observation y_i and its neighbours. Moran's I is thus derived as follows:

$$I = \frac{n}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \cdot \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(p_i - \bar{y})(p_j - \bar{p})}{\sum_{i=1}^{n}(p_i - \bar{p})^2} \tag{5.2}$$

with the Pearson residual p_i, its spatial neighbour p_j and their spatial weight w_{ij}.

Common ways to model spatial relationships are k nearest neighbours, Inverse Distance Weighting (IDW), or polygon contiguity such as Rook's and Queen's case (Fischer & Getis, 2010). In the context of this work, the latter definition appears suitable on the first sight, as parcels depict polygons which share borders. However, in some cases, off-street parcels may not share borders with other off-street parcels, for example if neighbouring parcels are omitted for analysis when not classified as off-street (see Section 3.1.1) or not yielding values for all determinants. At the same time, k nearest neighbours and IDW are certain to consider parcels from other blocks as neighbours, which leads to an inaccurate neighbourhood definition in an urban context. Instead, this study uses the block structure for the spatial weight matrix, implying that w_{ij} is 1 if two parcels i and j are located in the same block. As blocks are available as geo-referenced features

Table 5.6.: Moran's I test on Pearson residuals with block-based neighbourhood matrix.

	I	$\mathrm{E}[I]$	Variance	p-value
Residential panel				
Hamburg derived	-0.000430	-0.000006	0.000001	0.573
Hamburg surveyed	0.000044	-0.000006	0.000001	0.947
Munich derived	0.001061	-0.000010	0.000001	0.369
Non-residential panel				
Hamburg derived	0.016443	-0.000129	0.000084	0.071
Hamburg surveyed	0.007417	-0.000129	0.000081	0.401
Munich derived	0.002429	-0.000259	0.000202	0.850

both for Hamburg and Munich, they are utilized for the neighbourhood definition by performing a spatial join of the parcel's centroid with the block polygon.

Table 5.6 depicts the result of the conducted autocorrelation test. Spatial autocorrelation is present, if the calculated I deviates from the expected value $\mathbb{E}[I]$, with $p < 0.05$ indicating statistical significance on the 5% level. For all six models, the calculated Moran's I converges towards zero and thereby coming close to the expected Moran's I. All models show statistical insignificance with p-values above 0.05, meaning that the null hypothesis of parcel residuals not being spatially autocorrelated cannot be rejected. Non-residential parcels yield slightly higher I values, with the derived model for Hamburg coming close to statistical significance. Overall, spatial autocorrelation does not violate the model assumption of independent residuals, indicating that spatial autocorrelation—if present—is well controlled for by the parking supply determinants.

5.3. Model Transferability

Having analysed model estimates and residuals as well as the correlation of parking supply with its determinants, the model results are now investigated regarding their transferability in order to find answers on Research Question 2. Two methods are chosen to gain knowledge on the model performance on unknown samples. First, a resampling method is utilised, simulating the application of the model on an urban context that does not differ from the environment where the model was trained. Second, the Hamburg models are applied to predict parking supply in Munich, with predictions validated against the surveyed supply available on block level.

5.3.1. Cross-Validation

Model performance on unknown samples can be assessed using resampling methods such as Cross Validation (CV) or bootstrapping. The goal of resampling is to gain knowledge about the test error which occurs when applying the model on an unknown sample. As those samples are usually not available, CV yields the option to approximate the test error by repeating the model experiment within the original sample (James et al., 2021).

CV can be conducted in two common ways: (1) Leave-One-Out Cross Validation (LOOCV) or (2) k-fold Cross-Validation. In the latter case, the sample is divided into k folds of similar size, with the model being trained on $k-1$ folds and then tested on the remaining fold k. $k=5$ or $k=10$ are fold sizes typically used to conduct CV (James et al., 2021). LOOCV carries out similar training, with k instead being the sample size n, meaning that the training is performed n times. While LOOCV reduces bias in the test error estimate, k-fold CV requires less computational power especially for large sample sizes, though it produces a higher test error variance, as the training sets have little overlap and are thus less correlated with each other (James et al., 2021).

In the context of this study, k-fold cross-validation is applied due to the large sample size and as variance analysis is seen as more useful in the context of transferability of the model results on other investigation areas. The Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are calculated for each model and can be defined as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{\mu}_i\right| \tag{5.3}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{\mu}_i)^2} \tag{5.4}$$

with the derived or surveyed count y_i and the expected count $\hat{\mu}_i$ predicted by the regression model. As residuals are heteroscedastic in count models (Cameron & Trivedi, 2013), the MAE of the whole sample would be biased by high residuals. Thus, MAE and RMSE are calculated for stratified classes using aggregated bins of parking supply distribution depicted in Figure 4.1.

Table 5.7 shows the results of the 5-fold cross-validation. The overall MAE of the residential panel lies around 2.2 to 2.6 parking spaces for all models, which is in all cases accompanied by an RMSE more than thrice as high. This indicates that errors are driven by outliers. The supply

Table 5.7.: 5-fold cross-validation results.

Model	MAE (RMSE)	MAE (RMSE) by observed count group $y_i = 0$	$1 \leq y_i \leq 5$	$6 \leq y_i \leq 20$	$y_i > 20$
Residential panel					
Hamburg derived	2.47 (8.07)	1.64 (4.05)	1.49 (4.30)	6.58 (12.38)	26.43 (42.78)
Hamburg surveyed	2.58 (9.74)	2.25 (7.32)	1.09 (3.01)	6.92 (12.62)	29.56 (50.79)
Munich derived	2.15 (7.85)	1.52 (4.26)	1.30 (3.92)	5.83 (11.83)	24.07 (42.51)
Non-residential panel					
Hamburg derived	20.07 (58.18)	6.44 (9.37)	10.90 (18.11)	11.93 (22.62)	43.10 (101.72)
Hamburg surveyed	21.28 (71.70)	12.66 (20.33)	11.00 (17.77)	10.77 (19.13)	57.73 (152.51)
Munich derived	16.69 (67.42)	5.69 (8.91)	8.51 (18.64)	10.25 (19.80)	43.73 (134.35)

of parcels yielding no parking is on average overestimated by the training models by 1.5 to 2.2 parking spaces, with the lowest error observed for the Munich model. The MAE shows the lowest values when predicting capacities of 1 to 5 derived or surveyed parking spaces, albeit with an RMSE still three times as high. Nevertheless, the training models perform best for these classes, with the lowest error observed for the Hamburg surveyed model. The MAE increases for the next capacity class to an average misestimation of 6 to 7 parking spaces. The RMSE-MAE ratio in this class is reduced to around factor two. The MAE is the highest for predicting capacities above 20 parking spaces, which is expected given the heteroscedasticity of the residuals. Overall, the Munich derived supply model shows the lowest MAE.

The computed cross validation on the non-residential panel yields substantially higher MAEs. Similar to the residential panel, the RMSE sits at around triple to quadruple the size of the MAE, indicating that errors are strongly driven by outliers. The overestimation for $y_i = 0$ is substantially higher than in the residential panel, albeit with less exposure to outliers. The Hamburg surveyed panel stands out with an error double the size of the other models. These results contrast the observation of Figure 5.1, where zeros were structurally overestimated by the model. Capacities of 1 to 20 derived or surveyed parking spaces show similar error sizes at 8.5 to 11.9 parking spaces, which is severe in the range of 1 to 5 parking spaces. The highest MAE is observed for capacities larger than 20. High RMSEs indicated that these errors are again driven by outliers. Similar to the residential panel, the Munich derived model shows the lowest errors.

Overall, residential models perform best when predicting parking supply in the range of 1 to 5 parking spaces. Most errors here are driven by outliers. The non-residential models reveal substantially higher errors, especially for low capacities, where errors are less driven by outliers

Table 5.8.: Block-level prediction of Munich surveyed supply.

Model	MAE	RMSE
Hamburg derived	76.45	146.20
Hamburg surveyed	73.21	141.90
Munich derived	78.45	149.35

than in higher ranges. While the Munich derived model shows the best cross-validation results, the Hamburg surveyed model tends to over- or underpredict the strongest of all samples.

5.3.2. Cross-City Transfer

Concluding the results chapter, this work investigates if the regression model fitted in one study area yields accurate parking supply predictions in another area of interest. In this context, the models of Hamburg are applied on parcels in Munich which are located within the blocks yielding surveyed parking supply as mentioned in Section 3.3. The predicted parking supply is then aggregated on block level and compared with surveyed values. To see if the supply is driven by possible local effects, the surveyed supply is additionally predicted by the Munich derived models.

To account for blocks where sample parcels are not representing enough block area, only blocks with at least 80% parcel coverage are considered for the prediction. This reduces the block sample from originally 2,514 blocks to 1,959 blocks. Out of 101,596 residential parcels, 25,736 and thus one quarter of parcels are located in the block sample. The share of non-residential parcels located in the block sample is around 40% (1,982 of 5,332 parcels). On average, each block in the surveyed parking supply dataset contains 13.1 parcels for which parking supply is predicted by the models, though the distribution varies from 1 to 106 parcels per block.

Table 5.8 depicts the error statistics of the transferability test. The MAE is similar in all three estimations, showing that the estimation of parking supply is wrong by on average 73 to 78 parking spaces. The Hamburg surveyed model yields the lowest error, while the contrary can be said about the Munich model. The RMSE is in all three estimations around double the MAE, indicating that the MAE is less driven by outliers than for example most MAEs in the CV of the residential panel (see Table 5.7).

Given the average of 13.1 parcels per block, the MAE per parcel is roughly around 5.6 to 6.0 parking spaces, though this value is a rough approximation and may vary with the count of parcels per

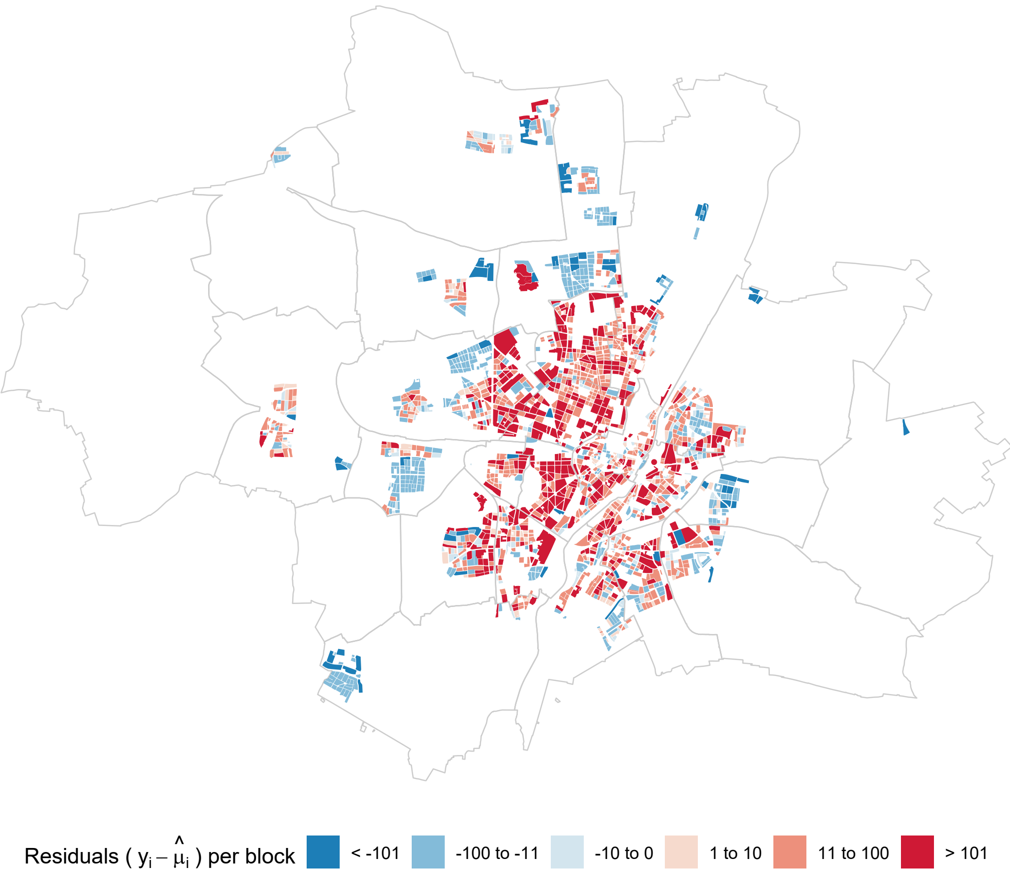

Figure 5.2.: Difference of predicted supply (Hamburg surveyed supply model) and surveyed supply on block-level in Munich.

block. It is also unknown if the error is mainly driven by residential or non-residential parcels, as the aggregation of surveyed parking supply in Munich on block level does not allow for deeper differentiation of parking type.

The MAE does not yet reveal the occurrence of structural over- or underestimation. To discover these and spatial patterns of the errors, Figure 5.2 depicts the residual $(y_i - \hat{\mu}_i)$ of the predicted and surveyed supply per block i across Munich in residual bins. Predictions are computed using the Hamburg surveyed supply model. Positive values indicate underestimation, as the predicted value is smaller than the observed value.

The map depicts that the majority of blocks are underestimated by at least 10 parking spaces, with a substantial amount of blocks exceeding a residual of 100. Overestimation is present too, albeit less frequent and with lower values. While blocks towards the city centre tend to be underestimated by the Hamburg surveyed model, blocks towards the outskirts are rather experiencing overestimation. The predictions of the other two models reveal similar spatial patterns (see Appendix C).

6. Discussion

This study presents a regression-based approach to modelling off-street parking supply at the parcel level, investigating both derived and surveyed parking data from two German cities. The regression results contribute to the understanding of factors driving off-street parking supply and provide a baseline for further research. In this chapter, the findings are evaluated in the context of existing literature, model limitations are discussed, and implications for policy making and future research are derived.

The chosen framework benefits from several methodological strengths. First, the use of both derived and surveyed parking data allows for a direct comparison of modelling results across different quantification approaches. Second, the city-wide coverage of both study areas ensures that a wide range of urban structures is represented, improving the robustness of results despite the presence of outliers. Third, the use of count regression controls overdispersion in parking capacities, making it more appropriate than linear regression for handling count data. Fourth, splitting the sample into residential and non-residential panels proves necessary, as the two groups differ both in their parking distributions and in the factors driving supply.

To provide answers to Research Question 1, the expected effects of parking supply determinants are compared to the observed coefficients. As the literature generally refers to absolute parking counts rather than the density measured in this study, direct comparison of coefficient magnitudes is limited — particularly for GFA and open space ratio, both of which show moderate correlation with parcel area. For all other determinants, correlations with parcel area are low, making their coefficients broadly comparable to findings in the literature.

The GFA is seen as one of the driving legal factors for parking supply defined in parking requirements for both residential and non-residential parcels (Weidner, 2012). This is confirmed for the residential panel, as the GFA shows a positive effect on parking space density, albeit at a low elasticity level and declining with rising GFA. On the other hand, non-residential models show a negative linear relationship of GFA and parking space density. This is unexpected as both parking requirements in Hamburg and Munich are directly bound to the GFA (Freie und Hansestadt

Hamburg, Behörde für Stadtentwicklung und Wohnen, 2022; Landeshauptstadt München, 2025). However, the parcel area as an offset may partially hold the GFA effect, as both variables are positively correlated. This is even more relevant in the context of non-residential parcels, which are on average four times larger than residential parcels (see Tab. 4.1). Whether the negative relationship between non-residential GFA and parking spaces reflects a genuine pattern or is an artefact of the modelling approach cannot be determined conclusively and needs further investigation. Should the pattern be confirmed, it would suggest that GFA-based parking requirements do not adequately reflect parking provision for non-residential uses.

The open space ratio effect contrasts findings by Liu et al. (2019), as higher values and thus a lower building density lead to more parking spaces. The effect of open space ratio on parking density is stronger than that of GFA, which is unexpected given its low correlation with parking depicted in Fig. 4.2. A possible explanation is the negative correlation between open space ratio and GFA, potentially causing the former to act as a suppressor variable reducing the effect of the latter (Cohen et al., 2013). Furthermore, the open space ratio is positively correlated with the parcel area, indicating that the latter may partially hold the effect strength. This could also explain the negative coefficient observed for the surveyed supply model of Hamburg. Overall, future research should focus on a clearer distinction of area-based determinants such as the parcel area, the GFA and the building density, for example by including the floor area ratio.

Good PT access can reduce the need for a private car and reduces MPRs in Germany (Weidner, 2012). Even though Liu et al. (2019) find varying effects for PT accessibility across space, the observed effects in both regression panels are unexpected, as higher PT access in this study leads to an increase in parking space density. The effect has to be considered under the circumstance that most parcels in the samples show high PT access ranks (see 4.1). In rural areas, PT access is generally lower, suggesting that future studies could adjust access ranking depending on the investigated area. Additionally, PT access was calculated as the crow flies, with a detour factor of 1.5 accounting for longer walking distances. It can be expected that evaluating PT access with pedestrian routing as typically conducted (Ministerium für Verkehr Baden-Württemberg, 2025) yields more accurate results. Nevertheless, policy-makers should consider whether reducing MPRs with higher PT accessibility is a sufficient incentive for lower parking provision. Maximum parking requirements as applied in the Netherlands and Switzerland (Merten & Kuhnimhof, 2024) offer an alternative approach to addressing parking oversupply (Derschmeier et al., 2023; Jung, 2011).

The observed negative coefficient of SLVs (except for the non-residential surveyed supply model in Hamburg) is in line with reviewed literature (Derschmeier et al., 2023). Furthermore, it partly reflects the city's spatial structure, with higher values towards the city centre (see 3.2). Apart from the increasing pressure to use land efficiently, the SLV coefficient may thus capture broader centre-periphery relations beyond land efficiency effects. The more negative SLV coefficient of the derived models compared to the surveyed model may partly reflect the systematic underestimation of cadastral parking facilities in central areas, where underground parking is most common.

Purchasing power shows negative coefficients throughout all models, albeit with low to no significance for the non-residential panel. At first sight, this contradicts evidence that wealthier households generally show higher car ownership levels (Ritter & Vance, 2012) which is expected to reflect increased parking supply. However, purchasing power as derived from the household dataset is an income proxy rather than a direct measure of car ownership. The positive income-car ownership relationship may not hold in metropolitan contexts where car ownership rates are generally lower and higher income does not automatically lead to car-centric mobility behaviour (Follmer, 2025). Further studies could therefore include more direct indicators of car ownership such as vehicle registration statistics, and consider the quality of active mobility infrastructure as an additional determinant.

Reflecting on the construction year, the residential and non-residential panels reveal a different development of parking supply over time. As for all residential models, parking supply density increases consistently across younger construction year classes. Considering the trends of parking requirements observed in literature, the effect was expected to peak for buildings constructed after World War 2, when car ownership was actively subsidised (Weidner, 2012). Unexpectedly, the highest increase is mainly observed for the construction year between 2006 and 2021. This effect has to be interpreted with three limitations. First, the small bin size of this class might bias regressors. Second, the availability of cadastral parking data, on which the derived parking supply mainly depends, may be more complete for newer buildings. Third, an undeveloped land parcel with a building constructed in 2021 or later may yield surface parking segments, which were removed as the new building was constructed, though this is considered a rare exception. The non-residential parcels show inconsistent patterns throughout different construction year classes, although they all show a significant increase in parking compared to the baseline category, which can be connected to the introduction of parking requirements after 1939 (Weidner, 2012). Future research could implement the building age as continuous variable in order to obtain fine-grained effects of building trends on the parking supply.

Although introduced as control variables for residential building type, large and multi-residential parcels show higher parking space density on average. The two building types are likely to be positively correlated with the GFA and thus may hold part of its effect on parking space density.

It is recommended to introduce GFA and building type as a combined determinant when aiming to investigate coexisting effects.

The use category estimates show uniform coefficient signs across both models in Hamburg, while Munich shows diverging patterns. For each category, lower parking density compared to the workplace category does not automatically translate to lower parking capacities. For example, industrial parcels with higher parcel area can distribute their parking across a larger area. In Hamburg, industrial land use is concentrated near the harbour, where large parcel sizes may drive parking density patterns that are not representative of industrial parcels in general. At the same time, workplace buildings are typically built in a dense environment, thereby increasing parking space density.

While cadastral data provide detailed use classifications across over 200 categories, aggregation to a smaller set of classes was necessary for regression modelling. This aggregation may cover relevant differences on the exact use of a parcel. For example, a church and a recreational area could both be aggregated in the *leisure/assembly* category, although their parking requirements differ. Furthermore, the use of a building may change over time and it is unclear whether this change is maintained in the cadastral data. Future research could therefore explore other sources such as point of interest data.

Overall, these findings provide an answer to Research Question 1. For residential parcels, ground floor area, open space ratio, standard land value, construction year, and building type are consistently identified as significant determinants of parking supply density across all three samples. For non-residential parcels, results are less conclusive: while construction year and public transport access show consistent directions, GFA, open space ratio, and standard land value yield diverging patterns across samples, limiting the reliability of these estimates. The factors driving non-residential parking supply therefore remain only partially understood.

An important finding is the differences in effect strength between derived supply and surveyed supply modelling results. Surface and park deck capacities are overestimated, while covered, garage, and underground supply are mostly underestimated when deriving parking capacities from the three sources used in this study. As a consequence, the model trained with derived parking is trained on a different input compared to the surveyed parking model. For the residential panel, this primarily affects effect strength, whereas sign reversal can be observed for the open space ratio and the SLV in the non-residential panel. The scenario analysis confirms these differences, where all archetypes except the industrial show higher predicted capacities for the surveyed supply model. The high difference in surface parking raises the question of unobserved surface parking in the survey dataset, as the difference is unlikely to be attributed solely to measurement errors. A similar pattern has been reported for public parking in Berlin, where the city's survey captured around 40% fewer spaces than aerial imagery-based estimates using the same traffic area segmentation method (Rauch et al., 2025). For off-street parking, possible deviations could come from informal parking such as in front of garages or on access ways. As the occlusion by trees or shadows leads to underestimation of the true capacity of a surface parking segment (Hellekes et al., 2023), it is recommended to combine surveyed parking with derived surface parking segments to gain a more accurate image of parking supply, which would simultaneously lead to more robust results of modelling parking supply.

The approach to model parking on a parcel level offers the advantage of a precise assignment of determinants to the available parking spaces. In a minority of cases parking facilities such as underground parking had to be split over many parcels, which may be inaccurate since the parking facility can usually be accessed from one parcel only. To account for this, future research could analyse parking supply at the block level, though consider how to implement fine-grained variables that can vary within a block such as uses, building types, or construction years. One approach is the use of compositional data to implement variable shares on a block level. In this case, special attention has to be paid to the entry of these determinants into the regression model, as compositional data introduce fundamental problems for regression models (Hron et al., 2012). Another approach could be the use of building typologies as developed by Louen et al. (2022) to account for the heterogeneity of urban environments.

To find answers to Research Question 2, the model outcomes of Hamburg and Munich are first compared. Despite differences in individual coefficient magnitudes—particularly for construction year and building type—the residential models show consistent coefficient signs, suggesting that the identified determinants are directionally stable across both cities. This supports the feasibility of cross-city transfer for residential parcels, even if effect strengths vary locally. The PT access coefficient of Munich not significantly deviating from zero indicates that the relationship with PT adjacency may be spatially varying, in line with evidence from Shenzhen (Liu et al., 2019).

The non-residential model comparison reveals several inconsistencies. Industry and retail uses show negative coefficients in Hamburg but positive coefficients in Munich, suggesting that use category effects are shaped by city-specific spatial patterns such as the Hamburg harbour area. Construction years show consistent patterns across both cities and can therefore be considered the most robust finding of the non-residential panel. Unlike the residential panel, the non-residential models show sign reversals for industry, retail, and SLVs across cities, indicating that the identified determinants are not directionally stable and that city-specific factors play a more important role for non-residential parking supply. The comparison of both residential and non-residential model results have to be interpreted given the missing SLV data for Munich, which limits the comparability across cities.

The moderate errors observed for the CV are highly driven by outliers, indicating that the model is able to predict residential parking supply for parcels without extreme outlying capacities. The substantially higher errors of non-residential parcels indicate limited predictive capabilities. As this can be mainly attributed to a lower model fit, the key challenge is finding a regression model that is able to adequately capture the heterogeneity of non-residential uses. It is thus recommended to model non-residential uses separately by category to account for high deviations and improve the prediction capabilities. This could be done by pooling non-residential data across multiple cities. Interestingly, the surveyed models yield higher errors compared to the derived models. This is a confirmation of high heterogeneity that can be observed on the parcel level in an urban context.

The transferability of the regression model is relevant in the context of scarce data on off-street parking supply, which is necessary for municipalities to develop effective parking policies (Bauer et al., 2024). The prediction errors observed after transferring the Hamburg models to Munich are moderate and similar across all three models. However, they cannot be disaggregated further, as data are only available on a block level. Given the differing model fit between residential and non-residential panel, it is likely that errors are driven by non-residential rather than residential parcels. A crucial challenge thus remains in a more accurate investigation of prediction deviations across study areas.

Surprisingly, the model trained with surveyed parking supply does not outperform the derived supply models in terms of prediction accuracy. Although the surveyed model might be expected to yield the most accurate predictions given its ground truth input, prediction errors are similar across all three models for both the cross-validation and the cross-city transfer.

A notable finding concerns the spatial similarity of residuals between the three models. Model predictions appear to adequately control for spatial differences between Hamburg and Munich, as the Munich model shows similar residuals to the Hamburg models. This indicates that prediction uncertainties are more a matter of model specification than of spatial disparities between cities. Future work should continue evaluating the transferability when developing new approaches for parking supply prediction.

In summary, these findings provide an answer to Research Question 2. The regression model can be transferred across cities with moderate errors for residential parcels, where prediction uncertainties are driven more by outliers than by spatial disparities between Hamburg and Munich. For non-residential parcels, however, inconsistent coefficient signs and substantially higher errors indicate that transferability is weak and strongly constrained by model misspecification and city-specific spatial patterns. Future research should therefore prioritise improving non-residential model specification before applying the framework in unknown spatial contexts.

Beyond the regression model, the derivation framework developed in this study offers a scalable alternative to resource-intensive parking surveys, applicable to any municipality where aerial imagery, cadastral and OSM data are available. While derived capacities deviate from ground truth—particularly if underground and garage parking are not well maintained in cadastral data—the framework provides a useful baseline for municipalities lacking comprehensive parking inventories.

7. Conclusion

This study presented a data-driven approach to derive and model off-street parking supply as well as its determinants. Combining surface parking segments, cadastral data, and OpenStreetMap features, over 1.3 million parking spaces were derived in Hamburg and over 600,000 in Munich. Comparison with surveyed data revealed systematic deviations: underground and garage parking were substantially underestimated, while derived surface parking exceeded surveyed capacities by more than double in Hamburg.

Regression modelling at parcel level using negative binomial models showed consistent results for residential parcels across all three samples, with ground floor area and open space ratio as the strongest determinants of the parking supply density. Non-residential models were less conclusive, with several coefficients showing sign reversals or low significance. Cross-validation revealed moderate residential prediction errors driven by outliers, while non-residential parcels were substantially misestimated. When transferred to an unknown spatial context, the surveyed supply model did not outperform models fitted with derived parking data.

This study makes three contributions to gain better knowledge on off-street parking supply. First, count regression modelling on two city-wide datasets captures a wide range of urban structures and shows that residential and non-residential parcels differ substantially in their parking distributions and driving determinants. Second, the cross-city comparison offers empirical evidence on the transferability of parking supply models, suggesting that model specification rather than spatial disparities is the primary source of prediction uncertainty. Third, the derivation framework offers a scalable approximation of off-street parking supply, wherever aerial imagery, cadastral and OSM data are available.

The main limitations of this study concern the non-residential panel, where heterogeneous land uses and city-specific spatial patterns limit the generalisability of results. The interaction of area-based determinants complicates the interpretation of individual effects, and the measurement of variables such as PT access and use categories may not fully capture the underlying phenomena they represent. Furthermore, transferability could only be assessed at block level, hiding differences between residential and non-residential prediction errors.

The most important suggestion for future research concerns non-residential parking supply modelling, as it requires improved specification, ideally by modelling use categories separately and pooling data across multiple cities. Furthermore, the transferability of model results has to be investigated in more detail to gain knowledge about prediction errors on a fine-grained spatial level. Finally, combining derived and surveyed parking data sources may help to obtain more accurate supply estimates and, consequently, more robust model results.

As municipalities face increasing pressure to manage parking supply effectively, reliable data on off-street parking capacities becomes essential for evidence-based policy. The framework presented here offers a reproducible starting point for cities lacking comprehensive parking inventories and a foundation for more refined models as data availability improves.

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A. Data Preparation

Table A.1.: Land use map.

english	access	off_street
Railway	public	FALSE
Area of Special Functional Character	private	TRUE
Mixed Use Area	private	TRUE
Watercourse	public	FALSE
Aviation	public	FALSE
Cemetery	semi-public	TRUE
Shrubland	public	FALSE
Harbour Basin	semi-public	TRUE
Spoil Heap	semi-public	TRUE
Heathland	public	FALSE
Industrial and Commercial Area	private	TRUE
Agricultural Land	private	TRUE
Bog	public	FALSE
Square / Plaza	public	FALSE
Shipping	private	TRUE
Sports, Leisure and Recreation Area	public	FALSE
Standing Water	public	FALSE
Road Traffic	public	FALSE
Swamp	public	FALSE
Open-cast Mine / Quarry	private	TRUE
Wasteland / Unvegetated Area	public	FALSE
Forest	public	FALSE
Path	public	FALSE
Residential Area	private	TRUE

Table A.2.: Use category mapping. Source for cadastral codes: Arbeitsgemeinschaft der Vermessungsverwaltungen der Länder der Bundesrepublik Deutschland (2025).

Use Category	ALKIS code	Aggregated use category
Allgemein bildende Schule	3021	education
Berufsbildende Schule	3022	education
Bibliothek, Bücherei	3037	education
Gebäude für Bildung und Forschung	3020	education
Hochschulgebäude (Fachhochschule, Universität)	3023	education
Kinderkrippe, Kindergarten, Kindertagesstätte	3065	education
Gebäude für Kurbetrieb	3240	gastronomy_accommodation
Gebäude für soziale Zwecke	3060	gastronomy_accommodation
Heilanstalt, Pflegeanstalt, Pflegestation	3052	gastronomy_accommodation
Hotel, Motel, Pension	2071	gastronomy_accommodation
Jugendherberge	2072	gastronomy_accommodation
Kinderheim	1021	gastronomy_accommodation
Krankenhaus	3051	gastronomy_accommodation
Obdachlosenheim	3064	gastronomy_accommodation
Schullandheim	1025	gastronomy_accommodation
Kantine	2083	gastronomy_accommodation
Gaststätte, Restaurant	2081	gastronomy_accommodation
Gebäude für Bewirtung	2080	gastronomy_accommodation
Campingplatzgebäude	2074	gastronomy_accommodation
Gebäude für Beherbergung	2070	gastronomy_accommodation
Gebäude für Gesundheitswesen	3050	gastronomy_accommodation
Seniorenheim	1022	gastronomy_accommodation
Dock (Halle)	2442	industry
Elektrizitätswerk	2521	industry
Fabrik	2111	industry
Fahrzeughalle	2464	industry
Flugzeughalle	2431	industry
Gaswerk	2571	industry
Gebäude der Kläranlage	2611	industry
Gebäude für Fernmeldewesen	2540	industry
Gebäude für Gewerbe und Industrie	2100	industry
Gebäude für Land- und Forstwirtschaft	2700	industry
Gebäude für Vorratshaltung	2140	industry
Gebäude für Wirtschaft oder Gewerbe	2000	industry
Gebäude zur Abfallbehandlung	2620	industry
Gebäude zur Abwasserbeseitigung	2610	industry
Gebäude zur Elektrizitätsversorgung	2520	industry
Gebäude zur Entsorgung	2600	industry
Gebäude zur Müllverbrennung	2622	industry
Gebäude zur Versorgung	2500	industry
Gebäude zur Wasserversorgung	2510	industry
Heizwerk	2580	industry
Kühlhaus	2141	industry
Lagerhalle, Lagerschuppen, Lagerhaus	2143	industry

(*continued*)

Use Category	ALKIS code	Aggregated use category
Land- und forstwirtschaftliches Betriebsgebäude	2720	industry
Lokschuppen, Wagenhalle	2422	industry
Müllbunker	2621	industry
Scheune	2721	industry
Scheune und Stall	2726	industry
Sonstiges Gebäude für Gewerbe und Industrie	2200	industry
Speditionsgebäude	2150	industry
Speichergebäude	2142	industry
Stall	2724	industry
Stall für Tiergroßhaltung	2727	industry
Umspannwerk	2522	industry
Wartungshalle	2412	industry
Wasserbehälter	2513	industry
Wasserwerk	2511	industry
Werft (Halle)	2441	industry
Werkstatt	2120	industry
Treibhaus, Gewächshaus	2740	industry
Produktionsgebäude	2110	industry
Betriebsgebäude	2112	industry
Gebäude zur Versorgungsanlage	2590	industry
Gebäude zur Gasversorgung	2570	industry
Schöpfwerk	2213	industry
Brauerei	2113	industry
Hallenbad	3221	leisure_assembly
Kapelle	3043	leisure_assembly
Kegel-, Bowlinghalle	2093	leisure_assembly
Kino	2092	leisure_assembly
Kirche	3041	leisure_assembly
Konzertgebäude	3033	leisure_assembly
Krematorium	3082	leisure_assembly
Messehalle	2060	leisure_assembly
Moschee	3046	leisure_assembly
Museum	3034	leisure_assembly
Parlament	3011	leisure_assembly
Pflanzenschauhaus	3273	leisure_assembly
Schloss	3031	leisure_assembly
Theater, Oper	3032	leisure_assembly
Tierschauhaus	3263	leisure_assembly
Trauerhalle	3081	leisure_assembly
Veranstaltungsgebäude	3036	leisure_assembly
Windmühle	2211	leisure_assembly
Jugendfreizeitheim	3061	leisure_assembly
Aquarium, Terrarium, Voliere	3262	leisure_assembly
Badegebäude	3220	leisure_assembly
Badegebäude für medizinische Zwecke	3241	leisure_assembly
Bootshaus	2444	leisure_assembly

(*continued*)

Use Category	ALKIS code	Aggregated use category
Festsaal	2091	leisure_assembly
Flughafengebäude	3092	leisure_assembly
Freizeit- und Vergnügungsstätte	2090	leisure_assembly
Freizeit-, Vereinsheim, Dorfgemeinschafts-, Bürgerhaus	3062	leisure_assembly
Friedhofsgebäude	3080	leisure_assembly
Gebäude fuer religiöse Zwecke	3040	leisure_assembly
Gebäude für Erholungszwecke	3200	leisure_assembly
Gebäude für kulturelle Zwecke	3030	leisure_assembly
Gebäude für Sportzwecke	3210	leisure_assembly
Gebäude im botanischen Garten	3270	leisure_assembly
Gebäude im Freibad	3222	leisure_assembly
Gebäude im Zoo	3260	leisure_assembly
Gebäude zum Sportplatz	3212	leisure_assembly
Gebäude zur Freizeitgestaltung	1310	leisure_assembly
Gemeindehaus	3044	leisure_assembly
Gewächshaus (Botanik)	3272	leisure_assembly
Gewächshaus, verschiebbar	2742	leisure_assembly
Gotteshaus	3045	leisure_assembly
Seniorenfreizeitstätte	3063	leisure_assembly
Spielkasino	2094	leisure_assembly
Sport-, Turnhalle	3211	leisure_assembly
Stall im Zoo	3264	leisure_assembly
Synagoge	3042	leisure_assembly
Gebäude im Stadion	3230	leisure_assembly
Reithalle	2728	leisure_assembly
Kloster	3048	leisure_assembly
Gartenhaus	1313	no_parking_required
Gebäude an unterirdischen Leitungen	2560	no_parking_required
Gebäude zum S-Bahnhof	3095	no_parking_required
Pumpstation	2512	no_parking_required
Pumpwerk (nicht für Wasserversorgung)	2591	no_parking_required
Schuppen	2723	no_parking_required
Schutzbunker	3074	no_parking_required
Schutzhütte	3281	no_parking_required
Stellwerk, Blockstelle	2423	no_parking_required
Toilette	2612	no_parking_required
Treibhaus	2741	no_parking_required
Umformer	2523	no_parking_required
Garage	2463	parking
Gebäude zum Parken	2460	parking
Parkdeck	2462	parking
Parkhaus	2461	parking
Tiefgarage	2465	parking
Ferienhaus	1311	residential
Forsthaus	1223	residential
Land- und forstwirtschaftliches Wohngebäude	1210	residential

(*continued*)

Use Category	ALKIS code	Aggregated use category
Schwesternwohnheim	1023	residential
Studenten-, Schülerwohnheim	1024	residential
Wochenendhaus	1312	residential
Wohngebäude	1000	residential
Wohngebäude mit Gemeinbedarf	1110	residential
Wohngebäude mit Gewerbe und Industrie	1130	residential
Wohngebäude mit Handel und Dienstleistungen	1120	residential
Wohnhaus	1010	residential
Wohnheim	1020	residential
Gebäude für Handel und Dienstleistung mit Wohnen	2310	residential_mixed
Gebäude für Gewerbe und Industrie mit Wohnen	2320	residential_mixed
Gemischt genutztes Gebäude mit Wohnen	1100	residential_mixed
Land- und forstwirtschaftliches Wohn- und Betriebsgebäude	1220	residential_mixed
Gebäude für öffentliche Zwecke mit Wohnen	3100	residential_mixed
Bahnhofsgebäude	3091	retail
Einkaufszentrum	2052	retail
Gebäude für Handel und Dienstleistungen	2010	retail
Gebäude zum U-Bahnhof	3094	retail
Geschäftsgebäude	2050	retail
Kaufhaus	2051	retail
Kiosk	2055	retail
Laden	2054	retail
Markthalle	2053	retail
Tankstelle	2130	retail
Waschstraße, Waschanlage, Waschhalle	2131	retail
Nach Quellenlage nicht zu spezifizieren	9998	unknown
Bahnwärterhaus	2421	workplace
Betriebsgebäude des Güterbahnhofs	2424	workplace
Betriebsgebäude für Flugverkehr	2430	workplace
Betriebsgebäude für Schienenverkehr	2420	workplace
Betriebsgebäude für Schiffsverkehr	2440	workplace
Betriebsgebäude für Straßenverkehr	2410	workplace
Betriebsgebäude zu Verkehrsanlagen (allgemein)	2400	workplace
Betriebsgebäude zur Schleuse	2443	workplace
Botschaft, Konsulat	3016	workplace
Bürogebäude	2020	workplace
Empfangsgebäude	3090	workplace
Empfangsgebäude des botanischen Gartens	3271	workplace
Empfangsgebäude des Zoos	3261	workplace
Feuerwehr	3072	workplace
Forschungsinstitut	3024	workplace
Gebäude für betriebliche Sozialeinrichtung	2180	workplace
Gebäude für Forschungszwecke	2160	workplace
Gebäude für öffentliche Zwecke	3000	workplace
Gebäude für Sicherheit und Ordnung	3070	workplace
Gebäude zum Busbahnhof	3097	workplace

(continued)

Use Category	ALKIS code	Aggregated use category
Gericht	3015	workplace
Justizvollzugsanstalt	3075	workplace
Kaserne	3073	workplace
Kreditinstitut	2030	workplace
Polizei	3071	workplace
Post	3013	workplace
Rathaus	3012	workplace
Rundfunk, Fernsehen	3035	workplace
Straßenmeisterei	2411	workplace
Versicherung	2040	workplace
Verwaltungsgebäude	3010	workplace
Zollamt	3014	workplace
Empfangsgebäude Schifffahrt	3098	workplace
Touristisches Informationszentrum	3290	workplace

Table A.3.: Public transport quality classes by vehicle category and frequency. Source: Ministerium für Verkehr Baden-Württemberg (2025).

	Vehicle Category		
Frequency / Interval	RE & RB, S-Bahn	Tram, Urban Rail, Regional Bus	Bus, On-demand services
$\leq$ 5 min	I	I	II
$>$ 5–10 min	I	II	III
$>$ 10–20 min	II	III	IV
$>$ 20–40 min	III	IV	V
$>$ 40–60 min	IV	V	VI
$>$ 60–120 min	V	VI	VII

Table A.4.: Public transport access classes by stop category and walking distance. Source: Ministerium für Verkehr Baden-Württemberg (2025).

Stop Category	Access: Walking Time to Stop				
	≤ 300 m (≤ 5 min)	300–510 m (5–8.5 min)	510–720 m (8.5–12 min)	720–1020 m (12–17 min)	1020–1260 m (17–21 min)
I	a	a	b	c	d
II	a	b	c	d	e
III	b	c	d	e	f
IV	c	d	e	f	g
V	d	e	f	g	h
VI	e	f	g	h	i
VII	f	g	h	i	–

```
[out:json][timeout:180];
{{geocodeArea:München, Deutschland}}->.a;

// Parking facilities
(
  way(area.a)["amenity"="parking"];
  relation(area.a)["amenity"="parking"];
)->.facilities;

// Parking entrances
(
  node(area.a)["amenity"="parking_entrance"];
  way(area.a)["amenity"="parking_entrance"];
  relation(area.a)["amenity"="parking_entrance"];
)->.entrances;

( .facilities; .entrances; );
out tags geom;
```

Figure A.1.: Overpass query to extract OSM features.

Table A.5.: Parking type mapping and dimensions. Sources: FGSV (2023) and Litman (2025).

Parking Source	Label (ALKIS code)	m^2 per space	Parking category
Cadastral building	Gebäude zum Parken (2460)	40	Park deck
Cadastral building	Parkhaus (2461)	40	Park deck
Cadastral building	Parkdeck (2462)	40	Park deck
Cadastral building	Garage (2463)	20	Garage
Cadastral building	Fahrzeughalle (2464)	40	Park deck
Cadastral building	Tiefgarage (2465)	40	Underground
Cadastral building part	Tiefgarage (2100)	40	Underground
OSM	parking_space	35	other
OSM	surface	35	Surface
OSM	carport	20	Covered
OSM	carports	20	Covered
OSM	sheds	20	Garage
OSM	underground	40	Underground
OSM	multi-storey	40	Park deck
OSM	level	40	Park deck
OSM	rooftop	40	Park deck
OSM	garage_boxes	20	Garage
OSM	layby	20	Surface
OSM	lane	20	Surface
OSM	half_on_kerb	20	Surface
OSM	street_side	20	Surface
OSM	on_kerb	20	Surface
OSM	shoulder	20	Surface
OSM	yes	35	other
OSM	NULL	35	other

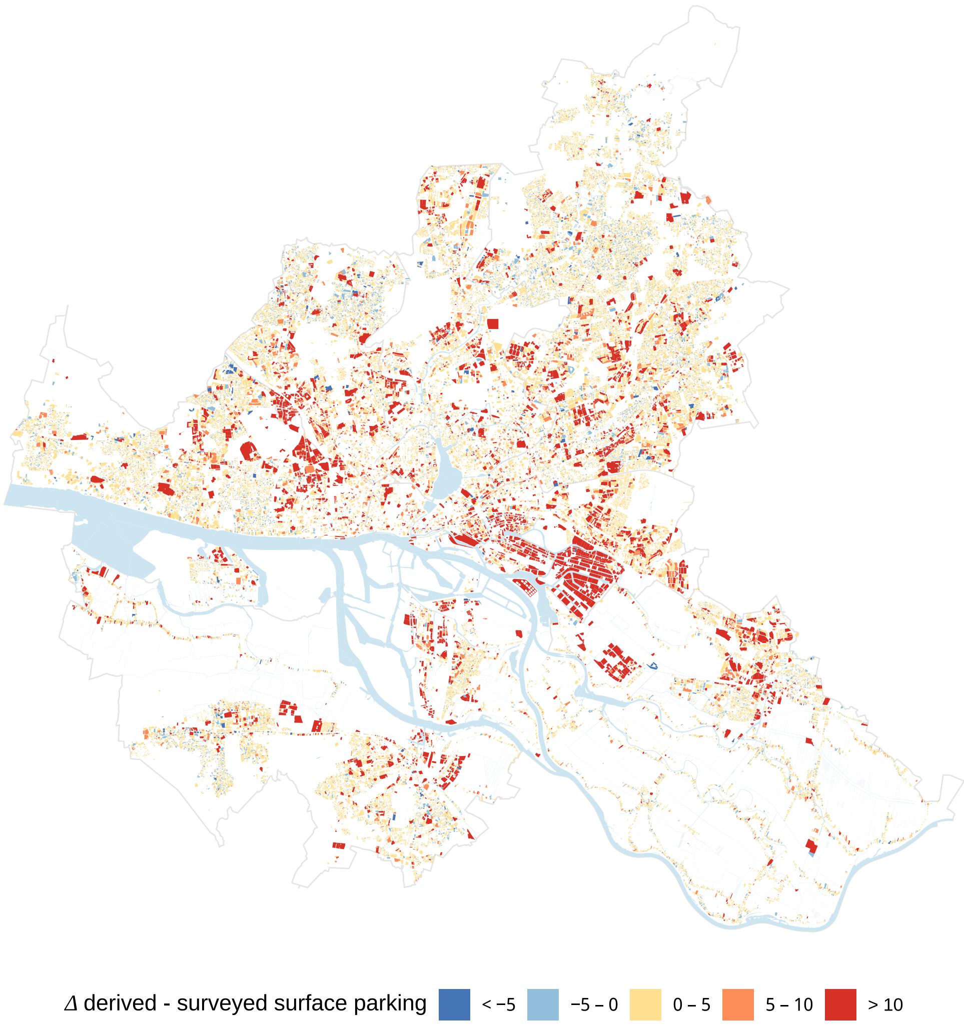

Figure A.2.: Surface parking difference per parcel in Hamburg.

B. Pre-Estimation for Hamburg Surveyed and Munich Derived

Table B.1.: Descriptive statistics of numeric variables (Munich).

Variable	Mean	SD	Min	P5	P95	Max	Skew
Residential (n = 102,017)							
Parcel area (m^2)	842	1,768	18	157	2,181	132,470	16.9
GFA (m^2)	761	1,899	10	108	2,751	115,765	11.7
Open space ratio	0.69	0.16	0.00	0.33	0.88	1.00	
PT accessibility rank	8.03	1	3	6	9	9	
Purchasing power (€)	63,595	12,622	25,858	42,492	82,245	240,070	0.8
Non-residential (n = 5,335)							
Parcel area (m^2)	4,420	13,731	21	282	15,906	564,944	23.4
GFA (m^2)	4,824	11,819	0	181	18,810	344,288	14.5
Open space ratio	0.54	0.23	0.00	0.04	0.85	1.00	
PT accessibility rank	8.41	1	3	7	9	9	
Purchasing power (€)	57,519	15,318	15,537	38,831	82,676	196,522	2.0

Table B.2.: Descriptive statistics of categorical variables (Munich residential sample).

Variable / Level	n	Share (%)
Construction year		
<1945	24,264	23.9
1946-1960	18,929	18.6
1961-1980	41,438	40.8
1981-2005	11,300	11.1
2006-2021	5,688	5.6
Building type		
small residential	66,321	65.3
multi-residential	34,205	33.7
large residential	1,093	1.1
Mixed-residential	11,722	11.5

Table B.3.: Descriptive statistics of categorical variables (Munich non-residential sample).

Variable / Level	n	Share (%)
Construction year		
<1945	1,744	32.7
1946-1960	703	13.2
1961-1980	1,813	34.0
1981-2005	814	15.3
2006-2021	261	4.9
Use category		
workplace	1,934	36.3
education	1,322	24.8
industry	1,121	21.0
retail	524	9.8
hospitality	434	8.1

Table B.4.: Logit results – residential sample

	Hamburg derived	Munich derived
	Coef. [95% CI]	Coef. [95% CI]
Intercept	13.047*** [12.215, 13.880]	12.429*** [11.295, 13.562]
Open space (%)	-7.849*** [-7.961, -7.737]	-8.130*** [-8.267, -7.993]
log(GFA)	-0.702*** [-0.720, -0.684]	-0.851*** [-0.878, -0.824]
log(Purchasing power)	-0.749*** [-0.824, -0.674]	-0.313*** [-0.411, -0.215]
log(SLV)	0.625*** [0.595, 0.656]	-
PT access	-0.024*** [-0.036, -0.012]	0.120*** [0.102, 0.138]
Construction year		
1946–1960	0.036* [0.004, 0.068]	-0.178*** [-0.225, -0.132]
1961–1980	0.093*** [0.062, 0.123]	-0.209*** [-0.250, -0.169]
1981–2005	-0.237*** [-0.273, -0.200]	-0.742*** [-0.802, -0.682]
2006–2021	-0.560*** [-0.651, -0.469]	-0.711*** [-0.789, -0.634]
Building type		
Multi-residential	0.008 [-0.031, 0.047]	0.068** [0.017, 0.120]
Large residential	-0.816*** [-1.020, -0.611]	0.370*** [0.186, 0.553]
Mixed residential	-0.764*** [-0.820, -0.708]	-0.821*** [-0.880, -0.763]

Table B.5.: Logit results – non-residential sample

	Hamburg derived	Munich derived
	Coef. [95% CI]	Coef. [95% CI]
Intercept	-2.483 [-7.065, 2.099]	6.717** [2.136, 11.297]
Open space ratio	-6.820*** [-7.201, -6.439]	-5.695*** [-6.123, -5.267]
log(GFA)	-1.029*** [-1.099, -0.959]	-0.663*** [-0.734, -0.591]
log(Purchasing power)	0.224 [-0.165, 0.613]	-0.086 [-0.482, 0.310]
log(SLV)	1.253*** [1.086, 1.420]	-
PT access	-0.043 [-0.160, 0.074]	0.103 [-0.026, 0.232]
Construction year		
1946–1960	-0.323** [-0.525, -0.122]	-0.272* [-0.520, -0.023]
1961–1980	-0.563*** [-0.745, -0.382]	-0.616*** [-0.815, -0.418]
1981–2005	-0.157 [-0.392, 0.078]	-0.489*** [-0.778, -0.201]
2006–2021	-0.789** [-1.383, -0.196]	-0.462* [-0.899, -0.025]
Use category		
Industry	-0.712*** [-0.974, -0.449]	-1.605*** [-1.921, -1.289]
Retail	0.017 [-0.179, 0.214]	-0.360* [-0.637, -0.083]
Education	1.990*** [1.713, 2.267]	0.890*** [0.676, 1.105]
Gastron./accomm.	0.591*** [0.336, 0.846]	0.112 [-0.167, 0.391]
Leisure/assembly	1.285*** [1.010, 1.560]	-

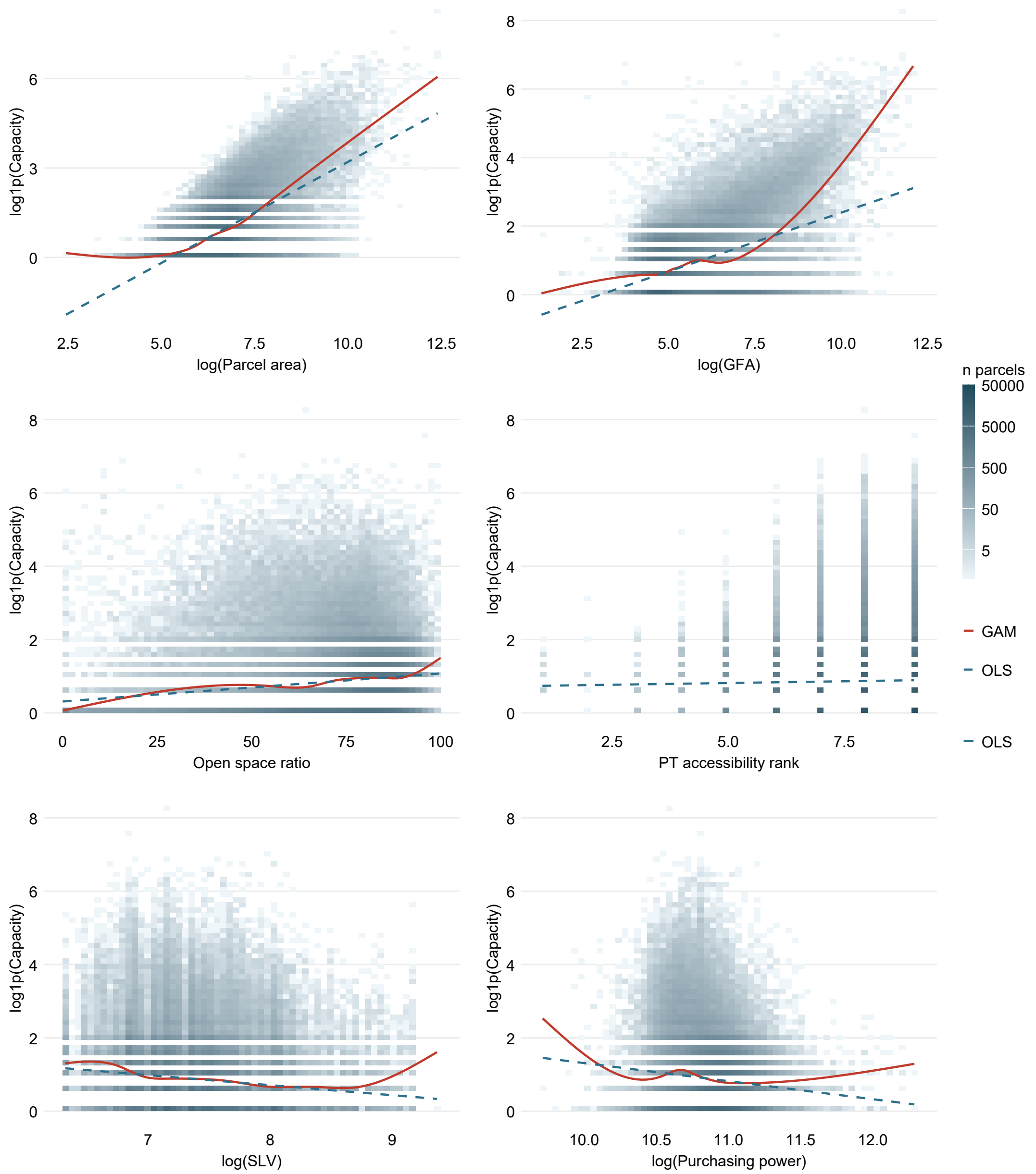

Figure B.1.: Scatter plot of parking capacity and numeric determinants with GAM line (Hamburg).

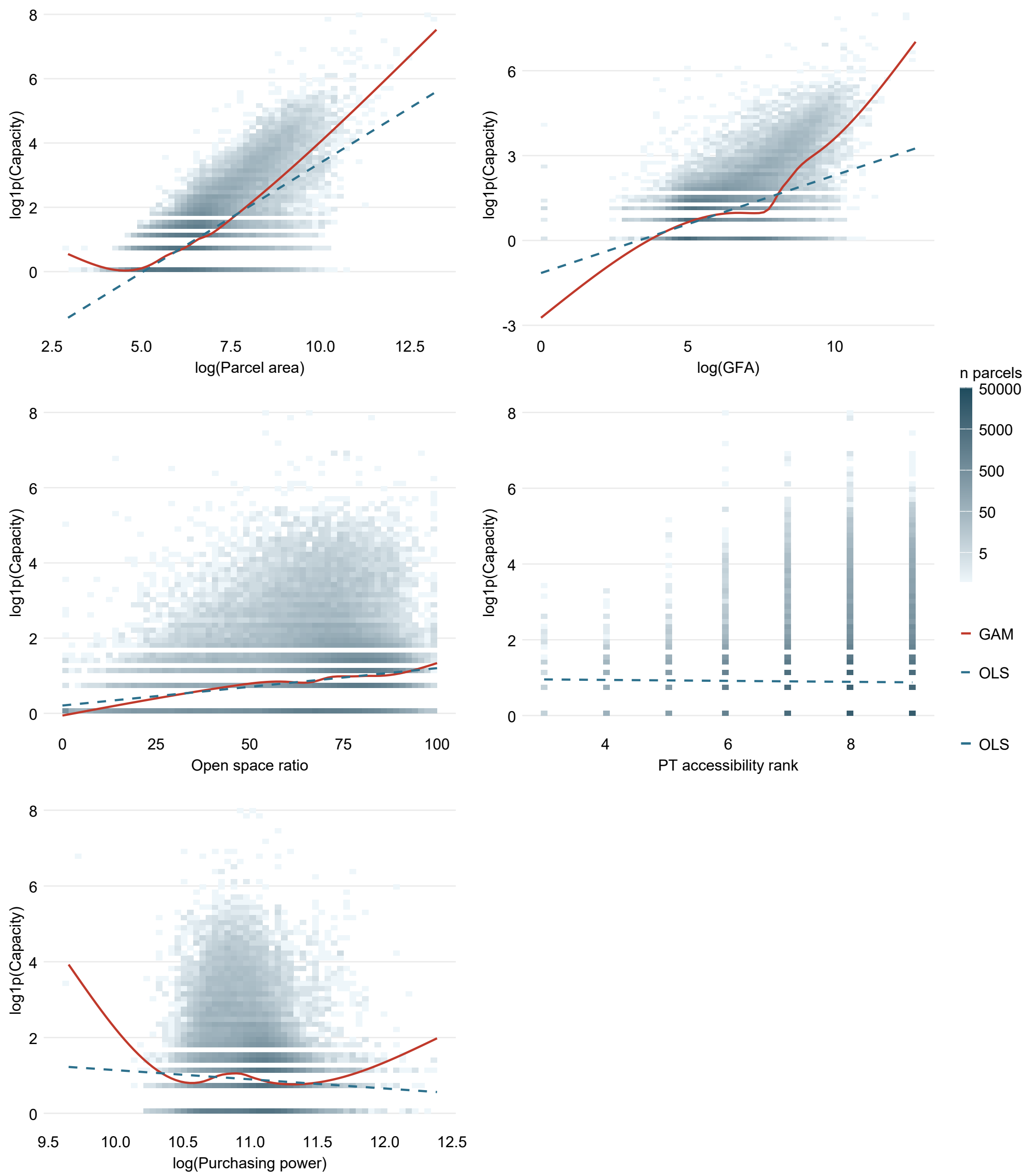

Figure B.2.: Scatter plot of parking capacity and numeric determinants with GAM line (Munich).

Table B.6.: Goodness-of-fit diagnostics by panel and sample

			Overdispersion test		Zero-inflation test	
Sample	Panel	Model	Disp. ratio	p	ZI ratio	p
Hamburg derived	Residential	Poisson	4.08	<0.001	1.55	<0.001
		NB1	1.02	<0.001	0.92	<0.001
		NB2	1.02	<0.001	0.99	0.030
		ZINB2	1.14	<0.001	0.96	<0.001
	Non-residential	Poisson	28.89	<0.001	4.90	<0.001
		NB1	0.99	0.836	0.80	<0.001
		NB2	1.29	<0.001	1.35	<0.001
		ZINB2	1.39	<0.001	1.13	<0.001
Hamburg surveyed	Residential	Poisson	5.86	<0.001	1.31	<0.001
		NB1	1.59	<0.001	0.82	<0.001
		NB2	1.28	<0.001	0.88	<0.001
		ZINB2	1.84	<0.001	0.85	<0.001
	Non-residential	Poisson	55.30	<0.001	8.33	<0.001
		NB1	1.44	<0.001	0.91	<0.001
		NB2	1.29	<0.001	1.17	<0.001
		ZINB2	1.64	<0.001	1.05	<0.001
Munich derived	Residential	Poisson	2.83	<0.001	1.23	<0.001
		NB1	0.975	1.000	0.84	<0.001
		NB2	0.942	1.000	0.92	<0.001
		ZINB2	0.99	0.972	0.88	<0.001
	Non-residential	Poisson	32.10	<0.001	4.02	<0.001
		NB1	1.39	<0.001	0.74	<0.001
		NB2	1.21	<0.001	1.21	<0.001
		ZINB2	1.21	<0.001	1.07	<0.001

Note. Dispersion ratio relative to $(n-k)$; values > 1 indicate overdispersion. ZI ratio > 1 indicates excess zeros relative to model prediction. p-values from respective LM/score tests.

Table B.7.: Variance inflation factors by model

Term	Hamburg derived (res.)	Hamburg derived (nonres.)	Hamburg surveyed (res.)	Hamburg surveyed (nonres.)	Munich derived (res.)	Munich derived (nonres.)
log(GFA)	91.15	55.86	93.81	58.59	112.89	32.30
$(\log(\text{GFA}))^2$	86.05	54.38	88.46	57.06	105.21	32.32
Open space ratio	1.58	1.58	1.60	1.56	1.68	1.30
PT access	1.10	1.19	1.10	1.14	1.14	1.20
log(SLV)	1.20	1.36	1.23	1.36	-	-
log(Purchasing power)	1.48	1.05	1.50	1.04	1.68	1.04
Construction year	1.13	1.10	1.13	1.11	1.14	1.19
Building type	2.13	-	2.20	-	2.45	-
Mixed-residential	1.05	-	1.04	-	1.22	-
Use category	-	1.80	-	1.68	-	1.49

C. Transferability Results

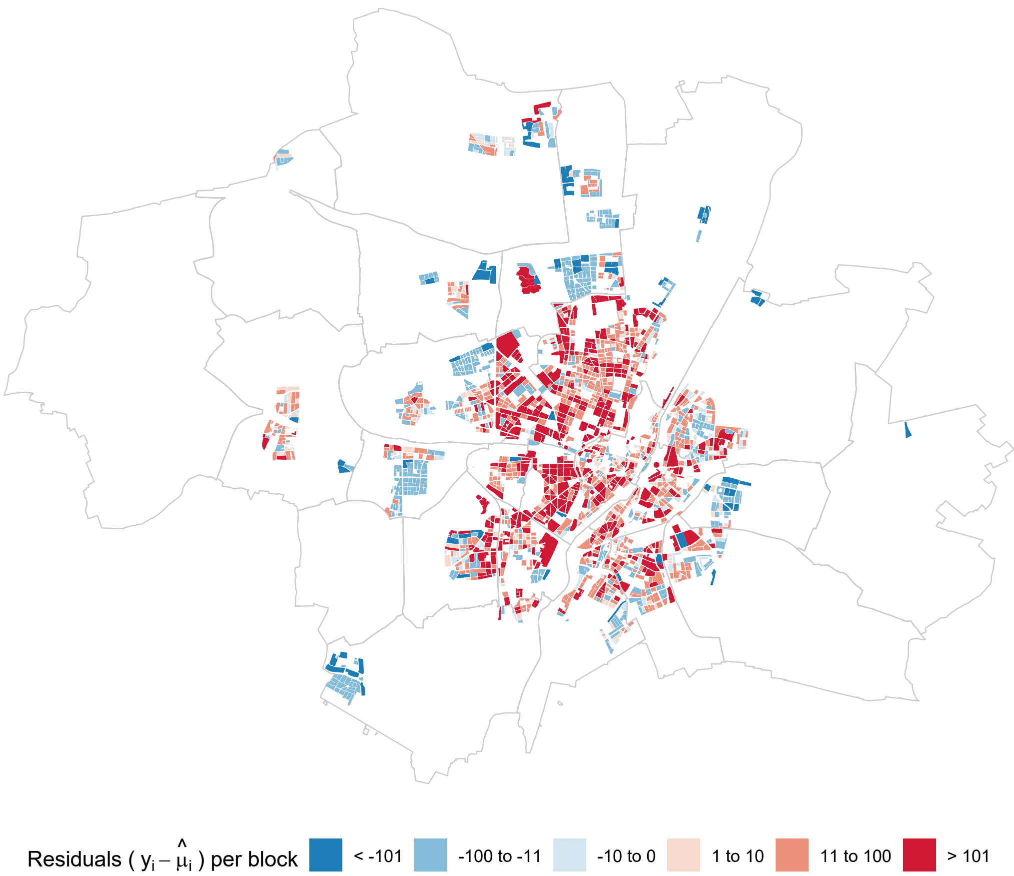

Figure C.1.: Difference of predicted supply (Hamburg derived supply model) and surveyed supply on block-level in Munich.

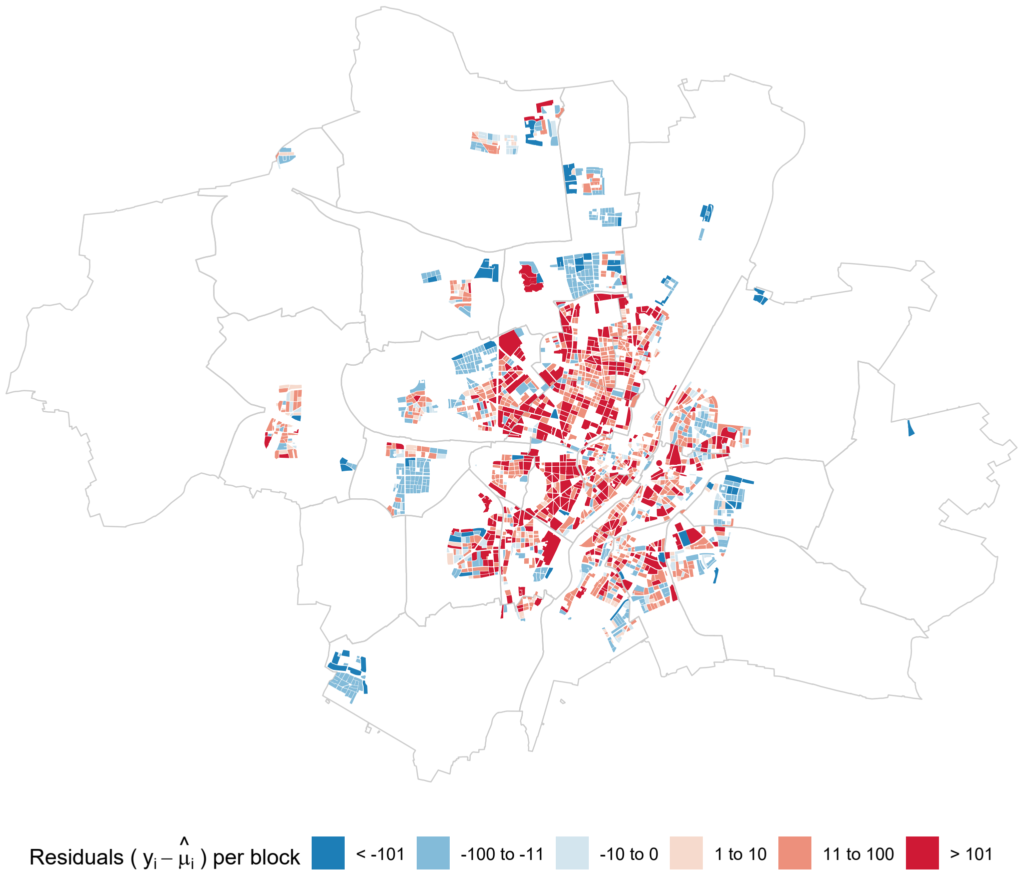

Figure C.2.: Difference of predicted supply (Munich derived supply model) and surveyed supply on block-level in Munich.