Estimating Rental Prices in Walkable and Connected Neighbourhoods

Assessing the Relationship Between Real Estate, Walkability, and Public Transport Accessibility in the City of Munich

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I hereby declare that this thesis is entirely the result of my own work except where otherwise indicated. I have only used the resources given in the list of references.

Munich, 26.04.2024 Paulo Nogueira Neto

Abstract

As the urban population continues to grow at a faster rate than the built environment, stress and limitations are posed on urban systems used by the city dwellers (Levy et al., 2010). Recurrent road congestion in not only causes delays and accidents, but also deteriorate human health in the long-term (WHO, 2021). The externalities of road traffic can reflect on the price of real estate, making areas less affected by vehicular pollution less affordable. Public transport and active modes have the power to reduce car trip generation and ultimately reduce the negative effects of vehicular pollution in urban centres. Conversely, investments in these modes of transport could also lead to an increase in land value in central, forcing households and companies to relocate in peripheral areas, in a process of de-centralisation or suburbanization. This increase of commute adds to excess commute levels (Jun et al., 2018) and affect affects human well-being (Chng et al., 2016). With data from over one million rental listings, this thesis analyse the relationship between land-use strategies and travel behaviour and the impacts on urban health in the metropolitan region of Munich in southern Germany. By combining hedonic price models (Poudyal et al., 2009; Nitsch, 2006) for long-term rental properties and spatial modelling tools (Loidl et al., 2016; Efthymiou and Antoniou, 2013), the study looks at public transport accessibility and neighbourhood walkability as indicators of urban quality. The results emphasises the urgency for housing policies and outlines relevant variables that contribute to over commuting and higher dependence on private motorised vehicles. Ultimately, mobility concepts are proposed to alleviate urban deterioration on the monocentric land-use model.

Acknowledgements

Every year, thousands of students move to Germany to secure a spot in highly ranked universities but are unaware of minor yet life-impacting complications off-campus. Although living standards are among the highest for cities around the world, residing in Munich is extremely complicated for many students and newcomers due to the abrupt housing shortage in German cities. As cities struggle to keep up with the demand they created for themselves, students are forced more and more to find residences further and further away from campus. The lockdowns during the COVID-19 pandemic have definitely absorbed some of the impact, putting transportation and housing demand on a downslope for almost 2 years. But as the restrictions have been lifted and borders are reopening, public transport collapses have become part of the routine, where monthly strikes and constant delays paralyse major transport lines. Lucky for those with a private vehicle, but unfortunate for those who try to reduce their carbon footprint by adopting sustainable travel modes and for those who cannot afford the cost of private transport. This work aims to contribute to the never-ending fight against a car-dependent future, deemed to destroy the very best of our cities and consequently many of the interactions required for innovation and the further development of our society. There is still time to rescue the built and natural environment and reestablish the place where students can freely interact with one another and connect with the world they learn from and are eager to improve.

List of Abbreviations

BRT Bus Rapid Transit. 9

CO_2 Carbon Dioxide. 1, 8

EV Electric Vehicle. 1, 36

GHG Greenhouse Gases. 8

GIS Geographical Information System. 4, 12, 15, 18

GTFS General Transit Feed Source. 15, 16, 20, 24

HPM Hedonic Price Models. 15, 17, 19–22, 34

LTR Long-Term Rental. 31, 32

MiD Mobility in Germany("Mobilität in Deutschland"). 16, 49

MITO Microscopic Transport Orchestrator. 16, 39

MMR Munich Metropolitan Region. 10, 16, 31

MoP German Mobility Panel("Mobilitätspanel"). 16, 49

MVV Munich Transport and Tariff Association (Münchner Verkehrs- und Tarifverbund). viii, 12, 14–16, 27, 28, 31, 34, 38, 39

OLS Ordinary Least Square. 5, 9, 21, 32

OSM Open Street Maps. 16–18, 39, 49

PKM Passenger Kilometres. 37

PLZ Postleitzahl (Postal Code). 17, 23, 27, 34

PM_{10} Particulate Matter 10. 3

$PM_{2.5}$ Particulate Matter 2.5. 3

PMV Private Motorised Vehicles. 3, 23, 39

POI Points of Interest. 18, 19, 23, 27, 28, 39

PuT Pubic Transport. 14, 25

TAZ Transport Analysis Zone. 17, 19, 23, 25, 27

TDM Travel Demand Model. 10

TOI Transport Opportunity Index. 5

VMT Vehicle Miles Travelled. 37

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1 Introduction

Urbanisation has always been a catalyst for socio-economic transformation, but the pace and scale of its impact have been profoundly influenced by recent global events. The COVID-19 pandemic, in particular, has not only tested the resilience of urban systems but has also accelerated several transformative processes within them. In Germany, the sharp increase in energy prices has placed considerable stress on economic structures and necessitated government intervention. Measures aimed at alleviating the financial burden on households—such as price breaks on essential utilities and the introduction of the "9 Euro Ticket"—have provided temporary relief and influenced mobility patterns, demonstrating the potential of policy interventions to modify behaviour and reduce overall energy consumption (Loder et al., 2023).

However, the challenge of rising energy demand remains a persistent issue, especially in the transportation sector, which is a significant consumer of energy and a major contributor to CO2 emissions globally (IEA, 2024). The European Union's commitment to becoming carbon-neutral within the next few decades has spurred a substantial shift in the automotive industry, particularly through the promotion of EVs. This shift is aimed at reducing the carbon footprint of transportation, yet it introduces new challenges, such as the need for vast amounts of electricity and the continued impact of non-CO_2 pollutants on urban air quality (Sadiq et al., 2022; Slezakova et al., 2013; Buckeridge et al., 2002).

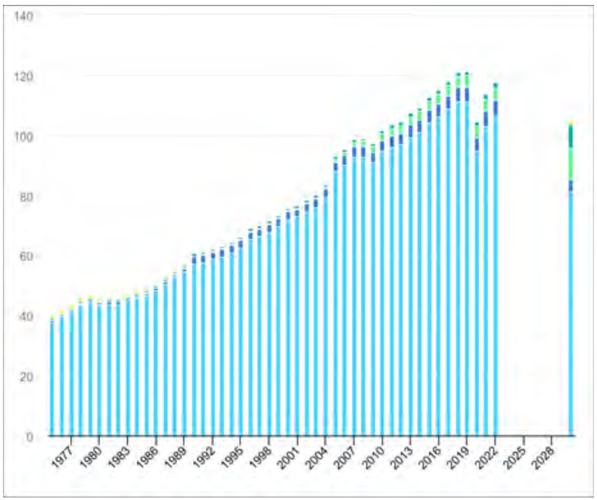


Figure 1.1 Energy consumption in transport by fuel in the Net Zero Scenario, 1975-2030(IEA, 2023).

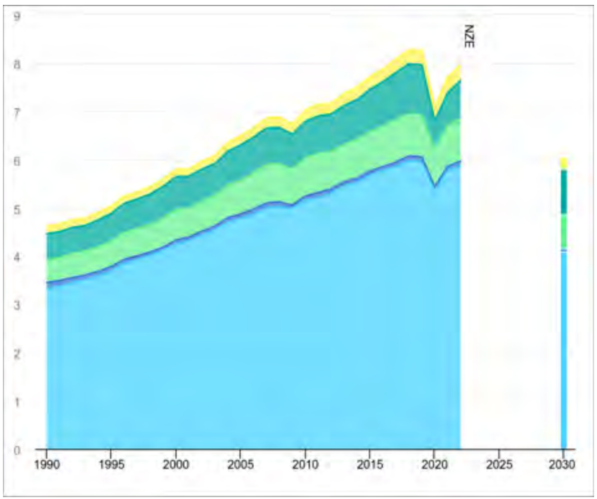


Figure 1.2 Global CO2 emissions from transport by subsector in the Net Zero Scenario, 2000-2030(IEA, 2023).

The rental housing market in Germany, and particularly in urban centres like Munich, vividly illustrates the intersection of historical, economic, and social factors shaping urban development. Post-World War II economic booms led to increased automobile ownership and suburban living. Today, with over 54% of all households in Germany renting—the highest rate among EU countries—and a high urbanisation rate of over 77%, the country faces a pronounced housing shortage, exacerbated by demographic changes and regulatory challenges (Eurostat, 2022; Statista, 2023). The proximity of housing to transit hubs, a crucial aspect of urban planning, often drives up rental prices, reflecting the standard urban economics model where lower commute costs can inflate housing costs, making affordability a critical issue.

This thesis navigates through these complexities in a structured manner, starting with the first chapter that sets the theoretical groundwork by reviewing relevant literature within the broader discourse on urban mobility and sustainability. The second chapter details the methodology, using analytical frameworks and data sources to dissect the interplay between Munich's transportation systems and urban form. In the third chapter, empirical findings are discussed, shedding light on the impacts of transportation modes and urban planning decisions on energy consumption and urban livability. The fourth chapter interprets these findings, considering their implications for policy and suggesting pathways for future urban development. Finally, the thesis concludes with a synthesis of the research in the fifth chapter, proposing actionable strategies for enhancing the sustainability and equity of urban environments.

The integration of this research into urban planning discourse aims to offer comprehensive insights into creating more sustainable urban environments that adeptly balance the demands of mobility, housing affordability, and environmental sustainability. This endeavour seeks to equip policymakers and urban planners with the knowledge to forge pathways that address the pressing challenges of modern urban centres.

2 Literature Background

This chapter contains the collection of works with insights and background knowledge on urban mobility and strategies that enhance urban living specially in areas with high population density where housing shortage is a problem. Section 2.1.2 provides the base knowledge to reduce the energy and spatial footprint in urban centres. Next, section 2.2.3 shines a light on housing and the complexities of the housing market. Section 2.3.4 scrutinises methods to assess travel behaviour and land use patterns. Lastly, section 2.4 introduces the study area for this research.

2.1 Sustainable Urban Planning

Urban planning around the globe increasingly adopts sustainable mobility practices to enhance living quality in urban centres (Banister, 2008;Grünig, 2012;Vargas-Maldonado et al., 2022). Excessive energy consumption in current land use models, primarily fuelled by PMVs, not only exacerbates energy demands but also severely impacts human health and urban vitality. The congestion seen in metropolitan regions causes far-reaching implications beyond traffic conditions, significantly affecting human health. Emissions from road traffic in urban centres have long been associated with several respiratory and cardiovascular diseases (WHO, 2021). Furthermore, dust from tire and brake wear contributes to $PM_{2.5}$ and PM_{10} emissions, complicating the urban pollution profile (Worek et al., 2022). The resulting micro-plastic particles from tire wear pose a risk of chronic and acute health effects (Wright and Kelly, 2017). Additionally, noise pollution from dense traffic disrupts sleeping patterns and increases stress levels, further deteriorating public health.

Cities have responded by implementing policies to reduce car usage in central areas, thereby improving air conditions and enhancing urban quality. These efforts are part of a broader shift towards sustainable urban planning that emphasises active transport modes such as walking and cycling, which not only support public health and environmental sustainability but also boost the local economy (Bott et al., 2019).

The push towards reducing reliance on PMV has led to significant changes in urban landscapes, promoting more active, vibrant environments. For example, in Germany, despite the feasibility of covering daily travel distances by biking or walking, the perceived time savings keep many opting for cars(Pucher, 1998; Buehler, 2011; Buehler et al., 2017). Yet, the concept of effective speed indicates that the time cost associated with vehicle maintenance and parking often negates the time saved by faster travel, prompting a reevaluation of transportation strategies (Buehler and Pucher, 2012; Litman, 2021).

This transformation from vehicle-centric to pedestrian-oriented spaces is not only motivated by health and environmental concerns but also presents substantial economic opportunities. Studies have shown that reducing vehicle miles travelled not only mitigates congestion but is also linked to higher economic vitality (Boarnet et al., 2021;Bigazzi et al., 2015;Shefer, 1994). Neighbourhoods with reduced vehicle dependency witness increased property values and heightened business activity as pedestrian traffic grows, which in turn boosts local economies (Boarnet et al., 2021; Wey and Chiu, 2013).

Moreover, the adoption of active transportation modes extends beyond reducing emissions; they are instrumental in enhancing public health. Regular physical activity, such as walking, significantly reduces the risk of chronic diseases including cardiovascular conditions, diabetes, and mental health disorders, promoting overall well-being (Blair et al., 1996; Kelly et al., 2014; Paul Kelly et al., 2018). Urban areas that have embraced walkability not only experience reductions in vehicular emissions but also see significant decreases in urban air pollution. Initiatives to promote walking and reduce car trips have been shown to lower carbon emissions and encourage sustainable urban living, making these areas more attractive and leading to increased real estate values and more vibrant local business sectors (Sun et al., 2021).

Car-free zones exemplify successful strategies in increasing walkability and enhancing urban quality of life. These zones reduce congestion and pollution, improve public health through enhanced air quality and increased physical activity, and boost local businesses due to increased pedestrian traffic(Ruokolainen et al., 2021;Vinnik et al., 2020). The economic and social interactions facilitated by these pedestrian-friendly spaces contribute to the overall vibrancy and sustainability of urban centres (Quercia and O'Brien, 2020;Adkins et al., 2021).

In conclusion, urban areas designed with a focus on reducing excessive energy consumption through sustainable transport and land use policies do not just enhance public health and reduce environmental impacts; they also significantly contribute to economic performance. As urban planners and policymakers continue to prioritise sustainable urbanism, incorporating such strategies into urban design remains crucial for fostering thriving, vibrant urban environments.

2.1.1 Neighbourhood Walkability

Neighbourhoods with higher walkability levels are associated with greater levels of individual physical activity, which in turn have several benefits for human health and urban quality (Leslie et al., 2005; Loidl et al., 2016; Rundle et al., 2016; Dalton et al., 2013; Sesso, 2000; Paul Kelly et al., 2018; Kitchen et al., 2011; Kelly et al., 2014; Keall et al., 2018; Cavill et al., 2008). Walkability enhances not only the physical health of residents but also the economic and environmental sustainability of urban centres.

Research on walkability has significantly improved methods for quantifying the built environment's impact on walking, primarily through the enhanced use of spatial data and GIS tools. However, others criticise these quantitative techniques as a form of "neo-environmental determinism," which presupposes a direct, deterministic link between specified environmental attributes and walking behaviours (Meyer and Guss, 2017). Although these objective measures are precise, they often overlook important qualitative aspects such as the aesthetic appeal of the environment, perceived safety, and the overall enjoyment of walking (Arvidsson et al., 2012). Moreover, the replication of walkability indices across different locales is complicated by the need to choose a suitable analysis scale, which varies significantly by country and urban morphology (Shashank and Schuurman, 2019).

Social and individual characteristics, such as socioeconomic status, community identity, and demographic factors, also play critical roles but are frequently overlooked. These factors highlight a disconnect between objective walkability and perceived walkability, suggesting that living in a walkable neighbourhood does not necessarily lead to increased walking and social interaction due to the complex interplay between walkability and social factors (du Toit et al., 2007).

The importance of active modes of transport, such as walking and cycling, in the sustainable development of cities has been reiterated by the challenges of climate change and urban congestion. Despite their low carbon footprint and the significant health benefits they provide, the shift from car-oriented to pedestrian-oriented neighbourhoods has faced numerous challenges. Bipedalism, for example, has been shown to be as efficient as typical mammalian quadrupedalism and much more efficient than bipedal or quadrupedal locomotion in chimpanzees, highlighting the energy efficiency of human walking (Rau et al., 2019). However, cities continue to grow with the expectation of meeting motorised vehicular demand, often at the expense of promoting active modes. The benefits of active modes have been demonstrated in studies across the globe, from reductions in kilometres travelled to decreased risks of cardiovascular diseases (Laverty et al., 2013;Paul Kelly et al., 2018;Kitchen et al., 2011). These modes are crucial for reducing long-distance trips by meeting individual necessities within a limited radius, which not only promotes higher rates of physical activity but also contributes to less pollution and fosters positive urban experiences.

The literature indicates that issues in walkability are closely related to urban planning strategies and design. Factors such as distance and lack of infrastructure can deter walkability levels in urban centres (Kitchen et al., 2011). The significant association of street intersection density with increased space utilisation and physical activity, while high residential and subway stop density within a kilometre of the home negatively impacts these outcomes, was highlighted in a study by Rundle et al., 2016. using GPS loggers and accelerometers (Rundle et al., 2016).

Planners study and analyse various factors to identify the optimal combination of parameters that enhance walkability within urban areas. The correlation of street density and walkability was also observed in cities like Porto and Bologna (Gori et al., 2014), and in a study evaluating the pedestrian network around the city centre of Guimarães, Portugal (Fonseca, Fernandes, et al., 2022). This study derived 19 variables from a comprehensive GIS-based analysis, demonstrating the intricate relationship between urban planning and walkability.

2.1.2 Public Transport Connectivity Assessment

Public transport connectivity is a pivotal aspect of urban planning and transportation engineering, encompassing various dimensions such as the frequency of service, network coverage, operational hours, and the availability of multimodal transfer points. This connectivity is essential not only for facilitating efficient travel but also for reducing car trips, lowering energy consumption, and conserving urban space, all of which align with the goals of sustainable urban planning.

Evaluating public transport connectivity requires sophisticated methodologies that address different facets of transportation networks. The TOI, proposed by Mamun et al., 2013, offers a comprehensive framework for quantifying public transit performance. This index integrates spatial coverage, temporal coverage, and trip coverage to calculate a transit accessibility score for each origin-destination pair within a network. By incorporating connectivity parameters, the TOI reflects the effectiveness of service provisions between various points, highlighting the operational efficiency of public transport systems.

Simultaneously, Lam and Schuler, 1982 developed an index to assess the connectivity of routes and schedules across an entire public transit system. Their approach utilises connectivity indicators as quantitative tools to evaluate how well different components of the public transport system meet the transportation needs of a service area. This methodology aids in the evaluation of service delivery strategies, providing insights into the systemic integration of route and schedule data.

Moreover, the application of graph theory in analysing public transport networks offers a robust analytical perspective. Cano, 2011 applied graph theory to evaluate network properties such as connectivity and complexity, demonstrating how these factors influence ridership levels and safety within bus systems. This method underscores the importance of network design in enhancing the efficiency and safety of public transport systems.

The enhancement of public transport connectivity directly contributes to the reduction of car dependence in urban areas. By providing efficient, reliable, and accessible public transport options, cities can significantly decrease the number of private vehicle trips, which in turn reduces traffic congestion, lowers greenhouse gas emissions, and lessens urban sprawl(Woodcock et al., 2009; Barrero et al., 2008). Effective public transport systems also free up significant amounts of urban space, typically consumed by road infrastructure and parking (Kubis and Plocova, 2023; Juozapavičius and Buteliauskas, 2018). This space can be repurposed for public use, such as parks, community spaces, and pedestrian paths, further enhancing the quality of urban life and contributing to the sustainability of the city.

In summary, public transport connectivity is not only about providing efficient transit options but also plays a critical role in shaping sustainable urban landscapes. Enhancing connectivity through comprehensive planning and sophisticated analytical tools can lead to a substantial decrease in car usage, promote energy efficiency, and facilitate the wise use of urban spaces, all of which are crucial for sustainable urban development.

2.2 Housing and Hedonic Price Models

2.2.1 Housing Econometrics and Location

The integration of spatial econometrics into real estate modelling marks a significant advancement in addition traditional methods like OLS(Anselin, 1988). Spatial econometric models offer a more nuanced understanding of property values by accounting for the spatial relationships among properties, which is essential in a market influenced by both visible and invisible boundaries.

As highlighted by Marcelo Cajias and Sebastian Ertl, the significance of spatial relationships and the utility of large datasets in hedonic models cannot be overstated, especially when assessing the impact of environmental factors and urban planning on property values (Cajias and Ertl, 2020). These models consider how proximity to various amenities or undesirable features affects real estate values, integrating a broader range of variables compared to standard econometric models.

The influence of transportation infrastructure on property values is a well-documented phenomenon across various studies. Proximity to transportation facilities, such as rail stations or bus terminals, generally increases property values due to the enhanced accessibility they provide. However, this impact is not uniformly positive. For example, Bowes and Ihlanfeldt (2001) found dual effects of rail stations on local house prices in Atlanta: positive due to reduced commuting costs and increased retail activity, and negative due to the potential for increased crime (Bowes and Ihlanfeldt, 2001).

Similarly, research in California by Weinberger (2000) and Cervero and Duncan (2002) highlighted positive valuation effects on properties located near light-rail stations (Weinberger, 2000, Cervero and Duncan, 2002). These findings are consistent with those from studies in other cities like Portland, Buffalo, and Dallas, where proximity to light-rail stations typically commanded higher property prices (AlMosaind et al., 1993).

Moreover, Debrezion et al. (2006) revealed a nuanced view from the Netherlands, showing a significant price premium for houses near rail stations, albeit moderated by the negative impacts of noise pollution (Debrezion et al., 2006). This complexity is mirrored in studies of other transportation infrastructures like the Metro systems in Madrid and Toronto, where accessibility to metro stations was found to either increase house prices or have a negligible impact, depending on specific local conditions ("Comparative Study of Effects of Metro Accessibility on Property Values in Madrid and Toronto", 2020).

In Bogota, the bus rapid transit (BRT) system's impact on property values was analysed by Rodriguez and Targa (2004), who discovered that proximity to BRT stations increased rental prices, reflecting the value of travel time savings. However, these benefits varied significantly across different income groups, highlighting the socio-economic dimensions of transportation infrastructure impacts (Rodriguez and Targa, 2004).

These diverse findings underscore the critical role of spatial econometrics in capturing the complex realities of real estate valuation. By incorporating spatial dependencies and non-linearities, spatial econometric models offer a more accurate and holistic view of how proximity to amenities and undesirable features influences property values. This capability is particularly important in urban planning and policy-making, where understanding the precise effects of infrastructure developments on property markets is key to effective decision-making and community development.

2.2.2 Price Forecastability

The ability to accurately forecast real estate prices has been an enduring focus of economic research, with historical analyses providing foundational insights into the dynamics of housing markets. Seminal studies by Case and Shiller (1989, 1990) have documented that housing returns exhibit positive autocorrelation, suggesting that past prices can be a reliable indicator of future prices. These researchers also found that various economic variables can effectively predict these returns, establishing a methodological baseline for real estate pricing studies.

Further contributions to this field have been made by Crawford and Fratantoni (2003), who demonstrated the efficacy of simple ARIMA models in forecasting house prices, highlighting the utility of time series analyses in capturing price dynamics within housing markets (Crawford and Fratantoni, 2003). Malpezzi (1990, 1999) reinforced the economic foundations of real estate pricing by identifying income as a fundamental determinant of housing value (Malpezzi, 1990).

Market tightness metrics, as expounded by Carrillo, de Wit, and Larson (2015), have also been shown to serve as robust predictors of housing prices, indicating the influence of supply constraints on price movements (Carrillo et al., 2015). Comprehensive studies by Gallin (2008), Campbell et al. (2009), Plazzi, Torous, and Valkanov (2010), Ludvigson, and Van Nieuwerburgh (2017) have further highlighted the predictive value of the price–rent ratio among other economic indicators (Gallin, 2008;Campbell et al., 2009;Plazzi et al., 2010).

For a thorough survey of the literature on economic variables affecting house prices, Ghysels et al. (2012) provide an extensive overview, mapping the evolution of forecasting methodologies and their applications in real estate economics (Ghysels et al., 2012). This diverse range of variables reflects the complexity of the real estate market and the multifaceted nature of price formation.

As the field has evolved, hedonic price models have become increasingly prominent, particularly for their ability to incorporate a wide array of property-specific characteristics into price predictions. Hedonic models analyse the impact of individual features such as location, size, and the condition of the property on its overall value. This approach has been exemplified in studies by Clapp and Giaccotto (2002), who evaluated the accuracy of hedonic models in forecasting house prices, finding them capable of providing nuanced price predictions (Clapp and Giaccotto, 2002).

2.2.3 Hedonic Price Models

Several studies on the real estate market have focused on developing models to estimate property prices, often for selling purposes. The use of Hedonic Price Models (HPM) to predict real estate prices is prevalent due to their ability to incorporate various property characteristics. For instance, Nitsch (2006) found through the application of hedonic models that the most variation in rental prices for offices is in the location (Nitsch, 2006).

The analysis by Ignatenko and Mikhailova (2015) on the pricing in the office rental market in Moscow used hedonic models to estimate the influence of building class and location characteristics on office rental prices, demonstrating the significant role of these factors (Ignatenko and Mikhailova, 2015). Similarly, research by Le et al. (2018) on Ho Chi Minh City's office rental market used hedonic models to determine the impact of building classification, management fees, and district location on office rental prices, highlighting the predictive power of these models in different geographic contexts (Le et al., 2018). Moreover, the use of hedonic models has been refined with advanced statistical techniques to improve accuracy. For example, Koo et al. (2015) employed Ridge Regression to address multicollinearity in the variables used in hedonic models for apartments in Seoul, enhancing the model's stability and interpretability (Koo and Shin, 2015).

These studies underscore the versatility and effectiveness of hedonic price models in capturing the nuanced dynamics of real estate pricing across different markets. The application of such models is crucial in real estate economics, where they help in accurately forecasting property values by considering a comprehensive array of influencing factors.

2.3 Environment and Transportation Models

2.3.1 Mobility and Travel Behaviour

In mobility research, every journey — whether physical or conceptual — has a defined point of origin and termination within specific geographic parameters. Within the context of global mo-bility, these parameters might span urban metropolises or isolated rural terrains (Cresswell, 2012). A single journey may cover varied terrains, thereby connecting distinct cultures, economic zones, and ecosystems.

Transport ecosystems comprise an extensive range of modes, enabling a multitude of activities (Rodrigue, 2020). They guarantee the uninterrupted transit of people, goods, and information. Such ecosystems have pronounced implications on regional transit behaviours. The implications of these behaviours extend beyond the boundaries of contemporary scientific comprehension. For instance, urbanisation in a particular geographic region might affect mobility trends in an entirely different region (Seto and Reenberg, 2014). Similarly, the geographically isolated locations might attract tourists from disparate locations.

Globally, geographic characteristics invariably influence human behaviours (Montello, 2009). Factors such as locale appeal, perceived safety, dwell time, and available activities define a region's transport ecosystem. While numerous theories on global travel behaviour strive to elucidate how geographic characteristics dictate movement, these theories predominantly harness data from mobility surveys, especially comprehensive national household travel surveys.

It's crucial to understand the bidirectional relationship between humans and their geographic surroundings on an international scale (Golledge and Stimson, 1997). Even though human behaviours are moulded by varying geographic characteristics and associated transport systems, humans possess the capability and obligation to modify and impact these systems. Empirical studies suggest that strategic urban planning, infrastructure enhancement, and legislative measures have the potential to dictate macro level mobility trends (Banister, 2008). Variables such as regional economic metrics, climatic conditions, and geographical barriers contribute to this effect and shape the mobility guidelines.

The phenomenon of suburbanization emerges as a direct result of these evolving urban needs, influenced by land use policies that drive up land prices and push residential and commercial development further from city centres (Wolch and Gabriel, 1981). This suburban expansion is not merely a spread of urban boundaries but also a transformation in mobility patterns and infrastructure demands. As more people move to suburban areas, the dependency on automobiles increases, and the demand for efficient public transportation systems becomes more acute.

Suburbanisation, often driven by higher housing prices in the city centre and the allure of larger property sizes in peripheral areas, has significant repercussions for travel behaviour and land use. The migration to suburban areas, while offering more affordable and spacious living conditions, paradoxically leads to a higher reliance on personal vehicles due to inadequate public transport options (Allen and Farber, 2020). This shift not only exacerbates traffic congestion but also places an overwhelming burden on existing transit systems, which are often not designed to cater effectively to sprawling suburban landscapes Newman and Kenworthy, 1996.

Moreover, even though individuals opt for residences outside of the urban core, many continue to commute back to city centres for employment and essential services, thereby intensifying the daily load on transportation networks. The resultant travel patterns contribute to increased CO_2 and other GHG emissions and a decline in air quality, undermining efforts towards sustainable urban living Ewing and Cervero, 2010a. The reliance on cars for longer commutes further diminishes the potential health benefits that could be derived from more active forms of travel, such as walking or cycling, which are more feasible within denser urban settings Frank et al., 2004.

Predictive models are instrumental in understanding how population shifts to suburban areas affect travel patterns, aiding in the strategic planning of transit routes and schedules to accommodate these changes(Pullar et al., 2016). This strategic planning is crucial for managing the increased demand for public transportation and mitigating the traffic congestion typical in suburban areas. However, the efficacy of these models depends heavily on their integration with sustainable urban planning strategies that consider not only the current but also the future demographic and economic trends (Banister, 2008).

As suburban areas continue to expand, the role of predictive models in ensuring efficient and sustainable urban mobility becomes increasingly vital. These models enable cities to strategically invest in infrastructure that supports evolving mobility needs and to implement policies that manage travel demand effectively (Kumarage et al., 2021). However, for these efforts to be truly successful, a holistic approach that includes improvements in public transport accessibility and the promotion of sustainable travel behaviours is essential (Calthorpe, 2011).

Suburbanisation and De-Centralisation

Literature reviews highlight various land use characteristics, such as density and diversity measures, that impact urban and suburban development (Ewing and Cervero, 2010b; van Wee, 2002). The complexity of mobility research encompasses journeys that span diverse geographic terrains—from urban metropolises to isolated rural areas (Cresswell, 2012). Transport ecosystems, comprising a vast range of modes, facilitate a multitude of activities and are crucial in shaping regional transit behaviours Rodrigue, 2020.

The influence of geographic characteristics on human behaviour is well documented, affecting everything from local appeal and safety to mobility patterns across different regions (Montello, 2009; Seto and Reenberg, 2014). Strategic urban planning and infrastructure enhancements are vital in managing these mobility trends, with regional economic conditions, climate, and geographical barriers playing significant roles (Banister, 2008).

Studies focusing on human psychology within mobility frameworks reveal distinct travel tendencies. For example, Hausigke et al., 2021 examine mobility from a user perspective, identifying behavioural characteristics that aid urban planners in making informed decisions Hausigke et al., 2021. Similarly, Bachmaier highlights the importance of understanding user-centric mobility to enhance transport systems (Bachmaier, 2022). Research linking land use with travel behaviour demonstrates a significant correlation, suggesting that urban planning should consider these factors to support effective mobility strategies (Van Acker and Witlox, 2009; Zhang et al., 2012).

Travel Modelling and Predictors

The integration of spatial econometrics into real estate modeling offers a refined approach to understanding property values, especially when compared to more traditional methods like OLS. As the studies by Marcelo Cajias and Sebastian Ertl, and other researchers highlight, the importance of spatial relationships and large datasets cannot be overstated in hedonic models, particularly when evaluating the effects of environmental and urban planning factors (Cajias and Ertl, 2020).

Spatial econometrics provides a framework that accounts for neighbour's spatial relations, which is crucial when properties are influenced by their proximity to transportation infrastructure. The impact of such proximity on dwelling and commercial property values has been extensively studied across different continents with varying results, emphasising both the benefits and detriments of transportation facilities. For instance, research by Bowes and Ihlanfeldt, 2001 on the influence of rail stations in Atlanta showed dual effects on local house prices: positive due to reduced commuting costs and increased retail activity, and negative due to the potential for increased crime (Bowes and Ihlanfeldt, 2001). Similarly, findings by Weinberger, 2000 and Cervero and Duncan, 2002 in California underscored the positive valuation effects on properties located near light-rail stations. These findings align with those of AlMosaind et al., 1993 in Portland and further studies in Buffalo and Dallas, which consistently found that properties near light-rail stations command higher prices (Weinberger, 2000;Cervero and Duncan, 2002; AlMosaind et al., 1993).

Moreover, the research by Debrezion et al., 2006 reveals the nuanced impact of proximity to rail stations in the Netherlands, showing a significant price premium for nearby houses, albeit counterbalanced by the negative impact of noise pollution(Debrezion et al., 2006). This complexity is mirrored in studies of other transportation infrastructures such as the Metro systems in Madrid and Toronto, where accessibility to metro stations was found to either increase house prices or have a negligible impact, depending on the context and the specific attributes of the locality.

Additionally, the influence of transportation infrastructure on property values is not limited to rail systems. For example, the BRT system in Bogota was analysed by Rodriguez and Targa, 2004, who discovered that proximity to BRT stations increased rental prices, reflecting the value of travel time savings (Rodriguez and Targa, 2004). However, the benefits varied significantly across income groups, highlighting the socio-economic dimensions of transportation infrastructure impacts.

These diverse findings illustrate the critical role of spatial econometrics in capturing the complex realities of real estate valuation. By incorporating spatial dependencies and non-linearities, spatial econometric models offer a more accurate and holistic view of how transportation infrastructure and other spatial factors influence property values (Uberti et al., 2018). This capability is particularly important in urban planning and policy-making, where understanding the precise effects of infrastructure developments on property markets is key to effective decision-making and community development.

In conclusion, the integration of spatial econometrics into hedonic models not only enhances the understanding of property values in relation to environmental and transportation factors but also underscores the need for comprehensive, context-sensitive approaches in urban economic research and policy formulation. This evolving methodology reflects a growing recognition of the importance of large datasets and sophisticated modelling techniques in capturing the nuanced effects of spatial relations on real estate markets.

2.3.2 Land use and Commute Patterns

Commuting patterns are integral to urban mobility, dictating the 'high priority' nature of work-related trips and influencing the scheduling of other daily activities. In Munich, the monocentric structure of the MMR draws a significant number of workers and students from suburban areas, exacerbating congestion and emphasising the need for efficient public transportation systems. Although commuting provides a transition period between home and work, it also presents significant challenges in terms of traffic management and environmental impact.

The commuting pattern, characterised by high peak demand and low off-peak ridership, makes it challenging to devise a public transport system that efficiently manages this variability. TDM strategies aim to find an equilibrium, providing just enough network capacity to handle peak demands while fostering the use of alternative mobility options to mitigate the environmental and economic impacts of increasing commuter traffic (Bachmaier, 2022).

Furthermore, commuting distances significantly influence the choice of transport mode. Research indicates that shorter commutes encourage the use of active modes of transportation, such as walking and cycling, which contribute to better health outcomes and less environmental impact. Conversely, longer commutes often necessitate the use of cars or public transport, as these modes are perceived as more practical for covering greater distances (Gerber et al., 2020;Phithakkitnukoon et al., 2017). This dichotomy highlights the need for urban planning that promotes closer proximity between residential areas and workplaces to facilitate more sustainable commuting practices.

Additionally, Bachmaier's survey reveals a strong public interest in Integrated Mobility Concepts (IMCs), suggesting that people are willing to alter their mobility habits in favour of more sustainable options if appropriate alternatives to private car use are available. This willingness is particularly pronounced in urban settings where commuting distances can be effectively managed through well-planned urban development and transportation policies (Bachmaier, 2022).

In essence, the effective management of commuting patterns through the application of TDM, coupled with strategic urban planning that minimises commute distances, can significantly enhance the sustainability and livability of urban environments. Understanding and forecasting travel demand, crucial for this endeavour, relies not only on extensive data collection from various sources but also on sophisticated modelling techniques that incorporate employment trends and the spatial distribution of workplaces (J. Zhao et al., 2017).

2.3.3 Environment and Travel Choice

To effectively examine the environmental impacts on individual mobility behaviour, particularly in the context of modal choices influenced by the built environment, the following integration provides a comprehensive view of how urban design affects travel decisions.

Commuting patterns and the choice of transportation modes are significantly influenced by the built environment. Studies demonstrate that residence location often plays a more crucial role than workplace location in shaping mobility behaviours. For instance, Kinigadner et al., 2016 highlights that the environmental and infrastructural elements of residential areas have a substantial impact on the modal choices of individuals, often more so than the features surrounding their workplaces (Kinigadner et al., 2016).

The characteristics of the built environment—such as land use, accessibility, and the density of transit networks—strongly influence long-distance travel mode choices as well. Arbués et al., 2016 found that socio-demographic factors, the cost of transport, and geographical attributes critically affect the choice between private cars, buses, and trains for long-distance journeys (Arbués et al., 2016).

Moreover, historical trends in Germany from 1976 to 2002 by Scheiner, 2010 illustrate a modal shift towards private cars across similar distance categories over several decades, not just due to increasing trip distances but also due to higher car availability and changing urban forms (Scheiner, 2010). This shift suggests that once car access is considered, the preference for private vehicles appears more stable across various trip distances. Additionally, fare changes in public transportation can significantly affect modal choices for long-distance travel, as shown by Taniguchi et al., 2001, who demonstrated that economic factors could sway people's decisions to switch between private and public modes (Taniguchi et al., 2001). Similarly,Ren et al., 2020 noted that factors like income levels, travel time, and trip costs heavily influence the adoption of new transportation technologies such as high-speed rail (Ren et al., 2020).

The perception of distance and choice difficulty also plays a role in decision-making, as explored by Schneider et al., 2020. They found that closer spatial proximity of options can lead to increased decision-making complexity, affecting mode choice behaviours, particularly when the options are within the same category (Schneider et al., 2020). Finally, Berkowitsch et al., 2015 discuss how subjective evaluations of spatial attributes contribute to mode choice, indicating that not just physical but perceived distances influenced by urban design are crucial in shaping travel behaviours (Berkowitsch et al., 2015).

Trip Generation and Urban Structure

Trip generation is a critical first step in the widely utilised four-step transportation modelling process, which also includes trip distribution, modal split, and trip assignment. This phase focuses on quantifying the number of trips originating from different zones within a study area based on various attributes such as land use, demographic data, and economic factors.

Studies on the built environment and travel often concentrate on the neighbourhood scale without considering these neighbourhoods' placement within the broader urban structure, potentially overlooking significant contextual factors that influence travel behaviour (Cervero, 2002). The interplay between built environment characteristics and travel behaviour is complex, often assuming an implicit causality between spatial conditions and human actions. However, transportation research seldom explores these causal mechanisms in depth, leaving a gap in understanding how physical and spatial conditions directly influence mobility (Næss et al., 2018).

The environmental and urban planning literature highlights that urban structures, combined with societal and natural environmental conditions, create a dynamic framework that can facilitate or inhibit certain behaviours (Cohen et al., 2000, Mouratidis, 2017Archer2000,Næss et al., 2018). These structures define the opportunities available for individuals, which are constrained by previous decisions, social obligations, organisational structures, resource availability, and distances between places (Ellegård, 1999).

Cervero and Kockelman, 1997 examined how attributes such as density, diversity, and design within the built environment influence trip generation for personal vehicle (PV) and non-personal vehicle (NPV) trips in the San Francisco Bay Area (Cervero and Kockelman, 1997). Their findings suggest that higher density and mixed-use developments generally lead to lower trip generation rates, promoting sustainable mobility through thoughtful land use planning.

The relationship between trip generation and the environment is bidirectional. Extensive commuting can have adverse long-term effects on individuals' time and well-being, emphasising the need for urban planning that promotes proximity and integrates active modes of mobility. By facilitating shorter and more sustainable trips, urban planners can enhance the quality of life and reduce environmental burdens.

This comprehensive view of trip generation within the transportation planning model underscores the importance of considering both environmental impacts and human factors in shaping urban mobility policies. By understanding these interactions, planners can create more sustainable and efficient transportation systems that align with broader environmental and social goals.

2.3.4 Spatial Models

Spatial modelling significantly enhances transport mode decision models by incorporating spatial and cluster effects. This approach, which utilises hierarchical logistic regression, identifies areas of high or low public transport utilisation after adjusting for various attributes and effectively captures the dynamics of urban mobility (Czado and Prokopenko, 2008). Complementing this, the integration of big data into spatial interaction models offers further insights. For example, NYC taxi trip data refines these models by capturing temporal variations and assisting in modelling high-frequency temporal dynamics, although it faces limitations in addressing distinct phenomena (Oshan, 2020).

Furthermore, spatial-temporal data models within GIS environments support activity-based transport demand modelling. These models facilitate analyses and queries that are crucial for identifying opportunities for activity participation, based on location, time, and person (Wang and Cheng, 2001). Additionally, the analysis of spatial context from mobile sensed data through machine learning techniques, such as support vector machines, significantly enhances transport mode recognition, proving vital for smart city and mobility platform integration (Šemanjski et al., 2017).

Lastly, the integration of GPS data with contextual spatial information deepens our understanding of human mobility patterns. This integration is instrumental in influencing urban planning and transport services, showcasing how advanced data integration can shape the future of urban mobility and planning (Siła-Nowicka et al., 2016).

2.4 Context and Background

Located in Upper Bavaria in southern Germany, the territory where today lies the city of Munich has been under human presence as early as the Neolithic era. Advancements in farming and hunting activities in the area gave space to the first fortifications in the 12th century, and the city became since then an important trade and cultural hub (Maier, 1999). Once the Bavarian kingdom was reunited in 1506, by Duke Maximilian I, Munich became the kingdom's capital and attracted many thinkers and scientists that contributed to the city's development. The city's prestige rose to a European scale in the 19th century with King Ludwig I, who established the Technical University and brought along the first railways, marking the beginning of rapid modernisation and pioneering in the city (Hagen, 2009; Smolka, 1999; Herrmann, 2018).

In today's context, Munich is known worldwide by its thriving industries, renowned universities, historical attractions, and quality infrastructure. These attributes forged an innovation wave created by highly skilled workers or 'knowledge workers' (Hafner et al., 2007; J. Zhao et al., 2017). The city shows increase employment and income levels but has shown eminent capacity issues, specifically in the housing and transportation fields. Although these issues are familiar across many European cities, the city of Munich is expected to expand its metropolitan region.

Munich's housing market is characterised by high demand and limited supply, contributing to a competitive rental environment. The city's appeal as an economic and cultural centre attracts a constant influx of new residents, intensifying competition for available housing units. The rental process in Munich is notably challenging, with potential renters often facing bidding wars and needing to provide extensive documentation to secure leases (Hübscher and Borst, 2023).

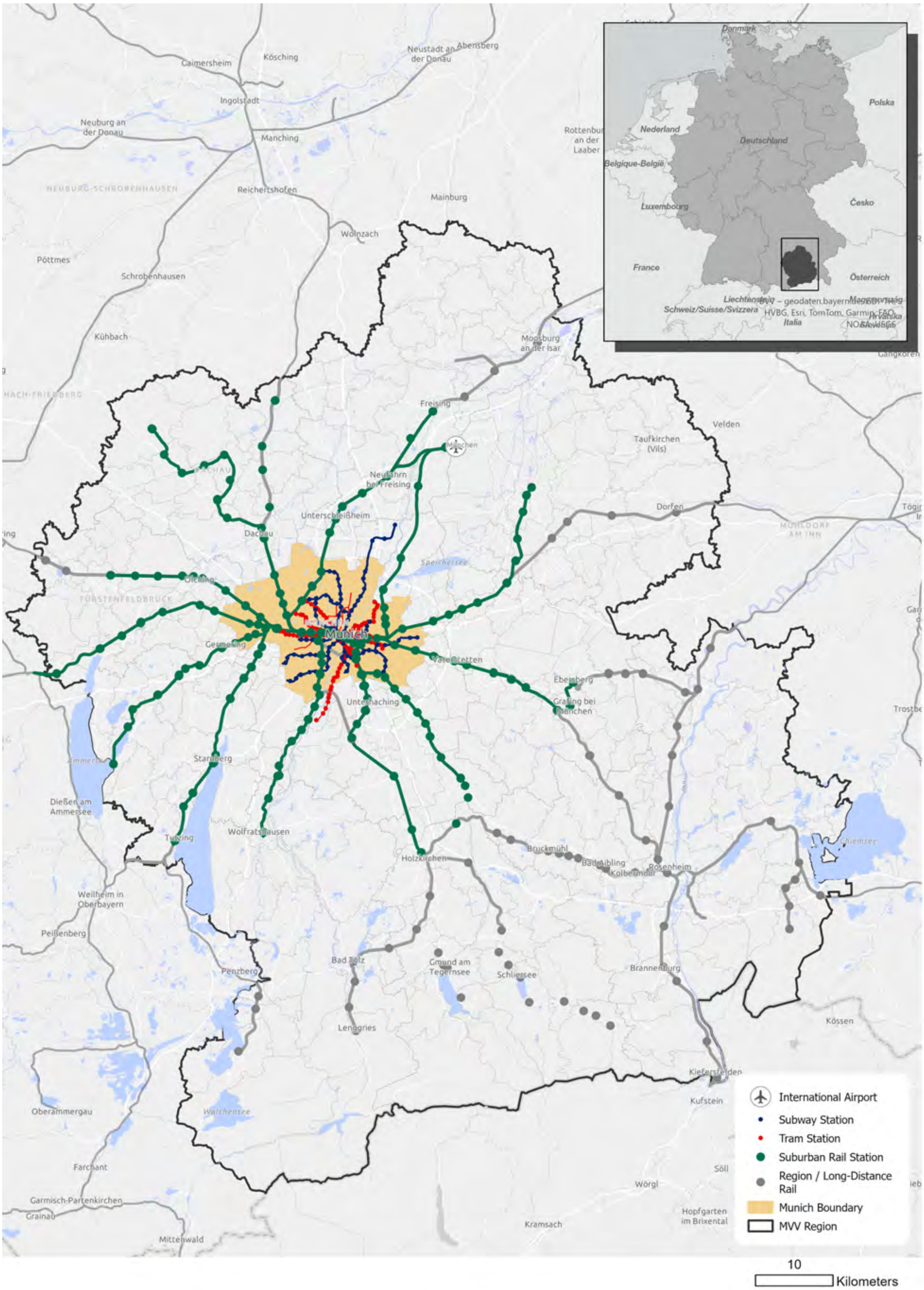
The public transportation system in Munich is extensive and well-integrated, managed by the Munich Transport and Tariff Association (Münchner Verkehrs- und Tarifverbund) (MVV). This association is responsible for coordinating the U-Bahn (subway), S-Bahn (suburban train), trams, and bus services across the metropolitan area as illustrated in figure 2.1. Given the vital role of the transport network in the city's functioning and vitality, the Munich Transport and Tariff Association (Münchner Verkehrs- und Tarifverbund) (MVV) area has been chosen as the study area for this research. However, the centralization of routes has also led to congestion and overburdened services, especially during peak hours.

Featuring a monocentric layout, most routes converge in the city centre, facilitating access to major employment centres and amenities within the city centre (Bauer, 2021). However, inter-suburban public transit is limited resulting in increased travel times. This has become more of an issues with the on-going suburbanisation of jobs and current land use patterns that pushes people to relocate in less central areas.

The scarcity of affordable housing in central Munich has pushed many residents to seek accommodation in the outskirts or suburban areas, leading to longer commutes and increased dependency on cars. This spatial mismatch between residence and workplace has implications for public health and environmental sustainability, contributing to less active lifestyles and higher carbon emissions (Weber, 2018). The challenge is compounded by the public transport network's monocentric nature, which, despite its efficiency, struggles to cope with the growing commuter volume.

To attract and retain more knowledge workers within the metropolitan region of Munich, it is necessary to have a better understanding of their choices of residence, workplace, and commute mode. As the city continues to grow, strategic planning and investments in housing and transportation infrastructure will be crucial to maintaining Munich's livability and economic dynamism (J. Zhao et al., 2017).

Figure 2.1 The MVV Region and PuT Lines



3 Methodology

As specified in the 1 chapter, this study focus on the relationship between neighbourhood walkability, public transport connectivity, and rental prices within the context of the MVV region. To answer the question raised in 1, this paper relies on models to predict rental prices based on spatial attributes associated with walkability and connectivity inputs. Literature indicates a certain preference to HPM to quantify the contribution of individual real estate attributes to the final price of properties. The model should test whether walkability and connectivity are significant factors in setting rental prices in a region and to what degree they can raise living costs. The main inputs are data on rental prices from 2007 to 2022 combined with georeferenced data extracted using GIS modellings tools.

This chapter illustrate in detail the methods and analysis performed in each stage of this study. First the origin and purpose of each data set is described in 3.1, the spatial analysis methods to extract desired variables is found in 3.2.2. Ultimately the methodology applied to create the HPM used in this study is dissected in the last section of this chapter.

3.1 Data Collection

The data analysed in this study comes from 5 external main sources: the first being the General Transit Feed Source to assess public transport accessibility, and the second comes rental housing listings from the ImmoScout24 server spatial analysis. Both datasets offer data covering entire Germany, but only datasets including values within the MVV were analysed, and further processed in spatial and statistical analysis tools. In addition,

Economic and Social-Demographic

Key indicators and characteristic of the region encompassing the region are acquired at the municipality level. The are available in the Bavarian State Authority for Statistics (Bayerisches Landesamtes für Statistik). The data available on the online portal show insights on several themes in the field of mobility and urban transport. In this study, trends on employment and commute rate, housing supply, vehicle accidents, vehicle registrations, land price, budgets and expenditures in different sectors are analysed to highlight emerging mobility patterns.

Public Transport

General Transit Feed Source (GTFS) is utilized in this study to assess connectivity levels of public transportation systems. GTFS, a common format for public transit data used globally, allows for the systematic representation of schedule data and transit routes, making it an invaluable resource for analyzing transit systems. Established by Google, GTFS facilitates the integration of transit data into applications like Google Maps, enhancing user access to public transportation information (Boeing, 2017; Wong, 2013). The application of GTFS data in this research allows for an in-depth analysis of transit service location, accessibility, and frequency, key attributes in defining connectivity levels.

Rental Property Data

Rental housing data in Germany is essential for understanding the impacts of public transport on the current market landscape within the study area. The private company ImmoScout has developed an online platform that efficiently connects landlords and tenants. On this platform, landlords can list their rental properties, providing key information such as rental price, location, utility costs, and amenities. Tenants, in turn, can search through these listings based on their criteria, budget, and location constraints. This platform has significantly increased in popularity, especially during the pandemic, appealing particularly to newcomers who are unfamiliar with the German language and the local housing market. For this study, a comprehensive dataset encompassing all rental properties in Germany was obtained from ImmoScout through the RWI-Essen Institute. This dataset includes 2 subsets: houses for rent and apartments for rent. It provides prospective renters with crucial information about available rental objects online. The platform's popularity has surged in recent years as renting has become more prevalent, making it a valuable tool for assessing the housing market dynamics in Germany.

Spatial Data

Open source geospatial data has grown in reliability and is widely available online (Boeing, 2017; Zenou, 2010; Haklay and Weber, 2008). This study relies on open source georeference data from OSM to create a spatial model of the study area outlined in section 2.4. The data obtained from the GEOFABRIK server contains geospatial data for the sub-region of Upper Bavaria in southern Germany and will serve as base network, land-use, points of interests, and building dataset.

Transport Demand Model

To assess transport demand, a trip list from a synthetic population created for the MMR. The data comes from the MITO travel demand model, recently updated to be more sensitive between discretionary (leisure) and mandatory (commute) trips. This data provides a robust foundation for analysing relationships between public transport connectivity, neighbourhood walkability, and rental prices in Munich.Its updated version is an advancement from its predecessor, focusing on individual-level travel behaviour rather than household-level, to better capture the nuances in travel patterns influenced by mandatory and discretionary travel times. The model, grounded in Zahavi's travel time budget (TTB) theory, posits that individuals have a relatively fixed time budget for travel, leading to an inverse relationship between mandatory and discretionary travel (Moeckel et al., 2020). This relationship is pivotal in understanding urban mobility and can inform the analysis of urban housing markets and their interplay with transportation systems.

Data Field	**Method**	**Sources**
Social-Demographics	Descriptive Analysis	MiD(2017),MoP, Bundesamt für Kartographie und Geodäsie, and extensive Literature Review
Rental Property		ImmoScout24 (RWI – Leibniz Institute for Economic Research)
Geo-Reference	Spatial Analysis	Openstreetmaps
Public Transport		GTFS (Delfi)
Transport Demand	Statistical Analysis	TUM - MITO 2

Table 3.1 Overview of Data Sources For Model Estimation

3.2 Geospatial and Network Modelling

A spatial model encomapssing the MVV region is created to primarily assess peculiarities in the network and urban environment. In this step, the initial data is processed and defined variables extracted. The data extraction processes form the foundational step in developing the land-use mobility model, integral to the urban planning analysis. From the urban planning analysis, spatial variables can be extracted to be later tested in the HPM. This section explains the procedures undertaken from the initial data acquisition to the application of geoprocessing tools that facilitate the creation of the model. The core objective is to integrate and synthesise the various data layers to form a coherent model of land use and mobility within the study area.

3.2.1 TAZ and Aggregation Methods

As explained in **??** transport models rely on aggregated zonal data for estimating trip production. Zone-based can greatly reduce calculating efforts and save time running simulations. However, zone aggregation can also misrepresent true observed data if certain characteristics are overgeneralised. Therefore a good balance needs to be find when choosing the aggregation zone size so key aspects and mobility patterns do not go neglected. Another issue comes when merging datasets from different sources. To prepare for an eventual distortion on the data, different aggregation techniques were employed to fully capture true values for the variables in question.

Postal Code and Municipalities Borders

Since this study deals with rental property and residence location, the chosen zonal aggregation method was performed using Postal Code(PLZ) zones. Those have also the advantage of indicating neighbourhood similarities in densely populated areas, and municipal characteristics in predominantly rural area.

Analysis Grid

Grids have the advantage to increase the analysis resolution without the zonal limitation. Grids can evenly analyse elements contained within a certain area, becoming useful when analysing density and frequency of certain variables. Grids also have the flexibility of being scaled down or up to conform with the analysis demand and computational power available. In this study, a 1km grid is employed.

Zone Centroids

The use of TAZ generally relies on a centroid as the originator/end point of trips. Different then grid or zones, centroids have a XY coordinates, indicating a precise location. This is useful to running accessibility analysis and assessing walkability levels. For this study, the centroids are generated based on urban density, to account for uneven population distribution in certain areas (Nishikawa, 2020).

3.2.2 Spatial Variables

Spatial models offer significant advantages in transportation planning by analyzing fields and features according to their geolocation. This approach facilitates a more nuanced understanding of how different variables interact within a given space, enhancing the precision and relevance of transportation models. Specifically, the integration of spatial data allows for the aggregation and adjustment of stop locations, land-use configurations, and network layers, providing a clearer and more comprehensive view of urban and transportation dynamics.

Stop Locations

From the GTFS stop file, stop locations are the combination all of stops associated with one specific "parent station" into a single point. single points not only are easier to integrate into a network but for producing cleaner results. This produces an adjusted stop density rather than counting two or 4 points to a single location, only one is used. Information attributed to each of the stops is then passed to the stop location, which can be a sum, an averaged value or a dummy variable. This allows the model to quantify the total number of modes, the frequency of departures, and hours of operation.

Land-Use and Built Area

Five categories of land-use are defined and extracted from the OSM shapefile: residential, productive, recreation, greenspace, agricultural. Residential areas represent the liveable area whereas productive is the working area and is the aggregation of military, commercial, industrial and retail areas. Greenspace and recreation are both green spaces but greenspace representing areas that are not primarily intended for human use whereas recreation areas comprise parks and recreational grounds. Agricultural and greenspace occurrence is therefore more frequent in rural areas. For the built area value, each land use is summed up to derive the footprint of each areas values according to their usages. The footprint for each building is summarised according to its respective land-use. The value of all footprint combined represents the built area and is what explain a zone's built density in the model.

Network Layer

The road network is categorised into Roads, Streets, Cycling, Pedestrians, and Others as indicated in table 3.2.2. Each road item may adopt a value for maximum allowed speed when available, else a value in inherited from the class type. the road network is relevant for this study because it allows for an accessibility calculation using service areas to create walking and public transport isochrones.

Assigned Category	OSM Class	Max Speed (Km/h)	Lanes	Width (m)
Pedestrian	pedestrian	4	4	2.4
Pedestrian	footway	4	3	1.8
Pedestrian	steps	2	1	0.6
Pedestrian	path	3	2	1.5
Street	residential	30	1	7
Street	living street	15	1	4
Road	primary	60	2	15
Road	primary link	40	1	6
Road	secondary	60	2	12
Road	secondary link	40	1	4
Road	tertiary	50	2	10
Road	tertiary link	40	1	4
Road	trunk	70	2	12
Road	trunk link	40	1	6
Road	motorway	120	3	18
Road	motorway link	60	1	8
Cycling	cycleway	20	2	2

Table 3.2 Value attribution based on OSM classification

Points of Interest

Because there is no clear guidelines of what points of interest may entail, a new classification systems is applied. The data from OSM contains over different classification of POIs ranging from urban furniture and recycling station to restaurants and universities. Therefore a new classification method is employed to associate POIs to activity types.

Mobility Points

This category encompass mobility fixed mobility elements such as car-sharing and bike-sharing stations. Parking places and rental-car stores also make into this category.

3.2.3 Land Use Model

Utilising GIS software, spatial analyses are performed to understand and visualise the spatial distribution of various features such as residential areas, commercial zones, public facilities, and transportation networks. This analysis helps in identifying patterns of land use and their interrelations with mobility infrastructures.

Network Analysis

The transportation data extracted from the OSM dataset is used to construct a detailed network model of public transportation and road systems. Network analysis tools are applied to assess connectivity, calculate travel times, and determine accessibility across different zones within the region. Travel times are calculated according to the maximum allows speed indicated in table 3.2.2.

Overlay Techniques

By overlaying different data layers—such as land use, transportation networks, and demographic data—a comprehensive land-use mobility model is created. This model represents the interplay between urban form, transportation accessibility, and demographic characteristics, providing a basis for evaluating current urban planning configurations and proposing strategic modifications.

Proximity Analysis

The distance between the observed elements and their distance to certain elements are key in many HPM variable(Nitsch, 2006, Efthymiou and Antoniou, 2013). The application in this study comprises an Euclidean distance analysis to the centre of city of Munich as well as to the Munich International Airport.

3.3 Neighbourhood Walkability and Connectivity

As previously stated, this research is interested in finding out how walkable and well connected areas differ in price from remote or car dependant places. This section explains the process to generate scores that present the level of walkability and connection associated with each location analysed.

3.3.1 Walkability Analysis

The methods applied by Gori et al., 2014, Leslie et al., 2005 and Fonseca, Papageorgiou, et al., 2022 provide the foundation to perform a qualitative walkability analysis for each TAZ. In developing a methodology for calculating walkability scores, this study builds upon established models that focus on three primary dimensions identified in existing literature: **density**, **diversity**, and **design**. These dimensions are calculated using geographical and urban data centred around a pre-defined centroid, which serves as the basis for analysis.

Walkability Score

The calculation process begins with the determination of a centroid as described in section 3.2.1 for the area under study. Around this central point, a buffer zone with a radius equivalent to a 10-minute walk, based on speeds established in 3.2.2, delineates the maximum walkable area and geographical region within which walkability features are assessed.

Density, which measures the built environment's compactness, is calculated first. This dimension assesses how land use encourages or discourages walking by evaluating the extent and accessibility of building footprints within a set perimeter. According to Fonseca, Papageorgiou, et al., 2022, higher density often correlates with increased walkability due to the closer proximity of necessary amenities and services. Density is defined by the equation:

$$\text{Density} = \frac{\text{Sum of all building footprints within the buffer}}{\text{Area of the buffer}} \tag{3.1}$$

Diversity, reflecting the abundance and variability of points of interest (POIs) within the area, is another critical dimension. Leslie et al., 2005 suggest that a greater variety of amenities within a walkable distance significantly enhances an area's walkability by providing more reasons to walk. It is calculated using the equation:

$$\text{Diversity} = \frac{\text{Total number of POIs within the buffer}}{\text{Number of distinct POI categories}} \tag{3.2}$$

The third dimension, design, relates to the layout and connectivity of the road and path network. Gori et al., 2014 state that the quality of pedestrian paths and the overall connectivity of the transport network within the buffer can greatly influence walking habits by improving safety and reducing walking times. The design score is derived with the following equation:

$$\text{Design} = \frac{\text{Area within the isochrone}}{\text{Total buffer area}} \tag{3.3}$$

The composite walkability score is calculated by integrating the scores from the density, diversity, and design dimensions. Each dimension is weighted according to its perceived importance to the overall walkability. The formula for the composite score is:

$$\text{Composite Walkability Score} = \alpha \cdot \text{Density} + \beta \cdot \text{Diversity} + \gamma \cdot \text{Design} \tag{3.4}$$

Where α, β, and γ are the weights assigned to each dimension.

This methodology provides a quantitative measure of the area's accessibility and pedestrian-friendliness, crucial for urban planning and real estate evaluation. By integrating these scores, we can assess the comparative walkability of different neighbourhoods or observe changes over time, contributing to more informed urban development decisions.

3.3.2 Connectivity Analysis

Similarly to the walkability score, a connectivity score is developed to measure the efficiency of public transport for each centroid, identifying highly connected neighbourhoods. This score is pivotal for urban planning, as it aids in the identification of areas with superior public transport access, facilitating strategic development and enhancements.

Connectivity Score

For this assessment, we leverage the GTFS data, which provides detailed information on transport routes, frequencies, and operational timings. This comprehensive dataset forms the backbone of our analysis, enabling a precise evaluation of transport connectivity across different urban areas. The connectivity score is calculated using three key components—each reflecting crucial aspects of transportation network accessibility. These components are:

- **Spatial Coverage (S)**: This is measured by the reachable area, representing the total area accessible from each node within a standard travel time:
  $$S = A$$
  where A represents the reachable area directly.
- **Temporal Coverage (T)**: This component evaluates the total operational hours of transit services, adjusted for the frequency of service (average headway). The inverse of the headway is used to ensure that more frequent services contribute positively to the overall score:
  $$T = \frac{H}{h + 1}$$
  where H represents the summed operational hours for the services, and h is the average time between services.
- **Trip Coverage (C)**: This is measured by the number of routes available from each node, reflecting the network's density and service diversity:
  $$C = R$$
  where R represents the number of routes available from each node.

Combining these components using predetermined weights, the connectivity score for each node is computed as follows:

$$\text{Connectivity Score} = \alpha \cdot S + \beta \cdot T + \gamma \cdot C$$

Where α, β, and γ are weights reflecting the relative importance of spatial, temporal, and trip coverage, respectively. This formula effectively synthesizes spatial, temporal, and trip coverage characteristics to provide a nuanced representation of public transport connectivity. By factoring in the extent of areas served, frequency of services, and diversity of transport modes, this approach not only reflects the physical and operational dimensions of public transport accessibility but also aligns with contemporary urban planning needs to enhance mobility and sustainability. This updated method offers urban planners and transportation engineers a robust tool to assess and optimize public transport systems, thereby facilitating informed decision-making aimed at improving urban mobility infrastructure.

3.4 Rental Properties Price Forecastability

3.4.1 Descriptive Analysis and Data Aggregation

Prior to building a price prediction model, performing a descriptive analysis of the real estate dataset is crucial to bring light on emerging patterns within the current housing market, providing insights that are essential for selecting the variables to be included in the model. By identifying key trends and relationships among the data, researchers can make informed decisions about which features are most influential in predicting real estate prices.

For this hedonic model, data aggregation plays a pivotal role in simplifying the environmental representation of properties. The model aggregates property data into grid cells to assume homogeneity within each cell. This assumption posits that properties within the same grid cell share similar global characteristics such as price and size. Such an approach reduces the complexity of the model while maintaining a focus on spatial relationships that influence property values. Moreover, traditional dummy variables representing property amenities —– such as Parking, Furnishing, Garden, Balcony, and others —– are transformed into probability values. This transformation reflects the likelihood of properties within a grid cell possessing these features, rather than indicating a binary presence or absence. This probabilistic approach allows for a more nuanced understanding of how amenities contribute to property valuation in different areas, enhancing the predictive power of the HPM.

3.4.2 Hedonic Price Model

The HPM assumes that the price of a rental property zone is determined by its characteristics or attributes. Therefore, the rental price, P, of a cell can be expressed as a function of various attributes:

$$P = f(X_1, X_2, X_3, \ldots, X_n) \tag{3.5}$$

where:

- P is the rental price of the property.
- $X_1, X_2, X_3, \ldots, X_n$ represent property attributes such as average size, distance to centre, distance to the airport, presence of grocery store, proximity to public transport, quality of amenities, and other relevant factors.

For empirical estimation, the hedonic price function can be approximated using a linear regression model:

$$P_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_n X_{ni} + \epsilon_i \tag{3.6}$$

where:

- P_i is the rental price of the i-th cell.
- $X_{1i}, X_{2i}, \ldots, X_{ni}$ are the values of the attributes for the i-th cell.
- β_0 is the intercept term.
- $\beta_1, \beta_2, \ldots, \beta_n$ are the coefficients to be estimated, representing the implicit prices of the attributes.
- ϵ_i is the error term, capturing unobserved influences on rental prices.

This paper uses OLS to estimate the coefficients of the linear regression model on a subset of the dataset. The validation process takes place using a subset of the data not used in the estimation (e.g., through cross-validation techniques) to test the predictive accuracy of the model.

The estimated coefficients $\beta_1, \beta_2, \ldots, \beta_n$ provide the marginal contributions of each attribute to the rental price, assuming other factors are held constant. These coefficients are essential for understanding what attributes are valued in the rental market and by how much. Once validated, the model can be used to predict rental prices for properties based on their attributes, assist in investment decisions, policy-making, and urban planning, or contribute to academic research on housing markets.

4 Results

This chapter presents the results obtained from analysing the datasets described in section 3.1 of the Methodology. First it thoroughly investigates the land-use model described in section 3.2 highlighting the relevant findings and patterns on the data. Secondly, it illustrates the results from the walkability and connecivity analysis outlined in section 3.3 within the selected study area. Lastly, it shows the patterns explored in the descriptive analysis processes on rental data and outputs of the HPM, dissected in section 3.4.

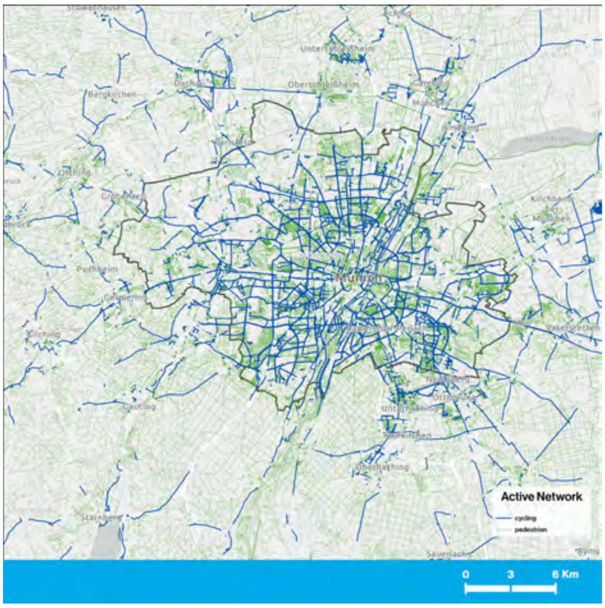


Figure 4.1 Active Networks

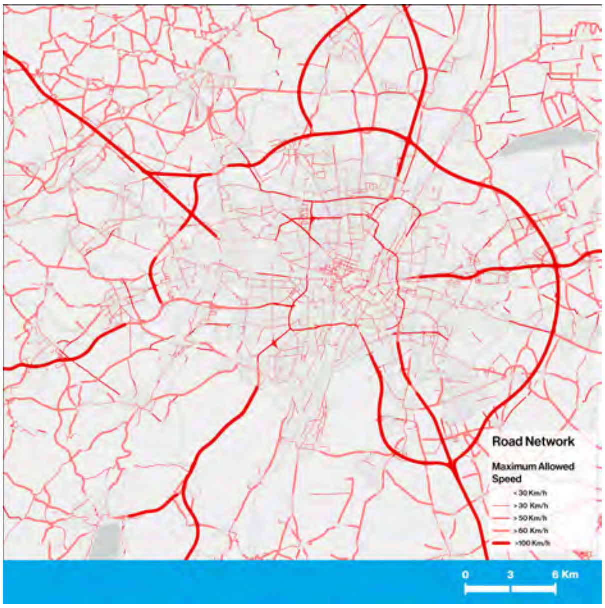


Figure 4.2 Motorised Network

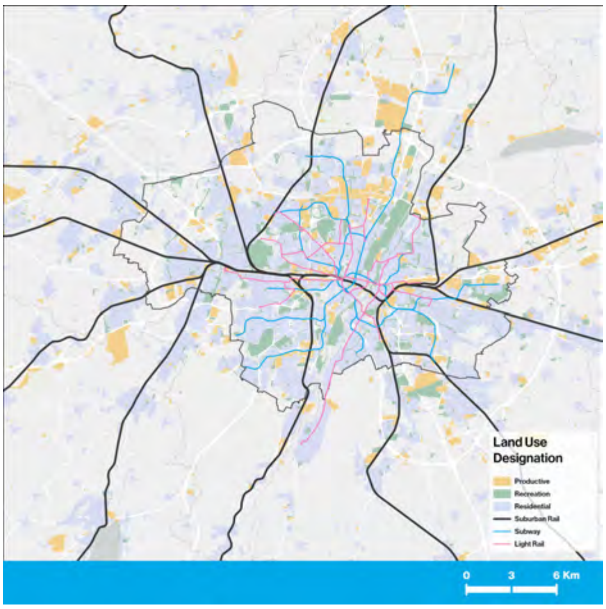


Figure 4.3 Categorised Land use

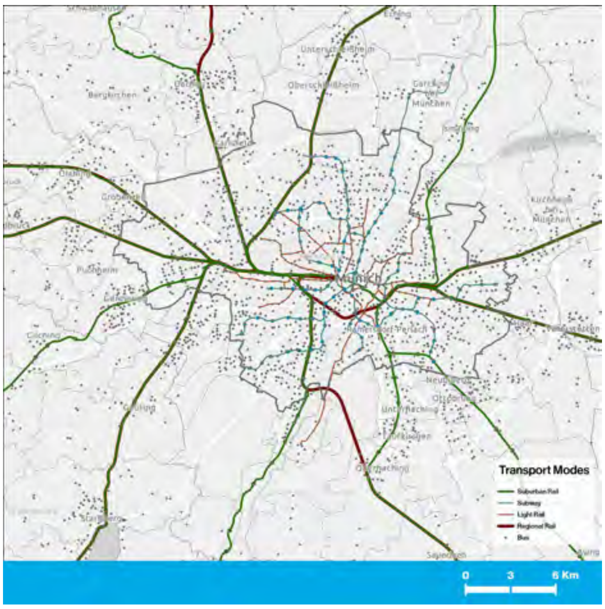


Figure 4.4 Public Transport Modes

4.1 Spatial Model and Variables

The spatial analysis allow for a richer interpretation of the study area. Spatial data manipulation and geoprocessing tools were applied and aggregated for 1Km$_2$ grid cells and for PLZ zonal divisions. Grid cells provide better resolution of data with regards to point density and concentration of certain variables (see 4.7and . This is the case for POIs and transit stops, but due to the structure of the datasets acquired, zonal resolution proved to be a better scale to assess socio-economics indicators, which is usually accounted for at the municipal level. The zonal assessment also provide better depiction for land-use distribution and motorised network percentage.

4.1.1 Weighted Centroid Locations

Different methods were tested to produce the centroids for the TAZ. **Geometrical Centroids** are created on the central point of polygon shape for TAZs and could land in remote or non-populated areas. The use of **Weighted Centroids** correct this bias, shifting the centroid location according to the population distribution within each TAZ. Another centroid selection method applied was the **Highest Density Point**, where the centroid location is based on the most populated cell within the analysed area. The location therefore rely on the urban density (see figure 4.5) and are likely to fall in areas with higher urban density. The variation of location for each method is visible in figure 4.6.

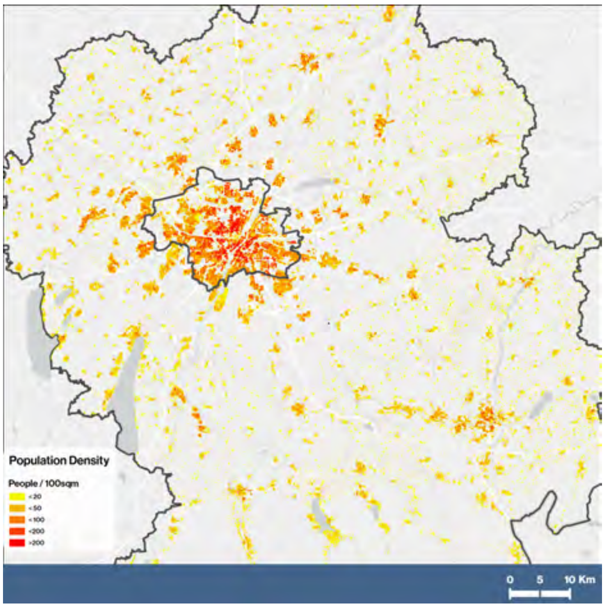


Figure 4.5 Urban Density Heat Map

Figure 4.6 Centroid Locations

4.1.2 Road Network and Distribution

The road network analysis is concerned in assessing the degree in which motorisation impacts the environment. Roads with higher speeds produce more noise and therefore require a large buffer area to mitigate the effects of noise pollution. This enlarges the consumption area of the network, which could also have an impact on rental prices. The variables extracted in this analysis are summarised in 4.1. The road network is categorised between active network where only actives modes such as walking and cycling can circulate, and motorised network (see figure 4.2 where the main occupancy is represented, but not exclusively, by PMV.

4.1.3 Pois Density and Diversity

The spatial model indicates different clusters of high POIs density in urban centre outside the city of Munich. The cities of Dachau, Erding, Freising, Fürstenfeldbruck, and Rosenheim have similar POI density to central Munich, as well as Schwanthalerhöhe and Pasing — the highest scoring areas witin the city of Munich.

Statistic	Types	Net Length (m)	Area (m^2)	Active Percent (%)	Min Noise Clearance (m)	Average Speed (Km/h)
Minimum	0	0	0	0.0%	0.00	0.00
1st Qu.	3	9591	0	40%	1.00	21.67
Median	4	12662	0	57%	26.63	38.00
Mean	3.36	14693	666.6	60%	77.89	38.38
3rd Qu.	5	17067	542.6	82%	128.50	55.00
Maximum	5	79863	18373.7	100%	2048.00	107.50

Table 4.1 Summary statistics for network parameters

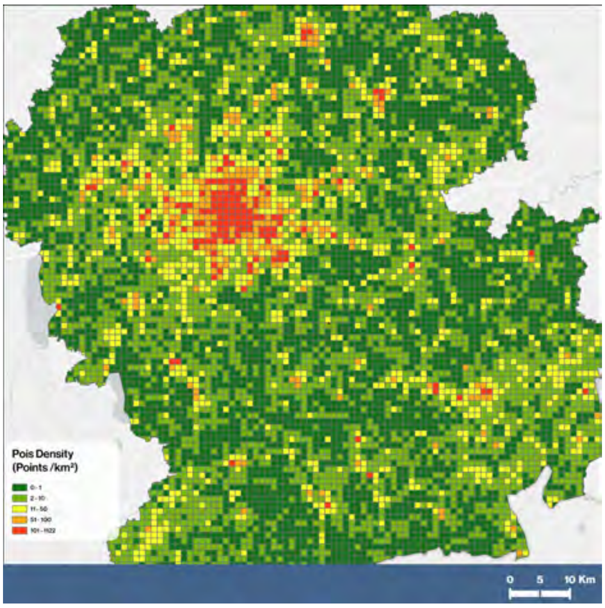


Figure 4.7 Pois Density

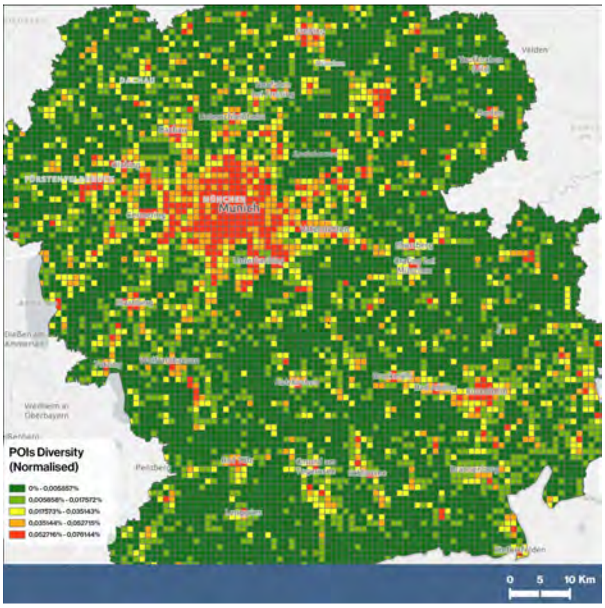


Figure 4.8 POIs Diversity

Statistic	POIs Total	POIs Variety	Has Groceries	Has Uni	Basic Area	Leisure Area
Minimum	0	0	0	0	0	0
1st Qu.	0	0	0	0	0	0
Median	1	1	0	0	0	0
Mean	8.022	2.002	0.1284	0.0075	2776	5494
3rd Qu.	4	2	0	0	0	245
Maximum	1119	13	1	1	1776722	4513414

Table 4.2 Summary Statistics for POIs and Related Attributes (Excluding Count Data)

4.1.4 Public Transport Accessibility

To assess the accessibility of public transport and derive the variable necessary for the calculation of the connectivity score described in section 3.3.2, a public transport travel time model was created. The first stage extracted information from the GTFS database and compiled a dataset based on public transport locations. Each location is assigned a number of physical stops, trips, routes, modes, operation hours and average headway. The second step comprises an accessibility analysis where a service area is generated — using centroids as origins — representing the reachable area within a 30 minute time frame.

Public Transport

Transit points are the interface between transit riders and the public transport network since users must enter vehicles at a stop or station. Areas with higher density PuT location yield better access to PuT but do not necessarily means higher accessibility. The total number of routes is indicates more variation in destinations possibilities and are usually correlate to the total modes present at the same location. From the 8526 cells analysed, 2808 contained stop locations and its values are summarised in table 4.1.4. The spatial distribution for the stop locations is represented in figure 4.9. The value for each stop location headway is averaged for each cell and seen in figure 4.10. Stops with single day trips or no no longer served are represent by the value of 1440.

Table 4.3 Summary Statistics for Public Transport Variables

Variable	Min	1st Qu.	Median	Mean	3rd Qu.	Max
Bus Amenities	0.000	2.000	2.000	4.012	5.000	35.000
Rail Amenities	0.0000	0.0000	0.0000	0.1859	0.0000	11.0000
Walk Amenities	0.00	0.00	2.00	10.67	8.00	319.00
Locations	1.000	1.000	1.000	2.161	3.000	16.000
Routes	1.000	1.000	1.833	1.996	2.500	21.000
Trips	1.0	20.5	46.0	127.0	130.0	4913.2
Average Headway	0.00	18.27	37.88	54.76	61.13	1440.00
Modes	0.000	1.000	1.000	1.106	1.000	5.000
Service Hours	0.00	11.96	15.72	15.29	18.72	31.75

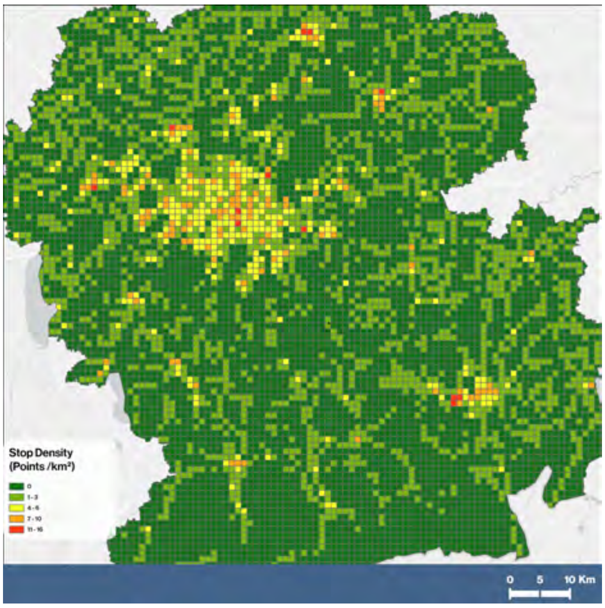


Figure 4.9 Transit Stop Density

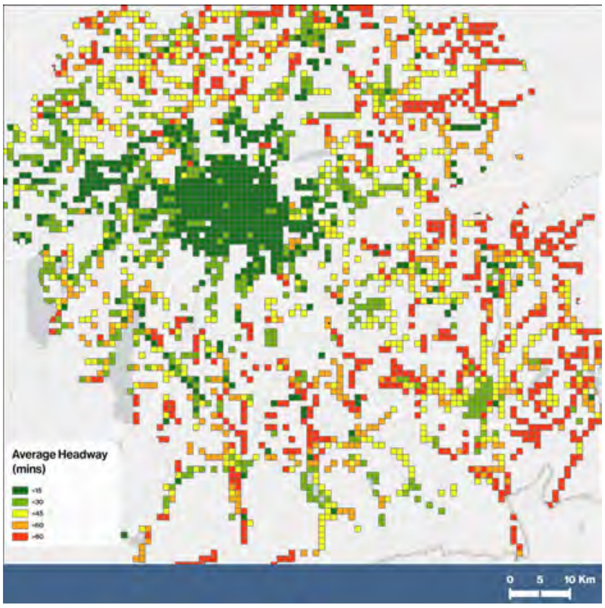


Figure 4.10 Average Departure Headway

The second step in PuT spatial analysis used the Network Analysis Tool to create polygons representing the maximum travel area accessible for any given origin point. The area or isochrones indicating accessibility was constructed on the assumption that 30 minutes in the acceptable commute time. Since this thesis understands connectivity as the degree in which one can reach other areas, the area of the polygon represents the accessibility level. These polygons were further assess in terms of access to amenities, education as well as employment as shown in figure 4.11 using data from the Bavarian Office for and aggregated into the TAZ.

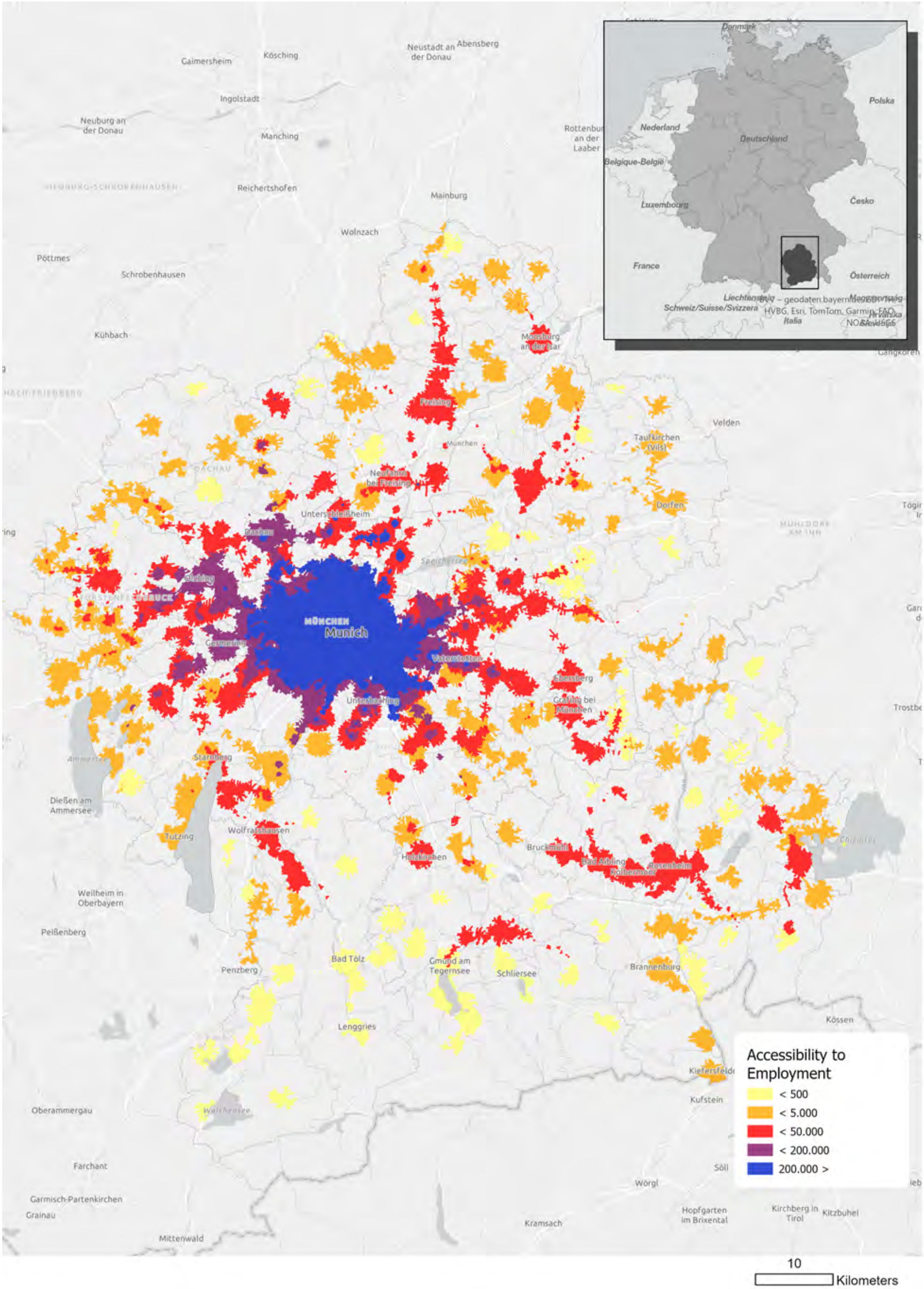


Figure 4.11 Employment Access

4.1.5 Land Use and Demographics

The built environment and land-use analysis focus on calculating the the built density and distribution of land-use areas across the study area. Higher built density is found in central urban areas, as shown in fig4.12. Commercial areas are also of great significance in terms of mobility since they represent areas with high employment rates and generate commute traffic. The relationship between build density and commercial density is similar in smaller centres but in larger areas a de-concentration of these areas can be observed.

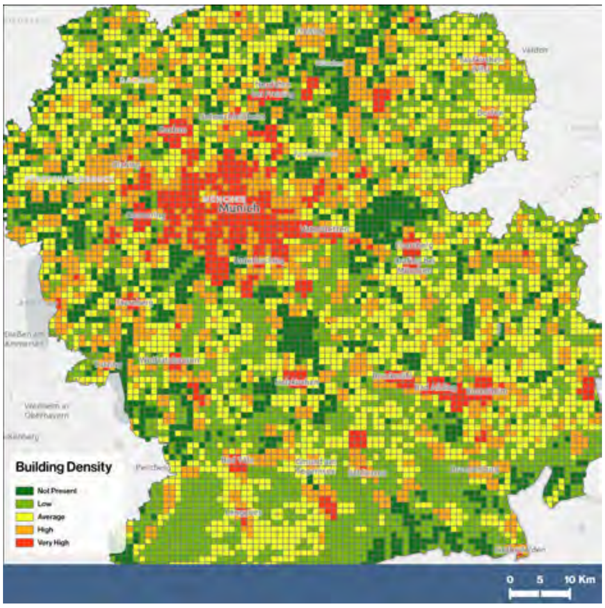


Figure 4.12 Transit Stop Density

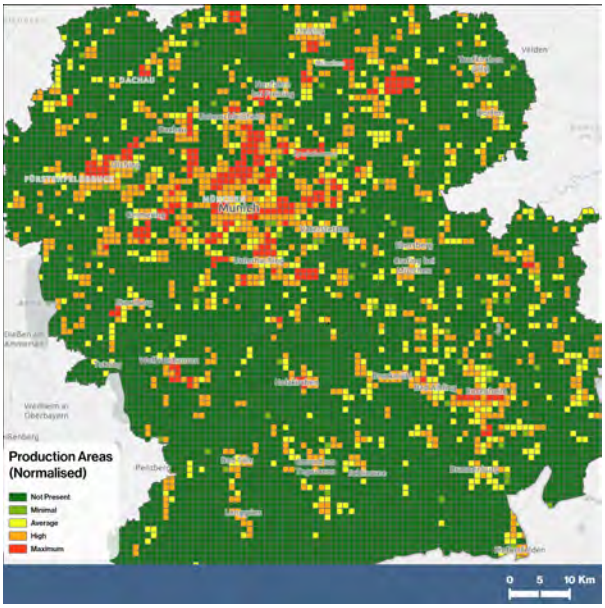


Figure 4.13 Average Departure Headway

4.2 Walkability and Connectivity

The walkability and connectivity analysis was performed for each PLZ that lies within the MVV area of operation. Weighted generated centroids were selected to account for the population distribution within the TAZ defined. Using weighted centroids to calculate scores have the advantage of generating locale values. This can be applied in the assessment of real estate and site specific analysis as it accounts for the immediate context of the centroid coordinates. However, because of the time specified walking time constraint of 10 minutes, any element that falls outside of the analysis area are discarded, which could yield different values if the time constrain is increased or decreased.

4.2.1 Walkability Scores

The walkability is based on a 10 minute walking threshold, assuming a walking speed of 4,8 km/h. The maximum walking distance is therefore 800m and is represented as in figures 4.14 and 4.15 by the black circle. The effective walkable area is represent by the blue polygon and is a function of the street network layout. The POIs within the maximum walking distance are computed in terms of density and diversity. The last variable used in the calculation of the walkability score is the building density.

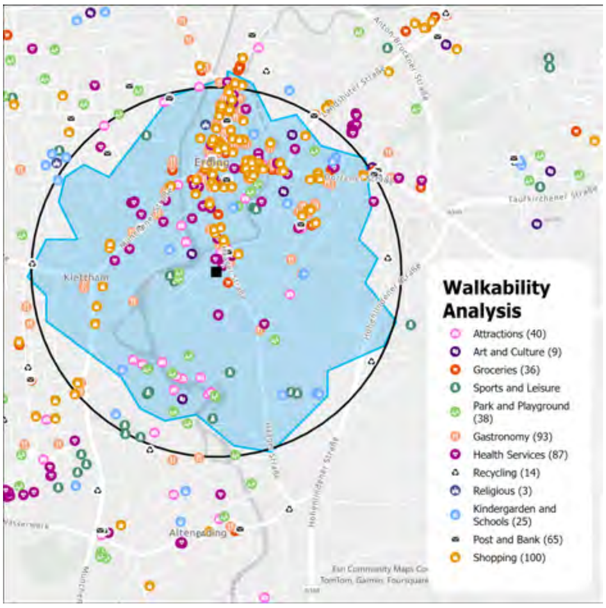


Figure 4.14 Walkability Score

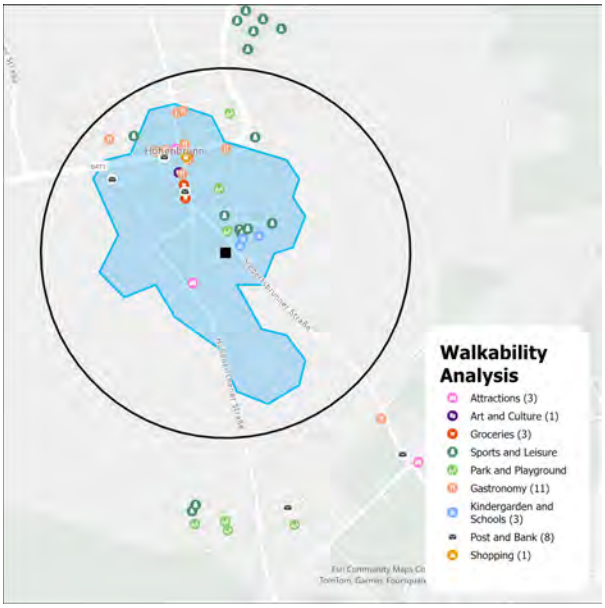


Figure 4.15 Connectivity Score

The walkability score results are illustrated in figure 5.8. It can be observed that high scores were expected for the region of Munich, other towns in the vicinity have also shown good walkability rates. This can be partially explained by the old layout of these cities and town along with the concentration of activities in their core area. The city of Erding has a historical centre and is the site of many business such as restaurants and shops, arranged in a extensive network and encompassing a densely built core. In contrast, the municipality of Hohenbrunn had a much more recent development, in which its street network and level activities follow those of suburban nature, yielding a lower walkability score.

Table 4.4 Summary Statistics of Walkable Areas and POIs

Statistic	Walkable Area	WA Ratio	Adj POI Density	Adj POI Variety
Minimum	0.03781	0.02201	0.00	0.00
1st Quartile	0.70969	0.41319	15.37	11.72
Median	1.07156	0.62350	39.51	22.87
Mean	0.98549	0.57361	78.14	23.60
3rd Quartile	1.26375	0.73557	99.26	35.11
Maximum	1.56438	0.91022	1119.29	79.34

4.2.2 Public Transport Connectivity

When looking over the operation area of MVV, an uneven distribution of services is noted. This is reflected in the connectivity scores present in 5.8. The city of Munich is equipped with several modes of transport with average headway of 10 minutes whereas municipalities that are not served by train lines experience headways of over 60 minutes. An exception can be made for the municipalities in the Munich-Augsburg corridor, where more frequent trips are explained by the heavy rail traffic connecting Munich to other urban centres in Bavaria as well as Germany. Areas served by suburban train lines have also showed low connectivity scores. This could be due to the high reliability on these services, which operates at 20-minute headway. Another reason is that these locations have less stops and routes that can serve those areas resulting in longer headways.

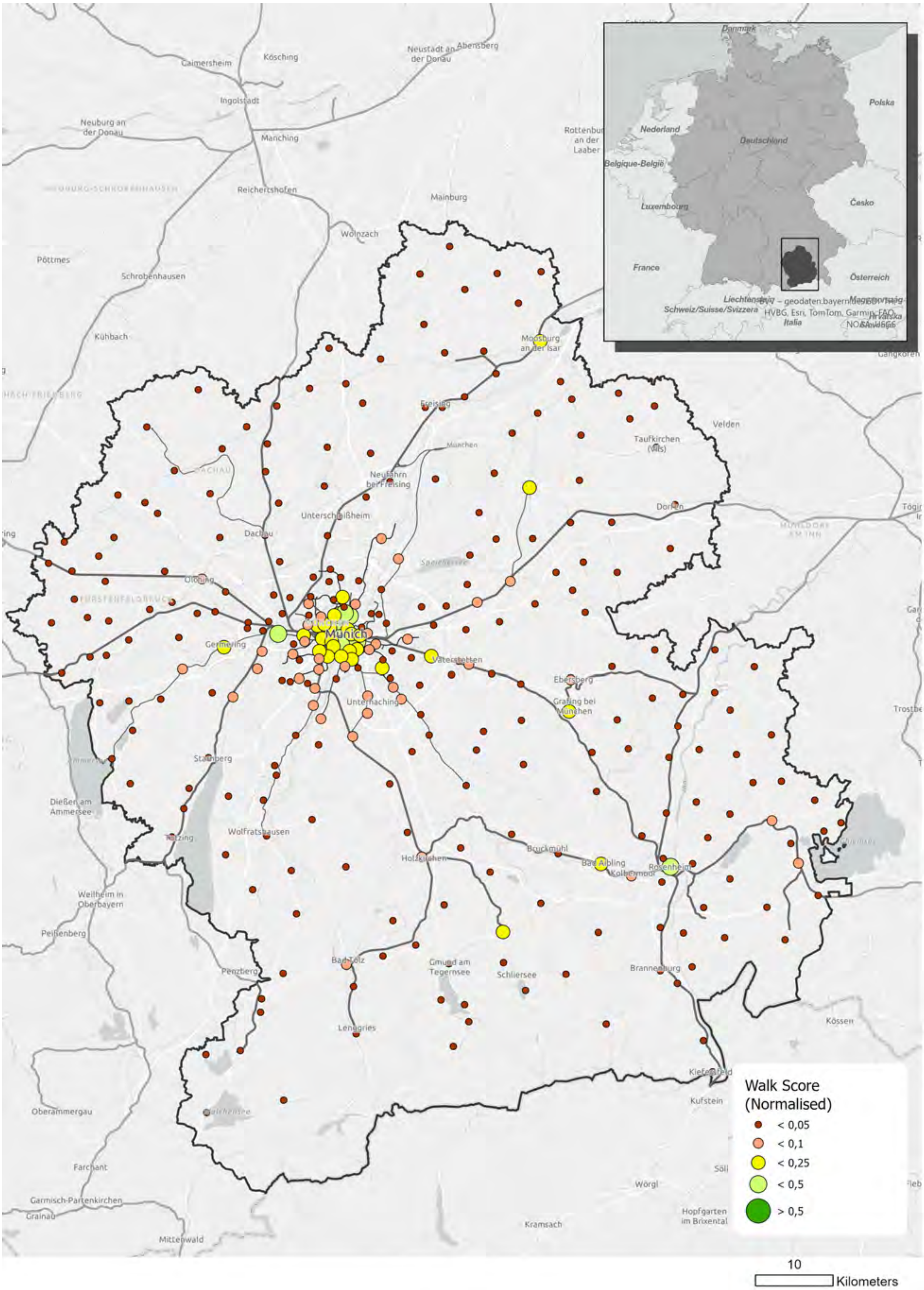


Figure 4.16 Walkability Score

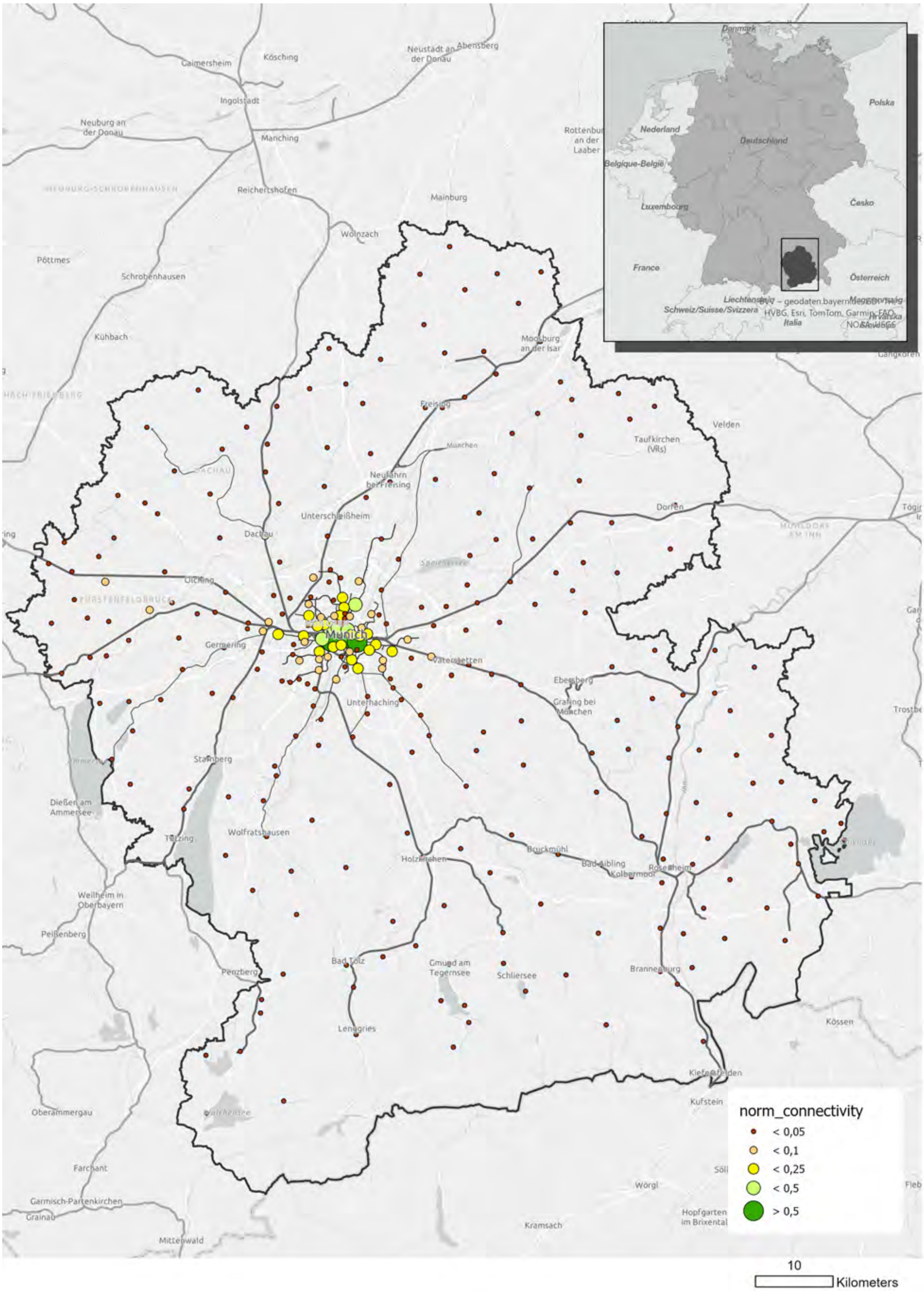


Figure 4.17 Connectivity Score

4.3 Real Estate Descriptive Analysis

The data used to analysed real estate price comprised over thirty one million observations for the period of 2007 to 2023 for the entire German territory. A query where only listing within the MMR region returned 1.701.614 listings from which nearly 89% are for apartment properties. These listing have different providers and have been categorised as: private offers, housing associations offers, real estate agencies offers and third-party offers for listings from the financial sectors.

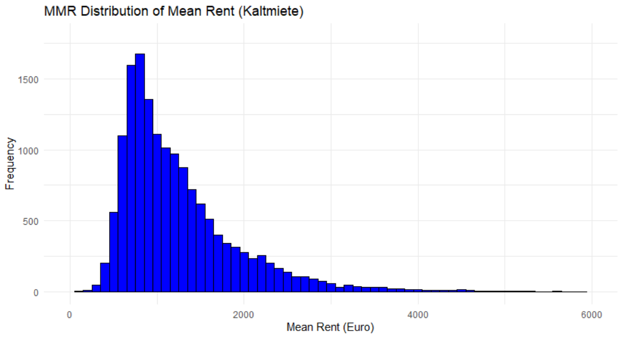


Figure 4.18 Distribution of Mean Rent in The MMR

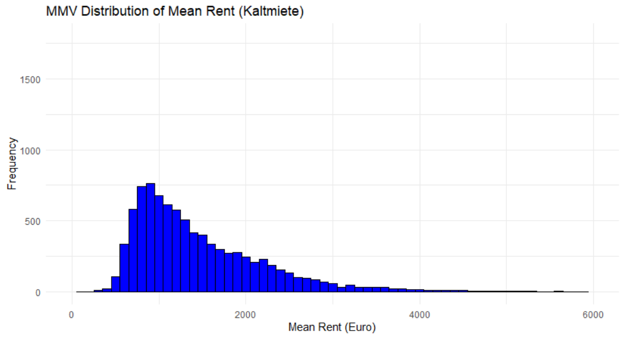


Figure 4.19 Distribution of Mean Rent in The MVV

4.3.1 Rental Price Evolution

Table 4.5 Summary of Apartment Listings and Market Dynamics

Year	Apartments	Applicants	Supply Ratio	Rent	Rent Warm	Living Cost	Living Area	Free Parking
2007	99749	414181	0.241	7.40	8.26	0.861	96.9	0.386
2008	101502	809645	0.125	7.64	8.48	0.845	96.5	0.169
2009	117599	1519956	0.0774	7.60	8.36	0.754	95.4	0.00908
2010	122786	1737508	0.0707	7.71	8.61	0.902	94.5	0.00723
2011	102879	2069767	0.0497	7.73	8.66	0.926	94.1	0.00364
2012	84971	2445333	0.0347	7.95	8.83	0.877	96.6	0.00323
2013	87313	2742777	0.0318	8.39	9.19	0.796	97.8	0.00398
2014	87122	3456036	0.0252	8.57	9.47	0.899	99.0	0.00196
2015	76522	4170647	0.0183	9.11	9.89	0.786	98.7	0.00471
2016	66942	4368184	0.0153	9.88	10.8	0.956	98.5	0.222
2017	68426	5528069	0.0124	10.3	11.6	1.29	98.1	0.340
2018	63726	5369580	0.0119	10.8	12.1	1.34	97.4	0.332
2019	66240	2318898	0.0286	11.4	13.0	1.55	92.5	0.291
2020	92246	456184	0.202	11.5	13.0	1.51	94.5	0.315
2021	106320	791995	0.134	11.8	13.6	1.75	92.6	0.305
2022	74607	7449132	0.0100	12.4	14.3	1.87	92.5	0.305
2023	39613	7557314	0.00524	13.2	14.9	1.70	95.1	0.318

The effects of public transport on LTR over time was analysed for the last 15 years. The variation is represented by the standard deviation of the mean value of the years of 2007, 2012, 2017 and 2022. Figures 4.20, 4.20, 4.20, and 4.20 show the rent variation over that period.

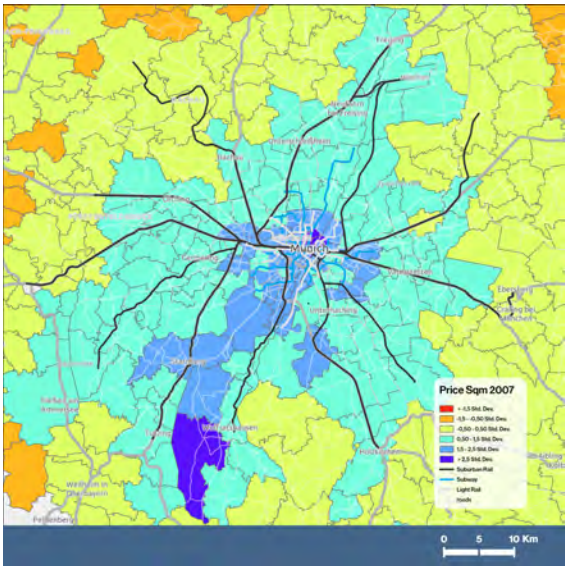


Figure 4.20 Price per Square Meter (2007)

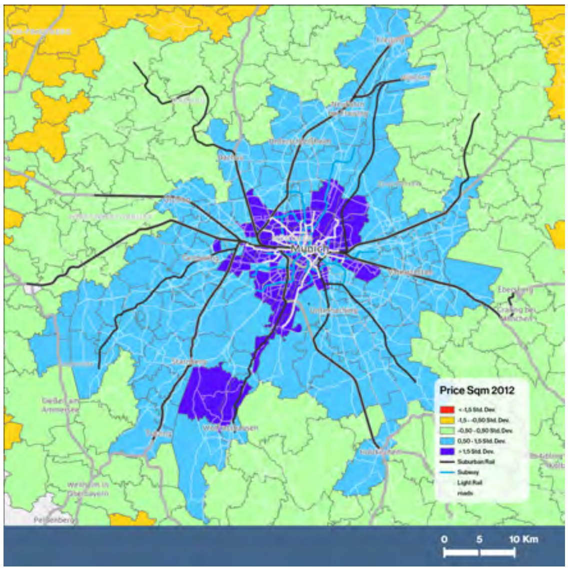


Figure 4.21 Price per Square Meter (2012)

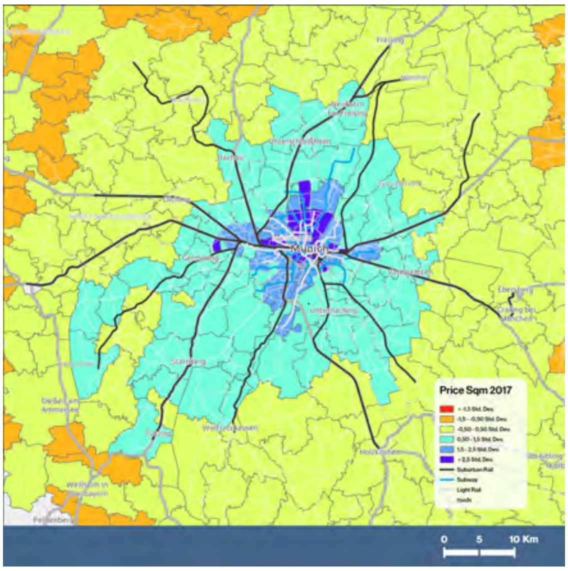


Figure 4.22 Price per Square Meter (2017)

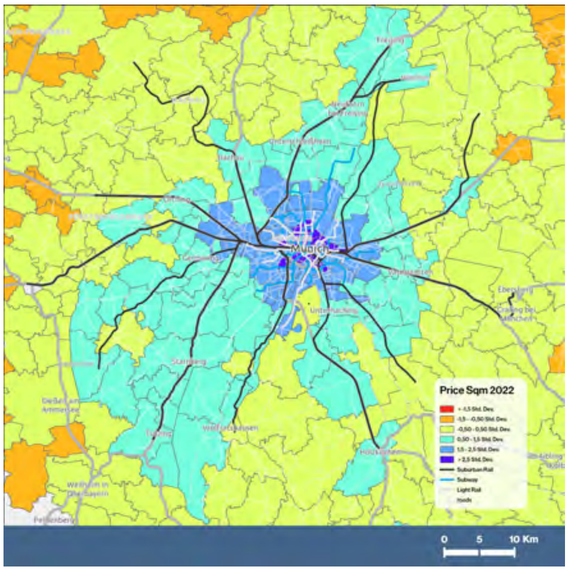


Figure 4.23 Price per Square Meter (2022)

4.3.2 Real Estate Availability

Location is an essential part of real estate since the price is highly dependant on the environment around it.

An OLS analysis was performed to assess the ground situation in terms of LTR properties. Looking at the residuals of the fitted model, it is observed in Figure 4.24 that listing frequencies are under predicted in the larger towns around Munich, whereas the immediate districts in the vicinity of Munich are over predicted. In terms of price, higher than usual prices are seen in the central areas of Munich and lower prices in rural regions with lower transport connectivity.

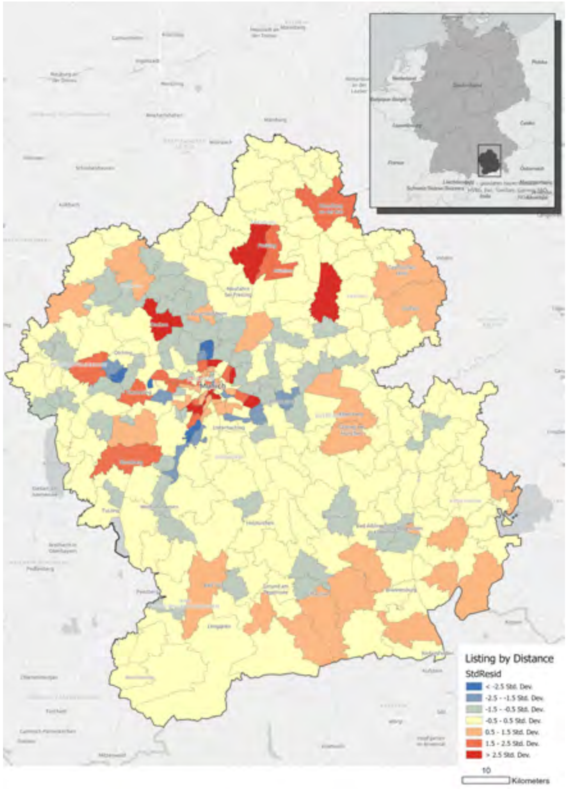


Figure 4.24 Listing vs Distance Regression

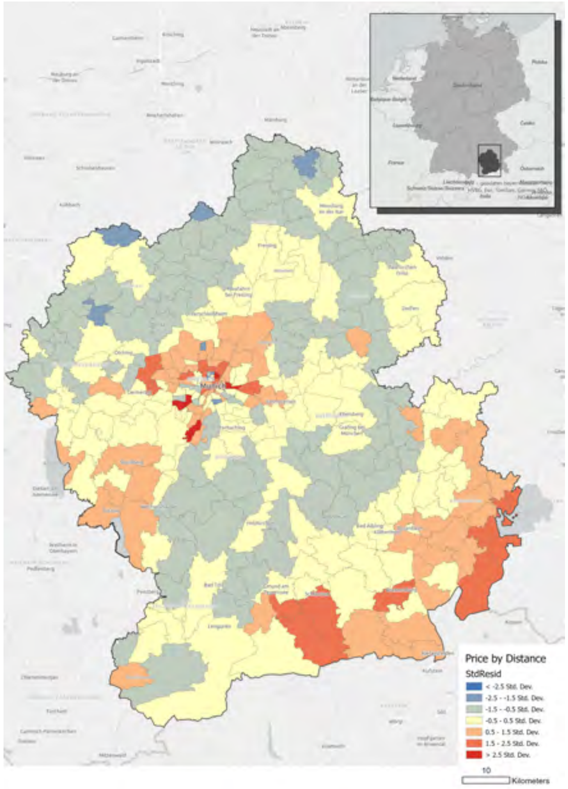
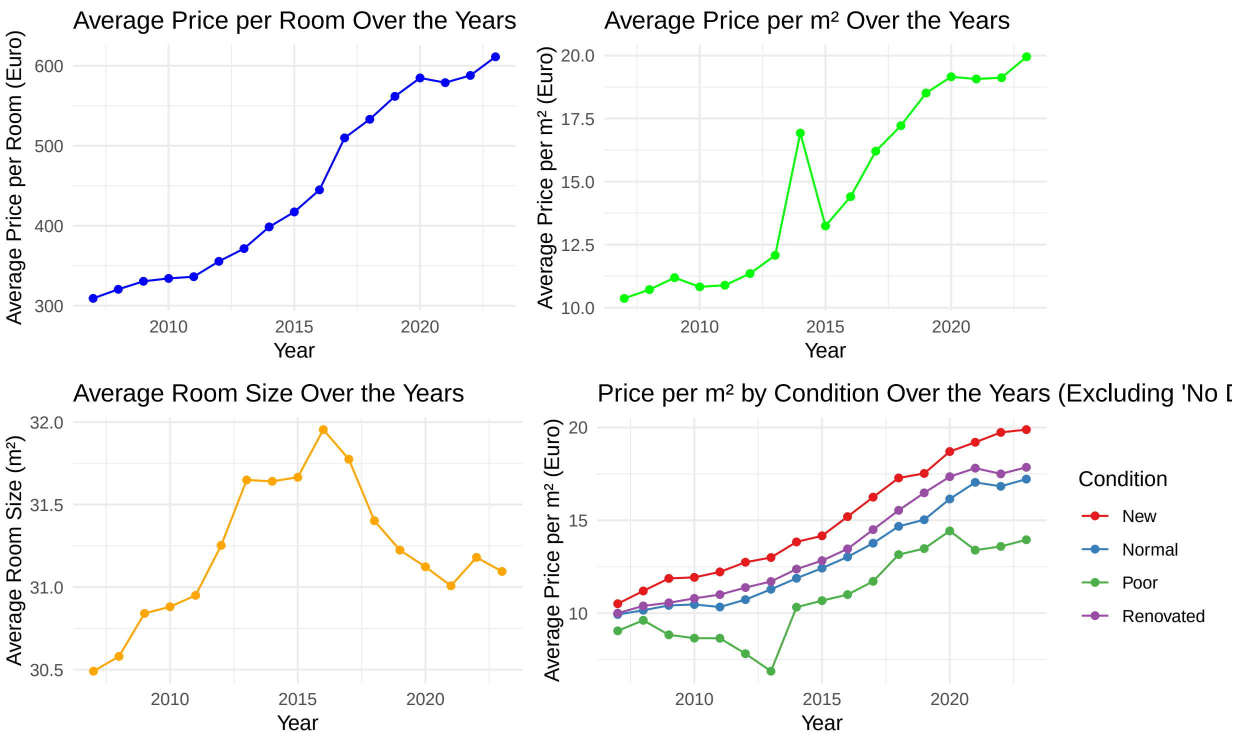


Figure 4.25 Price vs. Distance Regression

Figure 4.26 Rent Price per Room Count



4.3.3 Price Per Square Meter

The price for square meters is a measure widely employed in real estate since it adjusts the value of the property to its usabale area. Calculating the price per square meter allows for true comparison of the spatial value associated to a given location. Similarly, the price per room is the calculated by dividing the total area by the number of rooms, multiplied by the price per meter. There is a steady increase in the price per square meter of rental objects in the observed period from 2007 to 2023, which is explained mostly by inflation. However, the average price per room went from 300 Euros to 600 Euros, while room sizes saw a decrease of almost of almost $2m^2$. It is commonly agreed that to keep up with the housing demand, the average space occupied per individuals has to decrease. This strategy increases urban density at the cost of reducing individual's private space, and although high density is desirable as it increases frequency of cycling and public transport alternatives, a threshold can be reached where density benefits are net negative.

4.4 Hedonic Price Model

Similar to all other datasets, the data was filtered to contain only observations within the MVV area of operation. To minimise missingness and distortion during the model fitting step, missing values and outliers were excluded. The filtered dataset was aggregated first based on grid cells to account for better location resolution. Listings within the same grid cell were averaged, facilitating calculations and addressing missing values for certain variables. Afterward, a zonal aggregation based on PLZ is performed to include socio-economic indicators in the model.

4.4.1 Model Fitting

The first iteration of the HPM takes into account the variables distance from Munich and living area. These variables resulted in high R^2 values in the models proposed by Nitsch, 2006. The results obtained in the first linear regression are expressed in Table 3. The R^2 value here is significant and validates the impact of distance on the rental price.

Table 4.6 Regression results of rental price on living area and distance from Munich center (in km)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	209.527	0.9042	231.7	$< 2 \times 10^{-16}$ ***
living_area	13.141	0.00964	1362.7	$< 2 \times 10^{-16}$ ***
muc_dist_km	−14.161	0.02828	−500.8	$< 2 \times 10^{-16}$ ***

Residual standard error: 431.2 on 1,128,867 degrees of freedom
Multiple R-squared: 0.6342, **Adjusted R-squared:** 0.6342
F-statistic: 9.785×10^5 on 2 and 1,128,867 DF, **p-value:** $< 2.2 \times 10^{-16}$

The performance of the model increases when taking into account transport modes operating in the MVV region. Special services such as nocturnal lines and express bus services are also added to the model. At this stage, two models were tested — one with continuous variables for distances and another with discrete variables indicating the presence of these modes within an 800m radius. No significant variation in the R^2 was observed (See 1).

Since the study area is composed of heterogeneous areas — from high density to rural — models were tested in different contexts. This also helped address overestimating the variables related to public transport available only in the city of Munich (subway, tram, express bus routes, and night lines). When walkability and connectivity are factored in, a discrepancy is noted when observing values within Munich and outside the city. For the dataset containing all observations, the model showed higher significance for the variable connectivity while when selecting only the observations within Munich (See 1), walkability had much higher significance. The best fitting model that showed high R^2 among all datasets tested is shown in Table 4.4.1.

Table 4.7 Regression results of rental price on living area and distance from Munich center (in km)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	276.758	6.012	46.038	$< 2 \times 10^{-16}$ ***
wohnflaeche	15.465	0.044	350.885	$< 2 \times 10^{-16}$ ***
MUC_DIST	−15.837	0.171	−92.634	$< 2 \times 10^{-16}$ ***
Has_ubahn	183.429	4.929	37.214	$< 2 \times 10^{-16}$ ***
Has_tram	142.632	5.461	26.120	$< 2 \times 10^{-16}$ ***
Has_sbahn	23.711	5.458	4.344	1.40×10^{-5} ***
Has_regional_trains	−32.721	8.324	−3.931	8.47×10^{-5} ***
Has_express_lines	−73.033	5.211	−14.016	$< 2 \times 10^{-16}$ ***
Has_night_shifts	36.143	5.308	6.809	9.97×10^{-12} ***

Residual standard error: 414.4 on 47734 degrees of freedom
Multiple R-squared: 0.7374, **Adjusted R-squared:** 0.7374
F-statistic: 16760 on 8 and 47734 DF, **p-value:** $< 2.2 \times 10^{-16}$

Table 4.8 Regression model summary for rental prices based on apartment features, connectivity, and walkability

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	−70.68	6.40	−11.05	$< 2e-16$ ***
wohnflaeche	12.24	0.03	373.68	$< 2e-16$ ***
MUC_DIST.x	−17.88	0.44	−40.28	$< 2e-16$ ***
UBAHN_DIST.x	6.14	0.54	11.42	$< 2e-16$ ***
SBAHN_DIST.x	9.51	0.35	27.55	$< 2e-16$ ***
Regional_DIST.x	−6.45	0.70	−9.20	$< 2e-16$ ***
pois_total	0.148	0.012	12.69	$< 2e-16$ ***
max_noise	−0.210	0.019	−11.03	$< 2e-16$ ***
aufzug	30.83	1.97	15.69	$< 2e-16$ ***
parkplatz	222.70	2.43	91.55	$< 2e-16$ ***
einbaukueche	55.79	1.90	29.29	$< 2e-16$ ***
has_many_bath	122.30	3.65	33.53	$< 2e-16$ ***
condition_integer	6.86	1.04	6.59	$4.45e-11$ ***
equipment_integer	30.25	0.92	32.97	$< 2e-16$ ***
connectivity_score	1.30	0.17	7.82	$5.24e-15$ ***
Walkability_score	0.00282	0.00041	6.87	$6.50e-12$ ***
is_central	93.75	3.37	27.81	$< 2e-16$ ***

Residual standard error: 258.5 on 85297 degrees of freedom
Multiple R-squared: 0.7458, **Adjusted R-squared:** 0.7458
F-statistic: 1.564e+04 on 16 and 85297 DF, **p-value:** $< 2.2e-16$

5 Discussion and Outlook

This section contains insights based on the results presented in chapter 4 and its subsections. In first section a brief explanation of the limitation present on the data analysed and methods applied are discussed.

5.1 Sustainable Housing

Through rigorous spatial modelling and accessibility analysis, this study has demonstrated that the prices landlords ask for or the value they estimate for long-term property are significantly influenced by a variety of environmental factors. Housing scarcity, a critical issue identified, is exacerbated by the low availability ratio, which is currently at one apartment per 90 interested parties. This scarcity drives up real estate prices, particularly evident in high-density urban centres where the price per square metre is markedly higher than in more dispersed areas. Simultaneously, there has been a noticeable reduction in the average apartment size over the last decade as new constructions aim to maximise footprint usage to increase urban density.

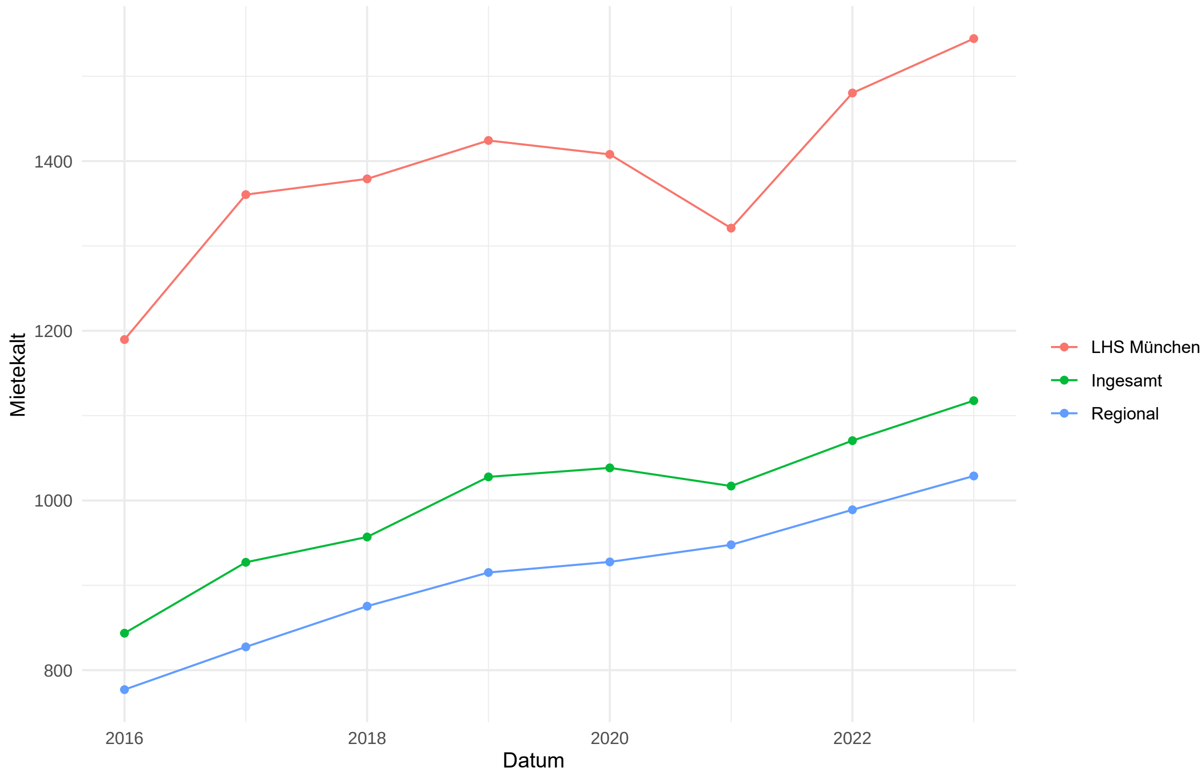


Figure 5.1 Rent Price Comparison

To be sustainably viable, cities must address mobility demands using an integrative system due to the scale and complexity of urban challenges. While improvements in transport system operations can enhance vehicle performance and travel conditions, the escalating demand necessitates increasingly complex solutions. For instance, EVs offer potential improvements in air quality by emitting virtually no CO2. However, the requirements for manufacturing sufficient batteries and generating the necessary energy to power these vehicles pose significant challenges for sustainable growth.

Furthermore, cities should focus on minimising commute distances to enable a shift from car trips to active trips, such as walking and cycling. This strategic shift could alleviate congestion and reduce the saturation of urban centres, thereby contributing to more liveable, efficient, and environmentally sustainable urban environments. Research shows that urban forms that promote compact development can significantly reduce the necessity for long-distance commuting, thus lessening traffic congestion and related environmental impacts (P. Zhao et al., 2010). Additionally, shifting commuting from car to bicycle not only decreases emissions but also significantly improves public health outcomes, as evidenced by studies in Stockholm which showed a substantial reduction in exposure to air pollutants (Johansson et al., 2017). These strategies, if effectively implemented, have the potential to transform urban living, making cities more sustainable and healthier for their residents.

Moreover, the alarming housing scarcity in the centre of Munich is likely to accelerate the suburbanization process of the city, pushing more residents to the peripheries in search of affordable living spaces.

5.2 The Cost of Commuting

Despite the establishment of "Sustainable Communities" and efforts to limit car usage in urban centres, minimal progress has been made to reduce travel distances. Data from this study reveals that although commuting constitutes only a portion of total trips (approximately 10% of total trips), it is responsible for the highest volume of VMT, underscoring the persistent challenges in urban mobility management (Xiao et al., 2018).

Automobiles have facilitated family mobility, especially in areas lacking public transport access. However, the excessive commute can be mitigated by minimising the distance to workplaces. Incentives for residential relocation's closer to employment centres could alleviate some of the strain caused by the monocentric model of Munich, which contributes to public transport capacity issues, congestion, and parking shortages. These challenges are exacerbated by the significant influx of immigrants over the past decade, likely surpassing forecast levels based on 2011 census data, thereby intensifying urban housing shortages (Hasan et al., 2018). The economic and environmental costs of commuting are significant. Under baseline conditions (circa 2003), the cost to operate personal vehicles in city conditions is considerably higher than on highways, largely due to frequent stops and starts (Rossolov et al., 2021). Furthermore, the cost of air emissions from automobiles in urban areas has been estimated at $145 million/day across 86 U.S. metropolitan areas, illustrating the substantial social costs associated with urban vehicle use (Mashayekh et al., 2011).

Relocating to areas where active commuting is feasible could reduce these costs and free up capacity on major urban roadways. This approach requires a rethinking of urban planning to prioritise proximity between residences and workplaces. While subsidies could encourage such relocations, personal choices and existing urban structures may limit their effectiveness. In a democratic society, while individuals should have the autonomy to choose their residences, the spatial realities of modern urban environments often limit these choices, particularly in dense metropolitan areas like Munich where housing availability is constrained by high demand and regulatory complexities.

5.3 Public Transport Diversity

Public Transport Accessibility is an important indicator in urban planning as it explains how well serviced individuals are by jobs and education as well as hospital and food sources. The use of public transport has been affected by the two years following the COVID-19 Pandemic significantly affecting the number of passengers(Fig.5.2 and 5.3). Although the data indicates a that former ridership levels are returning, reliance on the monocentric model has an impact reliance on the monocentric model has an impact on commuting patterns, potentially exacerbating congestion and reducing the efficiency of the transport network. This model can lead to overburdened central areas while undeserving peripheral regions, highlighting the need for a more polycentric approach to urban development. Integrating diverse and well-distributed transit hubs could enhance accessibility and sustainability, supporting a balanced urban growth and improved public transport usage.

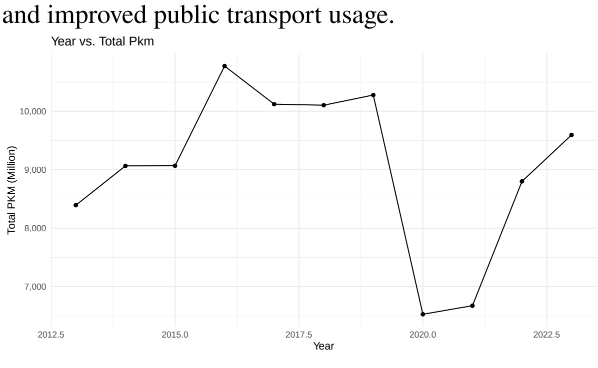


Figure 5.2 Total PKM

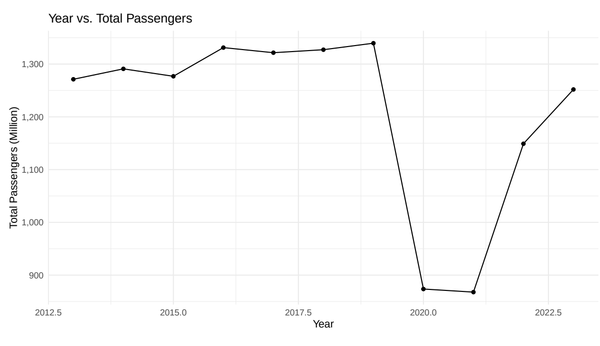


Figure 5.3 Total Passengers

The monocentric urban model typically features radial transit lines, which can make inter-suburban travel inefficient due to the necessity of travelling towards the centre before reaching another suburban location. This inefficiency is exacerbated by radial transit networks that do not cater effectively to the direct travel demands between suburban areas, leading to increased levels of vehicle ownership in regions poorly serviced by frequent public transport. Additionally, while buses may serve as auxiliary connections, their effectiveness is often diminished by multiple stops and extended travel times, reducing their attractiveness as a viable alternative to private car usage (Badia et al., 2014).

Given these conditions, there is a clear need for the development of new centres or nodes in the periphery to reduce trip distances and reliance on central hubs. Creating these new centres can facilitate more direct travel routes between suburbs, potentially transforming the radial model into a more polycentric one where travel can be more evenly distributed across the network. This shift could significantly enhance the efficiency of public transport systems by reducing the need for lengthy, indirect routes and decreasing overall vehicle usage in urban areas. Such developments require a concerted effort in urban planning to integrate land use with transport infrastructure to support a more dispersed yet connected urban form.

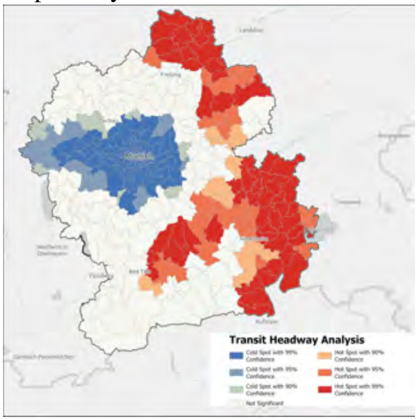


Figure 5.4 Average Headway Analysis

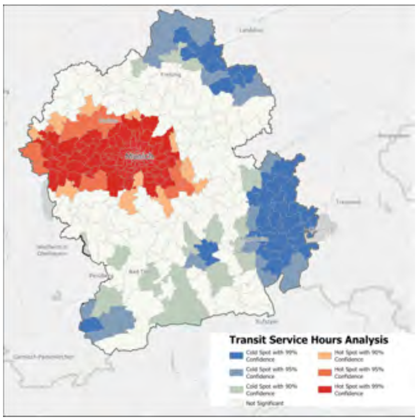


Figure 5.5 Extended Service Analysis

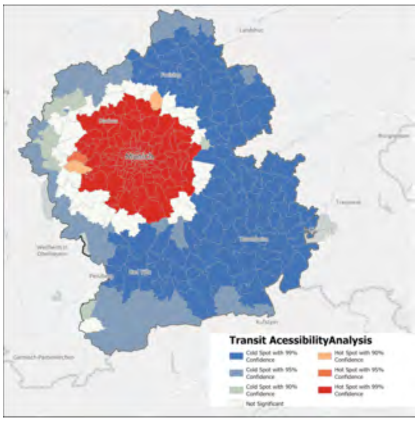


Figure 5.6 Accessible Area Analysis

5.4 Walking Within the MVV Region

The monocentric setup within the MVV distributes most of its passengers within the central core of Munich. This centralization often hinders the potential for walkability in peripheral areas, where transit and pedestrian infrastructure is less developed.

Contrary to the common perception that high walkability scores are exclusively a feature of dense urban cores, evidence suggests that smaller centres can also exhibit excellent walkability. Figures 5.7 and 5.8 show the relationship of connectivity and walkability as distance from the centre of Munich increases. This observation underscores the fact that walkability is not inherently dependent on a monocentric urban model. For instance, many smaller urban centres or neighbourhoods within larger cities display commendable walkability scores due to well-planned pedestrian infrastructures, appropriate scale of buildings, and the presence of multiple points of interest which facilitate shorter trips and promote more active modes of transportation.

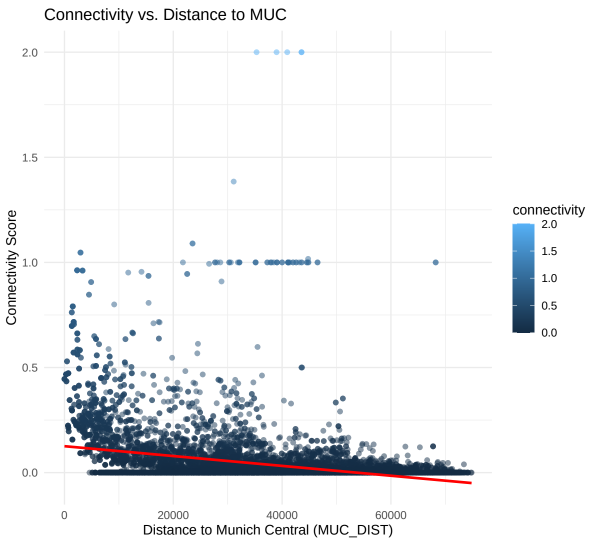


Figure 5.7 Connectivity Score in relation to Munich

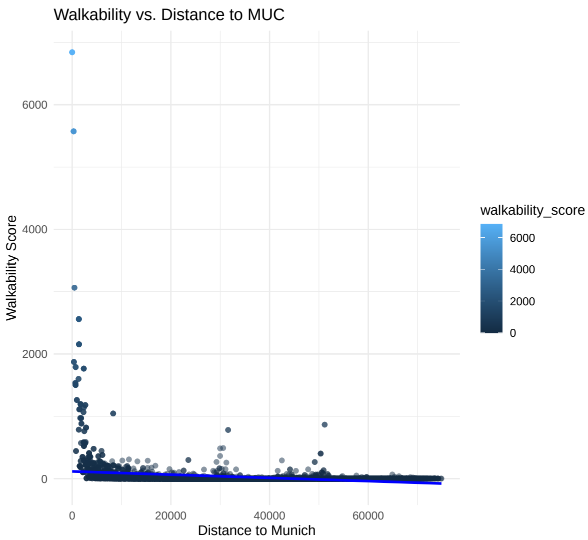


Figure 5.8 Walkability Score in relation to Munich

To improve urban environments further and make them more conducive to walking, several strategies can be employed:

- **Adjusting Building Scale:** Urban planning should focus on adjusting the scale of new developments to better suit the human scale, creating an environment that feels safe and comfortable for pedestrians. This includes the design of street facades, building heights, and open spaces that are proportionate and accessible to people.
- **Increasing Points of Interest:** By increasing the density of POIs, such as retail outlets, parks, and community centres, cities can facilitate trip reduction. This strategy not only enhances the urban experience but also significantly contributes to increasing active modal share by reducing the need for long-distance travel and encouraging walking and cycling.
- **Restructuring Pedestrian Networks:** Designing or restructuring the pedestrian network to make it safer, more comfortable, and more porous is crucial. This involves improving sidewalk quality, ensuring safe pedestrian crossings, and implementing traffic calming measures to reduce vehicle speeds in residential and high pedestrian traffic areas.

For the MVV region, hotspot analysis results indicate a reduction in parking and auto availability within the commuter rail lines, suggesting a lesser reliance on private motor vehicles PMV in these areas. However, there remains a much heavier reliance on PMVs past these zones, underscoring the need for improved walkability and transit connectivity that extends beyond the central core into the suburban areas.

Improving walkability across various scales of urban settings, from large monocentric cities to smaller centres, can significantly contribute to urban sustainability. These strategies ensure that cities are not only more liveable but also environmentally friendly and supportive of healthier lifestyles.

5.5 Study Limitations

The idenitified key limitations of this study follows:

Generalization of Results

The findings of this study, while robust within the analysed contexts, may not be readily generalised to other urban settings or temporal frameworks due to the unique socioeconomic and geographical characteristics specific to the Munich Metropolitan Region during the study period.

Sample Representation

The study's reliance on the MITO data and a synthetic population model based on the 2011 census raises concerns about its current representatives. This limitation is particularly poignant given the significant demographic shifts, primarily due to immigration, that have occurred since 2011 and were not fully captured in the model.

Model Constraints

The exclusion of recent expansions in the MVV operational area, such as Rosenheim, Bad Tölz, and Garmisch, from the transportation demand model used in the study, may lead to underestimations or inaccuracies in the modelling of transportation dynamics and accessibility.

Data Granularity and Quality

This study's spatial analysis is potentially compromised by the limitations inherent in the granularity and quality of the OSM data and the reliance on online real estate listings, which may not consistently reflect accurate or comprehensive property details.

Balancing Quantitative and Qualitative Data

The integration of qualitative insights, specifically employee responses regarding commuting preferences and behaviours in the MMR, complements the quantitative data. This dual approach enriches the understanding of commuting dynamics beyond what is measurable through quantitative methods alone.

Statistical Model Robustness

The robustness of regression models employed to assess the impacts of public transport accessibility and neighbourhood walkability on rental prices may be limited. These limitations stem from the assumptions embedded within the model structure and potential omissions of influential variables.

5.6 Conclusion

This thesis has critically examined the impacts of the monocentric urban model on mobility and housing in the Munich Metropolitan Area, employing rigorous spatial modelling, accessibility analysis, and evaluation of public transport systems. Through this comprehensive study, several key findings have emerged:

- **Influence of Environmental Factors on Housing Prices:** The analysis revealed that environmental factors significantly influence housing prices. High-density urban centres experience escalated prices due to scarcity, exacerbated by a low availability ratio of housing, with one apartment available per 90 interested parties. This scarcity is also driving a reduction in average apartment size, as new constructions aim to maximise footprint usage.
- **Sustainability and Urban Mobility:** The study highlighted the challenges of the monocentric model in addressing the mobility demands of a growing urban population. Although electric vehicles offer a reduction in CO_2 emissions, the energy and material demands for their production pose sustainability challenges.
- **Walkability and Urban Form:** Findings indicate that walkability is not solely dependent on the monocentric model. Smaller centres can achieve high walkability scores if they are well-planned. This underscores the potential for suburban and peripheral areas to improve their infrastructure to support more sustainable and active modes of transport.
- **Public Transport Efficiency:** The research identified inefficiencies in the public transport network, particularly in inter-suburban connectivity. The reliance on radial transit lines complicates mobility for those residing outside the central areas, leading to increased private vehicle usage and associated congestion.

The implications of these findings suggest a need for a paradigm shift in urban planning and policy-making. To mitigate the challenges posed by the monocentric model, it is imperative to foster polycentric development, enhance multi-modal connectivity, and improve infrastructure for active travel. Additionally, policies should encourage the development of amenities and residential options in suburban areas to reduce pressure on central areas.

In conclusion, this thesis not only advances our understanding of the complex dynamics between urban form, housing, and mobility but also provides a foundation for future research and practical interventions aimed at creating more sustainable and liveable urban environments. As cities continue to expand, the lessons drawn from the Munich Metropolitan Area can guide urban development strategies worldwide.

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Appendix A

1 Classification Attributes

1.1 Regional Classification

Regions were classified based on the population attribute Based on the region designation adopted by the MiD & MoP:

Region Code	Designation	Population	Household Size	Trips per Household	Cars per Household
71	Metropolis	>1,000,000	1.86	4.86	0.69
72	Large City	>500,000	1.88	4.86	0.88
73	Middle City	>100,000	2.11	5.19	1.19
74	Small City	>20,000	2.19	5.10	1.35
75	Rural Center	>5,000	1.90	4.75	0.98
76	Rural Town	>2,000	2.10	5.14	1.20
77	Rural	<2,000	2.18	4.80	1.33

Table 1 Regional designation for municipalities.

1.2 Network Category Classification

Regions were classified based on the population attribute Based on the region designation adopted by the MiD & MoP:

Assigned Category	OSM Class	Max Speed (Km/h)	Lanes	Width (m)
Pedestrian	pedestrian	4	4	2.4
Pedestrian	footway	4	3	1.8
Pedestrian	steps	2	1	0.6
Pedestrian	path	3	2	1.5
Street	residential	30	1	7
Street	living street	15	1	4
Road	primary	60	2	15
Road	primary link	40	1	6
Road	secondary	60	2	12
Road	secondary link	40	1	4
Road	tertiary	50	2	10
Road	tertiary link	40	1	4
Road	trunk	70	2	12
Road	trunk link	40	1	6
Road	motorway	120	3	18
Road	motorway link	60	1	8
Cycling	cycleway	20	2	2

Table 2 Value attribution based on OSM classification

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Appendix B

1 Hedonic Model Outputs

Distance x Living Area

Table 1 Regression results of rental price on living area and distance from Munich center (in km)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	209.527	0.9042	231.7	$< 2 \times 10^{-16}$ ***
living_area	13.141	0.00964	1362.7	$< 2 \times 10^{-16}$ ***
muc_dist_km	−14.161	0.02828	−500.8	$< 2 \times 10^{-16}$ ***

Residual standard error: 431.2 on 1,128,867 degrees of freedom
Multiple R-squared: 0.6342, **Adjusted R-squared:** 0.6342
F-statistic: 9.785×10^5 on 2 and 1,128,867 DF, **p-value:** $< 2.2 \times 10^{-16}$

1.1 Modes by Year

Transport Modes (2016)

Table 2 Regression results of rental price on living area and distance from Munich center (in km) for 2016 data

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	173.257	6.596	26.269	$< 2 \times 10^{-16}$ ***
wohnflaeche	13.677	0.044	314.398	$< 2 \times 10^{-16}$ ***
MUC_DIST.x	−12.740	0.180	−70.710	$< 2 \times 10^{-16}$ ***
MAX_ubahn	88.432	5.463	16.189	$< 2 \times 10^{-16}$ ***
MAX_tram	120.999	6.031	20.064	$< 2 \times 10^{-16}$ ***
MAX_sbahn	−14.035	5.899	−2.379	0.0174 *
MAX_regional_trains	−14.688	8.677	−1.693	0.0905 .
MAX_express_lines	−75.252	5.521	−13.630	$< 2 \times 10^{-16}$ ***
MAX_night_shifts	31.202	5.705	5.469	4.55×10^{-8} ***

Residual standard error: 445 on 48182 degrees of freedom
Multiple R-squared: 0.6912, **Adjusted R-squared:** 0.6912
F-statistic: 1.348×10^4 on 8 and 48182 DF, **p-value:** $< 2.2 \times 10^{-16}$

Transport Modes (2019)
Transport Modes (2022) - Presence of Mode

1.2 Distance to Modes

Transport Modes (2022) - Distance to Mode

Table 3 Regression results of rental price on living area and distance from Munich center (in km)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	276.758	6.012	46.038	$< 2 \times 10^{-16}$ ***
wohnflaeche	15.465	0.044	350.885	$< 2 \times 10^{-16}$ ***
MUC_DIST	−15.837	0.171	−92.634	$< 2 \times 10^{-16}$ ***
Has_ubahn	183.429	4.929	37.214	$< 2 \times 10^{-16}$ ***
Has_tram	142.632	5.461	26.120	$< 2 \times 10^{-16}$ ***
Has_sbahn	23.711	5.458	4.344	1.40×10^{-5} ***
Has_regional_trains	−32.721	8.324	−3.931	8.47×10^{-5} ***
Has_express_lines	−73.033	5.211	−14.016	$< 2 \times 10^{-16}$ ***
Has_night_shifts	36.143	5.308	6.809	9.97×10^{-12} ***

Residual standard error: 414.4 on 47734 degrees of freedom
Multiple R-squared: 0.7374, **Adjusted R-squared:** 0.7374
F-statistic: 16760 on 8 and 47734 DF, **p-value:** $< 2.2 \times 10^{-16}$

Table 4 Regression results for the rental price model

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	203.399	5.440	37.389	< 2e-16 ***
wohnflaeche	17.221	0.044	395.449	< 2e-16 ***
MUC_DIST.x	-14.240	0.154	-92.220	< 2e-16 ***
MAX_ubahn	105.564	4.374	24.135	< 2e-16 ***
MAX_tram	95.547	4.840	19.741	< 2e-16 ***
MAX_sbahn	-4.022	4.895	-0.822	0.411
MAX_regional_trains	10.973	7.139	1.537	0.124
MAX_express_lines	-39.080	4.382	-8.918	< 2e-16 ***
MAX_night_shifts	48.425	4.582	10.570	< 2e-16 ***

Statistic	Value
Residual Standard Error	384.6 on 54032 degrees of freedom
Multiple R-squared	0.7543
Adjusted R-squared	0.7543
F-statistic	20740 on 8 and 54032 DF
p-value	< 2.2e-16

Table 5 Regression results for the rental price model (2022 data)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	444.405	6.621	67.117	< 2e-16 ***
wohnflaeche	17.281	0.043	403.489	< 2e-16 ***
MUC_DIST.x	-46.934	0.951	-49.365	< 2e-16 ***
UBAHN_DIST.x	17.935	0.816	21.983	< 2e-16 ***
TRAM_DIST.x	12.123	0.925	13.107	< 2e-16 ***
SBAHN_DIST.x	12.220	0.639	19.108	< 2e-16 ***
Regional_DIST.x	-21.826	1.147	-19.037	< 2e-16 ***
MAX_express_lines	-8.384	4.220	-1.987	0.046921 *
MAX_night_shifts	15.034	4.401	3.416	0.000636 ***

Residual standard error: 376.8 on 54032 degrees of freedom
Multiple R-squared: 0.7642, **Adjusted R-squared:** 0.7642
F-statistic: 21890 on 8 and 54032 DF, **p-value:** < 2.2e-16