

*Essays on Spatial Dependencies and Political Interests in Real
Estate Development*

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Abbreviations

AABB	Axis-Aligned Bounding Box
AI	Artificial Intelligence
API	Application Programming Interface
BASt	Bundesanstalt für Straßen- und Verkehrswesen (Federal Highway and Transport Research Institute)
CNN	Convolutional Neural Network
COVID-19	Coronavirus Disease 2019
EPU	Economic Policy Uncertainty Index
EU-SILC	European Union Statistics on Income and Living Conditions
FStrG	Bundesfernstraßengesetz (German Federal Trunk Road Law)
GDP	Gross Domestic Product
GDR	German Democratic Republic (DDR)
GIS	Geographic Information System
GPS	Global Positioning System
GPU	Graphics Processing Unit
GS2SLS	Generalized Spatial Two-Stage Least Squares
HGV	Heavy Goods Vehicle
IoU	Intersection Over Union
I-81	Interstate 81
IV	Instrumental Variable
LDA	Latent Dirichlet Allocation
mAP	Mean Average Precision
NUTS-2	Nomenclature des Unités Territoriales Statistiques (Classification of Territorial Statistical Units)
OBB	Orientation-Aware Bounding Box
OMERS	Ontario Municipal Employees Retirement System
R3Det	Refined Single-Stage Detector with Feature Refinement for Rotating Object
RETT	Real Estate Transfer Tax
RMSE	Root Mean Square Error

RWI	Leibniz-Institut für Wirtschaftsforschung (Leibniz Institute for Economic Research)
SAR	Spatial Autoregressive Regression
SEM	Spatial Error Model
TPP	Tradable Planning Permit
UPI	Uncertainty Perception Indicator
VAT	Value-Added Tax
VwV-StVO	Allgemeine Verwaltungsvorschrift zur Straßenverkehrs-Ordnung (German General Administrative Regulation on the Road Traffic Regulations)
YOLOv8	You Only Look Once Version 8

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1 Introduction

1.1 Motivation and Background

Economic, ecological, and social change constantly reshapes the world we live in. Global trends, such as climate change, demographic ageing, digital transformation of society and economy, urbanization, and shifting geopolitical conditions shape the human habitat. This habitat, in turn, is predominantly the built environment. Although only 0.65 percent of the Earth's surface is built on (Liu et al., 2014), the average human being spends 87 percent of their life inside buildings or, at a minimum, within man-made environments (Klepeis et al., 2001). Assuming that individuals deliberately shape their living environment, two mutually dependent players exert a decisive role in defining society's habitat: policymakers and the real estate industry. While minor environmental alterations are brought about by individuals themselves, policymakers initiate far-reaching changes, such as amended zoning and construction regulations, in their capacity as representatives of the majority interests. Ultimately, however, stakeholders in the real estate industry effect the most visible changes to human habitats by constructing, modifying, and demolishing buildings.

Providing affordable housing and ensuring adequate infrastructure are, according to the United Nations Sustainable Development Goals, among the key challenges facing both policymakers and the real estate industry (United Nations DPI, 2017).¹ Transformative currents, including urbanization, migration and demographic change, combined with market failure, have generated persistent excess demand for housing and infrastructure. Addressing these imbalances poses shared challenges for policy and practice. Eventually, they are addressed at the local level, where appropriate measures are implemented and local stakeholders are required to carry them out. As a result, the severity of imbalances, their consequences and the range of potential solutions may vary across regions. Yet, the underlying development goals, particularly housing and infrastructure provision, remain widespread. Their persistence stems from different causes. A lack of evidence-based decision-making coupled with pressing demands for action, can lead to misaligned resources, such as inappropriate zoning (Talen et al., 2016) or development projects that face public opposition (Monkkonen & Manville, 2019). The absence of cooperation or mismatch of political and commercial interests causes information asymmetry. When these interests are not reconciled, efficiency losses follow. In a real estate context, this may, for

¹ Sustainable Development Goal 9, Industry, Innovation, and Infrastructure, includes the first target of establishing sustainable, resilient, and inclusive infrastructure, while Goal 11, Sustainable Cities and Communities, pursues the first target of creating safe and affordable housing (United Nations DPI, 2017).

example, result in the absence of construction activity due to political uncertainty (Luo et al., 2022) or in the ineffectiveness of policy measures, such as rent control (Thomschke, 2019).² Neglecting spatial considerations in the design of living and working environments also hinders the emergence of synergies, such as shared infrastructure or regional amenities (Ferraresi et al., 2018; Yu et al., 2013). Instead, spatial separation or competition arises, as observed, for instance, in ruinous competition between municipalities for business or property tax revenue (Trojanek et al., 2021; Janeba & Osterloh, 2013).

Understanding causal relationships and making informed decisions within a spatial framework is becoming increasingly important in regional and urban development. Without robust, data-driven foundations for decision-making and broader approaches to issues that cross administrative boundaries, the big picture of potential solutions to overarching problems remains fragmented and spatially heterogeneous. Furthermore, the effectiveness of implemented measures cannot be adequately assessed if the evaluation is conducted solely from a local perspective. Without accounting for spatial effects, the identification, comparability, and transferability of best-practice examples remain limited. In addition, measuring the extent to which objectives are achieved becomes increasingly difficult (Elhorst, 2014; Ramachandra et al., 2012). Progress toward adequate housing and infrastructure provision, therefore, requires evidence-based decisions, coordinated efforts among stakeholders, and a shared framework for evaluating outcomes. Given the interplay of policy and practice, relevant examples include municipal land-use cooperation (David, 2015), public-private partnerships for infrastructure development (Osei-Kyei & Chan, 2021; Brinkerhoff & Brinkerhoff, 2011) and city-regionalism in regional development (Jonas et al., 2014). Even so, the need for data-driven research on housing and infrastructure provision remains pressing as long-term supply-demand imbalances persist.

The interplay between political interests and real estate or infrastructure development is complex and visible throughout the development processes. From planning through construction and use to redevelopment or demolition, political and real estate interests converge as economic, ecological and social concerns are negotiated. Conflicts of interest, however, arise from project-specific characteristics and vary by local circumstances. Germany, therefore, serves as an ideal laboratory for econometric analyses of the relationship between policy and practice in real estate development. Political responsibilities are fragmented across more than 10,000 municipalities, and the multiparty system produces continuous shifts in political priorities and influence (Berz & Kroeber,

² The effectiveness of rent control measures, such as the rent brake, remains a subject of academic debate. There is evidence both for the effectiveness (Autor et al., 2014) and ineffectiveness (Thomschke, 2019) of these measures.

2023; Wagner & Meyer, 2014). Meanwhile, major challenges related to real estate and infrastructure development persist, most notably those reflected in the Sustainable Development Goals on housing and infrastructure provision. This dissertation examines three distinct aspects of the interplay between policy and practice in a spatial context, with the aim of assessing mutual impacts and proposing decision-making frameworks.

First, land-use planning requires initial interaction between political decision-makers and real estate developers. Their cooperation is vital to align political, social, environmental, and economic interests and establish common ground for land development decisions. Soil erosion caused by land sealing, excess demand for affordable urban housing and municipal budget constraints all underscore the need for sustainable land-use planning (Owens & Cowell, 2011; Borrelli et al., 2017). The consequences of absent or incomplete land-use planning are readily observable. Urban sprawl increases infrastructure costs (Trubka et al., 2010) and contributes to biodiversity loss (Shochat et al., 2010). Greenfield settlement expansion can leave urban buildings vacant (Nassauer & Raskin, 2014). An unbalanced land-use policy also exacerbates housing inequality (Quigley & Rosenthal, 2005) and can contribute to unhealthy living environments (Barton, 2009). A growing body of literature examines the effects of urban sprawl and zoning from a sustainability perspective (Hersperger et al., 2018; Bovet et al., 2018; Searchinger et al., 2018; Henger & Bizer, 2010; Osterburg et al., 2023). However, decisions on land usage are made and enforced at the local level.³ There, local interests, such as business tax revenues, tend to outweigh broader societal goals (Langer & Korzhenevych, 2018). Without local incentives and evidence-based research, existing decision-making patterns are likely to remain unchanged. Although overcoming societal challenges ultimately requires executing construction projects, such measures cannot begin without adequate planning. Research on incentives for political and industry stakeholders, and on effective land-use policy, is therefore necessary to overcome existing barriers to housing and infrastructure provision.

Second, building and maintaining infrastructure requires aligning public and commercial interests, thereby creating mutual dependence. Although the provision of public services is a sovereign responsibility under Article 28(2) of the Federal Constitution, and critical infrastructure is predominantly state-owned, commercial stakeholders remain essential to construction and maintenance of infrastructure and related real estate. Having identified a growing need for investment to sustainably maintain Germany's infrastructure, the federal government established a special fund in 2025 totaling up to €500 billion to finance

³ In Germany, Article 28(2) of the Federal Constitution grants municipalities administrative sovereignty and thus the power to determine land-use policy.

infrastructure expenditures (Federal Ministry of Finance, 2025). Transport infrastructure accounts for the largest share of this fund. Given Germany's pivotal geographic location at the heart of the European Union and the strong reliance of domestic industry on reliable transport routes, the broader economic importance of Germany's transportation network is evident (Ignatov, 2024). With road freight accounting for 72 percent of total freight volume in Germany (DHL Freight, 2023), roads and highways represent the largest segment of the national transportation networks. When supply and demand for road infrastructure become misaligned, supply chains weaken, inefficiencies arise, users divert and satisfaction declines (Krasniuk et al., 2024; Nevland et al., 2020). Road users, especially commercial drivers, are often the first to experience these problems directly. Although policymakers and practitioners alike recognize the consequences of infrastructure deficits, systematic research on efficient infrastructure allocation remains limited. The literature on forecasting infrastructure demand is growing (Patel et al., 2022; Wu et al., 2024), as is research on driver decision-making in road transport (Sadek et al., 2020; Seya et al., 2020). Yet, given continued upward projections for freight transport (Federal Ministry for Digital and Transport, 2024), the need for comprehensive analyses and quantitative evidence remains substantial. Moreover, the quantitative assessment and modeling of road infrastructure beyond highways and transportation hubs, including parking facilities, has received comparatively little scientific attention to date.

Third, examining the expectations of political, industry and private stakeholders improves our understanding of behavior in real estate markets. Because built structures are immobile and involve high transaction costs, expectations and forecasts play a central role in decision-making (Huang, 2013; Monfared & Pavlov, 2019). Stakeholders continually seek information and embed their expectations in behavior. One of the most important influences on those expectations is the political environment, ranging from land-use planning and regulation to taxation, subsidies and monetary and social policies (Pfnür & Wagner, 2020). When expectations rest on incomplete or volatile information, uncertainty emerges and decision-making is disrupted. Because uncertainty cannot be measured directly, proxy indicators typically capture perceived uncertainty through media coverage. With uncertainty indicators rising in recent years due to geopolitical conflicts and the COVID-19 pandemic,⁴ a growing body of research has examined the effects of political uncertainty on real estate markets. This literature on economic policy shows that investment and construction activity decline when uncertainty rises (Antonakakis et al.,

⁴ The media-based uncertainty indices, the Economic Policy Uncertainty Index (EPU), developed by Baker et al. (2016), as well as the Uncertainty Perception Indicator (UPI), developed by Rieger et al. (2023), sharply increased with the emergence of the COVID-19 pandemic in 2020 and the Russian war in Ukraine beginning in March 2022.

2015; El-Montasser et al., 2016; André et al., 2017; Choudhry, 2020; Luo et al., 2022). However, the influence of perceived broad political uncertainty on stakeholders' expectations and ultimately on their action or inaction remains largely unexplored. In particular, the effects of political uncertainty that is not strictly economic in nature have received limited attention. Since the political impact on the real estate sector can be significant (Luo et al., 2022), analyzing changes in expectations and stakeholder actions following political uncertainty is increasingly important for understanding mutual behavior and overcoming emerging barriers. Ultimately, mutual understanding among interested parties is the basis for solving overarching problems, such as affordable housing and infrastructure provision.

This dissertation contributes to the scientific literature through quantitative analyses and proposes decision-making criteria for policymakers and practitioners. Using different data sets with spatial components, econometric methods, and machine learning algorithms, each paper contributes to research and practice on a distinct aspect of the interplay between political stakeholders and the real estate industry. The findings are intended to inform debate and encourage further research. The dissertation proceeds with three individual papers and concludes with a summary of the principal findings and a final discussion.

1.2 Course of Analysis and Research Questions

This section briefly outlines the objectives and corresponding research questions for each paper included in this cumulative dissertation. Each of the three papers examines a distinct interplay between policy and real estate development. The quantitative analyses are intended to provide the real estate industry and policymakers with sound information for decision-making in urban and land development. While the first two papers examine the tangible impact of political decision-making on the development of housing and infrastructure real estate, the third paper addresses the conscious and unconscious effects of political decisions and policies on German housing markets.

Paper 1 | Building Homes for Tax Revenues? Spatial Evidence on the Fiscal Effects of Residential Land Development

Paper 1 examines the fiscal effect of residential land development on municipal income tax revenues. Given the observable housing shortage in urban parts of Germany, this study aims to clarify the fiscal incentives, in the form of tax revenues, associated with housing development. The topic is relevant because spatial planning decisions now regularly prioritize commercial expansion and the business tax revenues it generates (Langer & Korzhenevych, 2018). Comparable decision-making criteria for residential expansion and related tax revenues remain scarce, even though similar considerations may influence land-use decisions. We use a cross-sectional dataset of 10,744 German municipalities to quantify fiscal benefits of residential land development, covering changes in tax revenues and land-use patterns. Methodologically, the paper uses spatial regression models to assess spatial patterns in municipal tax revenues. Potential simultaneity between land-use decisions and tax revenues is also addressed through an instrumental variable approach using initially vegetated area as an instrument for housing development. The empirical analysis aims to quantify the additional tax revenues associated with municipal land designation and focuses on the following research questions.

Research Questions:

- What is the average increase in income tax revenue for a municipality in Germany resulting from residential land development?
- How do economic and demographic factors influence the municipal tax revenue generated by residential land development?
- How do spatial dependencies and spillover effects between neighboring municipalities affect municipal tax revenues in Germany?

- Compared with the income tax revenue generated through the designation of residential land, what is the average effect on municipal tax revenue in Germany resulting from a general expansion of settlement area?⁵

Paper 2 | Living on the Highway? Addressing Highway Infrastructure Potential through Object Detection

Paper 2 aims to provide a local comparison of supply and demand for highway infrastructure to identify potential locations for special-purpose real estate development systematically. The increasing strain on transport infrastructure caused by globalization, urbanization and expanding e-commerce is reflected in local imbalances and structural deficiencies, prompting policymakers to launch investment programs (Federal Ministry of Finance, 2025). However, such investments carry the risk of resource misallocation when decisions are based on incomplete or error-prone information (Glaeser & Joshi-Ghani, 2014). Applying object detection techniques to high-resolution satellite imagery enables the automated identification of existing infrastructure facilities throughout the German highway network. The estimate of demand for highway infrastructure focuses on the need for Heavy Goods Vehicle (HGV) parking spaces and is based on an evaluation of BAST (2024) traffic volume data. Comparing supply and demand using driving-distance polygons enables data-driven identification of potential areas for infrastructure expansion. The paper, therefore, serves to establish a basis for decision-making for both specialized real estate developers and policymakers and to address the following research questions.

Research Questions:

- How is the existing stock of highway infrastructure spatially distributed along the German highway network?
- How does local demand for highway infrastructure on German highways compare with available supply?
- Which geographical regions show an imbalance between the supply of and demand for highway infrastructure, and which spatial patterns can be identified?

⁵ The settlement area includes residential, commercial, infrastructure facilities, and open spaces.

Paper 3 | The Price of Politics: A County-Level Analysis of Political Uncertainty and German House Prices

Paper 3 assesses the impact of media-perceived political uncertainty on the German housing market and homebuyer activity. Given the substantial relationship between policy and real estate through planning and regulatory legislation, taxation, and funding, political factors play a crucial role in shaping stakeholder expectations (Pfnür & Wagner, 2020). Because real estate markets are characterized by illiquidity and transaction costs, expectations strongly shape stakeholder decisions (Huang, 2013; Monfared & Pavlov, 2019). When expectation formation is disrupted by short-term changes in political objectives and ambiguous communication, uncertainty arises (Luo et al., 2022). Using the Uncertainty Perception Indicator (UPI) developed by Rieger et al. (2023) as a proxy for media-perceived generic political uncertainty, this paper investigates whether a portion of housing price variation can be explained by rising political uncertainty. To do so, it analyzes a panel data set of median transaction prices per square meter for detached houses and condominiums, covering all 400 German counties. The effect of proxied political uncertainty on housing prices is estimated using georeferenced data and spatial autoregressive regression models that account for identified spatial dependencies. The study focuses on the effects of both conscious and unconscious political decisions and media-shaped expectations, addressing the following research questions.

Research Questions:

- Does political uncertainty have a measurable impact on housing prices in Germany?
- If so, how does that effect differ across geographical regions, and housing asset classes?
- If so, to what extent do spatial spillovers explain variations in housing prices associated with political uncertainty?

1.3 Co-Authors, Submissions and Conference Presentations

The following section provides an overview of the co-authors, publication status, conference presentations and awards associated with the individual papers.

Paper 1: **Building Homes for Tax Revenues? Spatial Evidence on the Fiscal Effects of Residential Land Development**

Authors: Julius Leonhard Range and Albert Erasmus Grafe

Publication Status: Accepted (10th July 2026) and published in Land Use Policy (Volume 170, November 2026, 108220)

Conference Presentations:

- 30th Annual Conference of the Pacific Rim Real Estate Society (PRRES) in Broadbeach, Australia (2024)
- 3rd Workshop on Residential Housing Markets of the WU Vienna and University of Cambridge in Vienna, Austria (2024)
- 30th Annual Conference of the European Real Estate Society (ERES) in Sopot and Gdansk, Poland (2024)

Paper 2: **Living on the Highway? Addressing Highway Infrastructure Potential through Object Detection**

Authors: Albert Erasmus Grafe, Julius Leonhard Range, Benedikt Gloria

Publication Status: Accepted (14th September 2025) and published in Transport Policy (Volume 174, December 2025, 103814)

Conference Presentations:

- 30th Annual Conference of the European Real Estate Society (ERES) in Sopot and Gdansk, Poland (2024)
- 41st Annual Conference of the American Real Estate Society (ARES) in Tucson, USA (2025)

Recognition:

- 2025 ERES Award for Interdisciplinary Research on Real Estate Development
- 2025 gif-Immobilienforschungspreis

- ARES Manuscript Prize: Spatial Analytics/GIS Applications Award 2025
-

Paper 3: **The Price of Politics: A County-Level Analysis of Political
Uncertainty and German House Prices**

Authors: Julius Leonhard Range and Lars Jagemann

Publication Status: Revised and resubmitted to the Journal of Housing Research (5th January 2026)

Conference Presentations:

- 28th Annual Conference of the European Real Estate Society (ERES) in Milan, Italy (2022)
- 29th Annual Conference of the European Real Estate Society (ERES) in London, UK (2023)
- 41st Annual Conference of the American Real Estate Society (ARES) in Tucson, USA (2025)
- 31st Annual Conference of the European Real Estate Society (ERES) in Athens, Greece (2025)

Recognition:

- ARES Manuscript Prize: Real Estate Market Analysis Award 2025

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2 Building Homes for Tax Revenues? Spatial Evidence on the Fiscal Effects of Residential Land Development

2.1 Abstract

This study quantifies the tax revenue effects of residential land development in Germany. Whereas existing research and policy debates have concentrated on the fiscal returns of commercial land expansion, the tax revenue effects of residential development remain largely unexplored. We estimate the impacts of increases in living space and settlement area on municipal tax revenues using spatial instrumental variable regressions and a nationwide cross-sectional dataset covering all German municipalities. Accounting for spatial spillovers and potential endogeneity, we document a significant positive effect of residential living space expansion on municipal income tax revenues, with substantial heterogeneity between urban and rural municipalities and across regions with differing economic performance. A corresponding analysis of broader settlement area expansion indicates similarly positive effects on total municipal tax revenues. Multiple robustness checks support the validity of these findings. Finally, we outline a simple framework for approximating the fiscal payback period of residential land development by relating estimated revenue effects to average municipal development costs.

Keywords: Tax revenues, Land consumption, Spatial regression, Instrumental variable regression

2.2 Introduction

Housing shortages have re-emerged as a central policy concern in Germany. Current estimates suggest a deficit of roughly 700,000 dwellings (Guenther, 2023), and more than 9.5 million residents live in overcrowded housing according to the German Federal Statistics Office (Federal Statistical Office, 2025a). Referring to EU-SILC, this is defined as living space with no common room or no private room for children over 12 years of age (Eurostat, 2025). Despite sustained political attention and a federal target of constructing 400,000 housing units per year, actual completions have remained substantially below this benchmark (Bundesministerium für Wohnen, Stadtentwicklung und Bauwesen, 2025). Consequently, municipalities – who ultimately determine local land-use allocation – face mounting pressure to expand residential areas.

In the German context, municipalities exercise discretion over the local tax multipliers for both the business tax and the property tax, making these taxes important instruments of local fiscal policy. While property tax revenues result from both residential and commercial land, commercial development additionally generates business tax revenues, which are a major and relatively elastic source of municipal finance. This creates an asymmetry in fiscal incentives: the marginal revenue potential resulting from commercial land development can be higher and more immediate, whereas the fiscal returns resulting from residential development – primarily through property tax and the municipal share of income tax – are less direct and often perceived as weaker.

Residential and commercial land-uses are fundamentally interdependent. Municipalities require a stable resident population to supply labor, support local services, and sustain commercial activity, while households depend on proximity to employment opportunities and urban amenities. A balanced mix of both land-uses is therefore essential to maintain viable local economies. The challenge is not that municipalities disregard residential development per se, but that the fiscal benefits associated with commercial land-use are more visible and directly tied to municipal budgets, whereas the returns from residential development are more diffuse, accrue with a delay, and remain empirically underexplored.

This diffuseness has a mechanical explanation: the 15% municipal income tax share — Germany's primary residential revenue instrument — flows only to the municipality in which new residents formally register their primary residence, depends on the income distribution of those arrivals under a progressive rate schedule, and accrues with a delay of up to four years due to retroactive filing rules. Building a housing unit therefore generates no guaranteed fiscal return; the magnitude of that return depends entirely on

who moves in, how much they earn, and where else they might have lived (the full mechanics are described in Section 2.4).

Despite the relevance of these fiscal incentives, surprisingly little is known about the magnitude of the fiscal returns resulting from residential land expansion in Germany. Existing evidence focuses predominantly on commercial development. Langer and Korzhenevych (2018), for instance, document that each additional square meter of commercial land increases municipal business tax revenue by approximately €13 in Bavaria, underscoring the financial attractiveness of commercial designations. Yet, no comparable evidence exists regarding the extent to which residential development contributes to municipal budget by leveraging income tax revenues, nor how these effects vary across different spatial contexts. This paper addresses these issues by quantifying the relationship between residential land development and municipal income tax revenues across all German municipalities. Given that housing construction is contingent on the availability of zoned residential land, understanding its fiscal impact is essential for assessing whether the perceived incentives align with actual revenue outcomes.

A standard fiscal impact assessment — estimating the number of new residents attracted by a development and multiplying their expected income by the applicable tax contribution per resident — is insufficient to answer this question reliably for three reasons. First, residential development in one municipality may attract residents who previously lived in a neighboring municipality, generating a spatial displacement effect rather than a net fiscal gain at the regional level: the gaining municipality benefits, but its neighbor loses the same taxpayer. Second, municipalities with stronger fiscal positions are more likely to invest in the infrastructure needed to open new land for development (Langer & Korzhenevych, 2018; Buettner, 2023), meaning that observed correlations between land expansion and tax revenues may partly reflect reverse causality rather than a causal fiscal return. Third, the magnitude of the income tax gain depends critically on the income profile of new residents: Germany's progressive income tax schedule implies that attracting higher-income households generates disproportionately larger municipal tax receipts. Accounting simultaneously for these spatial dependencies, potential endogeneity, and cross-sectional heterogeneity in household income requires a spatial instrumental variable regression framework.

Using a comprehensive dataset of 2016–2022 changes in municipal tax revenues, land development measures and control variables, we estimate spatial autoregressive and spatial instrumental variable models that account for regional heterogeneity, spatial spillovers, and potential endogeneity between land-use decisions and fiscal capacity. Our

results show a robust positive association: a one square meter increase in living space is associated with a €47 increase in municipal income tax revenue, on average. To provide a point of comparison, we also examine how expansions in total settlement area – encompassing commercial, residential and infrastructure land – affect total municipal tax revenues.

By providing the first nationwide, spatially explicit evidence on the fiscal implications of residential development, our findings contribute to ongoing debates about local land-use incentives, housing supply constraints and municipal finance. They offer empirical grounding for evaluating whether local fiscal structures create distortions in zoning decisions and whether the long-run returns to residential land are stronger than commonly assumed. Germany offers an unusually informative setting for studying the fiscal effects of residential land development because municipalities face strong budgetary pressures but have limited tax instruments at their disposal. With income tax rates set federally and only the tax multipliers for business and property taxes under local control, population growth becomes one of the few channels through which municipalities can expand their long-run fiscal capacity. Germany therefore represents an ideal laboratory to quantitatively assess the impact of land development on tax revenues. However, the applied methodology can be adapted to other countries and regions, with any necessary country-specific adjustments.

Building on this motivation, we formulate three empirical hypotheses. H1: Residential land development has a significant positive effect on municipal income tax revenues, net of controls for local economic conditions and spatial interdependencies — tested in Section 2.6 and reported in Table 2.2. H2: Living space expansion in one municipality is associated with a negative spillover on income tax revenues of neighboring municipalities, consistent with the spatial displacement of taxpaying residents — tested via the indirect spatial impact measures in Table 2.3. H3: The positive fiscal return to residential development is larger in municipalities with higher average household incomes and in municipalities serving as local administrative and economic centers, reflecting income sorting and agglomeration effects — tested in Section 2.7.2 and reported in Tables 2.4 and 2.5.

The paper is organized as follows. Section 2.3 reviews the relevant literature and situates our contribution relative to existing empirical work on fiscal incentives and land development. Section 2.4 describes the German institutional setting — including the mechanics of municipal income tax distribution, the planning framework governing land designation, and the policy context — which motivates both our research question and our empirical approach. Section 2.5 details the data and variables. Section 2.6 presents the

empirical strategy, including the spatial autoregressive model and the instrumental variable approach used to address potential endogeneity between land development and fiscal capacity. Section 2.7 reports the main results, spatial heterogeneity analyses, and a series of robustness checks. Section 2.8 discusses the fiscal payback framework and policy implications. Section 2.9 concludes.

2.3 Literature Review

Having established in the Introduction that the fiscal returns to residential land development are largely unknown and that spatial spillovers and endogeneity require a regression-based approach, this section reviews what is known from the existing literature about the fiscal consequences of land-use decisions and identifies the gap our study addresses. Much of the classic literature on strategic fiscal interactions has focused on how jurisdictions compete on business taxation or public good provision (Wilson, 1999; Revelli, 2005), typically assuming local discretion over tax rates. Although this assumption does not apply to Germany's income tax system – where rates are federally set – the broader implications of fiscal interaction remain relevant. Yardstick competition models (Solé-Ollé, 2006; Bordignon et al., 2003) suggest that voters compare local fiscal performance to that of neighboring municipalities, generating political incentives that may influence land-use decisions even when local tax instruments are constrained.

More recent empirical contributions have begun to examine how fiscal incentives shape municipal land-use behavior. In Germany, Buettner (2023) provides causal evidence using a regression discontinuity design and shows that municipalities able to retain additional revenues — rather than having them redistributed to fiscally weaker municipalities through Germany's intergovernmental equalization system (described in Section 2.4) — convert significantly more agricultural land into residential and commercial uses. These findings resonate with research in other institutional settings: Gyourko and Krimmel (2021) document that greater local fiscal autonomy in the United States encourages more permissive zoning, while Getzner et al. (2025) find that fiscal surpluses in Austrian municipalities are associated with more extensive land consumption. Although these studies explain why municipalities may choose to expand residential or commercial land, they provide limited evidence on the fiscal consequences – particularly the tax revenue effects – of such expansions. Moreover, none of these studies incorporate a fully spatially explicit revenue analysis or examine how tax-base growth in one municipality may spill over to its neighbors. Our three empirical hypotheses (stated in Section 2.2) address precisely this gap: H1 tests whether the effect is positive on average, H2 tests whether spatial displacement of residents between municipalities partially offsets local gains, and

H3 examines whether income sorting and agglomeration moderate the magnitude of that effect.

The literature is less conclusive regarding whether residential or commercial development is fiscally more advantageous for municipalities. Early German studies (Gutsche, 2003; Reidenbach et al., 2007; Krause-Junk, 2007) suggested that residential development can generate fiscal surpluses under certain conditions, especially in urban areas with strong labor markets. These studies, however, are limited by their regional focus and lack of controls for spatial dependencies or unobserved heterogeneity. More recent work applies more rigorous empirical methods. Clapp et al. (2018), for example, use panel fixed effects in a U.S. context and find that once city-specific heterogeneity is properly controlled for, the fiscal impacts of converting land to residential, commercial, or open space become statistically similar. These findings challenge the traditional assumption that residential land inherently burdens local budgets, although institutional differences – particularly the German system of income tax sharing between national and municipal budgets and its weaker residential property-tax base – limit the direct transferability of such results. The absence of comparable German evidence, despite clear theoretical reasons to expect both income tax and property tax effects resulting from residential expansion, represents a notable empirical gap.

Within the German context, evidence on revenue effects remains scarce. Langer and Korzhenevych (2018) estimate that each additional square meter of commercial land increases municipal business tax revenues by roughly €13 in Bavaria, highlighting the immediate fiscal attractiveness of commercial development. This study, however, is geographically limited to a single federal state, provides no nationwide estimates and does not account for spatial spillovers between municipalities. Crucially, and despite the central role of housing in local fiscal capacity, there exists no empirical evidence at all on the fiscal returns on residential land development – neither statewide nor nationwide. In particular, how residential expansion affects the municipal income tax base, property tax capacity, or related revenues has not been studied systematically, leaving a major gap in understanding how land-use decisions translate into local fiscal outcomes. International studies indicate that the net fiscal effect of residential development is highly context-dependent – Yan et al. (2022), for instance, show that residential sprawl in China can generate fiscal stress – highlighting the importance of analyzing these relationships within the specific institutional environment of Germany.

From a tax policy perspective, Dolls et al. (2025) examine Germany's real estate transfer taxes (RETT) and find that increases in RETT are largely capitalized into lower home prices,

with a one-percentage-point increase reducing prices by roughly three percent. These results are consistent with Eerola et al. (2021), who find that transfer taxes in Finland substantially reduce mobility, thereby exacerbating housing misallocation. Cho et al. (2024) use a calibrated overlapping-generations model to show that replacing stamp duties with property taxes improves welfare and mobility. While these studies deal primarily with tax incidence and behavioral effects, they confirm the importance of understanding how local tax regimes interact with housing markets – an angle we explore through the lens of spatial clustering of tax revenues and economic output.

Infrastructure and service costs are an essential component of this evaluation. Vermeiren et al. (2022) show that dispersed residential expansion in Flanders substantially increases infrastructure expenditures relative to compact development. U.S. studies (e.g., Burchell et al., 2005) similarly document that low-density growth patterns can increase annual local government deficits. These findings highlight that the fiscal implications of residential development cannot be assessed solely on the revenue side; the spatial form of development materially affects the municipal budget balance. By acknowledging the cost side, our study complements the revenue-focused evidence and links the fiscal analysis to broader urban development patterns.

Finally, the methodological sophistication of recent studies has improved the causal identification of fiscal effects. Dolls et al. (2025) use staggered difference-in-differences designs, Buettner (2023) applies regression discontinuity, and Fraenkel and Krumholz (2025) leverage exogenous school finance reforms to assess how fiscal compensation shapes local decisions. Spatial econometrics is also increasingly used to account for spillovers and spatial autocorrelation, particularly in studies like Getzner et al. (2025) and Ruettenauer and Best (2021). Our study builds on these methodological advances by applying spatial instrumental variable regressions to a nationwide cross-sectional dataset, enabling us to identify robust regional patterns and spatial dependencies that influence municipal tax revenues.

In summary, our study contributes to a growing body of literature concerned with the fiscal consequences of land-use. By focusing specifically on residential development and its effects on municipal income tax revenues across all German municipalities, we provide new empirical evidence that complements earlier regional or case-based research. Our approach also adds value by integrating cost-side considerations and offering policy-relevant insights into the financial sustainability of land development.

The comparison of empirical literature (see Table 2.8) shows that existing studies either focus on commercial land (e.g., Langer & Korzhenevych, 2018), rely on regional case studies without nationwide coverage (Gutsche, 2003; Reidenbach et al., 2007; Krause-Junk, 2007), or analyze land-use incentives rather than fiscal returns (Buettner, 2023; Goetze & Hartmann, 2021). Importantly, no prior study provides nationwide evidence on the fiscal effects of residential land development in Germany, nor do existing studies combine causal identification with spatial econometric methods. To the best of our knowledge, our study is the first to address these dimensions simultaneously.

2.4 Institutional Setting

Building on the research gap identified in the literature review, this section describes the institutional framework that governs both land development decisions and municipal tax revenues in Germany — the two variables at the center of our empirical analysis.

Germany comprises approximately 10,786 municipalities, ranging from rural communities of a few hundred inhabitants to cities of over one million. Despite their heterogeneity in size and economic profile, all municipalities share the same core fiscal and planning powers under federal law. Under the Federal Building Code, municipalities exercise exclusive authority over local land-use planning: they decide independently whether to designate greenfield or brownfield sites for residential, commercial, or mixed use, making them the primary decision-makers on residential land expansion. Governance structure varies between two main types. County-equivalent cities exercise both municipal and county-level functions and are fiscally self-contained. county-member municipalities belong to a county, which provides supra-municipal administrative services. In both cases, the core fiscal instruments — business tax, property tax, and the income tax share — are received at the municipal level. Municipalities are required to provide local infrastructure (e.g., roads, drainage, parks) and, in most cases, primary school buildings. The most expenditure-elastic services — secondary education, residential elderly care, and child protection — are primarily financed at the federal state or county level, which means that the fiscal incentive to attract high-income, low-service-demand households is real but partially moderated by this vertical cost-sharing structure.

If we disregard the subsidies that municipalities receive from the European Union, the federal government, and the federal states, for example to implement major infrastructure measures, the municipal budget is primarily defined by tax revenues. According to article 106 of the Basic Constitutional Law of the Federal Republic of Germany, tax revenues are divided between the federal government, the states, and the municipalities. The

municipalities receive the total revenue resulting from business tax and property tax, as well as a proportionate share of revenue from income tax and value-added tax. Figure 2.1 visualizes the average portions of tax revenues within municipal budget. Around 80 percent of the municipal budget depends on how many companies and residents are located in the municipal area and the amount of tax they contribute.

The income tax is the largest person-related source of municipal revenue in Germany, constituting approximately one third of average municipal budgets over our sample period (see Figure 2.1). According to the first paragraph of the Income Tax Act, all income of natural persons with their domicile or habitual residence in Germany is subject to the income tax. This includes income revenues from agriculture and forestry, commercial operations, self-employment, employment, capital assets, renting and leasing, as well as all other income sources. Income tax is a progressive tax, meaning that the tax rate increases gradually as income rises. While income below €12,000 is tax-free, the top tax rate is 45 percent for taxable income above approximately €270,000. Income tax rates are uniform across the entire country. The distribution of income tax revenue is regulated in Article 106(5) of the Basic Constitutional Law of the Federal Republic of Germany. Therein, it is stated that tax revenues are to be distributed between the federal government, the federal states and the municipalities. The Municipal Finance Reform Act defines the municipal share of the income tax revenues at 15 percent. Accordingly, 15 cents of every euro of income tax revenue are passed on to the municipality in which the taxpayer resides. Critically, this share is allocated to the municipality in which the taxpayer maintains their primary registered residence — not where they work. Municipalities therefore have no influence over income tax rates, which are set uniformly at the federal level with a progressive schedule; their fiscal interest lies entirely in attracting and retaining income-earning residents. Municipalities, therefore, have an incentive to develop land and designate building plots to increase their tax revenues. However, decisions on land development are more complex and the potential uses are not independent of one another.

Business tax is the largest item in the municipal budget and accrues entirely to the municipalities. According to the Business Tax Act, any company or business based in Germany is subject to the business tax. Exceptions apply to specific industries, such as infrastructure services, and to small businesses. The tax rate is calculated in two steps based on a company's profit. In a first step, a tax base amount is calculated applying the federal tax rate of 3.5 percent. This tax assessment rate is uniform across Germany. In a second step, the tax base amount is multiplied with a business tax multiplier set by each

municipality. According to Article 106(6) of the Basic Constitutional Law of the Federal Republic of Germany, municipalities have the right to define the business tax rate individually. This enables municipalities to compete in terms of business tax rates.

Property tax revenues account for approximately 13 percent of municipal budget. As with business tax revenues, property tax revenues are also allocated exclusively to the municipalities in which the taxable properties are located (Article 106(6) of the Basic Constitutional Law of the Federal Republic of Germany). The Property Tax Act stipulates that every property within a municipal area is subject to taxation. Exceptions apply to properties for special use, such as churches or public administration buildings. The amount of tax is calculated in two steps, like the business tax. In the first step, a tax assessment amount is calculated as a percentage of the property value. This percentage depends on the usage of the property and is standardized nationwide in the Property Tax Act. In a second step, the actual amount of tax is then determined by applying a multiplier. Municipalities set this multiplier individually. A distinction is generally made between a multiplier for agricultural and forestry land (multiplier A) and a multiplier for all other land (multiplier B).

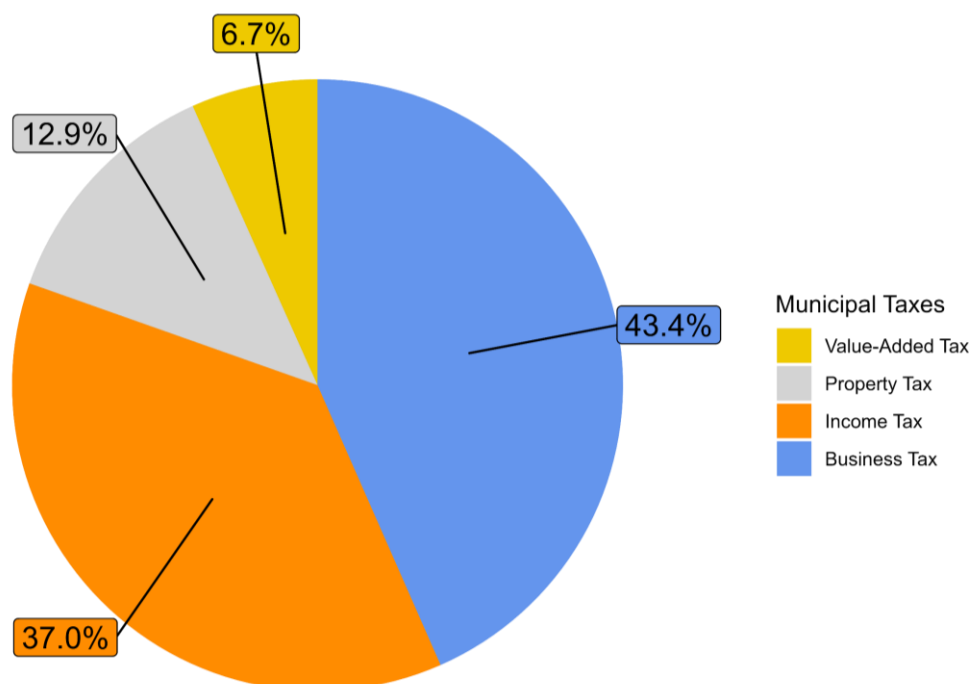
The smallest share within municipal budget refers to the value-added tax (VAT). In principle, all commercial transactions are subject to the VAT. Exceptions apply to transactions that are subject to their own taxes, for example in the transport sector, as well as for specialized transactions listed in the VAT Act. The standard nationwide tax rate equals 19 percent. A reduced tax rate of seven percent applies, for example, to sales of groceries. Revenue from VAT is divided between the federal government, the federal states, and the municipalities. The distribution ratio depends on the amount of revenue generated and is specified in the Fiscal Equalization Act. Within the sample, each municipality received, on average, approximately two percent of the VAT revenue generated within its municipal boundaries.

Two attribution rules govern which municipality receives which tax revenue. For income tax, the principle of residence applies: a 15% municipal share flows to the municipality in which the taxpayer is formally registered as their primary residence under paragraph 1(1) of the Income Tax Act. Taxpayers with multiple properties must declare one as primary; tax authorities have limited discretion to override self-reported registrations. For business tax, the principle of establishment applies: liability accrues to the municipality where the business is located, with multi-site firms apportioning tax across locations in proportion to payroll (paragraphs 28–29 Business Tax Act). One structural counterincentive operates through the horizontal fiscal equalization system: municipalities with above-average fiscal

capacity transfer resources to below-average municipalities, partially clawing back the gains from a growing income tax base. Our revenue estimates throughout the paper should therefore be interpreted as gross effects; net effects, after equalization transfers, would be somewhat smaller in high-capacity municipalities.

In the context of this paper, it is also important to understand the role of municipalities in facilitating land development in Germany. Vacant greenfield or vacated brownfield sites are sold either by the municipality itself or private owners. Land developers are required to draw up and present land-use plans before municipal authorities grant permission based on these plans. Within the framework of their self-administration based on the principle of subsidiarity, municipalities decide whether to change the use of their municipal territory and, if so, in what form. Initiatives such as the EU Soil Strategy for 2030 (European Commission, 2021) seek to influence municipalities' decisions regarding sustainability. The Federal Government's German Sustainability Strategy (German Federal Government, 2025) envisages a reduction in the designation of building land, so that a circular economy for land could apply from 2050 onwards. Henger and Bizer (2010) propose tradable planning permits (TPP) as a market-based instrument for municipalities to steer land designation sustainably. Henger et al. (2023) demonstrate in a field experiment that permit trading can effectively redirect land development toward more sustainably located sites. Despite this evidence, TPP has seen limited adoption in practice — a difficulty that partly reflects the political economy of inter-municipal coordination. We accord TPP particular attention because our spatial spillover results provide a direct fiscal rationale for such coordination: if residential development in one municipality partly displaces taxpaying residents from its neighbors, then uncoordinated municipal planning generates fiscal externalities that supra-municipal mechanisms like TPP are designed to internalize. This sustainability imperative stands in direct tension with the federal government's Baurturbos initiative. In November 2023, the federal government agreed a broad pact with the federal states to radically accelerate planning and approval procedures, aiming to reduce the time from planning decision to building permit and to enable residential construction under simplified conditions (Bundesministerium für Wohnen, Stadtentwicklung und Bauwesen, 2024). This policy direction has been actively reinforced in 2025 accelerating housebuilding as a centerpiece of the current government's housing agenda. The co-existence of a binding land-take reduction target and an accelerated construction mandate illustrates the central policy dilemma our paper addresses: without evidence on the fiscal returns to residential development, municipalities cannot rationally weigh the environmental cost of greenfield conversion against its fiscal benefit.

Figure 2.1 Average Distribution of Tax Revenues in Municipal Budget 2016-2022



This figure displays a pie chart of average municipal tax revenues as parts of municipal budget. We present average values for the observation period from 2016 to 2022. Shown data are calculated as sample mean values. Data source: Federal and State Statistical Offices (2025a).

The municipality is obliged to consider the interaction between different types of land-use in its land development plans. Residential areas, commercial areas, public infrastructure and natural areas are interdependent. Residential areas require commercial areas for local supply and to generate livelihoods. Commercial spaces, in turn, require employees and customers in the surrounding area to survive. Both residential and commercial areas require infrastructure. This, in turn, must be created and maintained by the municipality from its budget and, consequently, from its tax revenues. The municipality's urban land-use planning pursues two major goals. First, to create sufficient living space for its inhabitants. Second, generating sufficient tax revenue to maintain infrastructure and operate sustainably. While empirical evidence on the impact of commercial zoning on tax revenues is already available for the second objective (see Langer & Korzhenevych, 2018), there is a lack of research on the impact of residential zoning on municipal budgets.

The following analysis therefore quantifies the impact of residential development on municipal income tax revenues and compares this with the change in municipal revenues resulting from the general expansion of settlement areas, which includes not only residential areas but also commercial areas and infrastructure.

2.5 Data Description

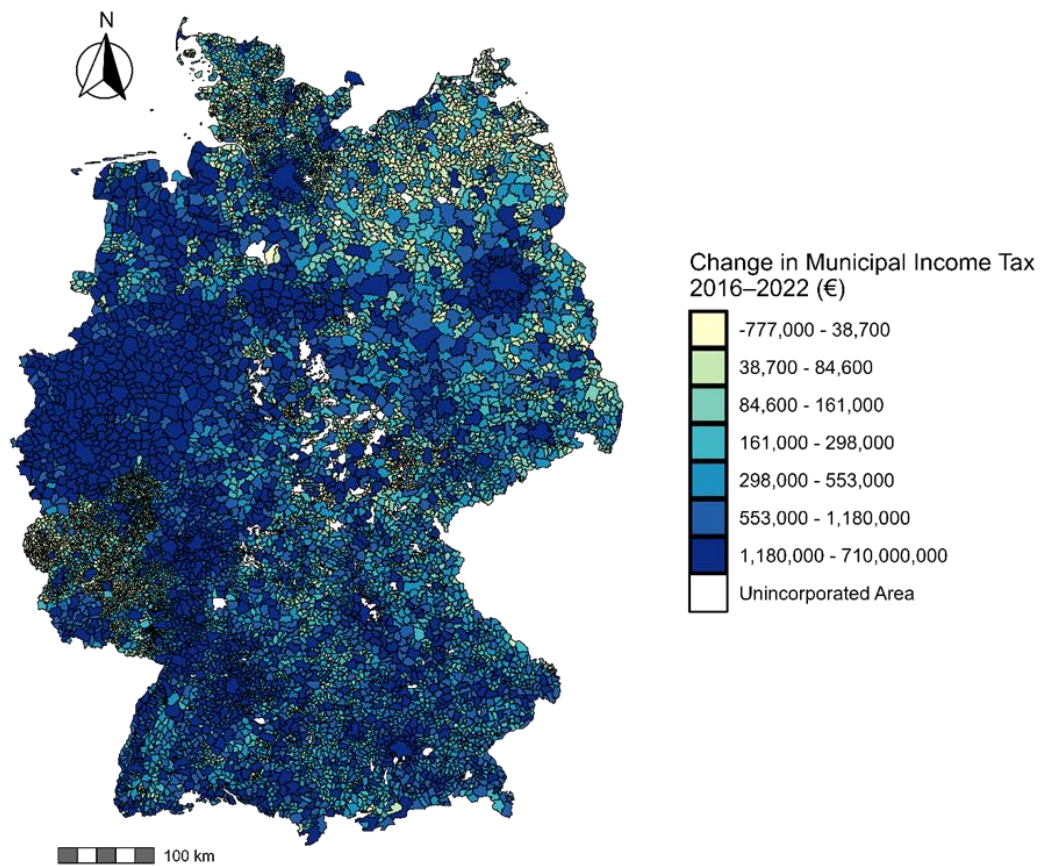
2.5.1 Municipal Income Tax

The institutional mechanisms described in Section 2.4 — in particular the residence-based allocation of the municipal income tax share — make the change in municipal income tax revenues a direct measure of the fiscal return to residential land development. This section describes the data used to operationalize this relationship across all German municipalities.

The income tax represents the largest person-related tax revenue in the municipal budget. Within our sample period, ranging from 2016 to 2022, it is also the second largest amount of all municipal revenues. Figure 2.1 shows, that about one third of the revenues of municipalities in Germany results from income taxation. The data on the municipal income tax revenue is retrieved from the Federal and State Statistical Offices (Federal and State Statistical Offices, 2025a). It covers 10,744 out of 10,786 municipalities in Germany. Missing municipalities are either not permanently domiciled and therefore do not impose income tax, or they do not disclose data on a regular basis. The retrieved sample covers the change in income tax revenue from 2016 to 2022. The data set is limited to this time frame because no more recent data was available at the time of analysis. One important reason for this is likely to be the possibility of filing a tax return retroactively for up to 4 years, stated in the Federal Tax Code. Therefore, definitive statistics on income tax revenues are regularly only available with a delay of four years. The data series is also limited in terms of historical availability, as in 2016 public statistics were converted from the automated property register to the official land cadaster information system. This change in data collection causes a structural break in the time series of public statistics. The surfaces and borders of municipalities have been recalculated, making it impossible to compare them with earlier data (Georg, 2016).

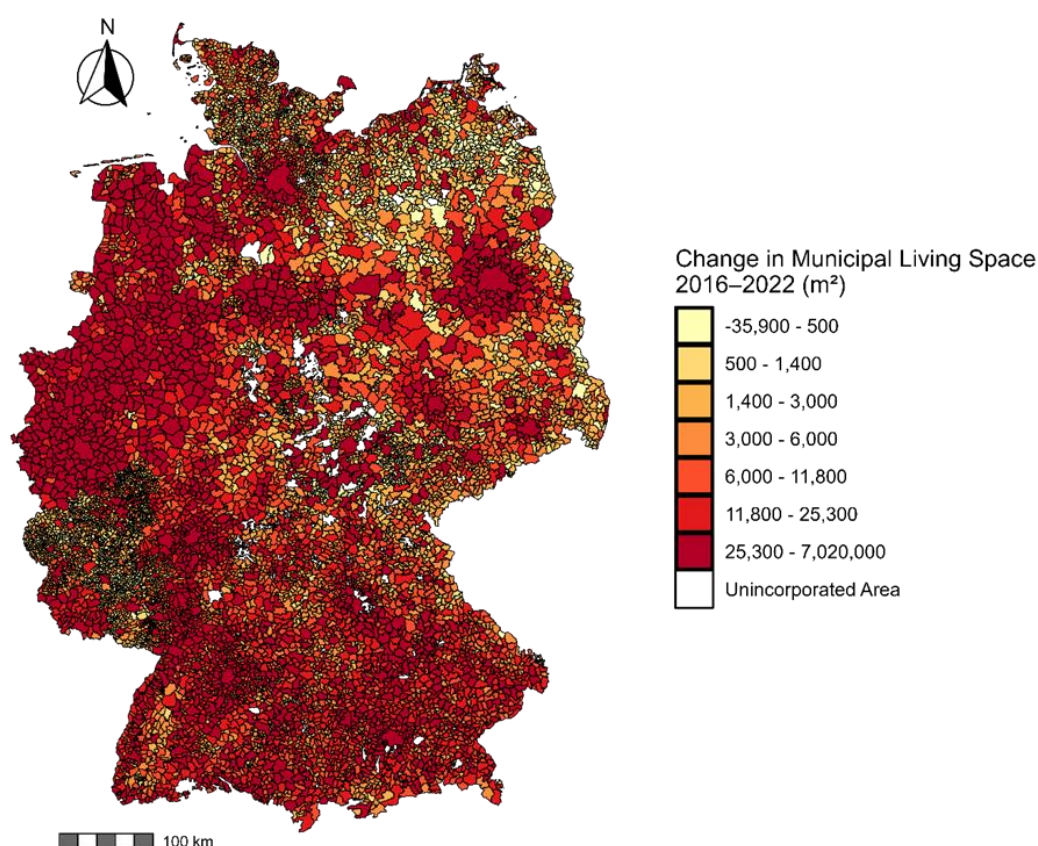
Figure 2.2 visualizes the data coverage and the change in municipal income tax revenues within the sample period for every municipality. Increases in income tax revenues, marked with darker color, as well as spatial clustering are particularly visible in metropolitan areas in the western and southern parts of Germany, as well as in the capital city Berlin in the north-eastern part.

Figure 2.2 Change in Municipal Income Tax Revenue 2016-2022



This figure displays the change in municipal income tax revenues in € between 2016 and 2022. Darker color refers to higher tax revenues increases. Data source: Federal and State Statistical Offices (2025a).

Figure 2.3 Change in Municipal Living Space 2016-2022



This figure displays the change in municipal living space in m² between 2016 and 2022. Darker color refers to higher increases in living space. Data source: Federal and State Statistical Offices (2025b).

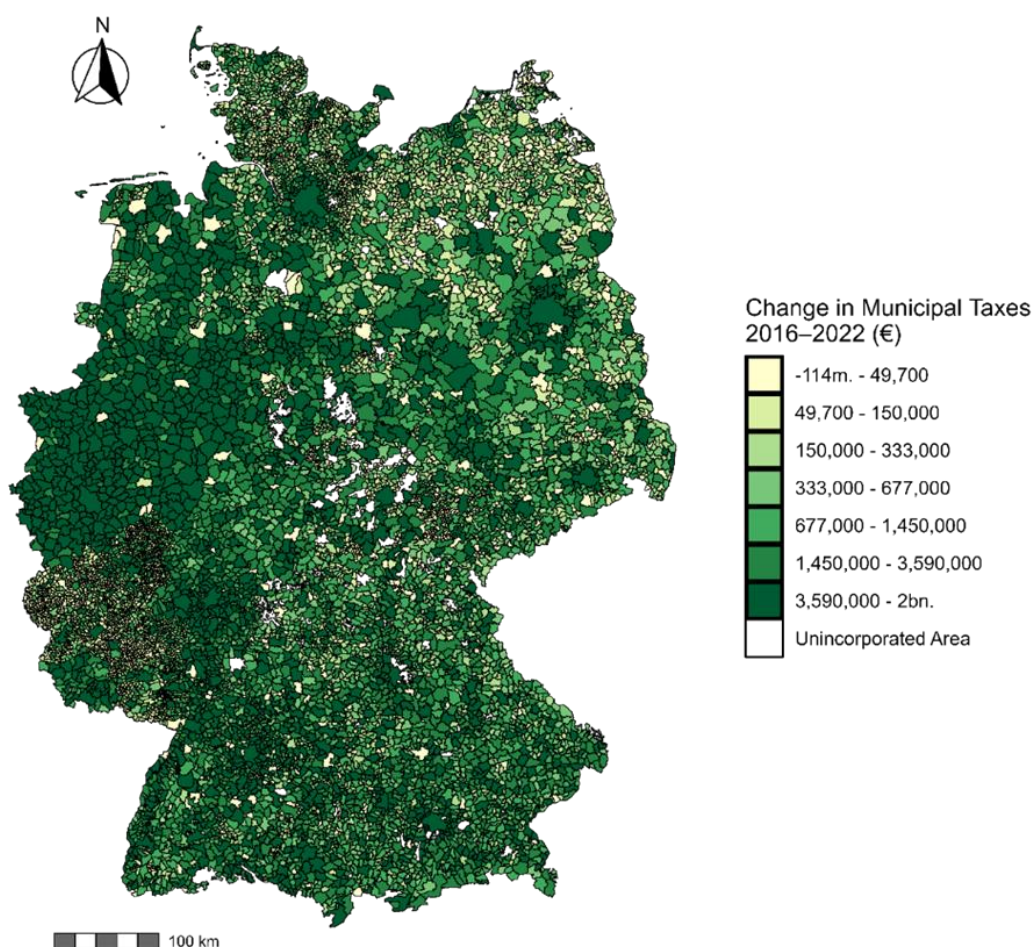
2.5.2 Total Municipal Taxes

To enable a comparative analysis of the impact of land development on municipal tax revenues, the total tax revenues of municipalities in Germany are examined in addition to income tax revenues. Figure 2.1 shows that business tax revenues are the most important share within municipal budget. Property tax and value-added tax complement the municipality's revenue alongside the income tax, whose institutional mechanics are described in Section 2.4. The total municipal tax revenues equal the sum of the four tax revenues depicted in Figure 2.1. The data on the municipal business tax revenue as well as on business tax multipliers is, similarly to the income tax revenue data, retrieved from the Federal and State Statistical Offices (Federal and State Statistical Offices, 2025a). Table 2.9 reports descriptive statistics. The change in tax multipliers within the sample period appears rather small, while the business tax revenues are reported as part of the total municipal tax revenues. The data on property tax revenues and tax multipliers is gathered from Federal and State Statistical Offices (2025a). The changes within the sample, shown

in Table 2.9, indicate that the multipliers are rarely adjusted and largely kept constant. The data on VAT revenues is retrieved from Federal and State Statistical Offices (2025a).

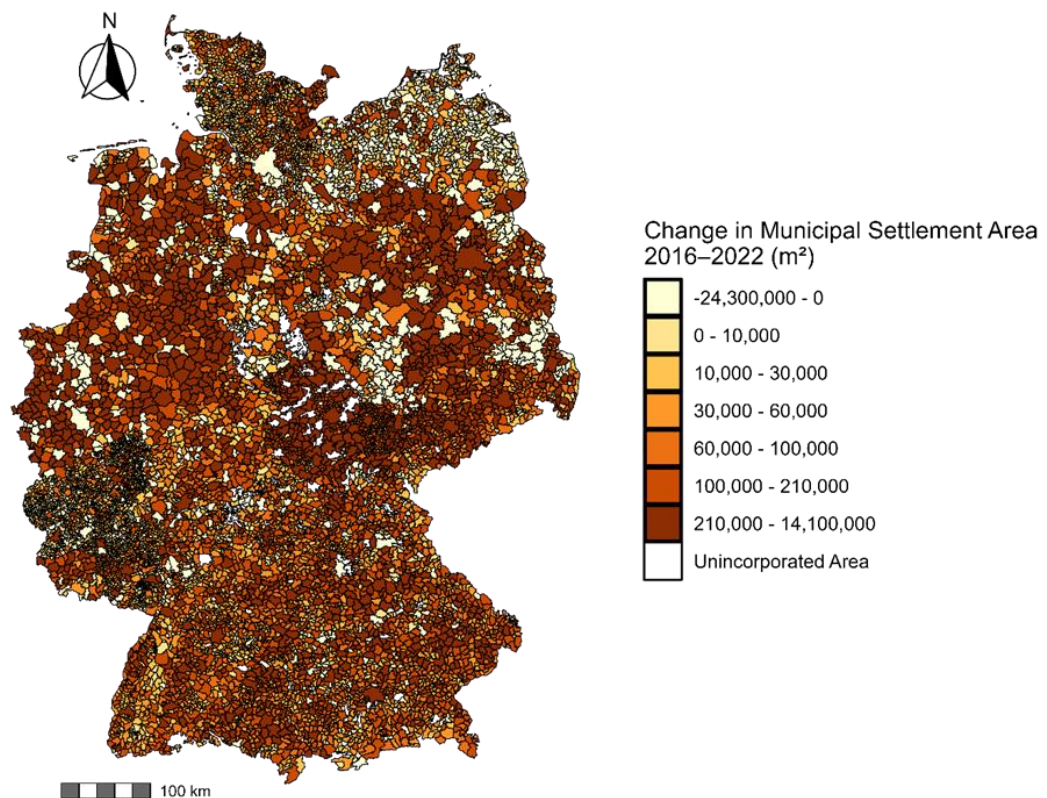
Figure 2.4 visualizes the data coverage and the change in total municipal tax revenues within the sample period for every municipality. Increases in tax revenues, marked with darker color, are again particularly visible in metropolitan areas in the western and southern parts of Germany, as well as in the capital city Berlin in the north-eastern part. Figure 2.4 also makes spatial clustering in terms of higher and lower changes in tax revenues apparent.

Figure 2.4 Change in Total Municipal Tax Revenue 2016-2022



This figure displays the change in total municipal tax revenues in € between 2016 and 2022. Darker color refers to higher tax revenue increases. Data source: Federal and State Statistical Offices (2025a).

Figure 2.5 Change in Total Municipal Settlement Area 2016–2022



This figure displays the change in municipal settlement area in m^2 between 2016 and 2022. Darker color refers to higher increases in settlement area. Federal and State Statistical Offices (2025c).

2.5.3 Residential Land Consumption

Residential land consumption is measured as the change in living space in each of the 10,744 municipalities in Germany during the sample period 2016 to 2022. Living space is defined as the sum of the floor areas of all rooms in an apartment or house. The data on living space is gathered from the residential building and housing stock statistics based on the German Census. This data is updated annually and published with a time delay of about two to three years. Corrective adjustments may be made during the annual data update due to identified data collection errors and plausibility checks. During the period under review, however, only minor retroactive corrections were made. The Federal and State Statistical Offices confirm the temporal and spatial consistency of the data (Federal and State Statistical Offices, 2025b). An increase in living space results from the construction of new buildings on land that was previously not used for residential purposes, or only to a limited extent. Similarly, the conversion of buildings, as well as extensions and additions, increase the amount of living space within a municipality. Figure 2.3 depicts the change in municipal living space in square meters (m^2) for the sample period 2016 to 2022. While living space increased in most municipalities, some municipalities are experiencing a

decline in living space resulting from the demolition of buildings, especially in northeastern Germany. The map visualizes higher increases in living space in darker color. Spatial clustering of higher increases in living space is observed especially around metropolitan areas, like Berlin in the northeastern part or Munich in the southeastern part of Germany.

In the following analysis of municipal income tax revenues, residential land consumption is the independent variable of interest. We aim to estimate the effect of each additional square meter of living space on a municipality's income tax revenue. The initial representation of municipal income tax revenue in relation to living space expansion shows a positive relationship, whose extent is estimated using regression analysis (see Figure 2.18). Also, we analyze the extent to which the municipal income tax revenue effect resulting from the expansion of living space is affected by local conditions, such as household income levels, building land prices, or geographical location. In line with Langer and Korzhenevych (2018), we expect significant spatial heterogeneity in the municipal income tax revenue effects across municipalities.

2.5.4 Settlement Area Land Consumption

Settlement area land consumption is measured as the change in settlement area within the sample period. Settlement area comprises areas dominated by buildings for residential and commercial use, as well as for infrastructure and open spaces in the context of settlement, in particular sports and leisure areas and green spaces. Data on municipal settlement area is derived from Federal and State Statistical Offices (2025c). An increase in this area results from the development of land for settlement purposes or from the conversion of previously agricultural or unused natural areas. Figure 2.5 visualizes the change in settlement area within the sample period as well as the data coverage for 10,744 out of 10,786 municipalities. The map chart shows an increase in settlement area for most municipalities, with some exceptions in the eastern part of Germany. Like residential areas depicted in Figure 2.3, Figure 2.5 shows spatial clustering around metropolitan areas, even though the clusters stand out comparatively less from the overall picture.

In the analysis of total municipal taxes, the change in settlement area is the independent variable of interest. Developed areas can either be used for residential purposes, thereby increasing income tax revenues by accommodating more residents, or they can enable commercial settlements or expansions, thereby increasing commercial and sales tax revenues. In addition, the development of previously undeveloped or sparsely developed areas could increase property tax revenues, as the tax is primarily based on the building area. However, we expect the effect of settlement area expansion on total municipal tax revenue to be significantly smaller than the effect of living space increase on municipal

income tax revenue, because settlement areas, unlike living spaces, include substantial areas designated for infrastructural purposes that do not initially contribute to tax revenue. The initial illustration of the relationship between total municipal tax revenue and settlement area expansion using a scatter plot (see Figure 2.19) supports this expectation.

2.5.5 Control Variables

An analysis of areas in Germany at the regional level, focusing on municipalities, reveals a complex and highly heterogeneous picture. German municipalities range from rural regions with sparse populations outside of agglomerations to urban metropolises with supra-regional conurbations and several million inhabitants in densely populated areas. Therefore, land-use does not proceed in isolation, but is shaped by heterogeneous requirements regarding size, amenities, infrastructure, and other factors that vary locally. The consequences of land development, including the tax implications that are at the heart of this analysis, may vary accordingly. Section 2.4 outlines the assessment of municipal taxes depending on individual economic parameters. If two municipalities with different demographic or economic characteristics undertake the same land development, the fiscal consequences are likely to differ, as these may depend on a variety of local factors, such as household composition, income level, business productivity, or infrastructure provision. To control for potential influences of heterogeneity in municipal characteristics on tax revenues, we include municipal and county-level control variables. Table 2.1 provides an overview of all variables applied and the rationale for their inclusion in the estimation of municipal tax revenue changes.

The change in population density is included to control for agglomeration effects (i.e. higher income sorting and productivity concentration) reported in earlier studies of Luthi and Schmidheiny (2014) and Andersson (2018). Population density is measured as inhabitants per square kilometer and derived from Federal and State Statistical Offices (2025d). The unemployment rate is included as an indicator for economic prosperity and derived from Federal and State Statistical Offices (2025e). We expect an increase in the unemployment rate to be negatively associated with tax revenues, because unemployed inhabitants of a municipality do not pay income tax. The higher the proportion of unemployed residents in a municipality, the smaller the group of taxpayers and, vice versa, the lower the tax revenue. Furthermore, to control for the effect of settlement structures on tax revenues, we include the change in the share of single and double family houses out of all buildings within a municipality into our analysis. This variable is calculated as the ratio between the number of single and double family houses and the total number of buildings. The data is derived from Federal and State Statistical Offices (2025b). We expect

higher shares of houses to be positively associated with tax revenues, because Kuhn and Grabka (2018) find evidence for single or double family homeowners to have higher incomes and wealth, which, in turn, result in higher tax revenues.

As business and property tax revenues are calculated applying multipliers set individually by municipalities, we include the tax multipliers for business tax, agricultural and forestry property tax (A) as well as for all other property tax (B). The calculation method for these taxes suggests a direct correlation between the multiplier and tax revenue, and, therefore, potential reverse causality. Given the absence of significant changes in tax multipliers during the observation period (see Table 2.9), we, however, refrain from adjusting these variables. Bénassy-Quéré et al. (2007), Hasset and Brill (2007) as well as Langer and Korzhenevych (2018) propose a possible way of addressing reverse causality in tax multipliers using time-delayed variables. Regarding data availability, applying this method would have in turn required a shorter observation period. Because the observation period is already limited due to data collection by statistical offices, time-delayed variables were not incorporated in favor of a longer observation period.

At a more aggregated level, we also include county-level data. In accordance with the principle of subsidiarity, smaller and more rural municipalities are assigned to higher-level counties that take on administrative tasks, while larger cities are independent and form their own county in terms of administration. We derive data on employment from Federal and State Statistical Offices (2025l) and include changes in the share of employees in different industries, including manufacturing, construction, trade and tourism, finance, services, and agriculture, to control for local economic structures. The change in the average debt burden ratio is included to control for tax revenue impacts of household debt, since French and McKillop (2016) find evidence for a significant relationship of indebtedness and household income. Data is derived from Creditreform Wirtschaftsforschung (2022). Other socioeconomic control variables include changes in the old-age dependency ratio (Federal and State Statistical Offices, 2025f), average household income (Federal and State Statistical Offices, 2025g), and GDP per capita (Federal and State Statistical Offices, 2025h). The amount of transferred building land and the average transaction price of building land are taken from Federal and State Statistical Offices (2025i) and changes in these variables are included to map regional property prices using proxy variables. Following the evidence of Padovani et al. (2018), changes in the municipal debt per inhabitant is included to address potential impacts of the municipality's financial health on firm locations and tax revenues. Data on municipal debt is gathered from Federal and State Statistical Offices (2025j). We are further in line with Langer and Korzhenevych (2018) by applying changes in taxable turnover as well as the contribution

of individual economic sectors to taxable turnover as additional control variables for local economic conditions in some model specifications. Data on economic output is taken from Federal and State Statistical Offices (2025k).

Table 2.9 contains descriptive statistics for the cross-sectional data set. All data is reported as difference between 2022 and 2016. The variation in variables is significant because of the heterogeneous characteristics of observed municipalities in terms of size, settlement, economic structure as well as geographic properties. We aim for a complete analysis of the German spatial structure and control for neighborhood effects. Therefore, we refrain from removing any outliers from the data set. To map the complex spatial differences among German municipalities, we apply a broad set of control variables. The combined application of a range of economic, social, and financial variables, however, poses the risk of multicollinearity and redundancy. We performed initial tests for multicollinearity by calculating pairwise correlations and variance inflation factors to minimize resulting biases in estimated coefficients. Indications of multicollinearity were addressed by removing correlated variables from the estimation model. Instead of including both the share of workers in the manufacturing sector and the share of workers in the processing sector simultaneously, for example, only one of the two correlated variables is included in the model to avoid redundancy. The resulting data set, displayed in Table 2.1 and Table 2.9, contains no signs of multicollinearity or redundancy.

Table 2.1 Variables and Rationales

Variable	Category	Rationale	Income tax estimation	Total tax estimation
Municipal income tax revenue in €	Taxation municipal-level dependent variable	Depicts change in largest person-related tax revenue in municipal budget	√	×
Total municipal tax revenue in €	Taxation municipal-level dependent variable	Represents change in total municipal revenue resulting from taxes	×	√
Built-up living space in m ²	Land-use municipal-level independent variable of interest	Measures changes in the housing stock and, therefore, the municipality's capacity to accommodate residents, i.e., taxpayers	√	×
Built-up settlement area in m ²	Land-use municipal-level independent variable of interest	Measures changes in the built environment and, therefore, the municipality's capacity to accommodate residents and firms i.e., taxpayers	×	√
Population density in inhabitants per km ²	Socioeconomic control variable	Agglomeration effects may increase tax revenues, e.g. because of higher income and business concentration (Luthi & Schmidheiny, 2014; Andersson, 2018)	√	√
Unemployment ratio in %-points	Economic control variable	Unemployed inhabitants of a municipality do not pay income tax, i.e. the higher the unemployment rate, the smaller the group of taxpayers and, vice versa, the lower the tax revenue	√	√
Share of houses out of all buildings in %-points	Land-use control variable	Single or double family homeowners tend to have higher incomes and wealth, which may result in higher tax revenues (Kuhn & Grabka, 2018); at the same time indicator for changes in settlement structure	√	√
Business tax multiplier in %-points	Taxation control variable	Higher business tax multiplier directly increases business tax revenue	×	√
Property tax (A) multiplier in %-points	Taxation control variable	Higher property tax multiplier directly increases property tax (A) revenue	×	√
Property tax (B) multiplier in %-points	Taxation control variable	Higher property tax multiplier directly increases property tax (B) revenue	×	√
Share of employees in the labor force by sector	Economic control variable	Proportions of economic sectors depict local economic structure, wage-levels and productivity between sectors may differ and thereby affect municipal tax revenues	√	√
Debt burden ratio in %-points	Economic control variable	Controls for tax revenue impacts of household debt, higher debt-levels may indicate lower income tax bases (French & McKillop, 2016)	√	√

Building Homes for Tax Revenues? Spatial Evidence on the Fiscal Effects of Residential Land Development

Variable	Category.	Rationale	Income tax estimation	Total tax estimation
Share of old population in %-points	Socioeconomic control variable	Proxy for non-working or part-time working populations, and thus for local employment, which in turn affects tax bases	√	√
Disposable household income per inhabitant in €	Socioeconomic control variable	Indicator of local purchasing power; increased purchasing power may translate into higher income and consumption taxes	√	√
GDP per capita in €	Economic control variable	Measure of local economic productivity that may influence municipal tax revenue	√	√
Transferred building land in 1,000 m ²	Land-use control variable	Monitors market activity in the local real estate market, which could have a particular impact on property and business taxes	√	√
Price for building land in € / m ²	Economic control variable	Indicator of the local cost of living that could affect location decisions and thus tax bases	√	√
Municipal debt per inhabitant in €	Economic control variable	Municipal debt may affect the municipality's spending capacity and, consequently, firms' and residents' location decisions (Padovani et al., 2018)	√	√
Taxable turnover in 1,000 €	Taxation control variable	Serves as a proxy for economic output; higher economic output may result in higher municipal business tax revenues (Langer & Korzhenevych, 2018)	×	√
Taxable turnover by sector	Taxation control variable	Accounts for size and structural changes in local economies that could be reflected in municipal tax revenues	×	√
Vegetation areas and green spaces 2016 in m ²	Land-use instrumental variable	Serves as a proxy for the municipality's potential for expanding settlement and residential areas (in line with Langer & Korzhenevych, 2018)	√	√

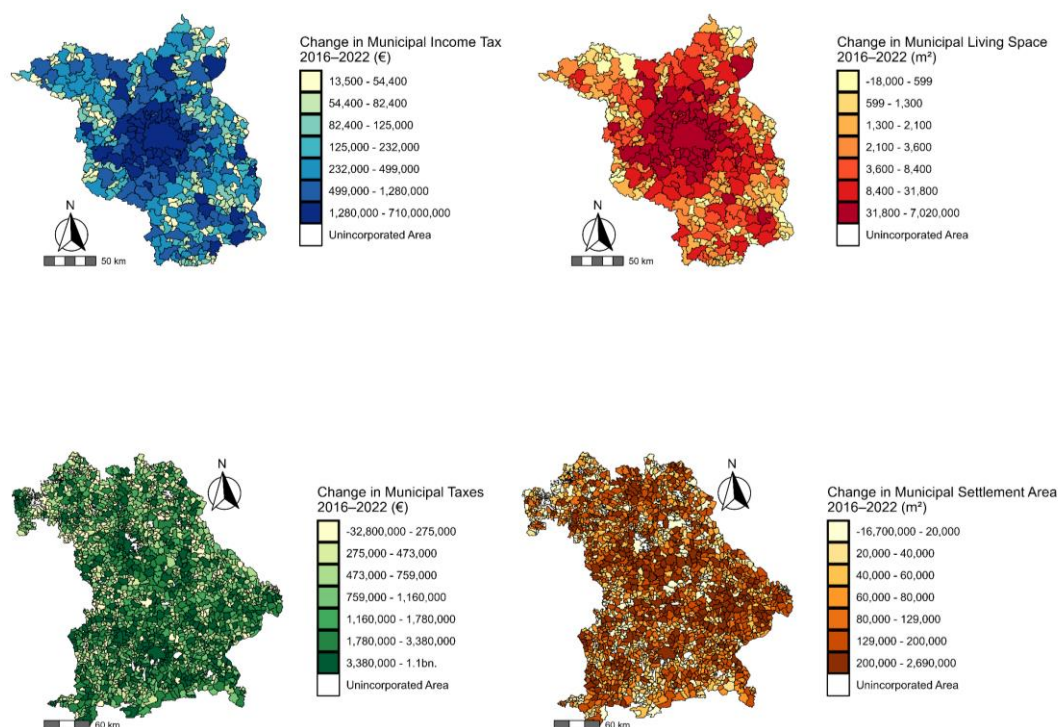
This table presents all variables of our data set and the according rationale for including them in the given model specifications. Monetary variables are in nominal prices and in euro. All variables, except for the instrument, are reported as changes between 2022 and 2016.

2.6 Empirical Analysis

2.6.1 Spatial Regression Approach

The data described in Section 2.5 display pronounced spatial clustering (see Figures 2.2 to 2.5), which motivates the spatial regression framework developed in this section. A closer look at the map sections in Figure 2.6 confirms this observation. The upper row shows substantial clustering of income tax revenues around Berlin. The lower row shows weaker and smaller clusters for total tax revenues in the state of Bavaria. We first establish the presence of spatial autocorrelation, then specify the spatial autoregressive model, and finally explain the instrumental variable strategy used to address the potential endogeneity of land development decisions.

Figure 2.6 Spatial Dependencies Exemplary for Berlin and Bavaria 2016-2022



This figure displays the change in municipal income tax and total municipal tax revenues in € between 2016 and 2022 in the first column, and the change in municipal living space and municipal settlement area in m² between 2016 and 2022 in the second column. Darker color refers to higher tax revenue increases and higher increases in settlement area, respectively. The maps in the first row show the federal states of Berlin and Brandenburg, while the maps in the second row show the federal state of Bavaria. Data sources: Federal and State Statistical Offices (2025a), Federal and State Statistical Offices (2025b) and Federal and State Statistical Offices (2025c).

Earlier studies of Buettner (2003) on spatial dependencies of local tax revenues and Bénassy-Quéré et al. (2007) on local tax competition already provide indications for a spatial component to explain local tax revenues. More recent studies of Janeba and Osterloh (2013) on business tax competition and Trojanek et al. (2021) on spatial patterns in property taxes strengthen this approach. For an analytical assessment of visually

observed spatial clusters, we apply Moran's I test on spatial autocorrelation, first developed by Moran (1950). The test statistics appear highly significant for income tax revenues and total municipal tax revenues (see Table 2.10 and Table 2.11).⁶ The identified spatial autocorrelation appears to be global rather than local. That is, spatial clusters of higher or lower tax revenues extend beyond directly neighboring municipalities. Spatial clustering occurs across multiple municipal boundaries, particularly in metropolitan areas. In line with the approach of Otto and Schmid (2018) dealing with German municipal data, we employ a spatial weight matrix for neighboring properties based on inverse distances. The characteristics of neighboring municipalities are given greater weight the nearer they are located to a given municipality under investigation. The shapefile used to compile the neighborhood matrix was taken from Federal Agency for Cartography and Geodesy (2025). The maximum distance at which neighborhood effects can be identified in terms of municipal tax revenues is 50 kilometers.

To analyze the effect of residential land development on municipal income tax revenues and the expansion of settlement areas on total municipal tax revenues, a spatial autoregressive model (SAR) is estimated in a first step. The global neighborhood effects identified in the preliminary analysis and the established neighborhood matrix are thereby considered. The spatial patterns of tax revenues and land development are approximately identical and primarily determined by metropolitan regions and conurbations. The spatial structure of the data is, therefore, addressed autoregressively for the dependent variable. This approach is based on the findings of Anselin (1988), LeSage and Pace (2009) and Elhorst (2014), which justify a one-time addressing of approximately identical spatial patterns to avoid overfitting and distortions. Consequently, there is no separate control for spatial autocorrelation in the land development variables alone. We apply the following baseline regression equation (1):

$$\Delta Tax_i = \rho \sum_{j=1}^N (W_{i,j} \Delta Tax_j) + \beta \Delta AREA_i + \sum (\gamma_i \Delta C_i) + \delta_i + \epsilon_i \quad (1)$$

where ΔTax_i refers to the dependent variable, i.e. the municipal income tax revenues or the total municipal tax revenues, respectively. The independent variable $\Delta AREA_i$ indicates the developed living space or settlement area, respectively. C_i refers to a $1 \times K$ vector of municipal-level and county-level control variables in a municipality i . Table 2.9 gives an overview of which control variables are included in what model specification. δ_i denotes

⁶ The test statistic is relatively low, but consistently significantly different from zero. According to Zhang et al. (2019), a declining test statistic with an increasing number of observation points in the spatial sample is methodologically determined.

federal state fixed effects. The sum of $W_{i,j}\Delta Tax_j$ describes the properties of neighboring municipalities. W represents the inverse-distances neighborhood matrix, wherein $W_{i,j}$ is the i,j th element of that matrix ($i, j = 1, \dots, N$). ρ measures the response factor with neighboring municipalities. ϵ_i refers to the error term.

We include federal state fixed effects in all model specifications to control for unobserved heterogeneity, such as differing local regulations, topography or exogenous shocks. Heteroskedasticity robust standard errors are applied in all model specifications.

2.6.2 Endogeneity and Instrumental Variable

Based on previous studies on the relationship between land development and tax revenues, there is reason to believe that not only does land development influence tax revenues, but tax revenues also influence land development. In this case, the explanatory variables for land development could not be considered entirely exogenous. Song and Zenou (2006) empirically prove the interdependence of property taxes and urban sprawl in the US. Chapman and Gorina (2012) find evidence for the simultaneity of municipal revenues and infrastructure expenditures. Langer and Korzhenevych (2018) argue that the designation of industrial and commercial land may be dependent on the financial health of municipalities due to the obligation of the municipality to provide necessary infrastructure.

As it cannot be ruled out that there exists a degree of simultaneity between municipal tax revenues and land development, the coefficients of the SAR regression could be estimated in a distorted manner. An instrumental variable estimation can be used to address this endogeneity issue. To conduct an unbiased estimation, the explanatory variables for changes in living space and settlement area must be represented by instruments that are not related to municipal tax revenues. We are in line with Langer and Korzhenevych (2018), who analyze the impact of the expansion of commercial space on business tax revenues of municipalities in the state of Bavaria, using an instrumental variable estimation. Within their study, open space area is applied as an exogenous instrument for commercial space expansion. Using a similar approach, we apply the vegetation area available within municipal boundaries in 2016 as an instrument for both the change in living space within a municipality and the change in the settlement area of a municipality. Vegetation area is defined as the sum of all areas within municipal boundaries that are not used for settlement or infrastructure purposes. This includes agricultural land, forests, heaths, moors, marshlands and other areas without vegetation. Data on municipal vegetation area is taken from Federal and State Statistical Offices (2025c). However, the available government data makes no distinction as to whether vegetation areas are subject to

protection. It therefore cannot be ruled out that protected areas for flora and fauna—such as those designated as Natura 2000 conservation areas in Germany under European Union Council Directive 92/43/EEC of 21 May 1992 on the conservation of natural habitats and of wild fauna and flora—are included within the total area of vegetation. In line with Langer and Korzhenevych (2018), we argue that the vegetation area within a municipality simultaneously represents the municipality's potential for expanding settlement and residential areas. The potential presence of areas designated for nature conservation and environmental protection within the total vegetation area does not inherently reduce this potential, as construction and development projects are permissible in protected areas, provided their environmental compatibility can be demonstrated (see paragraph 34 of the Federal Nature Conservation Act). Furthermore, the municipality's tax revenues are not reliant on its vegetation areas. The only exception to this applies to agricultural land, for which property tax is assessed.⁷ We, therefore, expect a significant positive relationship between vegetation area and living space expansion, as well as between vegetation area and settlement area expansion.

The derived instrumental variable is integrated into the existing methodology using the two-stage least squares method. The potentially endogenous variable is applied to the instrument and all control variables in the first stage. Equation (2) shows the functional form of the first stage regression model:

$$\Delta AREA_i = \alpha VEG_i + \sum (\mu_i \Delta C_i) + \delta_i + \nu_i \quad (2)$$

where $\Delta AREA_i$ refers to the change in living space or settlement area, respectively. VEG_i is the instrument representing municipal vegetation area in 2016. C_i refers to a $1 \times K$ vector of municipal-level and county-level control variables in a municipality i . δ_i denotes federal state fixed effects. ν_i refers to the error term.

In the second stage, we replace the potentially endogenous explanatory variable ($\Delta AREA_i$) with the fitted values of the first stage regression ($\widehat{\Delta AREA_i}$). In addition, the spatially lagged dependent variable $W_{i,j} \Delta Tax_j$ is treated as endogenous. The model is therefore estimated using a generalized spatial two-stage least squares (GS2SLS) approach, in which both $\Delta AREA_i$ and $W_{i,j} \Delta Tax_j$ are instrumented. This results in the functional form as follows:

⁷ The revenue that municipalities derive from agricultural property tax is however so small that it can be disregarded at this point.

$$\Delta Tax_i = \rho \sum_{j=1}^N (W_{i,j} \Delta Tax_j) + \beta \Delta \widehat{AREA}_i + \sum (\gamma_i \Delta C_i) + \delta_i + \epsilon_i \quad (3)$$

where ΔTax_i represents the dependent variables of interest, which are municipal income tax revenue or total municipal tax revenues, respectively. The explanatory variables of interest, change in living space and change in settlement area, are included using instrumental variable estimation. Identification is achieved by instrumenting $\Delta \widehat{AREA}_i$ with the external instruments and their spatial lags, and by instrumenting the spatially lagged dependent variable $W_{i,j} \Delta Tax_j$ with spatial lags of the exogenous variables. To allow for an assessment of instrument validity, the estimation results of the first stage regression as well as the corresponding Kleibergen-Paap F-statistics are displayed in the following regression outputs.⁸

2.7 Results

2.7.1 Estimated Effect of Land Development on Municipal Tax Revenues

We report the results of the spatial IV models specified in Section 2.6, testing each of the three hypotheses stated in the Introduction in turn. The estimation results for the spatial autoregressive models and the instrumental variable regression models are reported in Table 2.2. Therein, columns (1) to (4) report the results of the income tax estimation while columns (5) to (8) contain the estimated coefficients on the total tax revenue of municipalities.

The estimated coefficient on the change in living space on income tax revenue is consistently significant and, as expected, positive. We provide the coefficients of the spatial autoregressive models for comparison but focus on the instrumental variable estimates because of the potential bias in spatial autoregressive models. The instrument is statistically significant throughout and, as expected, results with a positive coefficient. Furthermore, the Kleibergen-Paap F-statistic is significantly greater than the value of 10, indicating, according to Kleibergen and Paap (2006), the strength of the instrument. Spatial impacts are calculated to interpret the coefficients of the spatial autoregressive estimates. These are calculated by applying the neighborhood matrix and the estimated spatial parameter and are categorized as direct, indirect, and total effects. We report spatial impacts in Table 2.3. Direct impacts depict the effect of an independent variable on the dependent variable within a municipality. Hence, the coefficient on the change in living space within a

⁸ The Kleibergen-Paap F-statistic allows to perform an econometric test to check whether the impact of the instrument is significantly different from zero. See Kleibergen and Paap (2006) for a detailed derivation.

municipality increases from 52 €/m² without including control variables to about 60 €/m² when including control variables. The indirect impact refers to the effect of the independent variable of one municipality on all neighboring entities. Referring to models (3) and (4), the indirect effect is significantly negative. Hence, an increase in living space in one municipality results in a decrease in income tax revenues of neighboring municipalities. This is a slight indication of tax competition between municipalities. The negative effect could result from taxpayers moving to housing in neighboring municipalities, causing the municipality of their former place of residence to lose tax revenue. The sum of direct and indirect effect, the total impact, can be interpreted as marginal effect. The nominal coefficient on living space increases from 50 €/m² to about 54 €/m² when including control variables. Considering the cumulated inflation rate of 15.2 percent for the period from 2016 to 2022 (Federal Statistical Office, 2025b), there remains a real increase in the municipality's income tax revenue of, on average, 47 euros per square meter of additional living space (*ceteris paribus*).

The unemployment rate per capita as well as the debt burden ratio show a negative relationship with income tax revenues, while population density, old age dependency ratio and the average transaction price for building land yield positive coefficients. Significance of these variables is, however, unstable. The amount of transferred building land shows a significant negative relationship with income tax revenues, as expected. Contrary to expectations, significant negative relationships emerge between the proportion of houses in a municipality and the average household income. This effect could arise, for example, from larger income disparities within a municipality, which are smoothed out in the average household income. Further explanations could lie in tax avoidance strategies employed by higher income groups, who reduce their taxable income, for instance, through real estate investments. We report the coefficients on all control variables in Table 2.12.

Models (5) to (8) provide the estimated coefficients on the impact of settlement area development on total municipal tax revenues. Focusing again primarily on the instrumental variable regressions, the coefficient on settlement area development appears to be consistently and significantly positive. The results of the first stage and the Kleibergen-Paap F-statistic also show that the instrument is relevant and strong in the context of settlement area and its influence on tax revenues. However, the spatial coefficient switches sign and comes out insignificant. This also results in only the direct and total spatial impacts being highly significant. Within a municipality, an increase in settlement area by one square meter results in an average nominal increase in total municipal tax revenues of €10 without

applied control variables and €14 with control variables applied. The neighboring effects (indirect impacts), however, result slightly insignificant and are therefore not interpreted. Considering the aggregated inflation rate of 15.2 percent (Federal Statistical Office, 2025b), the direct effect of an increase in settlement area by one square meter results in an increase in total municipal tax revenue of €12 in 2016 prices. Referring to applied control variables, population density and taxable turnover show significant positive coefficients and are in line with expectations. Furthermore, the transferred amount of building land as well as the municipal debt result in significant negative coefficients, which is also in line with expectations. Similar to the first regression on the impact of living space expansion on income tax revenue, household income displays a significant negative impact. This could, again, result from income concentration, distortions within average household income, or tax avoidance strategies. All coefficients are reported in Table 2.13.

To compare the results regarding the magnitude of the estimated values, we determine the effect of changes in settlement areas on changes in income tax revenues in a further step. This is done by re-estimating the models described in equations (1) to (3), modified as necessary. The estimation results are presented in Tables 2.14 and 2.15. Referring again to the results of the instrumental variable estimation following the calculation of spatial impacts, a municipality's income tax revenue increases by an average of €2.51 for every additional square meter of settlement area within the observation period. Considering inflation during the analyzed period, this amounts to €2.13 in 2016 prices. The municipal income tax revenue resulting from an expansion of the settlement area thus accounts for approximately 18 percent of the total additional tax revenue a municipality derives from this expansion.

Table 2.2 Effects of Residential and Settlement Development on Tax Revenues

	Income tax				Total municipal taxes			
	(1) SAR	(2) SAR	(3) IV	(4) IV	(5) SAR	(6) SAR	(7) IV	(8) IV
Built-up living space	61.949*** (4.949)	61.671*** (5.024)	52.078*** (2.752)	60.180*** (3.389)				
Built-up settlement area					1.909** (0.945)	2.057*** (0.747)	9.796*** (2.261)	14.146*** (3.266)
Spatial parameter (ρ)	-0.127*** (0.048)	-0.127*** (0.0049)	-0.051* (0.027)	-0.116*** (0.044)	0.611*** (0.142)	-0.233 (0.206)	0.481*** (0.134)	-0.275 (0.205)
Municipal-level controls	No	Yes	No	Yes	No	Yes	No	Yes
County-level controls	No	Yes	No	Yes	No	Yes	No	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,744	10,744	10,744	10,744	10,744	10,744	10,744	10,744
Sigma	1,322,912	1,299,901	1,422,495	1,301,775	22,907,127	19,566,642	23,557,175	21,228,697
AIC	333,389	333,028	334,949	333,059	394,664	391,304	395,266	393,056
BIC	333,520	333,275	335,080	333,306	394,796	391,632	395,397	393,984
First stage results								
Vegetation areas and green spaces 2016			0.0004*** (0.0001)	0.0004*** (0.0001)			0.0034*** (0.0002)	0.0032*** (0.0002)
F-statistic			410.164***	573.729***			201.803***	184.573***

This table presents the results of spatial autoregressive regressions analyzing the impact of land development on municipal tax revenues. The dependent variable in models (1) to (4) is municipal income tax revenue. The dependent variable in models (5) to (8) is the total amount of municipal tax revenues. All variables, except for the instrument, are shown as differences between 2022 and 2016. Models (3), (4), (7) and (8) include an instrumental variable, which is not included in the second stage estimation of the models. Heteroskedasticity robust standard errors are in parentheses. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 2.3 Spatial Impacts for Land Development and Tax Revenues

	Income tax				Total municipal taxes			
	(1) SAR	(2) SAR	(3) IV	(4) IV	(5) SAR	(6) SAR	(7) IV	(8) IV
Direct impact								
Built-up living space	61.957*** (4.937)	61.679*** (4.964)	52.104*** (2.626)	60.273*** (3.583)				
Built-up settlement area					1.918** (0.944)	2.057*** (0.731)	9.881*** (2.158)	14.159*** (3.190)
Indirect impact								
Built-up living space	-6.995 (113.370)	-6.967** (2.746)	-2.511* (1.310)	-6.369*** (2.406)				
Built-up settlement area					2.991 (9.629)	-0.390 (0.365)	11.548 (15.944)	-2.762 (2.676)
Total impact								
Built-up living space	54.961 (113.454)	54.712*** (3.388)	49.593*** (2.144)	53.904*** (2.427)				
Built-up settlement area					4.909 (9.919)	1.667*** (0.561)	21.429 (16.821)	11.397*** (3.147)

This table presents spatial impacts of spatial autoregressive regressions analyzing the impact of land development on municipal taxes. The dependent variable in models (1) to (4) is municipal income tax revenue. The dependent variable in models (5) to (8) is the total amount of municipal tax revenues. Models (3), (4), (7) and (8) include an instrumental variable, which is not included in the second stage estimation of the models. The given coefficients refer to direct, indirect and total spatial impact measures, respectively. Heteroskedasticity robust standard errors are in parentheses. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

2.7.2 Spatial Heterogeneity

The consideration of a large number of heterogeneous cities and municipalities raises the question of how generally observed effects vary between individual regions. Furthermore, findings from earlier studies suggest that the impact on municipal tax revenues varies depending on local conditions. The study by Langer and Korzhenevych (2018) demonstrates that business tax revenues are higher in urban areas than in rural areas. Agrawal and Shybalkina (2023) confirm this observation by analyzing municipal tax revenues generated from retail businesses. Anastasiou et al. (2024) further prove the sensitivity of local tax revenues to local conditions, particularly regarding the economic structure of regions.

We analyze the extent to which the effects of land development on municipal tax revenues differ because of the functional role of municipalities within agglomerations in a first step. For this purpose, we create a categorical variable based on a municipality's administrative status which serves as a proxy for the centrality and urbanity of municipalities. As outlined in Section 2.4, municipalities can be categorized into larger cities with county-equivalent status and municipalities belonging to a county that consolidates administrative tasks within its jurisdiction, based on their urban character and economic prominence within agglomerations. The Federal Agency for Cartography and Geodesy (2024) further subdivides county-affiliated municipalities based on their economic and administrative capacity. Independent municipalities fulfil a central role within agglomerations, but delegate certain administrative tasks to higher-level county administrations due to efficiency considerations. Associated municipalities are subordinate entities within settlements whose administration is handled by community institutions at a broader level. In the following, we distinguish between county-equivalent cities, independent county-affiliated municipalities, and smaller associated municipalities within counties.

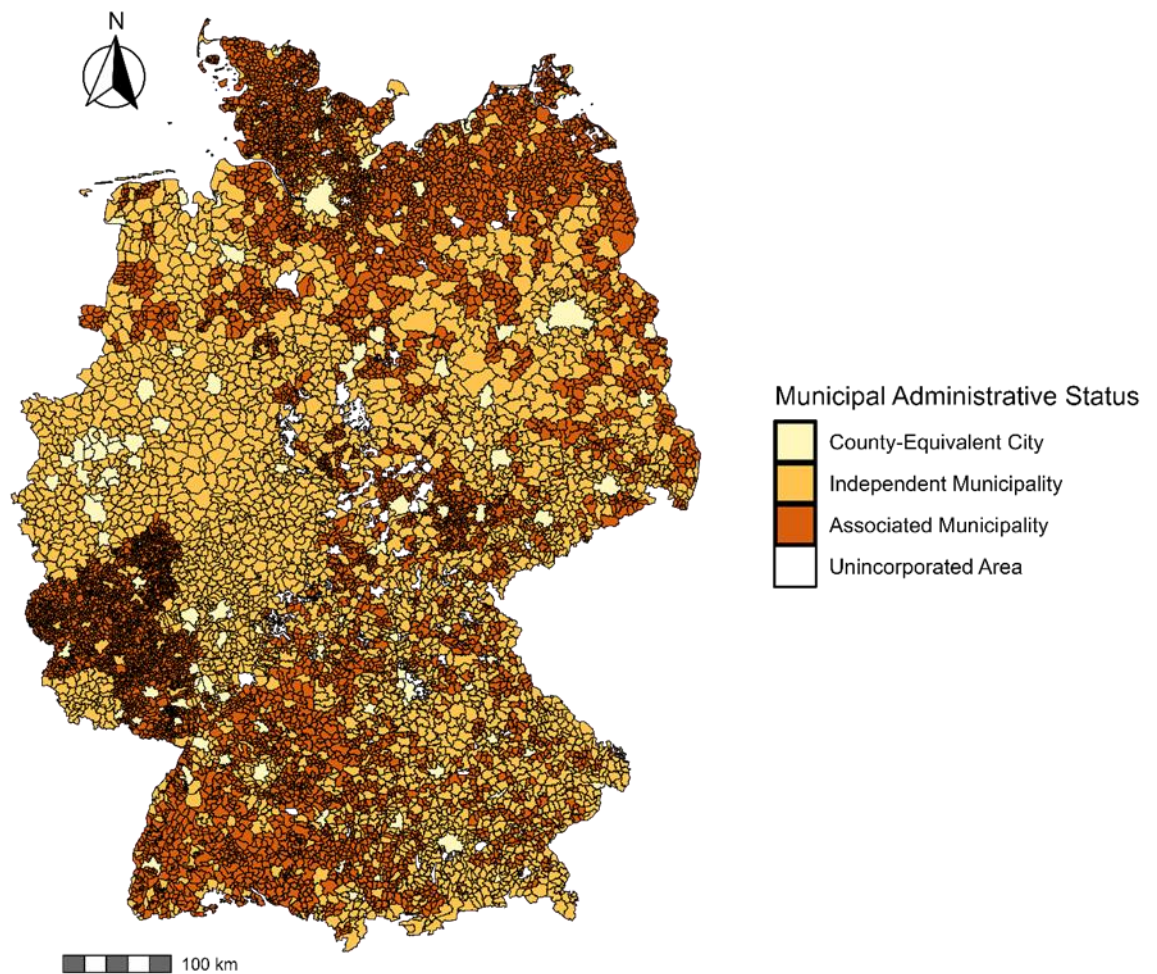
Figure 2.7 shows the distribution of the outlined administrative statuses of municipalities in Germany. It becomes evident that densely populated county-equivalent cities are primarily located in western Germany. Moreover, agglomerations are apparent around major German cities. Creating an interaction term from the categorical variables and the independent variables on the change of living space or the change of settlement area results in positive coefficients only in urban municipalities of central roles within agglomerations. Table 2.4 shows the results of regressions with interaction terms for

income tax revenues, while Table 2.5 shows the results of total municipal tax revenues.⁹ Even though the possibilities for land development in already urbanized areas are limited, this observation seems plausible. Income and commercial turnover are usually higher in central urban areas than in rural areas of minor regional importance (Gornig & Goebel, 2018; Ahrend et al., 2014).

In a second step, we examine whether the average income level has an impact on municipal tax revenues. We, therefore, form quartiles of the sample average disposable income of households per capita. The lowest first quartile serves as the reference category. Figure 2.8 shows the spatial distribution of the average disposable income in the sample. This reveals that there is some overlap between urban regions with higher incomes. However, some more rural regions also show high incomes, particularly in the southern and northernmost parts of Germany. Table 2.4 shows that only in municipalities belonging to the highest income quartile, a significant coefficient on the interaction term is achieved. The positive coefficient illustrates that the designation of living space in municipalities with above-average disposable household income is expected to generate particularly high-income tax revenues from the municipality's perspective. Looking at the effect of settlement area expansion on total tax revenue reported in Table 2.5, it is evident that the coefficients on all interactions with income quartiles are significantly positive. However, again, the coefficient on the highest income quartile is the largest.

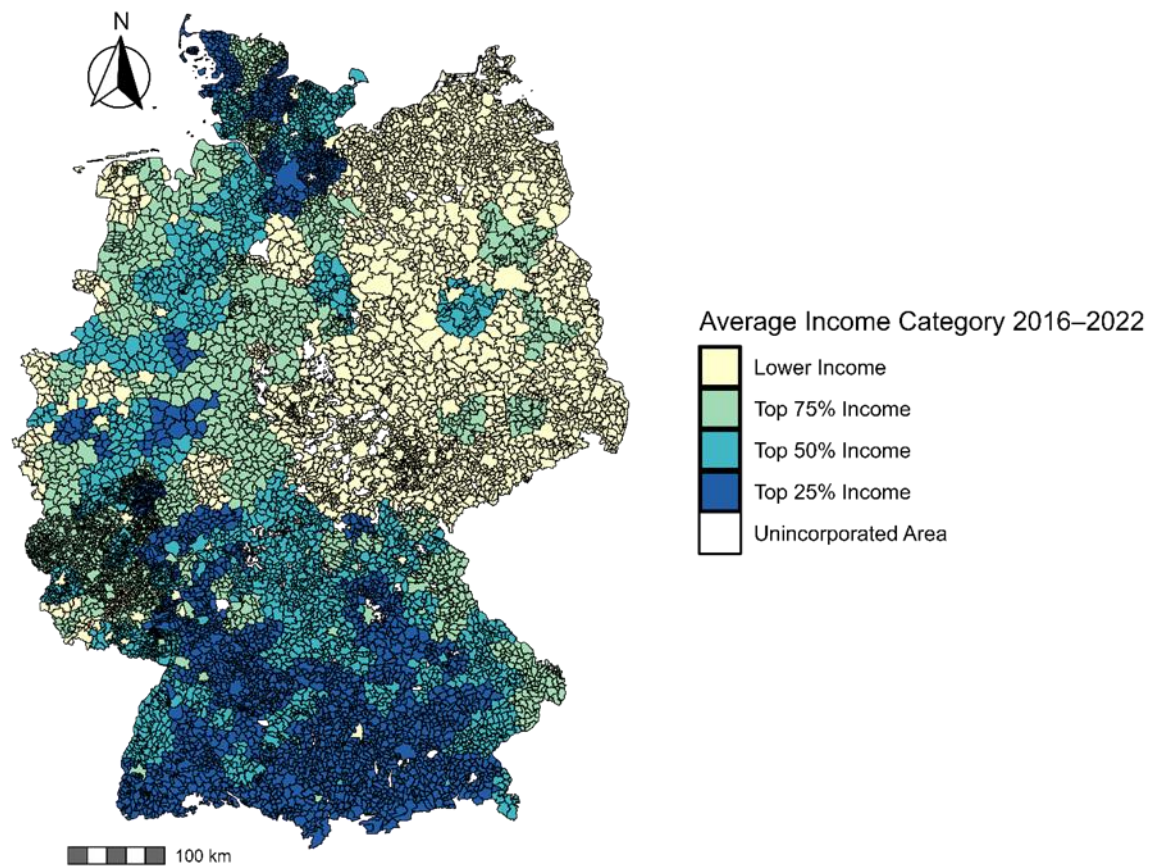
⁹ We report two coefficients in each column. Built-up living space and built-up settlement area refer to the effect of living space development on income tax revenue changes and settlement land development on total municipal tax revenue changes, respectively. The coefficient on the interaction term refers to how the impact on tax revenues changes in a region of interest. The sum of both coefficients refers to the impact on tax revenue changes in the region of interest, addressed by the interaction term.

Figure 2.7 Municipal Administrative Status



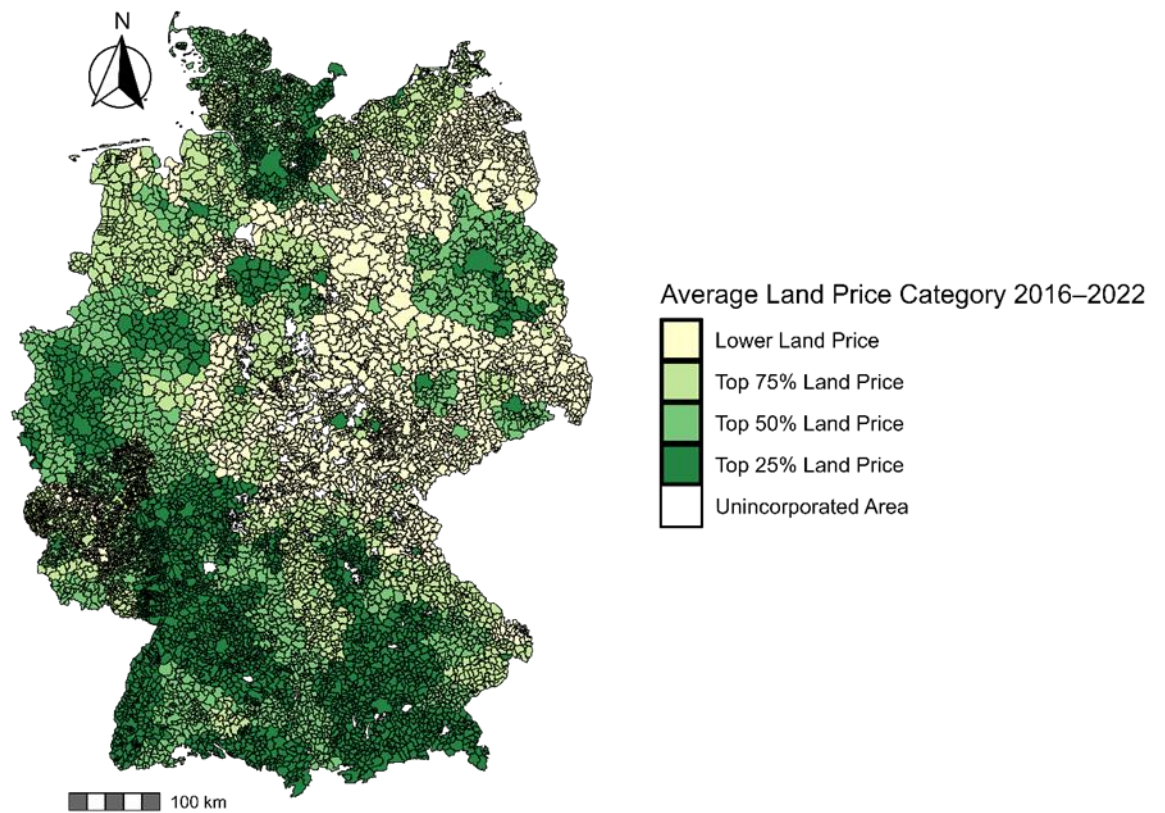
This figure displays categorial variables for municipal administrative status. Sample averages were applied to create categorial variables. Data source: Federal Agency for Cartography and Geodesy (2024).

Figure 2.8 Average Household Income



This figure displays categorical variables for household income on a municipal level. Sample averages were applied to create categorical variables. Data source: Federal and State Statistical Offices (2025g).

Figure 2.9 Average Land Prices



This figure displays categorial variables for building land prices on a municipal level. Sample averages were applied to create categorial variables. Data source: Federal and State Statistical Offices (2025i).

Table 2.4 Spatial Heterogeneity in Municipal Income Tax Estimation

	Income tax								
	(1) County- equivalent cities	(2) Independent municipalities	(3) Associated municipalities	(4) Top 75% income	(5) Top 50% income	(6) Top 25% income	(7) Top 75% land prices	(8) Top 50% land prices	(9) Top 25% land prices
Built-up living space	38.132*** (2.541)	62.967*** (3.455)	63.821*** (3.708)	62.157*** (5.102)	57.681*** (4.462)	56.093*** (2.844)	-13.940 (10.402)	19.174*** (5.364)	29.088*** (2.900)
Interaction term	29.238*** (6.265)	-36.942*** (7.587)	-45.655*** (9.708)	-2.026 (8.469)	5.255 (8.582)	16.498*** (4.825)	77.565*** (12.534)	45.980*** (7.688)	37.837*** (5.559)
Municipal-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial parameter (ρ)	0.062* (0.032)	0.036 (0.033)	-0.077** (0.036)	-0.110*** (0.038)	-0.092*** (0.032)	-0.088*** (0.023)	-0.071** (0.035)	-0.082** (0.036)	0.033 (0.032)
Observations	10,744	10,744	10,744	10,744	10,744	10,744	10,744	10,744	10,744
Sigma	1,106,591	1,184,296	1,258,756	1,316,329	1,282,232	1,241,984	1,185,964	1,164,500	1,149,152
AIC	329,570	331,028	332,339	333,300	332,736	332,051	331,059	330,666	330,381
BIC	329,832	331,291	332,601	333,562	332,998	332,313	331,321	330,928	330,643
First stage results:	0.0003***	0.0005***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***
Vegetation areas and green spaces 2016	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
F-statistic	367.023***	609.677***	352.446***	573.809***	572.448***	564.674***	574.886***	577.894***	581.224***

This table presents the results of spatial autoregressive instrumental variable regressions analyzing the impact of living space development on municipal income tax revenue. The dependent variable in models (1) to (9) is municipal income tax revenue. All models include interactions with the referred dummy variables. Each column reports estimates from a separate regression, in which municipalities outside the category indicated in the column header form the reference group. The coefficient on living space development reflects the effect for the reference group, while the interaction term captures the differential effect for the category indicated in the column header; the total effect for that category is given by the sum of both coefficients within a column. All variables, except for the instrument, are shown as differences between 2022 and 2016. The instrumental variable is not included in the second stage estimation of the models. Heteroskedasticity robust standard errors are in parentheses. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

We analyze the extent to which the local price level of building land affects the impact of land development on municipal tax revenues in a third step. Figure 2.9 shows the spatial distribution of the categories formed for average building land prices in Germany. The map shows that urban municipalities and municipalities with higher household incomes also tend to have higher building land prices. However, considerable differences are evident as well. Municipalities in southern and northeastern Germany, for instance, tend to have higher building land prices, even though they are neither urban nor do they show higher household incomes. This could possibly result from local geographic conditions or infrastructure advantages that increase the price of building land. Running the regression with interaction terms on the categories of building land prices reveals a nuanced picture. While the coefficients on the interaction terms of building land price categories and living space designation reported in Table 2.4 are consistently significantly positive, the absolute magnitude of the effect of living space designation on income tax revenue hardly changes. A different picture emerges for the coefficients on the effect of settlement area designation on total municipal tax revenues, moderated by the categories of building land prices, as reported in Table 2.5. In municipalities with higher average building land prices, the effect of designating settlement areas on municipal tax revenues increases.

Table 2.5 Spatial Heterogeneity in Total Municipal Taxes Estimation

	Total municipal taxes								
	(1) County- equivalent cities	(2) Independent municipalities	(3) Associated municipalities	(4) Top 75% income	(5) Top 50% income	(6) Top 25% income	(7) Top 75% land prices	(8) Top 50% land prices	(9) Top 25% land prices
Built-up settlement area	6.166*** (2.010)	36.813*** (9.510)	20.434*** (6.368)	8.472*** (3.279)	6.882 (4.340)	9.791*** (3.476)	-5.311 (5.080)	-0.490 (2.301)	3.152 (2.071)
Interaction term	-3.953 (8.365)	-38.803*** (11.943)	-33.578** (13.164)	32.562** (12.895)	74.246** (31.451)	94.190** (46.108)	51.740*** (12.066)	63.582*** (13.829)	70.426*** (18.590)
Municipal-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial parameter (ρ)	-0.099 (0.189)	-0.136 (0.206)	-0.234 (0.194)	-0.092 (0.156)	0.020 (0.152)	-0.043 (0.142)	-0.091 (0.213)	-0.050 (0.220)	0.235 (0.176)
Observations	10,744	10,744	10,744	10,744	10,744	10,744	10,744	10,744	10,744
Sigma	18,330,420	24,205,624	22,989,818	22,424,077	21,037,969	21,155,072	24,264,046	23,811,740	22,630,697
AIC	389,904	395,878	394,771	394,235	392,864	392,984	395,930	395,526	394,432
BIC	390,246	396,220	395,113	394,578	393,207	393,326	396,272	395,868	394,775
First stage results:	0.0029***	0.0033***	0.0030***	0.0032***	0.0032***	0.0032***	0.0032***	0.0032***	0.0032***
Vegetation areas and green spaces 2016	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
F-statistic	151.972***	163.344***	134.221***	184.447***	184.905***	182.691***	184.596***	186.147***	185.732***

This table presents the results of spatial autoregressive instrumental variable regressions analyzing the impact of settlement area development on total municipal tax revenues. The dependent variable in models (1) to (9) is the sum of total municipal tax revenues. All models include interactions with the referred dummy variables. Each column reports estimates from a separate regression, in which municipalities outside the category indicated in the column header form the reference group. The coefficient on living space development reflects the effect for the reference group, while the interaction term captures the differential effect for the category indicated in the column header; the total effect for that category is given by the sum of both coefficients within a column. All variables, except for the instrument, are shown as differences between 2022 and 2016. The instrumental variable is not included in the second stage estimation of the models. Heteroskedasticity robust standard errors are in parentheses. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

2.7.3 Robustness Checks

To ensure that the coefficients determined using spatial regression methods are robust, various tests and changes are made to the model setup in the following. All robustness checks are performed both for the estimation of municipal income tax revenues and for the estimation of total municipal tax revenues.

In a first step, a so-called Queen's neighborhood matrix is used instead of the inverse distance-based neighborhood matrix to address the neighborhood relationships between municipalities.¹⁰ This matrix specifies first-order neighborhood interdependencies whenever two municipalities share a common border, regardless of its length. This test serves to verify whether the coefficients determined on the variables of interest, namely built-up living space and built-up settlement area, depend mainly on the configuration of neighborhood relationships between municipalities. However, the coefficients on the variables of interest shown in the first column of Table 2.6 and Table 2.7 are likewise positive and significant at the 1% level. Furthermore, the instrument is positive and significant in the first stage in both model configurations, and the Kleibergen-Paap F-statistic continues to confirm the instrument's relevance.

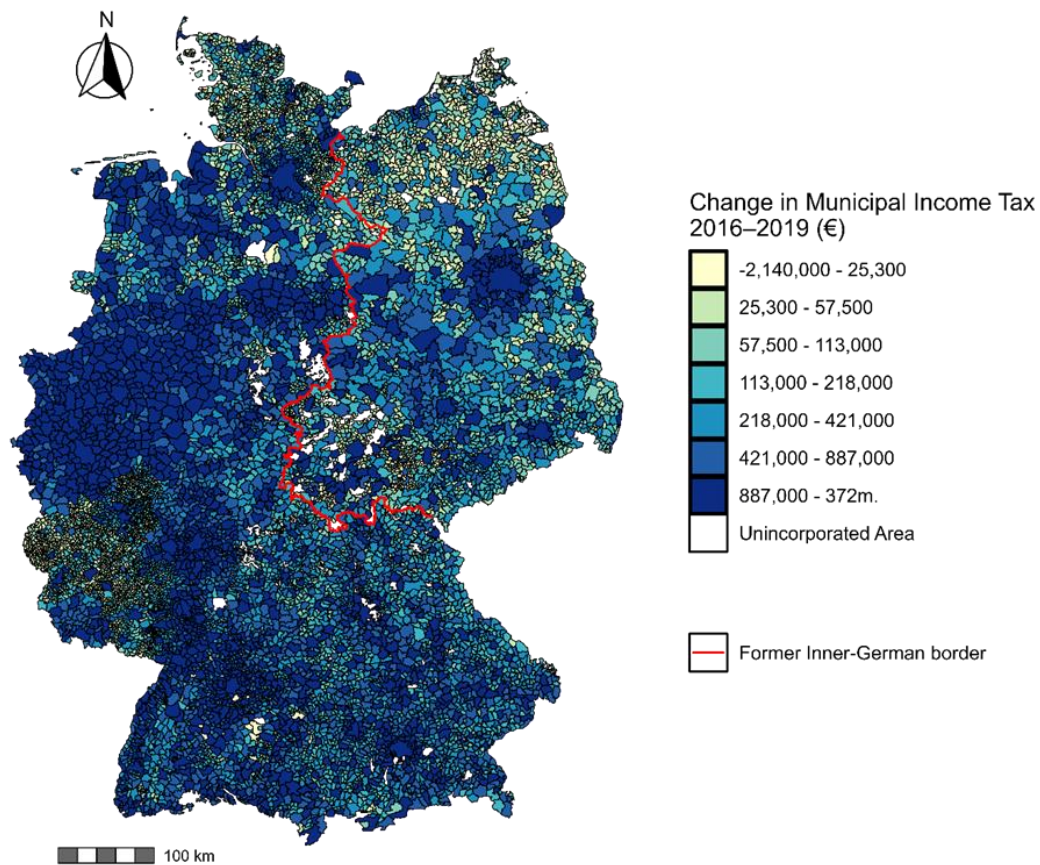
In a second step, we divide the sample time series into two sub-samples. A first sub-sample is formed for the period from 2016 to 2019. A second sub-sample is formed analogously for the period from 2020 to 2022. On the one hand, this test serves to examine the dependence of the results on the selection of a specific time period. On the other hand, dividing the sample by year serves to isolate any potential influence of the COVID-19 pandemic. Clemens and Veuger (2020) forecast declines in tax revenues, particularly in income tax and VAT, due to falling employment figures and declining purchasing power. Chernick et al. (2020) reinforce this forecast and extend it with decreases in property tax. In an initial analysis, Funke and Terasa (2022) determine that short-term reductions in VAT, as seen in Germany at times during the pandemic, initially cost the governments in Germany losses in tax revenue, but that these could be offset by catch-up effects. Figures 2.10 to 2.13 show the changes in income tax revenues and living space in German municipalities for the two subsamples. No significant differences in local dynamics are apparent. Referring to the scales of the diagrams, however, growth in the second subsample spanning from 2020 to 2022 is lower than in the first subsample spanning from 2016 to 2019.¹¹ The estimated coefficients on the impact of living space designation on

¹⁰ The name Queen Matrix refers to the comparison with chess, in which the queen figure can move to any directly adjacent square in a single move (Cliff & Ord, 1981).

¹¹ The small differences may also result from the short time spans and long development periods in construction.

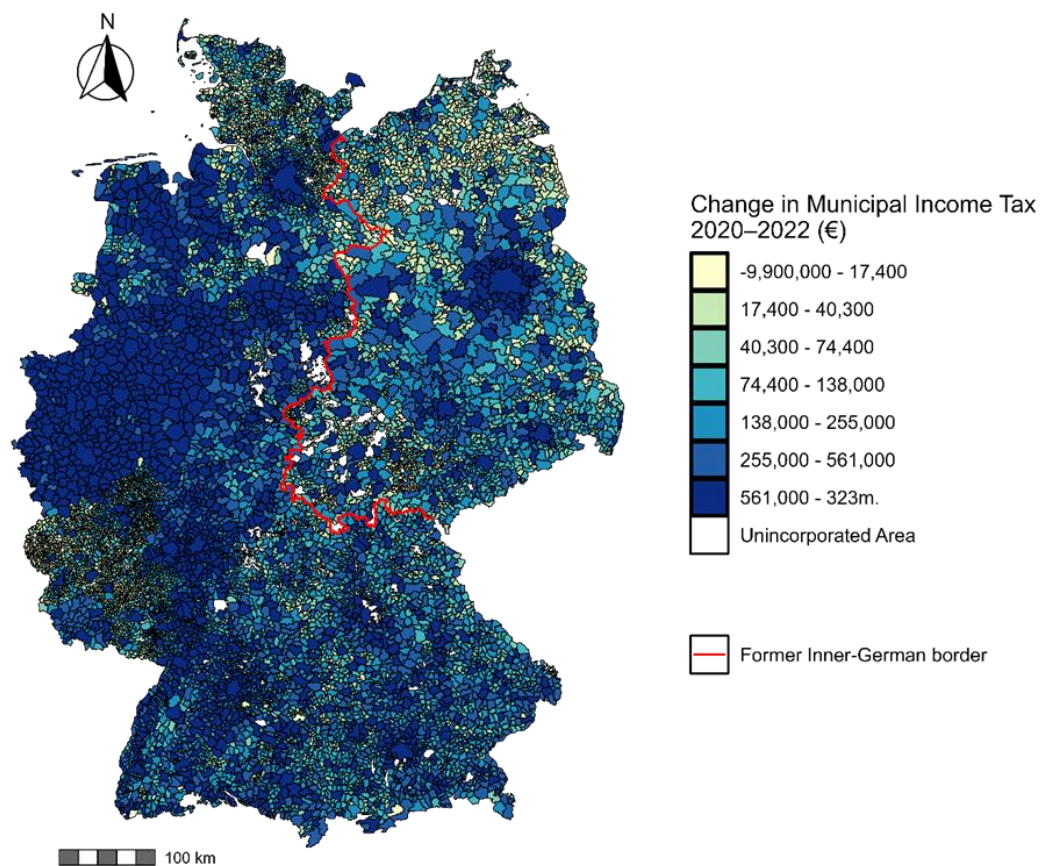
income tax revenue reported in Table 2.6, in columns (2) and (3), remain positive and significant. The spatial parameter turns slightly insignificant but remains negative. The instrument remains significantly different from zero and relevant.

Figure 2.10 Sub-Sampling of Income Tax Revenue 2016-2019



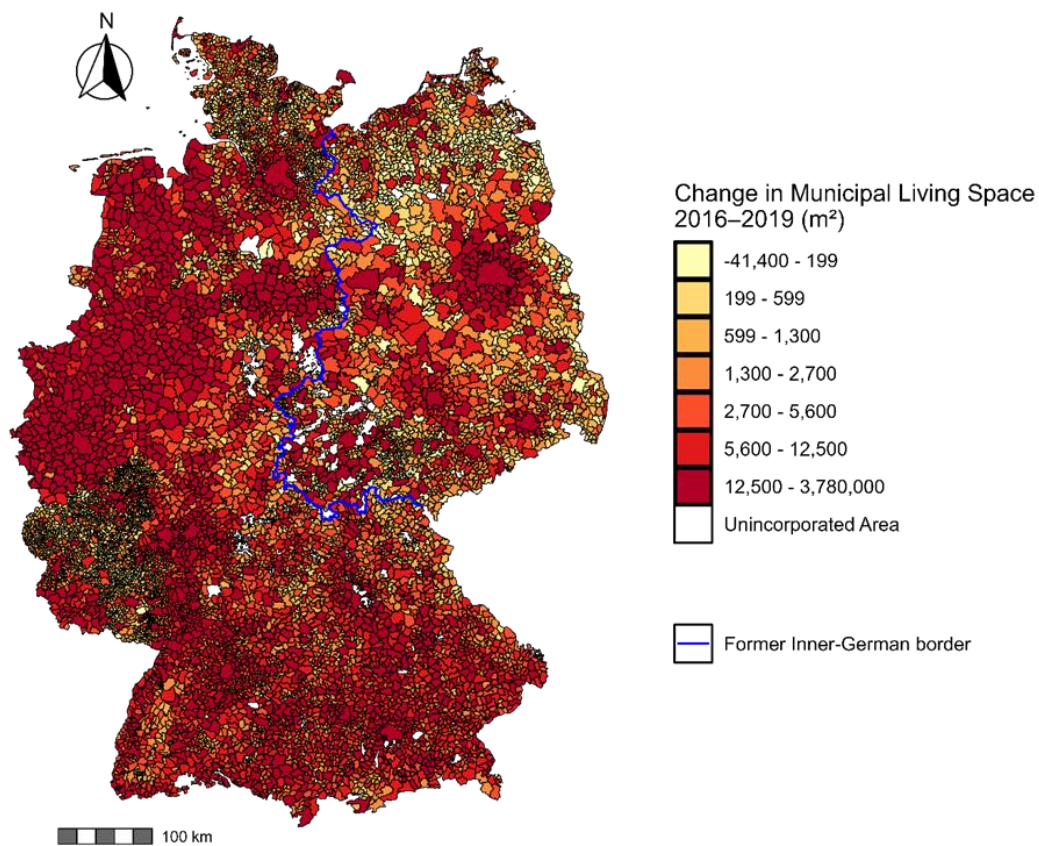
This figure displays the change in municipal income tax revenues in € between 2016 and 2019. Darker color refers to higher tax revenue increases. The course of the former inner-German border is shown in red color. Data source: Federal and State Statistical Offices (2025a).

Figure 2.11 Sub-Sampling of Income Tax Revenue 2020-2022



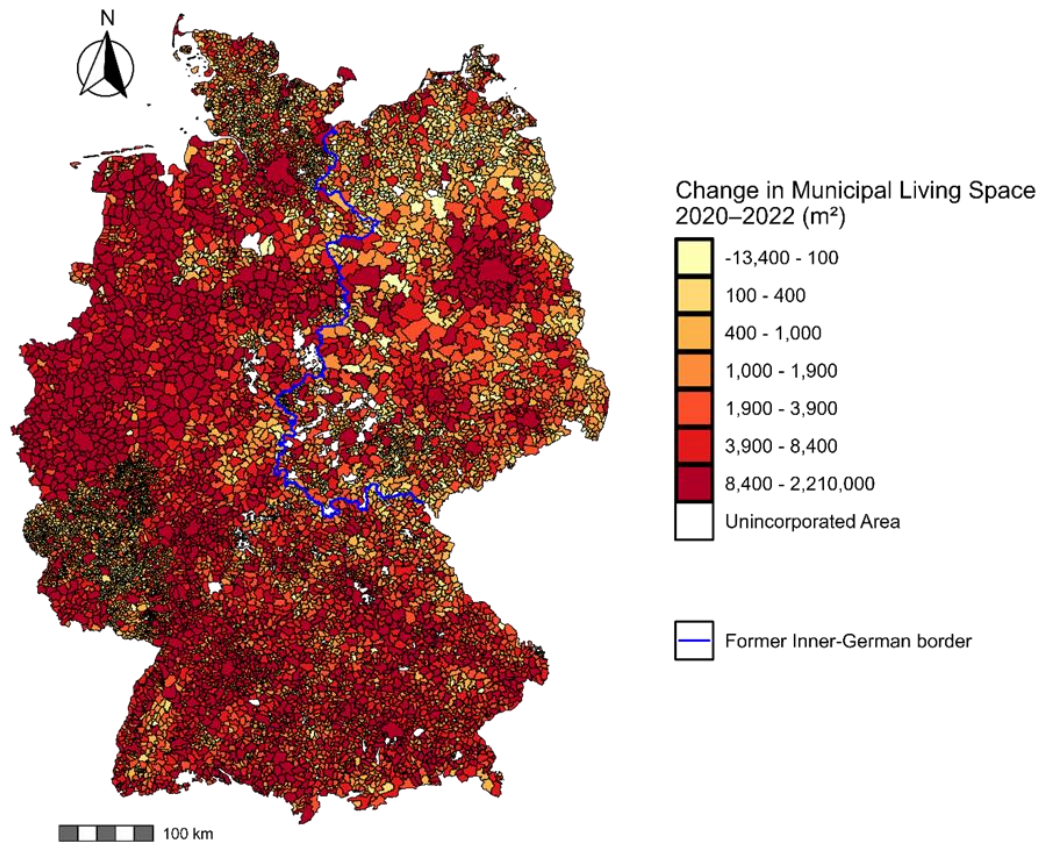
This figure displays the change in municipal income tax revenues in € between 2020 and 2022. Darker color refers to higher tax revenue increases. The course of the former inner-German border is shown in red color. Data source: Federal and State Statistical Offices (2025a).

Figure 2.12 Sub-Sampling of Built-Up Living Space 2016-2019



This figure displays the change in municipal living space in m² between 2016 and 2019. Darker color refers to higher increases in living space. The course of the former inner-German border is shown in blue color. Data source: Federal and State Statistical Offices (2025b).

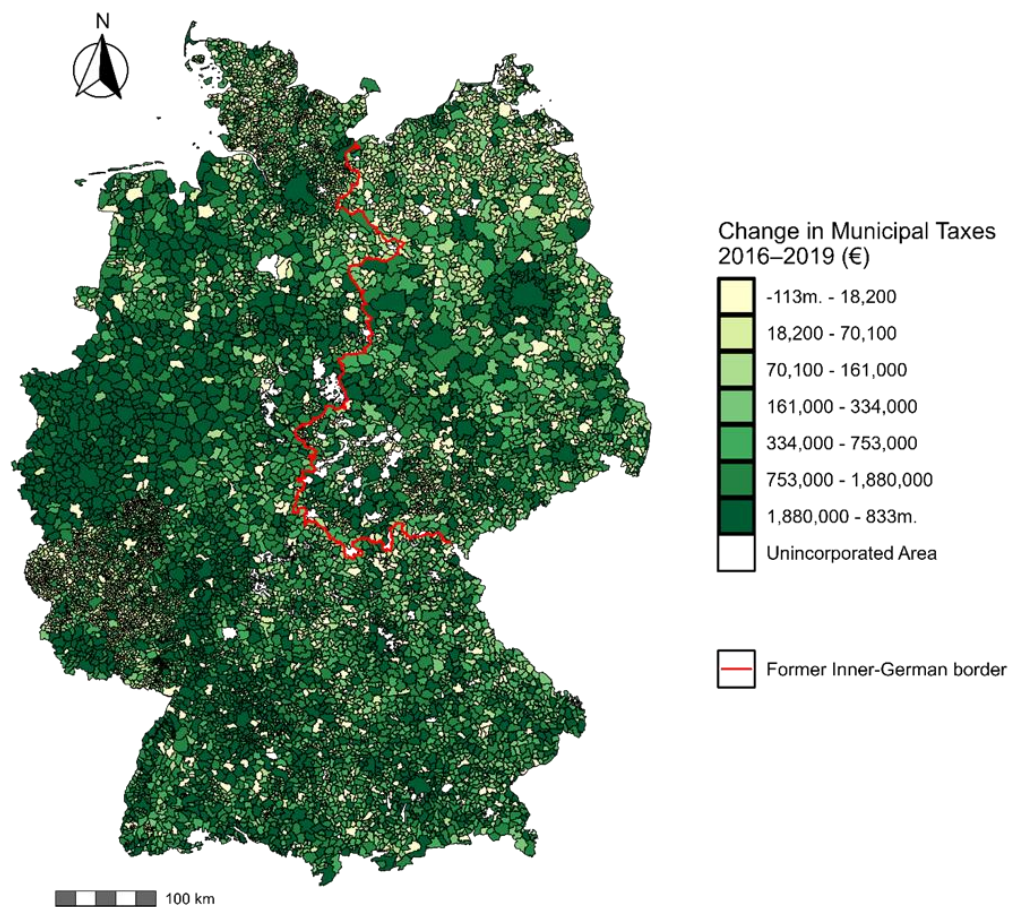
Figure 2.13 Sub-Sampling of Built-Up Living Space 2020-2022



This figure displays the change in municipal living space in m^2 between 2020 and 2022. Darker color refers to higher increases in living space. The course of the former inner-German border is shown in blue color. Data source: Federal and State Statistical Offices (2025b).

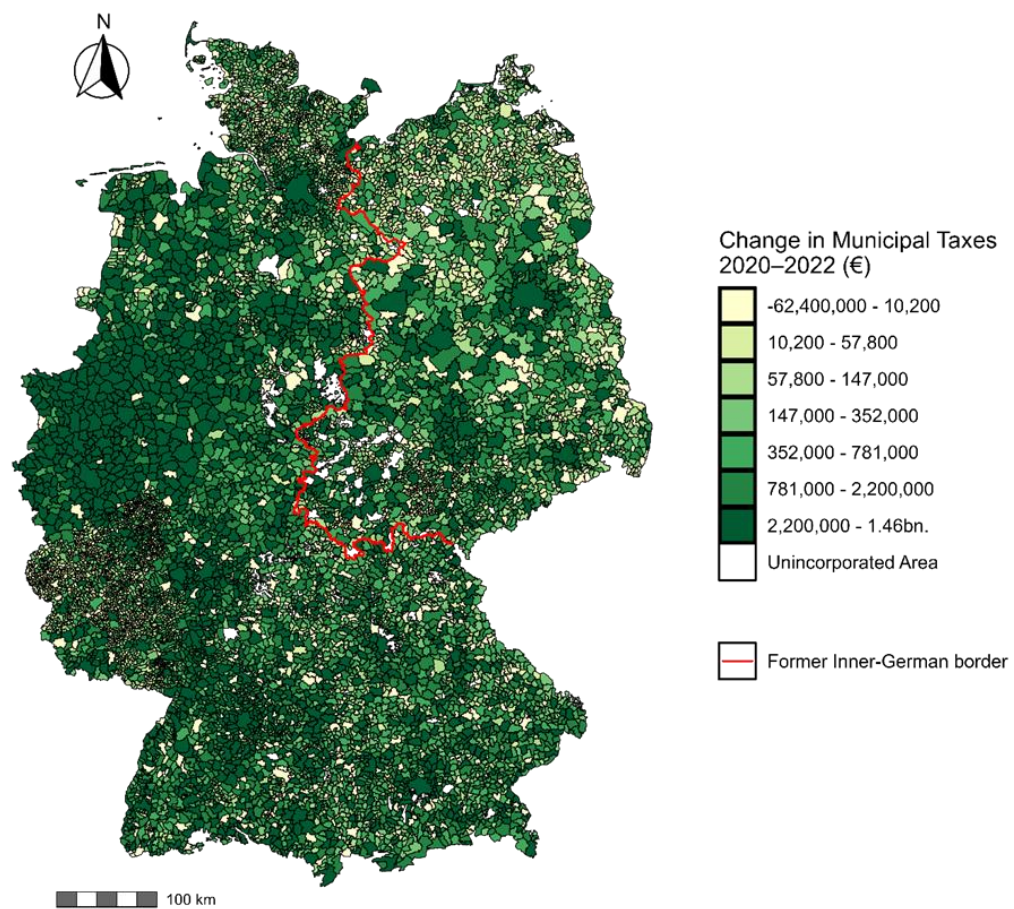
Figures 2.14 to 2.17 show a comparative representation of changes in total tax revenues and changes in settlement area between the subsamples. Similarly, little change in dynamics is apparent. The development of settlement areas stagnates somewhat from 2020 onwards, but only in the central and eastern parts of Germany. Table 2.7 shows the results of subsample regressions. Columns (2) and (3) reveal that the estimated coefficient on the development of settlement area on total municipal tax revenue declines from 2020 onwards. At the same time, the sign of the spatial coefficient turns negative. This suggests that from 2020 onwards, competition arises between municipalities that had previously benefited from agglomeration effects.

Figure 2.14 Sub-Sampling of Total Municipal Tax Revenues 2016-2019



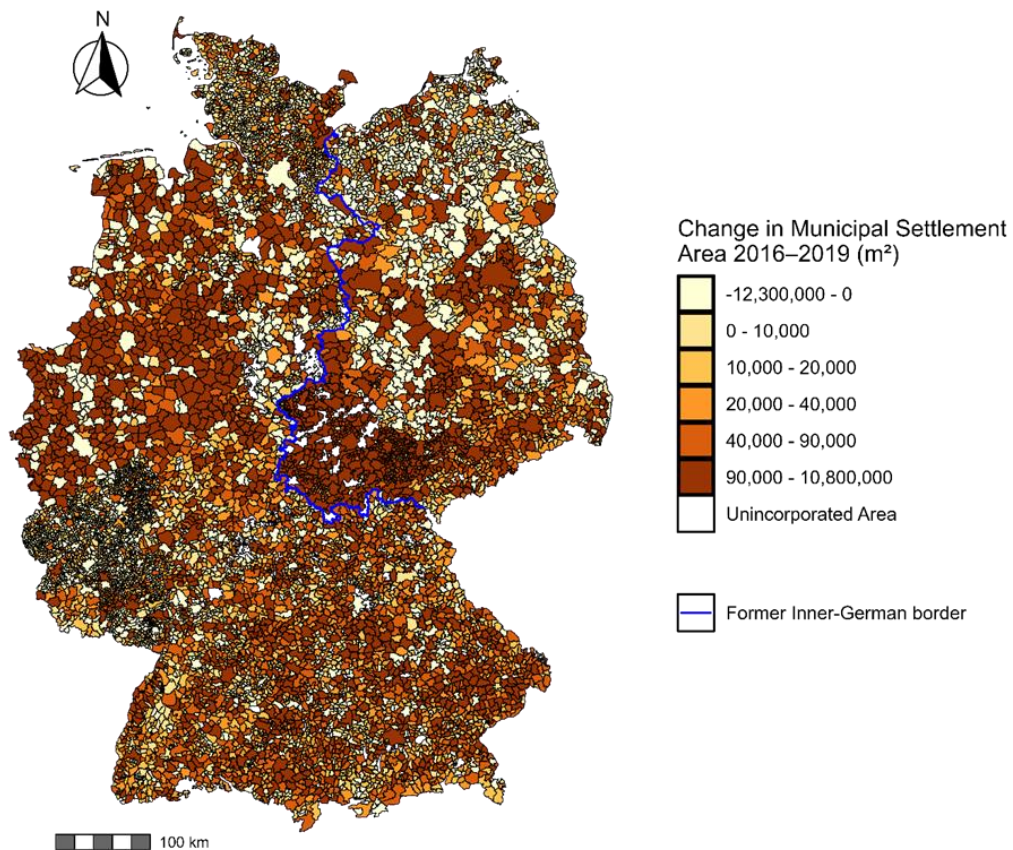
This figure displays the change in total municipal tax revenues in € between 2016 and 2019. Darker color refers to higher tax revenue increases. The course of the former inner-German border is shown in red color. Data source: Federal and State Statistical Offices (2025a).

Figure 2.15 Sub-Sampling of Total Municipal Tax Revenues 2020-2022



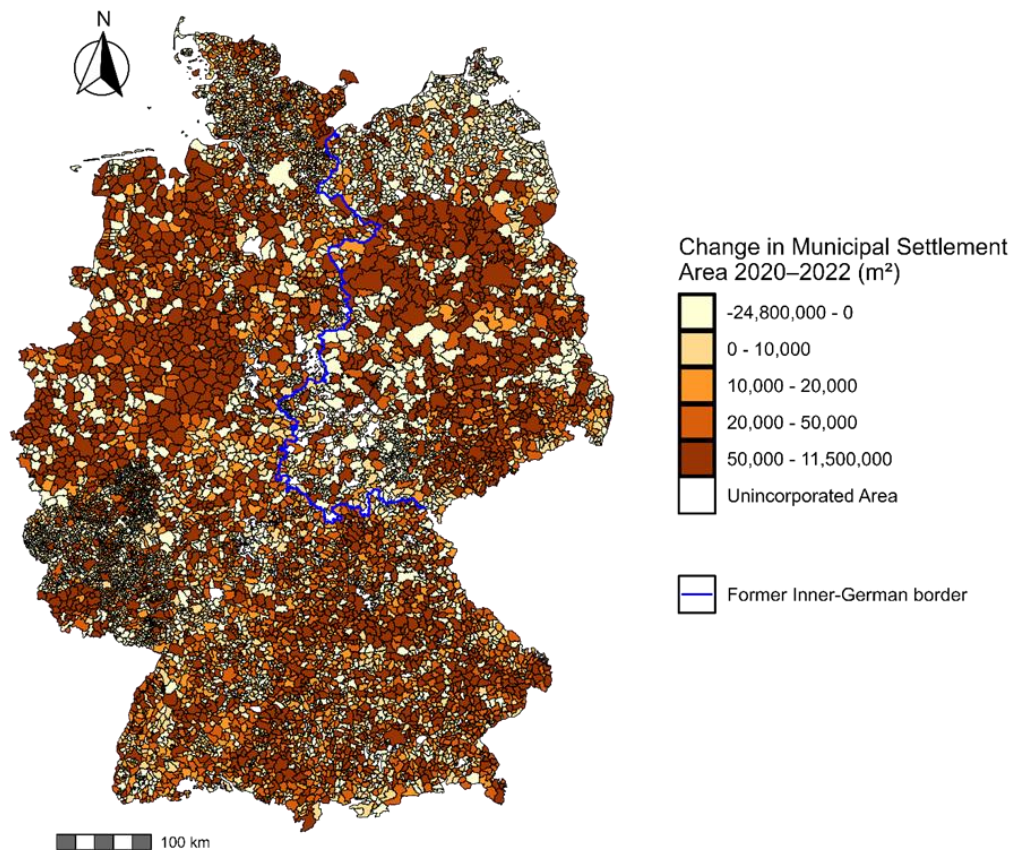
This figure displays the change in total municipal tax revenues in € between 2020 and 2022. Darker color refers to higher tax revenue increases. The course of the former inner-German border is shown in red color. Data source: Federal and State Statistical Offices (2025a).

Figure 2.16 Sub-Sampling of Built-Up Settlement Area 2016-2019



This figure displays the change in municipal settlement area in m² between 2016 and 2019. Darker color refers to higher increases in settlement area. The course of the former inner-German border is shown in blue color. Data source: Federal and State Statistical Offices (2025c).

Figure 2.17 Sub-Sampling of Built-Up Settlement Area 2020-2022



This figure displays the change in municipal settlement area in m² between 2020 and 2022. Darker color refers to higher increases in settlement area. The course of the former inner-German border is shown in blue color. Data source: Federal and State Statistical Offices (2025c).

In a third step, we divide the sample along the former inner-German border to analyze whether any lasting effects of the former division of Germany are apparent in terms of tax revenue analysis.¹² Findings by Bach et al. (2013) regarding income tax revenues in eastern and western Germany after the reunification of the two German states suggest that differences persist. Bossler and Schank (2023) furthermore demonstrate lower wage levels in eastern Germany, which in turn affect income levels, and, therefore, the income tax base. The study by Mertens and Mueller (2022) also suggests differences in business tax revenues, as it demonstrates an east-west divide in terms of taxable turnover. Figures 2.10 to 2.17 show the course of the former inner-German border marked in red and blue color, respectively. In terms of income tax revenue and living space development, visualized in Figures 2.10 to 2.13, growth in the former GDR is lower than in western Germany. The metropolitan region around Berlin is a clear exception. The illustration of changes in total tax revenue and settlement area development, shown in Figures 2.14 to 2.17, reveals

¹² Berlin is assigned to the territory of the former GDR, particularly regarding neighborhood relations. We thus follow the approach of Sunel and Grundke (2025).

similar trends. Table 2.7 shows the results of the subsamples divided along the former inner-German border in columns (4) and (5). The coefficient on the effect of living space designation on income tax revenue is significantly positive in both eastern and western Germany but is greater in absolute terms in the western German subsample than in the eastern German subsample. The instrumental variable is again significantly positive in the first stage, and relevant. The spatial coefficient is significantly negative in the East German subsample, while it is positive but insignificant in the West German sample. This might result from tax competition in eastern Germany on the one hand, but also from the agglomeration effects of the capital city Berlin on the other.

The persistent east-west divide visible in Figures 2.2 to 2.6 and 2.10 to 2.17 reflects three mutually reinforcing mechanisms. First, wage levels in eastern Germany remain substantially below western levels even three decades after reunification (Dickey & Widmaier, 2021; Bossler & Schank, 2023), directly reducing the income tax base available to eastern municipalities. Second, the horizontal fiscal equalization system provides eastern states with substantial intergovernmental transfers that cushion low own-source revenues — but simultaneously reduce the marginal incentive for eastern municipalities to expand their residential tax base, since a larger base reduces equalization entitlements. Third, demographic decline across much of eastern Germany structurally limits demand for new housing, constraining the revenue gains achievable through residential development. Together, these three mechanisms may explain why the regression coefficients on living space expansion are substantially smaller in eastern Germany than in western Germany across all specifications, reported in Tables 2.6 and 2.7.

However, the spatial coefficient might also change because of the lack of neighborhood relationships beyond the former inner-German border in this specification. Regarding the effect of settlement area expansion on total tax revenue, Table 2.7 shows the results of the subsample regressions for eastern and western Germany. This reveals a noticeable difference in the size of the coefficient on settlement area development. The coefficient is substantially larger in western Germany than in eastern Germany. Both coefficients are, however, significantly positive and different from zero. The instrumental variable also remains robust in terms of relevance and significance in the first stage.

In a fourth step, we combine the subsampling by period and by region of the former division of Germany from steps two and three. This allows for a more granular analysis of influencing factors on the main results. Table 2.6 shows the results of the analysis of income tax revenues in columns (6) to (9). The picture from the previous robustness checks is confirmed. While the coefficients on the expansion of living space are significantly

positive in all model specifications, higher coefficients are evident in western Germany. In addition, significantly negative neighborhood effects emerge in eastern Germany. The instrument remains robust in all specifications. The results for total tax revenue differ somewhat and are presented in Table 2.7. Columns (6) to (9) show the results of the combined subsamples. The coefficients on the effect of settlement area development on tax revenue are consistently positive and significant but lose their significance in the eastern German sample from 2020 onwards. Neighborhood effects appear positive in the first period of the sample and turn significantly negative again after the onset of the COVID-19 pandemic. The instrumental variable remains robust in the estimation of total tax revenues.

The robustness checks show that the results of the analysis of total municipal tax revenues are, to a certain extent, driven by positive effects in western Germany. This evidence corresponds to the existing literature on the continuing influence of the former division of Germany on municipal tax revenues (see Bach et al., 2013; Bossler & Schank, 2023; and Mertens & Mueller, 2022). Furthermore, neighborhood effects in municipal tax revenues are evident, as expected. These vary across regions and change over time.

Table 2.6 Robustness Tests of Municipal Income Tax Estimation

	Income tax								
	(1) First-order neighborhood matrix (queen)	(2) 2016-2019	(3) 2020-2022	(4) West Germany	(5) East Germany	(6) 2016-2019 West Germany	(7) 2020-2022 West Germany	(8) 2016-2019 East Germany	(9) 2020-2022 East Germany
Built-up living space	61.765*** (3.834)	80.045*** (4.794)	91.627*** (6.647)	64.581*** (3.348)	46.419*** (2.256)	91.359*** (5.650)	97.882*** (6.792)	59.402*** (3.719)	73.362*** (6.418)
Municipal-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial parameter (ρ)	-0.0073** (0.0031)	-0.068 (0.049)	-0.019 (0.042)	0.040 (0.062)	-0.117*** (0.032)	0.094* (0.055)	0.160** (0.065)	-0.122*** (0.044)	-0.109** (0.046)
Observations	10,744	10,744	10,744	8,369	2,375	8,369	8,369	2,375	2,375
Sigma	1,299,480	1,246,280	757,609	1,198,190	741,081	1,121,518	769,052	791,088	380,788
AIC	333,021	332,123	321,427	258,049	70,964	256,942	250,627	71,274	67,801
BIC	333,269	332,370	321,675	258,246	71,103	257,139	250,824	71,413	67,940
First stage results: Vegetation areas and green spaces 2016	0.0004*** (0.0001)	0.0002*** (0.0000)	0.0001*** (0.0000)	0.0006*** (0.0001)	0.0001*** (0.0000)	0.0003*** (0.0000)	0.0002*** (0.0000)	0.0001*** (0.0000)	0.0001*** (0.0000)
F-statistic	573.729***	374.448***	694.848***	666.701***	41.549***	425.383***	767.665***	31.008***	80.345***
Spatial impacts:									
Direct impact	61.880*** (3.658)	80.435*** (4.579)	91.124*** (6.752)	64.471*** (3.457)	46.347*** (2.378)	91.326*** (5.859)	97.595*** (6.564)	59.126*** (3.671)	72.970*** (6.119)
Built-up living space									
Indirect impact	-0.454** (0.202)	-4.897 (3.750)	-1.440 (3.679)	3.164 (4.116)	-4.459 (3.775)	9.717 (5.963)	19.381** (9.443)	-6.387** (2.622)	-7.140** (3.321)
Built-up living space									
Total impact	61.426*** (3.560)	75.538*** (4.199)	89.684*** (6.538)	67.636*** (4.266)	41.888*** (3.952)	101.043*** (6.269)	116.976*** (11.268)	52.739*** (3.165)	65.830*** (4.757)
Built-up living space									

This table presents the results of robustness tests applying spatial autoregressive instrumental variable regressions to analyze the impact of living space development on municipal income tax revenue. The dependent variable in models (1) to (9) is the municipal income tax revenue. For the full-period specifications, all variables, except for the instrument, are shown as differences between 2022 and 2016; for the sub-period specifications, variables are expressed as differences over the respective intervals indicated in the column headers. The instrumental variable is not included in the second stage estimation of the models. Heteroskedasticity robust standard errors are in parentheses. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 2.7 Robustness Tests of Total Municipal Taxes Estimation

	Total municipal taxes								
	(1) First-order neighborhood matrix (queen)	(2) 2016-2019	(3) 2020-2022	(4) West Germany	(5) East Germany	(6) 2016-2019 West Germany	(7) 2020-2022 West Germany	(8) 2016-2019 East Germany	(9) 2020-2022 East Germany
Built-up settlement area	27.477*** (5.705)	14.781*** (2.710)	7.750** (3.249)	58.380*** (10.869)	2.164** (0.956)	23.309*** (6.045)	110.850*** (36.218)	4.651*** (1.263)	1.293 (0.882)
Municipal-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial parameter (ρ)	-0.079*** (0.027)	0.1549 (0.169)	-0.617* (0.339)	-0.001 (0.307)	-0.086 (0.076)	0.266 (0.252)	-0.362 (0.335)	0.166* (0.088)	-0.218*** (0.075)
Observations	10,744	10,744	10,744	8,369	2,375	8,369	8,369	2,375	2,375
Sigma	26,160,100	10,101,493	19,831,398	28,111,574	6,138,674	10,027,269	31,361,390	5,077,710	4,438,498
AIC	397,545	377,098	391,593	310,874	81,018	293,619	312,705	80,116	79,477
BIC	397,872	377,425	391,921	311,148	81,220	293,894	312,980	80,319	79,679
First stage results:	0.0032***	0.0019***	0.0010***	0.0023***	0.0037***	0.0013***	0.0005***	0.0020***	0.0013**
Vegetation areas and green spaces 2016	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0006)	(0.0001)	(0.0001)	(0.0004)	(0.0005)
F-statistic	184.573***	153.826***	28.226***	205.336***	33.661***	183.227***	26.770***	22.749***	6.870**
Spatial impacts:									
Direct impact	27.917***	14.844***	7.786**	57.967***	2.163**	23.274***	109.964***	4.634***	1.237
Built-up settlement area	(5.433)	(2.665)	(3.172)	(10.549)	(0.913)	(6.170)	(36.617)	(1.282)	(0.922)
Indirect impact	-1.900	3.121	-3.008	6.806	-0.159	168.631	-19.041	1.071	-0.246
Built-up settlement area	(2.584)	(3.949)	(1.903)	(187.140)	(0.331)	(2,630.210)	(90.104)	(1.278)	(0.246)
Total impact	26.017***	17.966***	4.778***	64.774	2.003**	191.905	90.923	5.705***	0.997
Built-up settlement area	(5.443)	(4.396)	(1.810)	(188.688)	(0.853)	(2,630.804)	(90.697)	(1.878)	(0.752)

This table presents the results of robustness tests applying spatial autoregressive instrumental variable regressions to analyze the impact of settlement area development on total municipal tax revenues. The dependent variable in models (1) to (9) is the sum of total municipal tax revenues. For the full-period specifications, all variables, except for the instrument, are shown as differences between 2022 and 2016; for the sub-period specifications, variables are expressed as differences over the respective intervals indicated in the column headers. The instrumental variable is not included in the second stage estimation of the models. Heteroskedasticity robust standard errors are in parentheses. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

2.8 Discussion: Economic Efficiency and Sustainability of Land Development

The results in Section 2.7 confirm a significant positive fiscal return to residential and settlement land development and reveal important spatial heterogeneity. This section translates these findings into a practical payback framework and discusses their implications for municipal planning policy and the long-run fiscal sustainability of residential development.

Earlier studies of Gutsche (2003), Reidenbach et al. (2007) and Krause-Junk (2007) demonstrate the incentive for municipalities to designate building land to generate tax revenue. More recent studies of Langer and Korzhenevych (2018) and Buettner (2023) prove increased tax revenues resulting from land development. The results of our analysis on income tax revenues, reported in Tables 2.2 and 2.3, demonstrate that each square meter of living space designation results in additional income tax revenues of €47. A similar analysis of total municipal tax revenues reveals around €12 in additional tax revenue per square meter of developed settlement area. Our findings thus clearly indicate that the development of living space can result in significant revenue increases for municipal budgets. Even though the development of an additional square meter of living space may require the creation of supporting infrastructure — which explains why the estimated tax revenue effect for settlement area is significantly smaller than the effect for living space development alone—it would be negligent to disregard this revenue potential in urban planning. Based on the results shown, developing commercial land does not appear to provide a clear fiscal incentive for municipalities in Germany in terms of tax revenue compared to residential land-use. Even though a sustainably developed municipality needs a balanced mix of residential and commercial areas (see Section 2.2), an equal consideration of both land uses in terms of municipal tax revenue appears appropriate. Assessing potential tax revenues prior to land-use decisions should involve a comparative analysis of both business tax revenues and income tax revenues to avoid creating misleading incentives. Compared to simple cost-benefit analyses based on static indicators, the spatial regression model described above demonstrates substantial advantages when estimating tax revenues resulting from land-use decisions. Dynamic changes in observation periods and geographic examination areas may be modeled, along with spatial relationships between examined entities, regional disparities, and concurrent effects of various influencing factors.

Besides potential tax revenue, designating settlement areas in general, or living spaces in particular, also entails land development costs for the municipality. Paragraph 123 of the

Building Code stipulates that the municipality is responsible for developing land and maintaining its infrastructure. According to an older but very detailed breakdown by Koeller and Henger (2010), the municipality's development costs include expenditures for traffic infrastructure, drainage, lighting, green spaces, compensation and planning. In terms of economic sustainability, it is therefore important for municipalities to assess the balance between potential income and expenditure. Calculating the payback period provides an appropriate option for this consideration, when assuming constant tax revenues. Considering a municipality's capital costs for development expenditures and inflation-based indexing of potential tax revenues, the following baseline equation (4) allows for a consistent comparison of initial costs and potential tax revenues resulting from land development by expressing both sides in present-value terms.

$$\sum_{t=1}^{t^*} \frac{TR_{m,t}}{(1+i)^t} \cong \frac{I_0(1+r_f)^{t^*}}{(1+i)^{t^*}} \quad (4)$$

Therein, $TR_{m,t}$ represents the potential tax revenue of the municipality m as a function of time t . i denotes the discount rate or, in the illustrated case, the inflation rate. I_0 describes the initial investment of the municipality for the development of land. r_f denotes the capital costs of the municipality. Rearranging the formula for t^* allows to determine the period when tax revenues reach the expenditures for land development.

We provide a numerical example to calculate the payback period of living space development in a municipality, assuming fixed municipal costs and constant tax revenues. We, thereby, apply our main results, reported in Tables 2.2 and 2.3, and use the cost indicators derived from Koeller and Henger (2010) adjusted to the reference year of our analysis, 2022.¹³ The development costs per square meter of living space amount to around €226. Assuming an inflation rate of two percent and municipal capital costs of 2.5 percent, this results in a payback period of approximately 4.5 years.¹⁴ Repeating the calculation for the profitability of general settlement area expansion in relation to total tax revenue of a municipality results in a payback period of approximately 9.2 years.¹⁵ Using a comparable approach, Langer and Korzhenevych (2018) determine a payback period of seven years for industrial and commercial areas. These areas are part of the settlement area we analyze. Accordingly, the proximity of the determined payback periods appears

¹³ We use the Federal Statistical Office (2025c) construction price index for adjustment.

¹⁴ We use the European Central Bank inflation target rate of two percent per annum as a discount rate (European Central Bank, 2025). We use the yield on 30-year government bonds of around 2.5 percent at the end of the reference year as an example for the interest rate for long-term investments (German Federal Bank, 2025).

¹⁵ We, again, apply our main results reported in Tables 2.2 and 2.3. We furthermore assume the development costs for general settlement area to be around 40 percent of the costs for living space designation, in line with Koeller and Henger (2010).

plausible. However, these illustrative examples must be interpreted with caution. Potential tax revenues can vary substantially in time and spatial terms, as described in Section 2.7.2. The potential for income tax revenues is, for example, higher in urban areas than in rural areas. In addition, the costs incurred by municipalities for land development differ substantially depending on the region. Holcombe's and Williams' (2008) analysis of municipal cost structures, for instance, reveals that municipal size and population density have a significant impact on the expenditures required to maintain municipal infrastructure. Goodman (2019) also shows that the expense of creating and maintaining infrastructure depends crucially on the extent of urban sprawl.

Several important caveats apply to this payback estimate. Our calculation assumes constant annual tax revenues and static development costs, whereas the empirical literature — particularly from the United States — suggests that the long-run fiscal trajectory of low-density residential development is often negative. Burchell et al. (2005) document that sprawl development substantially increases cumulative infrastructure expenditures relative to compact growth. Holcombe and Williams (2008) show that larger, lower-density municipalities face systematically higher per-capita costs for maintaining roads, utilities, and public services. Goodman (2019) demonstrates that the long-run expenditure burden of aging suburban infrastructure can more than offset short-run revenue gains. Applying these insights to Germany, our 4.5-year estimate should be understood as a lower bound: municipalities that designate low-density residential land on the urban fringe may face significantly longer effective payback periods as infrastructure maintenance costs accumulate and the resident cohort ages — reducing income tax contributions while increasing demand for locally co-financed services. Our results therefore support residential land development most clearly in urban and higher-income contexts, where density, centrality and income levels combine to produce higher revenues and lower per-unit infrastructure costs.

A further structural qualification concerns the expenditure side. Even if residential development generates a positive short-run fiscal return, this gain may be eroded over time if the expenditure obligations associated with the new resident cohort grow faster than their income tax contributions. In Germany, the most expenditure-elastic services — long-term elderly care and child protection — are primarily financed at the federal-state or county level (see Section 2.4), limiting the direct municipal exposure. However, municipalities bear residual co-financing obligations and face rising political pressure as ageing populations increase demand for locally provided services. A municipality that designates housing predominantly attractive to older in-migrants may therefore find that the revenue gains from the income tax base are partially offset by growing expenditure

claims within a decade of development. Our payback framework does not capture this dynamic and should be interpreted accordingly.

Furthermore, a holistic view of land development should consider environmental aspects. Within our sample period, approximately 500,000 m² of land previously used for agriculture or left in its natural state are converted daily in German municipalities for urban sprawl (Federal and State Statistical Offices, 2025c). Agricultural land and uncultivated areas are scarce resources that must be managed sustainably to preserve biodiversity. Initiatives such as the tradable planning permits (TPP) by Henger and Bizer (2010), described in Section 2.3, demonstrate cross-regional steering elements for sustainable land development. Another approach by Osterburg et al. (2023) is based on maximizing synergy effects between different types of land-use to minimize the sealing of previously unsealed areas.

It is also worth noting that our independent variable in the income tax revenue regression framework — change in living space (m²) — captures two conceptually distinct mechanisms. At the extensive margin, additional living space accommodates more residents, expanding the income tax base proportionally to the income distribution of new arrivals. At the intensive margin, larger housing units — reflecting rising space standards and the preferences of wealthier or older households — tend to attract higher-income residents who contribute disproportionately to income tax revenues under Germany's progressive rate schedule, while making comparatively fewer demands on locally financed services. This second channel may itself be a deliberate municipal strategy is well-founded: zoning for larger single-family housing in suburban or peri-urban locations can selectively attract high-income, low-service-demand households. Our finding that the fiscal return to living space expansion is significantly larger in high-income municipalities (Table 2.4, columns 6–9) is consistent with this income-sorting mechanism. Disentangling the two margins empirically would require parcel-level data on housing type and occupant income not currently available at the national scale; we identify this as a direction for future research.

2.9 Conclusion

This study provides a comprehensive empirical analysis of the fiscal impacts of residential and settlement land development across German municipalities. We apply spatial regression techniques on a cross-sectional dataset of German municipalities, covering the time period 2016 to 2022. The findings of our research are threefold.

First, there is a positive and significant relationship between the expansion of living space and municipal income tax revenues, even after controlling for various economic and demographic factors. This effect averages at around €47 per m² of additional living space. The significant positive effect remains consistent in various robustness tests. However, the coefficient size changes when spatial effects are used for moderation, or subsamples are applied. The effect of living space expansion on municipal income tax revenues is, for instance, greater in western Germany than in eastern Germany. This observation testifies to the lasting effects of the former east-west division of Germany. Compared to their western German counterparts, eastern German municipalities may be more reliant on intermunicipal cooperation to capitalize on additional tax revenue resulting from economies of scale and agglomeration effects. Selective use of subsidies and a reform of the financial equalization system could further contribute to harmonizing the tax incentives for housing expansion in eastern Germany with those of western German municipalities. Tax revenues after 2020 are also slightly higher than in the period from 2016 to 2019. To enable a comparison of the findings on the effect of living space designation on municipal income tax revenues, a further model estimates the effect of expanding a municipality's total settlement area on its total tax revenues. This model expands the income tax estimate by including municipal tax revenues resulting from taxes on businesses, sales and properties. Instead of living space, the adapted settlement area includes land areas used for residential and commercial purposes as well as infrastructure areas. The average effect of designating one square meter of settlement area on the municipality's total tax revenue is estimated at around €12 per m². Given that a municipality can rarely designate living space without creating the associated settlement areas, in particular regarding infrastructure, both effects should be examined together. The significant difference in tax revenue resulting from living space versus settlement area designation, however, suggests that, from the perspective of municipal revenue potential, space-efficient residential development projects are preferable to land-intensive uses, such as industrial warehouses.

Second, spatial connections are identified, indicating that municipal tax revenues and land development of neighboring municipalities are not independent of each other. Given the significant spatial effects observed, it is evident that municipalities do not exist in isolation. Local governments should collaborate across municipal borders, to optimize land-use and infrastructure projects. The interconnectedness of municipalities also reinforces the potential efficacy of mechanisms that can promote a more coordinated and optimal land-use approach across regions, such as tradeable planning permits or inter-municipal land-use concepts. However, spatial relationships may also exist within municipalities that could not be modeled in this analysis due to a lack of data. Neighboring city districts may, for

instance, be interdependent, or effects of urban sprawl may alter the cityscape, and, thereby, a municipality's tax revenue.

Third, the results obtained provide evidence on average tax revenues of municipalities resulting from the designation of living space or settlement areas. Conducted tests for spatial heterogeneity have already shown that the results can vary significantly depending on their location. For instance, tax revenues resulting from land development in urban areas and in areas with higher incomes and higher prices for building land tend to be higher. Other factors, such as subsidies, surcharges, compensatory measures, local cost structures, environmental protection impacts, and infrastructure requirements may influence individual decisions on the designation of living space or settlement areas. The results of this study, however, provide a clear incentive for municipalities in Germany to consider potential tax implications of land use during the urban planning process. A thorough assessment of municipal costs and benefits should therefore compare all forms of land use, particularly residential and commercial. Although our findings are based on historical data and present average estimates, there is an incentive to reduce the housing shortage in Germany due to additional municipal revenue. Why the designation of residential development areas in Germany still falls short of demand, and whether a lack of awareness of existing incentives or other factors contribute to this, remains subject to further research.

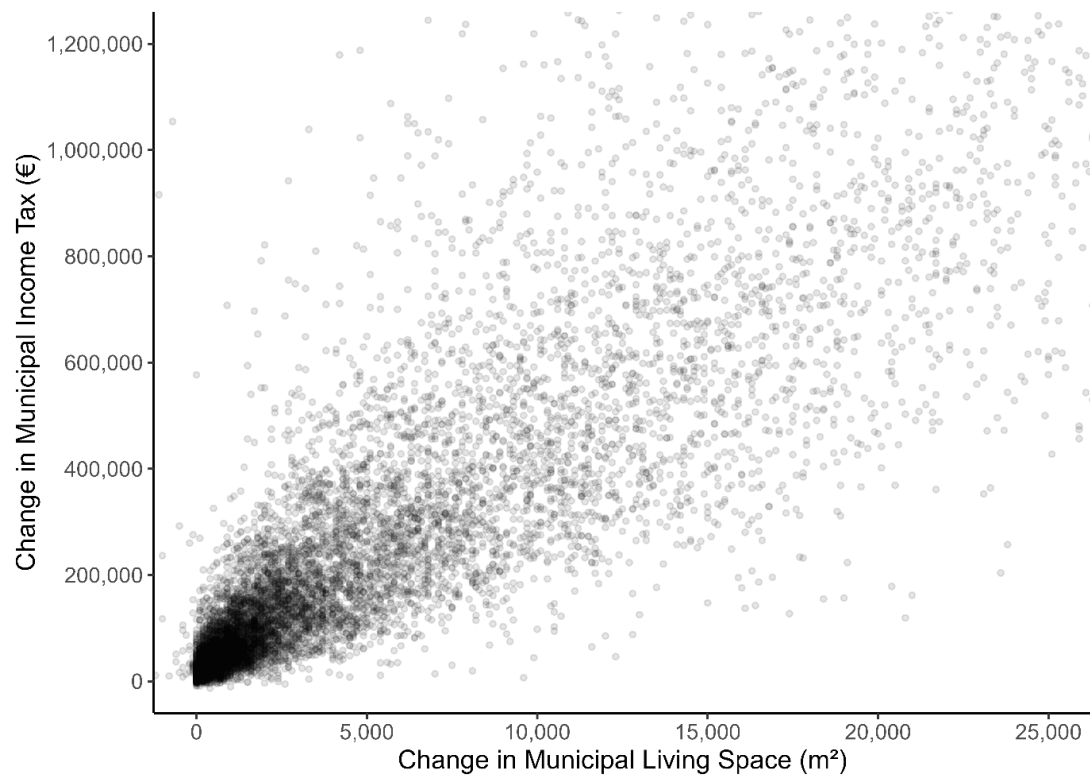
2.10 Appendix

Table 2.8 Literature Overview on Land Development and Municipal Fiscal Effects

Study	Effects of residential development	Effects of commercial development	Fiscal outcomes (tax revenues)	Nationwide evidence (Germany)	Spatial effects
Langer & Korzhenevych (2018)	X	✓	✓ (Business tax)	X (Bavaria only)	X
Buettner (2023)	~ (Residential as behavioral response)	X	X	✓	X
Gutsche (2003)	✓	X	✓	X	X
Reidenbach et al. (2007)	✓	X	✓	X	X
Krause-Junk (2007)	✓	X	✓	X	X
Goetze & Hartmann (2021)	X (Policy incentives only)	X	X	X (DE–NL comparison)	X
Clapp et al. (2018)	✓	✓	✓	X (USA)	X
Yan et al. (2022)	✓	✓	✓	X (China)	✓
Getzner et al. (2025)	X	X	X	X (Austria)	✓
Vermeiren et al. (2022)	✓	X	X (Costs only)	X (Belgium)	X
Burchell et al. (2005)	✓	X	X (Deficits only)	X (USA)	X
[Our Work]	✓	X	✓ (All related taxes)	✓	✓

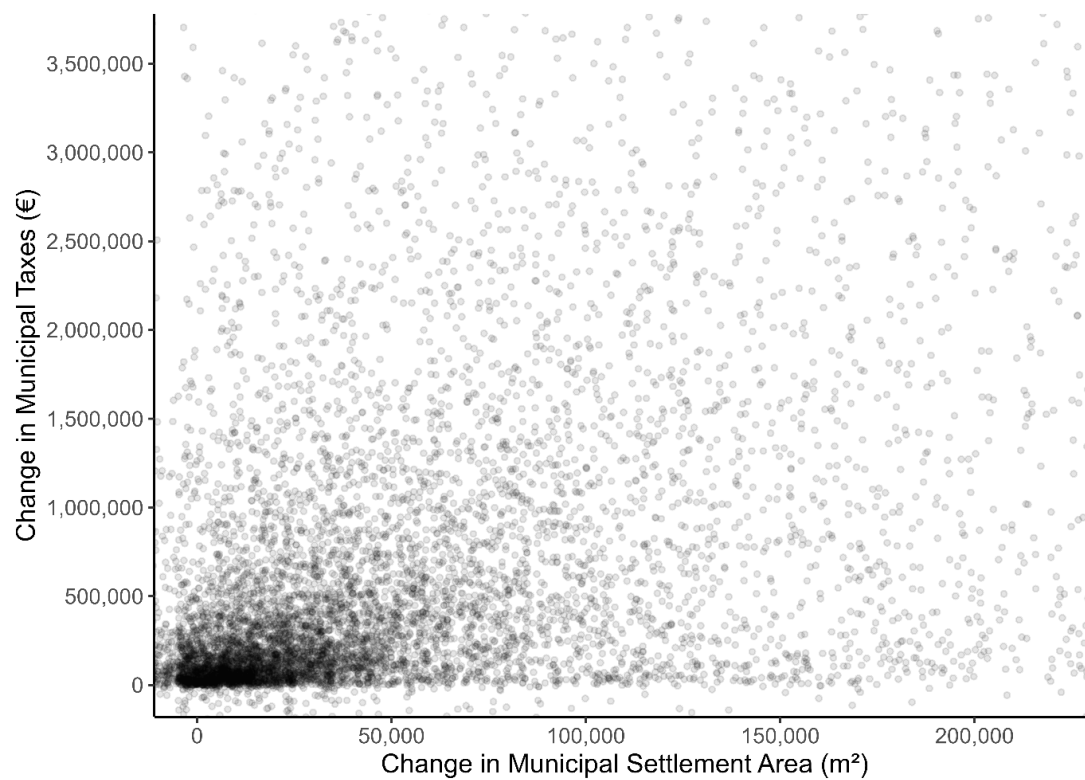
This table gives an overview of reviewed literature. A publication is marked with a check mark if it contains the stated methodologies or topics, and with a cross if it does not.

Figure 2.18 Scatter Plot of Municipal Living Space and Municipal Income Tax



This figure displays the relationship between the change in municipal living space (2016 to 2022, in m²) and the change in municipal income tax revenue (2016 to 2022, in €). The range displayed has been limited for illustrative purposes. Data sources: Federal and State Statistical Offices (2025a) & Federal and State Statistical Offices (2025b).

Figure 2.19 Scatter Plot of Municipal Settlement Area and Total Municipal Taxes



This figure displays the relationship between the change in municipal settlement area (2016 to 2022, in m²) and the change in total municipal tax revenues (2016 to 2022, in €). The range displayed has been limited for illustrative purposes. Data sources: Federal and State Statistical Offices (2025a) & Federal and State Statistical Offices (2025c).

Building Homes for Tax Revenues? Spatial Evidence on the Fiscal Effects of Residential Land Development

Table 2.9 Descriptive Statistics

	Obs.	Mean	Std. dev.	25%	50%	75%	Income tax estimation	Total tax estimation
Dependent variables								
Municipal income tax revenue in €	10,744	891,451	8,615,000	70,603	221,426	658,546	√	×
Total municipal tax revenue in €	10,744	3,389,293	33,877,530	120,440	467,248	1,776,900	×	√
Municipal control variables								
Built-up living space in m ²	10,744	16,618	97,354	1,200	4,300	14,000	√	×
Built-up settlement area in m ²	10,744	101,326	708,884	10,000	40,000	120,000	×	√
Population density in inhabitants per km ²	10,744	3.704	14.464	-1.090	1.198	5.674	√	√
Unemployment rate in %-points	10,744	-0.446	0.009	-0.780	-0.300	0.014	√	√
Share of houses out of all buildings in %-points	10,744	-0.062	0.554	-0.237	0.000	0.117	√	√
Business tax multiplier in %-points	10,744	8.976	19.442	0.000	0.000	15.000	×	√
Property tax (A) multiplier in %-points	10,744	16.710	38.176	0.000	0.000	24.000	×	√
Property tax (B) multiplier in %-points	10,744	21.150	40.608	0.000	0.000	31.000	×	√
County-level control variables								
Share of employees in the manufacturing industry in %-points	400	-0.332	0.013	-0.994	-0.243	0.385	√	√
Share of employees in the construction industry in %-points	400	0.237	0.005	-0.039	0.250	0.530	√	√
Share of employees in the trade and tourism industry in %-points	400	-0.503	0.011	-1.065	-0.521	0.056	√	√
Share of employees in the financial industry in %-points	400	-0.103	0.009	-0.663	-0.142	0.482	√	√
Share of employees in the service industry in %-points	400	1.080	0.010	0.419	1.116	1.607	√	√
Share of employees in the agricultural industry in %-points	400	-0.424	0.004	-0.577	-0.340	-0.176	√	√
Debt burden ratio in %-points	400	-0.355	0.230	-0.498	-0.354	-0.221	√	√
Share of old population in %-points	400	4.064	2.300	2.600	3.300	5.200	√	√
Disposable household income per inhabitant in €	400	4,481	798.30	4,031	4,524	4,938	√	√
GDP per capita in €	400	6,915	3,061	5,117	6,648	8,054	√	√
Transferred building land in 1,000 m ²	400	2,721	1,816	1,449	2,382	3,625	√	√
Price for building land in € / m ²	400	55.37	110.53	9.16	31.42	63.66	√	√
Municipal debt per inhabitant in €	400	-139.52	415.28	-346.00	-100.00	87.75	√	√

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	Obs.	Mean	Std. dev.	25%	50%	75%	Income tax estimation	Total tax estimation
Taxable turnover in 1,000 €	400	3,582,643	6,634,018	1,045,437	2,108,030	3,838,552	×	√
Taxable turnover: primary sector in %-points	400	0.652	1.015	0.129	0.449	1.065	×	√
Taxable turnover: industry sector in %-points	400	-2.892	8.645	-4.505	-1.695	0.883	×	√
Taxable turnover: public sector in %-points	400	1.236	3.817	0.085	0.814	2.046	×	√
Taxable turnover: real estate sector in %-points	400	0.531	2.232	-0.494	0.520	1.462	×	√
Taxable turnover: trade sector in %-points	400	-0.516	5.982	-3.254	-0.700	1.758	×	√
Taxable turnover: service sector in %-points	400	-0.444	2.670	-1.707	-0.400	0.781	×	√
Taxable turnover: financial sector in %-points	400	0.483	1.856	-0.054	0.104	0.552	×	√
Instrument								
Vegetation areas and green spaces 2016 in m ²	10,744	26,991,146	32,779,750	6,970,000	16,070,000	34,325,000	√	√

This table presents summary statistics for all variables of our data set. Monetary variables are in nominal prices and in euro. All variables, except for the instrument, are reported as changes between 2022 and 2016.

Table 2.10 Moran's I Test Statistics for Municipal Income Tax

Sample	Spatial weights matrix	Moran's I test statistic
2016-2022 Full sample	Inverse distance spatial weights	0.013***
2016-2022 Full sample	First-order spatial weights matrix (Queen method)	0.041***
2016-2019 Full sample	Inverse distance spatial weights	0.017***
2020-2022 Full sample	Inverse distance spatial weights	0.016***
2016-2022 West Germany	Inverse distance spatial weights	0.029***
2016-2019 West Germany	Inverse distance spatial weights	0.027***
2020-2022 West Germany	Inverse distance spatial weights	0.030***
2016-2022 East Germany	Inverse distance spatial weights	0.004***
2016-2019 East Germany	Inverse distance spatial weights	0.006***
2020-2022 East Germany	Inverse distance spatial weights	0.005***

This table presents the results of Moran's I test, developed by Moran (1950), applied on the municipal income tax revenues difference for various samples. Distance-based neighborhood matrices as well as a first-order queen neighborhood matrices were applied. For detailed information on the neighborhood set up, see Section 2.6.1. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 2.11 Moran's I Test Statistics for Total Municipal Taxes

Sample	Spatial weights matrix	Moran's I test statistic
2016-2022 Observation period	Inverse distance spatial weights	0.016***
2016-2022 Observation period	First-order spatial weights matrix (Queen method)	0.052***
2016-2019 Observation period	Inverse distance spatial weights	0.023***
2020-2022 Observation period	Inverse distance spatial weights	0.011***
2016-2022 West Germany	Inverse distance spatial weights	0.023***
2016-2019 West Germany	Inverse distance spatial weights	0.030***
2020-2022 West Germany	Inverse distance spatial weights	0.014***
2016-2022 East Germany	Inverse distance spatial weights	0.002***
2016-2019 East Germany	Inverse distance spatial weights	0.008***
2020-2022 East Germany	Inverse distance spatial weights	0.001**

This table presents the results of Moran's I test, developed by Moran (1950), applied on the total municipal taxes revenues difference for various samples. Distance-based neighborhood matrices as well as a first-order queen neighborhood matrices were applied. For detailed information on the neighborhood set up, see Section 2.6.1. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

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Table 2.12 Effects of Residential Land Development on Municipal Income Tax

	(1) SAR	(2) SAR	(3) IV	(4) IV
Built-up living space in m ²	61.949*** (4.949)	61.671*** (5.024)	52.078*** (2.752)	60.180*** (3.389)
Population density in inhabitants per km ²		2,620 (5,500)		3,916 (4,333)
Unemployment rate in %-points		-506,180 (1,876,200)		-697,700 (1,749,400)
Share of houses out of all buildings in %-points		-376,120*** (117,840)		-356,390*** (113,420)
Share of employees in the manufacturing industry in %-points		924,980 (4,053,600)		1,090,900 (3,974,100)
Share of employees in the construction industry in %-points		-8,449,600* (4,451,700)		-8,483,600* (4,418,800)
Share of employees in the trade and tourism industry in %-points		4,810,700 (4,257,500)		5,034,100 (4,258,600)
Share of employees in the financial industry in %-points		1,333,900 (4,162,200)		1,010,300 (4,062,300)
Share of employees in the service industry in %-points		1,576,400 (4,001,100)		1,847,500 (3,875,100)
Share of employees in the agricultural industry in %-points		16,456,000*** (4,262,000)		16,640,000*** (4,123,600)
Debt burden ratio in %-points		-94,759 (120,540)		-90,447 (125,100)
Share of old population in %-points		26,820 (37,702)		21,243 (34,330)
Disposable household income per inhabitant in €		-40.361 (27.386)		-49.206** (24.210)
GDP per capita in €		-3.578 (8.950)		-2.111 (8.468)
Transferred building land in 1,000 m ²		-49.595** (24.412)		-51.517** (24.405)
Price for building land in € / m ²		740.220 (584.690)		869.830 (762.310)
Municipal debt per inhabitant in €		54.041 (52.764)		61.026 (49.930)
Spatial parameter (ρ)	-0.127*** (0.048)	-0.127*** (0.0049)	-0.051* (0.027)	-0.116*** (0.044)
Municipal-level controls	No	Yes	No	Yes
County-level controls	No	Yes	No	Yes
State fixed effects	Yes	Yes	Yes	Yes
Observations	10,744	10,744	10,744	10,744
Sigma	1,322,912	1,299,901	1,422,495	1,301,775
AIC	333,389	333,028	334,949	333,059
BIC	333,520	333,275	335,080	333,306
First stage results				
Vegetation areas and green spaces 2016 in m ²			0.0004*** (0.0001)	0.0004*** (0.0001)
F-statistic			472.765***	586.537***

This table presents the results of spatial autoregressive regressions analyzing the impact of living space development on municipal income tax revenues. The dependent variable in models (1) to (4) is municipal income tax revenue. All variables, except for the instrument, are shown as differences between 2022 and 2016. Models (3) and (4) include an instrumental variable, which is not included in the second stage estimation of the models. Heteroskedasticity robust standard errors are in parentheses. Significance levels are indicated by *** p<0.01, ** p<0.05, and * p<0.10.

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Table 2.13 Effects of Settlement Land Development on Total Municipal Taxes

	(5) SAR	(6) SAR	(7) IV	(8) IV
Built-up settlement area in m ²	1.909** (0.945)	2.057*** (0.747)	9.796*** (2.261)	14.146*** (3.266)
Population density in inhabitants per km ²		247,650*** (52,867)		294,300*** (58,115)
Unemployment rate in %-points		-2,531,600 (14,693,000)		8,129,300 (15,693,000)
Share of houses out of all buildings in %-points		1,799,200*** (503,400)		-53,472 (553,380)
Business tax multiplier in %-points		-65,444 (48,833)		-54,466 (47,952)
Property tax (A) multiplier in %-points		9,005 (12,252)		8,142 (12,425)
Property tax (B) multiplier in %-points		-7,133 (8,185)		-8,109 (8,553)
Share of employees in the manufacturing industry in %-points		-19,681,000 (151,590,000)		168,020,000 (149,870,000)
Share of employees in the construction industry in %-points		-26,719,000 (100,009,000)		235,990,000** (117,570,000)
Share of employees in the trade and tourism industry in %-points		21,553,000 (133,530,000)		208,140,000 (139,570,000)
Share of employees in the financial industry in %-points		-54,784,000 (136,070,000)		138,300,000 (134,420,000)
Share of employees in the service industry in %-points		16,940,000 (986,880,000)		206,750,000* (106,510,000)
Share of employees in the agricultural industry in %-points		-185,280,000 (121,180,000)		71,486,000 (121,140,000)
Debt burden ratio in %-points		1,024,300 (1,961,300)		1,410,000 (1,996,700)
Share of old population in %-points		-902,690* (486,400)		-396,290 (471,020)
Disposable household income per inhabitant in €		-1,324*** (45.160)		-973.430** (442.600)
GDP per capita in €		365.030 (833,030)		344.010 (835.010)
Transferred building land in 1,000 m ²		-2,743*** (546.780)		-2,941*** (579.780)
Price for building land in € / m ²		10,559 (10,928)		8,749 (10,494)
Municipal debt per inhabitant in €		-2,596* (1,467)		-3,190** (1,596)
Taxable turnover in 1,000 €		1.816*** (0.585)		1.819*** (0.568)
Taxable turnover: primary sector in %-points		217,060 (224,790)		-88,381 (209,660)
Taxable turnover: industry sector in %-points		51,664 (36,221)		45,382 (37,208)
Taxable turnover: public sector in %-points		291,910** (119,250)		277,520** (119,300)
Taxable turnover: real estate sector in %-points		661,500** (265,050)		674,830** (271,570)
Taxable turnover: trade sector in %-points		21,389 (81,344)		22,397 (82,112)
Taxable turnover: service sector in %-points		255,070 (161,800)		179,080 (154,210)
Taxable turnover: financial sector in %-points		840,320 (547,960)		840,190 (542,010)

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	(5) SAR	(6) SAR	(7) IV	(8) IV
Spatial parameter (ρ)	0.611*** (0.142)	-0.233 (0.206)	0.481*** (0.134)	0.275 (0.205)
Municipal-level controls	No	Yes	No	Yes
County-level controls	No	Yes	No	Yes
State fixed effects	Yes	Yes	Yes	Yes
Observations	10,744	10,744	10,744	10,744
Sigma	22,907,127	19,566,642	23,557,175	21,228,697
AIC	394,664	391,304	395,266	393,056
BIC	394,796	391,632	395,397	393,984
First stage results				
Vegetation areas and green spaces 2016 in m ²			0.0030*** (0.0005)	0.0028*** (0.0005)
F-statistic			158.504***	143.357***

This table presents the results of spatial autoregressive regressions analyzing the impact of settlement land development on total municipal tax revenues. The dependent variable in models (5) to (8) is total municipal tax revenues. All variables, except for the instrument, are shown as differences between 2022 and 2016. Models (7) and (8) include an instrumental variable, which is not included in the second stage estimation of the models. Heteroskedasticity robust standard errors are in parentheses. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

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Table 2.14 Effects of Settlement Land Development on Municipal Income Tax

	(1) SAR	(2) SAR	(3) IV	(4) IV
Built-up settlement area in m ²	0.470** (0.205)	0.503** (0.202)	2.353*** (0.474)	2.972*** (0.527)
Population density in inhabitants per km ²		62,745*** (15,017)		73,033*** (14,414)
Unemployment ratio in %-points		-4,889,600* (2,899,800)		-2,541,200 (2,861,400)
Share of houses out of all buildings in %-points		404,780*** (123,270)		32,075 (122,800)
Share of employees in the manufacturing industry in %-points		12,716,000 (8,975,500)		45,160,000*** (16,150,000)
Share of employees in the construction industry in %-points		738,690 (9,632,000)		49,816,000** (20,716,000)
Share of employees in the trade and tourism industry in %-points		22,646,000* (11,555,000)		55,054,000*** (18,475,000)
Share of employees in the financial industry in %-points		-3,750,500 (8,491,200)		29,887,000* (15,435,000)
Share of employees in the service industry in %-points		18,932,000** (8,697,600)		51,172,000*** (15,640,000)
Share of employees in the agricultural industry in %-points		35,912,000*** (10,629,000)		84,496,000*** (19,196,000)
Debt burden ratio in %-points		-52,572 (370,010)		-9,754 (364,030)
Share of old population in %-points		-233,670** (100,420)		-137,520 (96,173)
Disposable household income per inhabitant in €		-396,200** (120,590)		-334,630*** (117,820)
GDP per capita in €		44,570 (29,861)		41,536 (31,790)
Transferred building land in 1,000 m ²		-106,720 (91,384)		-137,360 (92,121)
Price for building land in € / m ²		6,668 (4,719)		6,370 (4,564)
Municipal debt per inhabitant in €		363,670* (185,570)		279,770 (188,270)
Spatial parameter (ρ)	0.334*** (0.005)	-0.093 (0.154)	0.221*** (0.053)	-0.191 (0.151)
Municipal-level controls	No	Yes	No	Yes
County-level controls	No	Yes	No	Yes
State fixed effects	Yes	Yes	Yes	Yes
Observations	10,744	10,744	10,744	10,744
Sigma	3,557,639	3,324,212	3,792,641	3,726,316
AIC	354,646	353,204	356,021	355,658
BIC	354,777	353,542	356,152	355,905
First stage results				
Vegetation areas and green spaces 2016 in m ²			0.0030*** (0.0005)	0.0032*** (0.0002)
F-statistic			200.803***	181.152***

This table presents the results of spatial autoregressive regressions analyzing the impact of settlement land development on changes in total municipal tax revenues. The dependent variable in models (5) to (8) is the change in total municipal tax revenues. All variables, except for the instrument, are shown as differences between 2022 and 2016. Models (7) and (8) include an instrumental variable, which is not included in the second stage estimation of the models. Heteroskedasticity robust standard errors are in parentheses. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 2.15 Spatial Impacts for Settlement Development and Municipal Income Tax

	(1) SAR	(2) SAR	(3) IV	(4) IV
Direct impact				
Built-up settlement area in m ²	0.471** (0.207)	0.503*** (0.194)	2.361*** (0.456)	2.975*** (0.520)
Indirect impact				
Built-up settlement area in m ²	0.235** (0.118)	-0.043 (0.085)	0.686*** (0.264)	-0.460 (0.403)
Total impact				
Built-up settlement area in m ²	0.706** (0.313)	0.460*** (0.162)	3.046*** (0.641)	2.514*** (0.539)

This table presents spatial impacts of spatial autoregressive regressions analyzing the impact of settlement land development on municipal taxes. The dependent variable is the change in municipal income tax revenue. The Models (3) and (4) include an instrumental variable, which is not included in the second stage estimation of the models. The given coefficients refer to direct, indirect and total spatial impact measures, respectively. Heteroskedasticity robust standard errors are in parentheses. Significance levels are indicated by *** p<0.01, ** p<0.05, and * p<0.10.

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3 Living on the Highway? Addressing Highway Infrastructure Potential through Object Detection

3.1 Abstract

The rapid increasing demand for freight transport has precipitated a critical need for expanded highway infrastructure, including Heavy Goods Vehicle (HGV) parking spaces. Utilizing state-of-the-art object detection techniques in satellite imagery, we conduct a comprehensive analysis to assess the current availability of HGV parking facilities along German highways. We relate our results to HGV traffic volume data. Our findings reveal local disparities in infrastructure supply and demand. In a next step, we conduct location analysis to determine regions impacted the most by identified undersupply. Our results deliver valuable insights to both, specialized real estate developers and policymakers likewise.

Keywords: Satellite imagery, Machine learning, Transport infrastructure, Real estate development

3.2 Introduction

Advancing globalization and the rise of e-commerce have significantly increased international cargo traffic, thus intensifying Heavy Goods Vehicle (HGV) traffic on European highways. While the number of HGVs can rapidly grow, the necessary infrastructure, particularly HGV parking facilities, lags behind (Krasniuk et al., 2024). This results in a more heavily used infrastructure, accentuated by the scarcity of HGV parking facilities. This scarcity forces drivers into untenable situations, such as parking illegally in unsafe locations (Nevland et al., 2020). This often literally ends with drivers living on the highway. Fatigue due to insufficient rest also diminishes driver reaction times, heightening the risk of collisions in emergency situations (National Academies of Sciences, Engineering, and Medicine, 2016). With road freight accounting for an impressive 72.2% of Germany's total freight volume (DHL Freight, 2023) and a market size of USD 63.88 billion, the strategic importance of HGVs becomes unmistakably clear (Schenker, 2024). These figures not only highlight the sector's substantial contribution to the national economy but also draw attention to the urgent need to address infrastructural deficiencies, specifically the lack of truck parking facilities, that threaten to undermine this crucial economic pillar while at the same time offering a rare investment opportunity for specialized real estate developers. Moreover, the lack of necessary infrastructure prevents the settlement of companies that decide on their location based on prevailing infrastructure (Champagne & Dubé, 2023).

The existing literature extensively discusses the challenges of heavy goods vehicle parking shortages, often highlighting safety risks, economic impacts, and regional disparities. Most prior research has been limited in geographic scope or reliant on traditional methods – for example, localized corridor case studies and driver surveys – which fail to capture the full complexity of supply-demand mismatches at a broader network level. Recent data-driven efforts have begun to emerge (e.g., clustering of GPS trajectories or time-series forecasting of occupancy), yet advanced geospatial machine learning techniques remain underexplored in this domain. Notably, the use of high-resolution satellite or aerial imagery with object detection algorithms to systematically map HGV parking infrastructure is rare. A recent study by Hellekes et al. (2023) demonstrates the potential of deep learning on aerial images for general parking inventory, but such an approach has not been applied to large-scale HGV parking facilities. This leaves an evident gap in the literature regarding granular, up-to-date mapping of truck parking supply using geospatial machine learning, especially when aiming to assess entire highway networks rather than single sites. To overcome these limitations, our study employs satellite imagery obtained from Google Maps API and polygon coordinate data from OpenStreetMap. We utilize advanced

machine learning techniques, specifically the YOLOv8 object detection algorithm, to systematically quantify the availability and distribution of HGV parking spaces along German highways.

Unlike conventional studies, our methodology provides up-to-date, granular insights into parking supply while integrating demand-side traffic volume data from automated traffic count data (Bundesanstalt für Straßen- und Verkehrswesen, 2024) for a holistic assessment. Our traffic-driven demand model accounts for factors such as regulatory driving constraints, freight volume growth, driver behavior, and infrastructural capacity. By correlating the supply data with detailed demand-side traffic volume information, we establish local supply-demand equilibria highlighting regional disparities and identifying areas with the most significant undersupply. We also show actionable opportunities for specialized real estate developers and policymakers, offering a strategic framework to address the pressing shortage. This approach not only advances the field of transport infrastructure analysis but also lays the groundwork for scalable, technology-driven solutions across other regions and countries.

The critical nature of HGV parking availability and its implications for specialized real estate developers necessitate a comprehensive data set for systematic analysis, which has been lacking. Without accurate data, estimates of the HGV parking supply may be significantly distorted, hindering developers and investors from making informed decisions. Our novel data-driven approach aims to map HGV parking lots and relate them to their demand, thereby enhancing the understanding of the overall parking situation for long-haul trips and enables identifying location potential for infrastructure real estate developers. To the best of our knowledge, such a study has not been conducted for Germany or any other European country to date.

To understand the investment case this paper seeks to determine, it is essential to grasp how truck and rest stops as part of the highway service infrastructure generate revenue. Their business model is based on a variety of income streams that together can create a stable and profitable financial structure. Many infrastructure facilities earn revenue from the rental of parking spaces, especially for HGV drivers who are required to take their legally mandated rest periods. However, a substantial part of the monetization of these truck parking spaces comes not from the rental itself but from the presence of on-site real estate such as restaurants, shops, or sanitary facilities. These additional offerings make the infrastructure facilities an attractive destination for drivers and significantly contribute to overall value creation. Consequently, many truck stops operate restaurants, cafés, or fast-food chains. Another important revenue driver is the sale of fuel and automotive

accessories. Additional income is also generated through the sale of products, such as motor oil, windshield wipers, and other accessories.¹⁶ That this can be lucrative is illustrated by the figures from Germany's largest service station provider, Tank & Rast, which had a revenue of 537 million euros in 2021 (Piller, 2023).

Section 3.3 commences with a review of the literature. Section 3.4 presents our methodological framework, while Section 3.5 is dedicated to our results. Both aspects are integrated in Section 3.6, where we show regional differences and locational investment opportunities for specialized real estate developers. We conclude our findings in Section 3.7.

3.3 Literature Review

The significant role of trucks in local and long-haul commerce is well-documented, particularly given their crucial function in connecting production hubs with consumers across vast geographies (Sadek et al., 2020). However, the challenge of providing adequate parking infrastructure for HGVs remains pressing. In the U.S., Garber et al. (2002) identified severe shortages along I-81, while a broader state-level audit by Parametrix (2005) confirmed systematic overcapacity across Washington's interstates. Similar issues have been reported in Europe. Chatterjee and Wegmann (2000) showed that a significant share of HGV drivers park illegally due to the lack of legal alternatives, a finding echoed by Boris and Brewster (2016), who found that over 80% of U.S. drivers parked illegally at least once a week. A comparable situation was documented for Germany (Niederrheinische IHK, 2024).

Illegal parking is not only a regulatory failure but also a safety issue. Boggs et al. (2019) demonstrated a direct link between full parking facilities and increased ramp crashes, while Nourinejad and Roorda (2017) outlined the broader societal costs of such behavior. Anderson et al. (2018) and Horn (2015) further illuminated the regulatory dilemma: drivers often park on ramps to avoid exceeding legal driving limits, while enforcement agencies are reluctant to intervene. The lack of suitable amenities at existing stops exacerbates this behavior, as shown by Krasniuk et al. (2024), who emphasized that HGV drivers often bypass facilities that lack appropriate services.

Despite increasing demand and evident safety concerns, the evaluation and planning of HGV infrastructure remain fragmented. Most studies focus on small-scale observations,

¹⁶ Some infrastructure facilities also offer additional services, such as car washes, workshops, or shops for drivers' supplies, further enhancing their revenue streams.

regional case studies, or behavior-based surveys. For example, Mahmud et al. (2020) use clustering methods to explore how facility amenities influence parking duration, and Nevland et al. (2020) develop a typology of formal and informal truck parking based on GPS tracking – but neither study attempts to assess supply-demand balances at a network level. Patel et al. (2022) and Wu et al. (2024) utilize passive GPS and geofencing techniques, respectively, to identify parking behaviors and demand clusters, yet they do not quantify infrastructure supply or evaluate its adequacy. Likewise, Sadek et al. (2020) and Seya et al. (2020) focus on modeling parking occupancy or driver decision-making but offer no scalable methods to inventory parking infrastructure itself.

Building upon a year of extensive truck parking data collection, Sadek et al. developed a dynamic forecasting model capable of predicting truck parking occupancy at any given time within the current day (Sadek et al., 2020). The model's effectiveness is assessed using the Root Mean Square Error (RMSE), offering a quantitative measure of its accuracy. In their model, Irzik includes the capacity of truck parking facilities along a freeway section, the average daily traffic volume of heavy goods vehicles in the section, and the section's length (Irzik, 2019). This approach is encapsulated within a multiple regression analysis framework.

In parallel, real estate literature has explored location analysis for traditional asset classes, often through regression or GIS-based methods. Champagne and Dubé (2023) demonstrate that transportation infrastructure heavily influences industrial location decisions. Yet, site selection for infrastructure-specific assets like truck stops has received little empirical attention. Rabianski et al. (2001) and Fryrear et al. (2001) propose frameworks for community-specific or GIS-based site assessment, while Rymarzak and Siemińska (2012) highlight that specialized real estate is frequently constrained by immobile physical resources. However, all these approaches are either too general or reliant on highly localized datasets. As Kabir et al. (2020) point out, incomplete or missing data further complicates infrastructure site assessment, often requiring manual data collection to fill gaps.

Recent developments in computer vision and deep learning offer new pathways to overcome these limitations. Redmon et al. (2015) introduced the YOLO framework, revolutionizing object detection by enabling real-time processing of image data. Yu et al. (2019) and Jenkins and Burton (2008) have shown the accuracy and efficiency of deep learning applications across a range of domains. However, to date, very few studies have applied these methods to HGV infrastructure. A notable exception is Hellekes et al. (2023),

who used a CNN to detect general parking capacity in urban areas using aerial imagery. Yet even this effort did not address highway-specific or truck-specific parking supply.

A broader strand of research in remote sensing demonstrates how object detection techniques can be applied to high-resolution satellite imagery for infrastructure-related tasks. Comprehensive reviews by Ma et al. (2019) and Zhu et al. (2017) highlight the growing sophistication of convolutional neural networks (CNNs) and real-time detection architectures like YOLO, with successful applications in domains, such as building footprint extraction, road detection, and traffic surveillance. Empirical studies have illustrated the technical viability of these methods: for example, Yang et al. (2019) propose R3Det, a refined single-stage detector capable of accurately identifying rotated objects in aerial imagery, which is crucial for non-axis-aligned targets like parked trucks.

Despite advances in deep learning for satellite imagery, key limitations remain for logistics-focused infrastructure mapping. First, relying on axis-aligned bounding boxes (AABBs) compromises detection accuracy when objects – like trucks in rest areas – are rotated or angled. Orientation-aware detectors, such as R3Det (Yang et al., 2019), address this by refining bounding boxes to better fit rotated instances. Second, domain generalization remains problematic: models trained on urban datasets often underperform in highway or rural contexts due to differences in vehicle scale, background textures, and scene composition (Zhao et al., 2019). Finally, the field often lacks practical validation: while many studies report performance metrics like mAP or IoU, few benchmark their results against real-world infrastructure inventories or spatial planning requirements, limiting applicability for logistics decision-making.

Our study addresses these gaps by training a YOLOv8 model using orientation-aware bounding boxes (OBBs), tailored specifically to HGV parking layouts visible in high-resolution satellite imagery. This adjustment improves detection performance in rotated and spatially dispersed configurations and supports a more precise inventory of truck parking infrastructure. In doing so, we advance the application of geospatial deep learning beyond general object recognition and toward actionable infrastructure analysis.

As the literature reveals, although the problem of truck parking scarcity is well recognized, there remains a significant methodological and empirical gap: no existing study systematically quantifies the spatial distribution of HGV parking infrastructure at a national scale using scalable, real-time methods. Most research either analyzes driver behavior, focuses on urban delivery logistics, or employs static survey data without integrating dynamic traffic or supply-side geospatial data. Moreover, while object detection and

machine learning are increasingly used in real estate valuation (Stang et al., 2023) and parking analysis (Hellekes et al., 2023), their application to truck-specific highway infrastructure is virtually nonexistent.

Our study fills this gap by combining high-resolution satellite imagery with YOLOv8 object detection to assess the current supply of HGV parking infrastructure along Germany's entire highway network. We further integrate traffic flow data to estimate localized demand and evaluate regional supply-demand mismatches. This approach offers a scalable, technology-driven framework that advances beyond both survey-based and GPS clustering methods, enabling systematic infrastructure assessment across spatial scales. As such, it provides actionable insights for both policymakers and real estate developers in a domain where data limitations have long hampered planning and investment.

We have compiled overview Table 3.1 to include all relevant academic studies based on their methodological approach, data type and relevance to HGV parking infrastructure. This structured summary highlights where prior work stops short, thereby clarifying the novelty of our paper's geospatial machine learning approach.

Table 3.1 Overview of Key Literature on HGV Parking and Infrastructure Site Selection

Publication	Methodology	Focus area	Supply-demand gap modeled?	Real-time detection?	YOLO / deep learning used?	HGV-specific?	Data type / source
Anderson et al. (2018)	Survey	Driver ramp parking decisions	X	X	X	✓	Oregon highway observations
Boggs et al. (2019)	Correlation study	Crash rates vs. parking overcapacity	✓	X	X	✓	Crash & parking capacity data
Boris & Brewster (2016)	Survey	Illegal parking frequency	X	X	X	✓	U.S. truck driver diaries
Champagne & Dubé (2023)	Meta-analysis	Infrastructure & industrial site selection	X	X	X	X	Systematic literature review
Chatterjee & Wegmann (2000)	Survey	Legal vs. illegal parking split	X	X	X	✓	Driver-reported data
Fryrear et al. (2001)	Survey	GIS in real estate (not parking-specific)	X	X	X	X	U.S. commercial real estate data
Garber et al. (2002)	Case study	Corridor capacity shortfalls (I-81)	✓	X	X	✓	Survey and observational data
Hellekes et al. (2023)	CNN-based object detection	Urban curbside parking detection	X	✓	✓	X	Aerial imagery, GIS
Horn (2015)	Field interviews	Enforcement reluctance for ramp parking	X	X	X	✓	Local enforcement input
Jenkins & Burton (2008)	Deep learning demo	General model performance (not parking-related)	X	✓	✓	X	Visual recognition data
Kabir et al. (2020)	Data imputation	Missing infrastructure data	X	X	X	X	Infrastructure databases
Krasniuk et al. (2024)	Scoping review	Amenities & parking mismatch	✓	X	X	✓	Literature synthesis
Liermann et al. (2019)	Industry overview	AI in finance and infrastructure	X	X	✓	X	Industry use cases
Mahmud et al. (2020)	Cluster analysis	Amenities vs. parking duration	X	X	X	✓	GPS + facility inventory
Nevland et al. (2020)	Classification	Legal vs. illegal truck parking	X	✓	X	✓	GPS data (Canada)
Niederrheinische IHK (2024)	Industry survey	Illegal parking prevalence (Germany)	X	X	X	✓	Survey analysis
Nourinejad & Roorda (2017)	Simulation	Policy impact on parking demand	X	X	X	✓	Urban truck parking data
Parametrix (2005)	Descriptive audit	State-wide capacity utilization	✓	X	X	✓	Facility observations (Washington)
Patel et al. (2022)	Clustering & classification	Stop purpose classification	X	X	X	✓	Passive GPS traces
Rabianski et al. (2001)	Theoretical framework	Corporate real estate location analysis	X	X	X	X	Literature
Redmon et al. (2015)	Model development	YOLO introduction	X	✓	✓	X	Image datasets
Rymarzak & Siemińska (2012)	Empirical	Real estate placement constraints	X	X	X	X	Polish land-use data
Sadek et al. (2020)	Time-series forecasting	Truck parking occupancy	X	✓	X	✓	California truck parking data
Seya et al. (2020)	Tobit & choice modeling	Truck parking behavior (micro-level)	X	X	X	✓	Digital tachograph data (Japan)
Stang et al. (2023)	Explainable AI	Commercial property valuation	X	X	✓	X	Location & transaction data
Wu et al. (2024)	Spatio-temporal clustering	Stop clustering (demand identification)	X	X	X	✓	GPS trajectories (Shanghai)
Yu et al. (2019)	Computer vision	General object detection methods	X	✓	✓	X	Image data
[Our Work]	Deep learning (YOLOv8) + GIS analysis	Real-time HGV parking detection & supply-demand modeling	✓	✓	✓	✓	Aerial imagery + road network + geo-data

Note: This table gives an overview of reviewed literature. A publication is marked with a check mark if it contains the stated methodologies or topics and with a cross if it does not.

3.4 Determining the HGV Parking Situation

Our study addresses the outlined research gap by introducing a novel, data-driven approach that leverages state-of-the-art object detection models and comprehensive satellite imagery to evaluate HGV parking availability along German highways. Figure 3.1 shows why Germany is of particular relevance when considering transport infrastructure. The German highway network includes key logistics axes and connects the European north with the south and the east with the west. The transport infrastructure is therefore used by large numbers of Europeans likewise. However, it is certainly feasible to replicate this approach on similar transportation networks, for example in the US or China.

Figure 3.1 Germany's Position in the European Highway Network



Note: This figure visualizes European highway networks in blue color, while the federal borders of Germany are marked in red color. Geospatial data was acquired from Google API and OpenStreetMap.

The institutional setting in Europe differs between three categories of highway infrastructure facilities offering parking spaces. While service stations and truck stops are considered managed facilities, rest areas are usually unmanaged. Focusing on the situation in Germany, according to the German General Administrative Regulation on the Road Traffic Regulations (VwV-StVO), service stations are designated rest stops located directly along Germany's federal highway system. These service areas typically include amenities such as fuel stations, restaurants, restrooms and parking spaces. Service stations are accessible directly from the highway without the need to exit.

Truck stops offer similar amenities as service areas but are usually located near highway exits, rather than directly on the highway itself (§15 of the German Federal Trunk Road

Law (FStrG)). They offer a broader range of services, often including larger parking areas, more diverse dining options, repair services and overnight accommodations. Truck stops cater particularly to long-haul truck drivers. To access a truck stop, drivers need to leave the highway and then re-enter it again after their stop. These are comparable to Pilot Flying or TA Petro in the US.

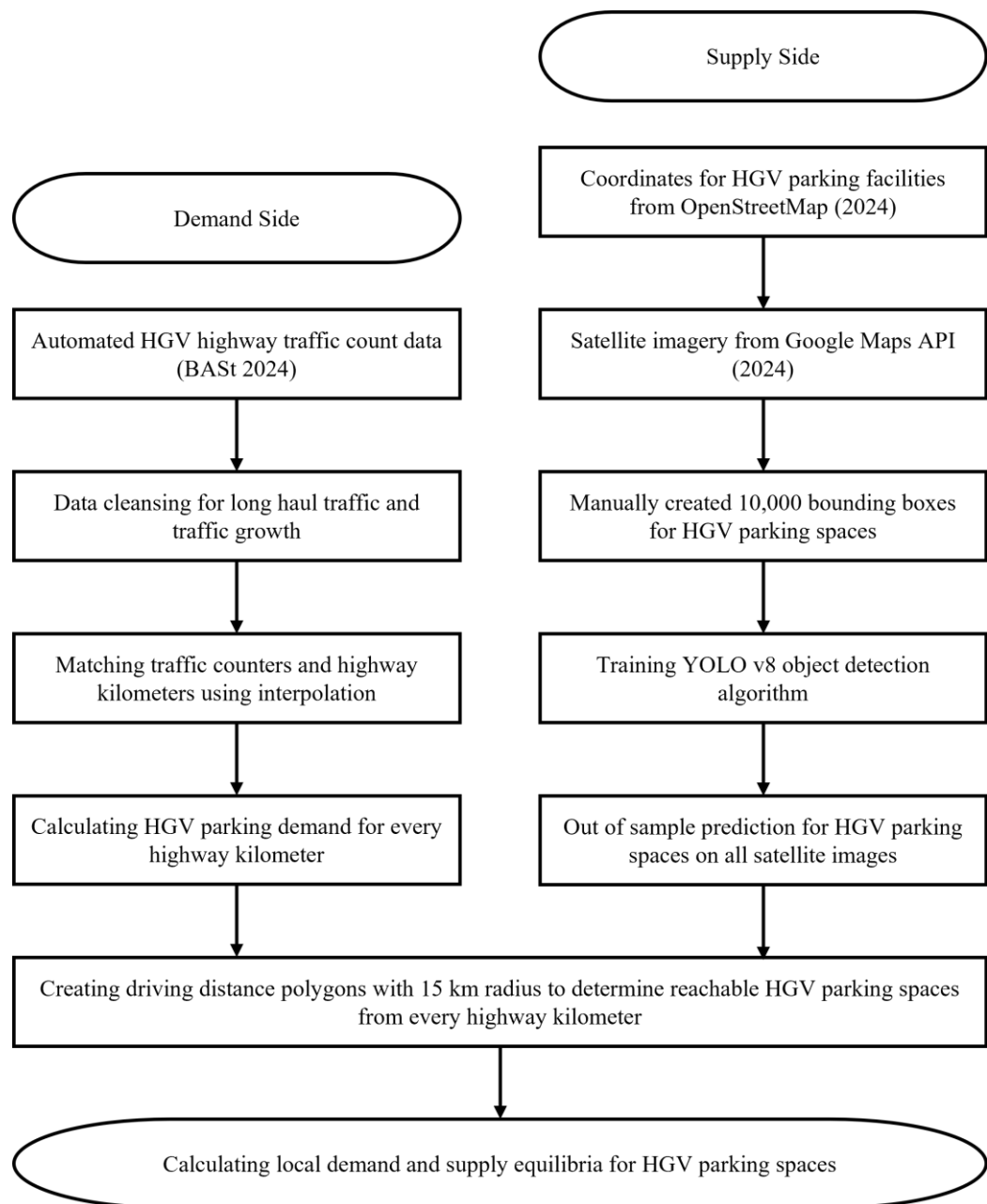
Rest areas are, just as service stations, located directly along the highway. However, they usually offer less amenities limited to parking spaces and washrooms. While a recent study by Mahmud et al. identified differences in usage of infrastructure facilities depending on HGV drivers' origin and break duration (Mahmud et al., 2020), all three mentioned categories offer HGV parking spaces and are therefore included in the following analysis.

3.4.1 Overview

Figure 3.2 gives an overview of our methodological approach addressing the infrastructure adequacy and potential of HGV parking facilities. We gain traffic and infrastructure data from two major sources and combine them once we isolated supply and demand estimates for HGV parking. First, we gather polygon coordinates for all HGV parking facilities along German highways from OpenStreetMap (2024). In a second step, we use Google Maps API to collect satellite imagery for all extracted polygon coordinates from the first step. After that, we manually create bounding boxes for 10,000 single HGV parking spots to train and validate a YOLO v8 object detection algorithm. Once the algorithm is sufficiently trained, we apply it for an out of sample prediction to assess all satellite images gained in the second step. This results in a holistic supply data set of HGV parking spots at each location identified in the previous steps. Parallel to the supply data processing, we collect traffic data from the automated traffic count (Bundesanstalt für Straßen- und Verkehrswesen, 2024). This data is cleaned up for long haul HGV traffic and updated with the 2024 growth rate for heavy goods traffic. In a next step, the traffic data counters are matched with highway kilometers to receive a local mapping of traffic flows. Further, we apply a simple economic model to estimate local HGV parking supply.

However, the adequacy of infrastructure can only be assessed when supply and demand are matched on a local level. We therefore combine the demand data estimated by simple economic modelling and the supply data gained from the object detection approach to set up local equilibriums. Based on deviations from the equilibria, we draw conclusions comparing local juxtapositions of HGV parking supply and demand. Our results may support the expansion of local HGV parking infrastructure by creating an independent database for authorities and real estate developers. The subsequent sections present our detailed procedure stepwise.

Figure 3.2 Methodological Framework

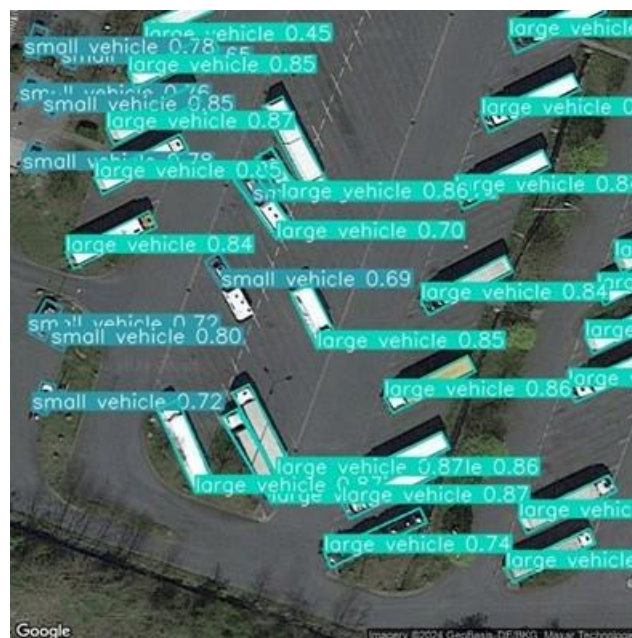


Note: This figure illustrates the stepwise methodological framework applied to determine supply and demand for HGV parking spaces along German highways resulting in the calculation of local equilibriums.

3.4.2 Supply Side

To determine the number of HGV parking spaces in Germany, we first acquired bounding boxes coordinates for truck stops, service stations and unmanaged rest areas along Germany's highways from OpenStreetMap. We retrieved both managed and unmanaged parking areas. Using the retrieved coordinates, we extracted recent (year 2024) satellite imagery from Google Maps API. To avoid potential overlapping and double counting, we implemented a custom algorithm that dynamically adjusted the queried coordinates while maintaining a constant zoom level of 19 across our satellite imagery, ensuring data accuracy in our analysis.¹⁷ A total of 11,398 images were retrieved, split into 931 images for truck stops, 6,802 for (unmanaged) rest areas and 3,665 for service stations.

Figure 3.3 Pre-Trained Model Output on Sample Image



Note: This figure illustrates a sample satellite image of HGV parking infrastructure along a German highway. The pre-trained model applies an object detection algorithm that classifies identified objects into previously known categories. Geospatial data was acquired from Google API and OpenStreetMap.

To estimate the number and spatial distribution of available parking spaces, we employed the YOLOv8 algorithm, leveraging the Oriented Bounding Box (OBB) technique. This model, pre-trained on satellite images, is adept at accurately delineating the angular orientation and shape of parking spaces. The YOLO model series is recognized as state-of-the-art and is constantly updated and improved. Although YOLOv8-OBB in its original version was not specifically trained on HGV parking lots (as can be seen in Figure 3.3, only large and small vehicles are recognized on the example satellite image), its capabilities can

¹⁷ Google's satellite images can be retrieved at different zoom levels. Level 0 is the most zoomed out, and level 22 is the most zoomed in. After manual testing, we found that zoom level 19 provides the best combination of high-quality images and detailed information across the country.

be enhanced through training and validation with an annotated dataset to address the unique characteristics of HGV parking spaces, which are often angled, as illustrated in Figure 3.4. The refined model should therefore be able to make out-of-sample predictions on unseen images regarding the availability and spatial distribution of HGV parking spaces. Alternative pre-trained object detection models beyond YOLO are of limited use in our research because our methodology requires orientation aligned information with OBBs. At the time of deployment and testing, only a few models had been pre-trained on the necessary type of data, primarily satellite imagery. Consequently, we did not conduct a comparative performance evaluation with other models. Other relevant models aside from YOLO include those from the MMDetection toolbox and Seodore.

For the creation of a structured training and validation dataset from satellite images, we manually had to annotate visible HGV parking spots. A total of 519 images were annotated, resulting in 10,483 parking spaces being identified. Each parking space within the images was annotated with an oriented bounding box mask to delineate its perimeter. This resulted in a dataset with one single class for the truck parking. The size of each image was fixed at 640x640 pixels. For the training and validation process, we utilized a pre-trained YOLOv8x-OBB model, running for 300 epochs on a Tesla T4 GPU with a batch size of 16. As the speed of the model was not an important factor in our research, the YOLOv8x-OBB model is the extra-large ('x') version of YOLOv8. We used the Adam optimizer with a learning rate of 0.002, a momentum of 0.9 and default settings for augmentation. An "epoch" refers to one complete pass through the entire dataset in both forward and backward propagation through the neural network. While more epochs can lead to better accuracy, there is also a risk of overfitting the data, whereby the model becomes too focused on the given data and is unable to generalize outside of the training or validation data. The hyperparameters were selected in accordance with the recommended settings provided by the model's developers. As we did not encounter any significant issues (e.g., overfitting or low accuracy) when running the model with these settings, and as the object detection task that we trained the model on aligns with standard satellite object detection tasks, we did not adjust the hyperparameters ourselves. Furthermore, we adopted a 70–15–15 randomized split for annotated images to train, validate, and test the model. Specifically, 70% of the annotated images were used to train the model to detect HGV parking spots, 15% were used to validate the model's performance, and the remaining 15% were reserved for out-of-sample testing to evaluate the model's generalization capabilities. This split seemed appropriate since the number of annotations, and thus ground truth data, was limited. A split with more training data (e.g.,

80–10–10) would have potentially resulted in lower reliability of the validation and test dataset outputs.

Figure 3.4 Manual Annotation of Parking Spaces



Note: This figure illustrates a sample satellite image of HGV parking infrastructure along a German highway. Bounding boxes in red color were created manually to mark HGV parking spaces. Geospatial data was acquired from Google API and OpenStreetMap.

3.4.3 Demand Side

To determine HGV traffic demand for infrastructure facilities, our approach uses data from the German Federal Roads Office (Bundesanstalt für Straßen- und Verkehrswesen, 2024) highway traffic meters from 2021. This includes 1,227 traffic meters on federal highways. First, we match highway meters with highway kilometers applying interpolation.¹⁸ Next, we generate driving distance polygons for 15-kilometer travel distances to determine the number of reachable parking spaces in each highway section. We thereby base our approach on the average driving distance drivers spend to find eligible parking spaces for a break (Niederrheinische IHK, 2024). This enables us to compare demand and supply for each highway kilometer. In a last step, we identify zones with varying levels of demand coverage.

The parking requirements of HGVs vary significantly between short-term and long-term needs. Short-term parking, which includes curbside spaces for urban and residential deliveries, is distinct from long-term parking that accommodates rest stops and overnight parking. This differentiation is crucial for accurate demand estimation (Amer & Chow,

¹⁸ We applied linear interpolation to fill in missing data gaps between traffic counters in line with Loder et al. (2019).

2017; Chen et al., 2017; Mitman et al., 2018; Schmid et al., 2018). Long-haul trips, often classified by distances exceeding 400 km (Pècheux et al., 2002) or 500 km (Ortúzar S. & Willumsen, 2011), necessitate longer stops due to the need for driver rest, with trips over 900 km requiring significantly more time (Gingerich et al., 2016).

Pècheux et al. (2002) first developed a simple demand model for HGV parking being dependent on traffic volume, driving times and seasonal peaks. Based on the evidence of Vital and Ioannou (2021), Wu et al. (2024) and Seya et al. (2020) on HGV drivers scheduling their breaks anticyclical to avoid overcrowding and traffic congestion, we enrich the baseline approach of Pècheux et al. (2002) by allowing for multiple daily usage of a single parking spot. Aligning with Patel et al. (2022), we further include the effect of temporary closures and construction into the demand estimation. Lastly, regulatory driving time constraints are added since the European Union imposes precise requirements regarding working conditions (European Union, 2024). Considering the above-mentioned studies and the described extensions, we apply the baseline equation (5) to estimate the average effective demand $D_{i,t}$ on HGV parking spaces based on the data obtained from the automated traffic count (Bundesanstalt für Straßen- und Verkehrswesen, 2024):

$$D_{i,t} = s_{LH} * \Delta_{t,t-1} N_{i,t} * p_{i,t} \quad (5)$$

$$s_{LH} = 1 - s_{SH} \quad (6)$$

where i indexes highway sections and t indexes time. $N_{i,t}$ refers to the average daily HGV volume, whereas $\Delta_{t,t-1}$ determines the aggregated growth rate for HGV volume applied on 2021 data to enable later comparison with 2024 supply data. s_{LH} and s_{SH} denote the average share of long and short haul traffic, respectively. Following the approach of Pècheux et al., (2002), we assume only long-haul traffic to demand resting facilities. Therefore, the total traffic volume is reduced by the share of short haul traffic s_{SH} as shown in equation (6). The probability of an HGV seeking a parking space exactly on a considered highway kilometer (rest probability) i is denoted by p and estimated applying equation (7).

$$p_{i,t} = \frac{n_t}{d_t O_{i,t}} * (1 + P_{i,t}) * (1 + v_{i,t}) \quad (7)$$

$$d_t = T_t * V_t \quad (8)$$

Thereby, d_t denotes the average driving distance that drivers can cover without a break. That value is expressed in equation (8) by the product of the average HGV speed on highways (V_t) and the allowed maximum driving time until a break is required by law (T_t). The number of breaks per day required by law and the occupancy factor of supplied parking spaces are denoted by n_t and $O_{i,t}$, respectively. A peaking factor $P_{i,t}$ is assumed

to allow for seasonal peaks. Further, a structural vacancy rate $v_{i,t}$ is applied to control for illegal parking and temporary closures. To estimate the demand for highway infrastructure facilities offering parking spaces for each observed highway kilometer, we use the data and necessary assumptions summarized in Table 3.2. We thereby rather underestimate than overestimate the actual demand. However, we cannot prevent including HGV traffic in the demand estimation which only arises due to the search for available infrastructure and would not occur if supply and demand were distributed locally equal.

Table 3.2 Overview of Assumptions

Notation	Description	Assumption	Source
s_{LH}	Average share of trucks that are long-haul	0.33	Bundesamt für Logistik und Mobilität, 2024
$\Delta_{t,t-1}$	Average aggregate growth rate for HGV volume on German highways	3.5 % per annum	Bundesministerium für Digitales und Verkehr, 2023
n_t	Number of breaks per day for HGV drivers	2.0	European Union, 2024
T_t	Maximum allowed driving time without break	4.5 hours	European Union, 2024
V_t	Average speed of HGV on German highways	80 km/hour	§ 18 of the German traffic law ¹⁹
$O_{i,t}$	Occupancy factor of parking spots	2.67	European Union, 2024
$P_{i,t}$	Seasonal peaking factor	0.15 ²⁰	Pècheux et al., 2002
$v_{i,t}$	Structural vacancy of parking spaces	0.012	Deutscher Bundestag, 2024

Note: This table lists the applied values for the demand estimation applying the afore mentioned equations (5) to (8). The assumptions were gathered with respect to the German highway and German regulation regarding HGV drivers. When applying the equations (5) to (8) on data other than Germany, assumptions may differ.

We use the average share of long-haul traffic s_{LH} to correct the average HGV volume $N_{i,t}$ derived from BASt (Bundesanstalt für Straßen- und Verkehrswesen, 2024) for long-haul traffic drivers in need for rest areas on their freight routes. The remaining volume of long-haul traffic vehicles is then adjusted for the growth in freight volume between 2021 and 2024, since the retrieved most recent data covers only the 2021 volume.

To calculate the rest probability, we primarily rely on EU regulation governing the working conditions of truck drivers on the road network in the European Union. Therein, the

¹⁹ A recent study by Trabert et al. (2018) on HGV accidents on German highways reveals an average speed of 89.7 km/h supporting our conservative approach of assuming an average HGV speed corresponding to the maximum allowance.

²⁰ No reason to assume that seasonal peaks differ between US and Germany.

minimum number of breaks per day n_t and the maximum driving time allowed without a break T_t are defined. Further, the occupancy factor of parking spots $O_{i,t}$ can be derived applying the mandatory rest periods (European Union, 2024). The average speed of HGVs on German highways is derived from §18 of the German traffic law. To further control for seasonal peaks $P_{i,t}$, we adopt the assumption of Pècheux et al. (2002) since peaks in freight volume appear similar comparing the US and Germany. The structural vacancy of parking spaces $v_{i,t}$ is derived applying the scheduled highway construction per year (Deutscher Bundestag, 2024).

3.5 Results

3.5.1 Identified HGV Parking Supply

The object detection approach outlined in Section 3.4.2 results in the following supply of HGV parking spots summarized in Table 3.3. We identified approximately 71,300 parking spots in three different categories. While service stations and unmanaged rest areas offer roughly the same number of parking spaces, truck stops provide a smaller part of the infrastructure.

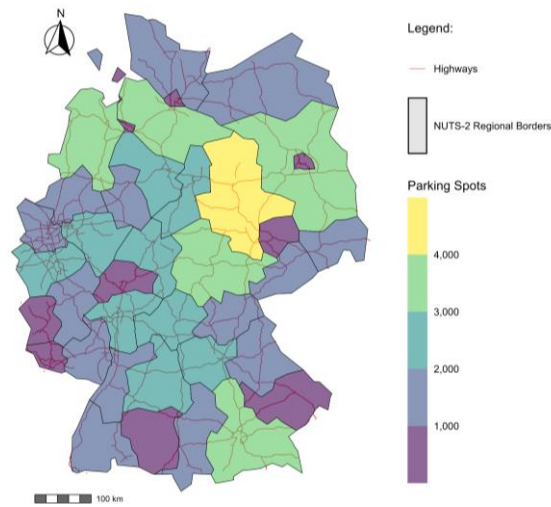
Table 3.3 Total Number of HGV Parking Spots

Category	Identified HGV parking spots
Service stations	29,194
Truck stops	13,927
Unmanaged rest areas	28,222
Total	71,343

Note: This table presents the adjusted results of the application of a trained YOLOv8 algorithm on satellite imagery containing HGV parking facilities. The algorithm assessed 4,596 images detecting 71,343 HGV parking spaces in total. The definitions for mentioned categories are in Subsection 3.4.

The German Ministry of Transport conducted a nationwide survey on the truck parking situation in April 2018. They recorded 2,200 locations. Based on the survey, the number of HGV parking spaces was estimated about 70,800 (Bundesministerium für Digitales und Verkehr, 2020). Our data suggests an increase in parking spaces of about 500 since the survey was conducted.

Figure 3.5 Parking Supply along German Highways



Note: Geospatial data acquired from Google API and OpenStreetMap. The applied R package was provided by Giraud (2022). The shapefile was taken from the Federal Agency for Cartography and Geodesy (2024).

Figure 3.5 illustrates the spatial distribution of HGV parking spots aggregated on a NUTS-2²¹ level in Germany using a color-coded map. The regions are shaded from dark purple, indicating fewer than 1,000 parking spots, to light yellow, indicating over 4,000 parking spots. Regions in the eastern and southeastern part of Germany, which are shaded in dark purple, have the lowest supply of parking facilities. In contrast, central regions, depicted in light yellow, have the highest number of parking spots, exceeding 4,000, indicating infrastructure capable of accommodating higher volumes of freight traffic. Figure 3.5 reveals notable regional disparities in the availability of HGV parking infrastructure.

3.5.2 Model Performance

The resulting metrics indicate a robust performance in both the training and validation processes. After 300 epochs, the model exhibits low loss levels, with precision at 0.89, recall at 0.85, and a mean average precision @ 50 of 0.92, all suggesting a high degree of model accuracy. Overfitting does not appear to be a significant issue up to Epoch 300, although there is a gradual increase in the disparity between training and validation losses.

The results from our test dataset containing 71 unseen images, follow the initial results from training and validation dataset metrics and indicate a high level of performance (see Table 3.4). The precision, measured at 88.7%, indicates a high rate of correct positive predictions for parking space detection. The model also achieved a recall rate of 85.4%, demonstrating its ability to reliably identify the vast majority of relevant instances within the dataset. The mean Average Precision scores provide an overarching indication of the

²¹ NUTS stands for Nomenclature of Territorial Units for Statistics in the European Union.

model's accuracy across different Intersection over Union (IoU) thresholds: 91.8% at an IoU of 0.50. The metrics collectively attest to the model's robust performance, rendering it a highly reliable tool for estimating the supply of HGV parking spaces. We refrain from describing the results in terms of F1 scores, precision-recall curve, and confusion matrix since we are only predicting one class.

Table 3.4 YOLOv8-OB B Model Performance Metrics on Test Data

Metric	Value
Total images processed	71
Total instances detected	1,523
Precision box	0.887
Recall (R)	0.854
mAP at IoU=0.50 (mAP50)	0.918
mAP at IoU=0.50-0.95 (mAP50-95)	0.647

Note: This table summarizes results of the application of a trained YOLOv8 algorithm on unseen satellite imagery containing HGV parking spaces. The algorithm assessed 71 images detecting 1,523 parking spaces with bounding boxes.

The utilized methodology to identify the supply of parking spaces through satellite imagery delivers granular up-to-date data and is designed to be universally applicable across different geographical regions, underscoring its potential for widespread implementation. In our case, we use the model to predict all parking spaces visible on our 11,398 images. While object detection offers high efficiency and scalability, it also involves uncertainties related to transparency and accuracy. Object detection mechanisms may be at a disadvantage in these respects compared to manual counts. The degree of explainability in object detection remains limited, and this – along with the underlying data sources – can introduce biases into the models. These biases may lead to errors in out-of-sample predictions, potentially resulting in the over- or underestimation of available truck parking spaces. Larger and more accurate training and validation datasets are essential in order to mitigate such biases. Manual counts, by contrast, are normally less prone to such errors and do not require extensive data preparation. Another challenge in our specific use case is that satellite imagery may obscure some parking spaces with obstacles such as trees or equipment, which limits visibility and detection accuracy.

As shown in Subsection 3.4.2, our approach demonstrates a high degree of accuracy. Since there are still missing parking spaces that are not correctly detected, we calculate a

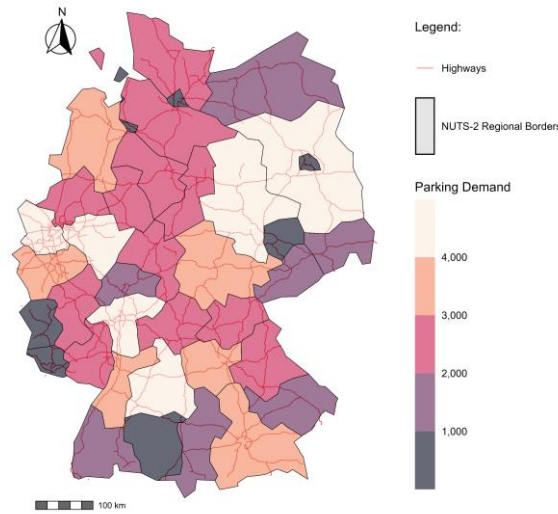
correction factor C for approach i as the difference between predicted parking spaces and actual parking spaces from the test dataset using the following equation (9):

$$C_i = \frac{\text{Actual Labels}}{\text{Predicted Labels}} \quad (9)$$

The resulting coefficient C for the approach i (see Table 3.3 for results) equals 1.068, with which we adjust our model results.

3.5.3 Estimated HGV Parking Demand

Figure 3.6 Parking Demand along German Highways



Note: Geospatial data acquired from Google API and OpenStreetMap. The R package was provided by Giraud (2022). The shapefile was taken from the Federal Agency for Cartography and Geodesy (2024).

Based on the equations (5) to (8) applying the previously described data and the assumptions listed in Table 3.2, Figure 3.6 illustrates the aggregated absolute parking demand for HGVs in NUTS-2 regions in Germany using a color gradient from dark grey to light beige. The regions shaded in dark grey represent those with the lowest demand. Notably, eastern and southern regions fall into this category, indicating lower freight parking demand. Conversely, regions shaded in light beige have the highest demand, with more than 4,000 parking spaces needed. These areas, particularly distributed in the southwest and northeast of Germany, experience comparatively higher HGV parking demand along German highways.

3.5.4 Local Equilibrium

Matching supply and demand enables us to identify local equilibriums as well as over- and undersupplied areas. Referring to a quotation of Glaeser and Joshi-Ghani stating that “the infrastructure need is enormous, but so is the possibility of building the wrong infrastructure” (Glaeser & Joshi-Ghani, 2014), it is essential to prioritize local over global

comparisons. Inefficiencies arise as soon as supply and demand are spatially distant from each other. Therefore, we distinguish between micro view evaluation at the level of highway kilometers and the macro view evaluation at the aggregated level of NUTS-2 regions. We thereby allow micro level insights relevant for specialized developers and macro level insights with special interest for regional planning authorities and policymakers.

3.5.4.1 Micro View

Equation (10) expresses the equilibrium $E_{i,t}$ for HGV parking spaces on a given kilometer i at time t . Whenever supply and demand are balanced, their quotient $Q_{i,t}$ equals 1 and a local equilibrium sets in.

$$E_{i,t} \equiv 1 \equiv Q_{i,t} \quad (10)$$

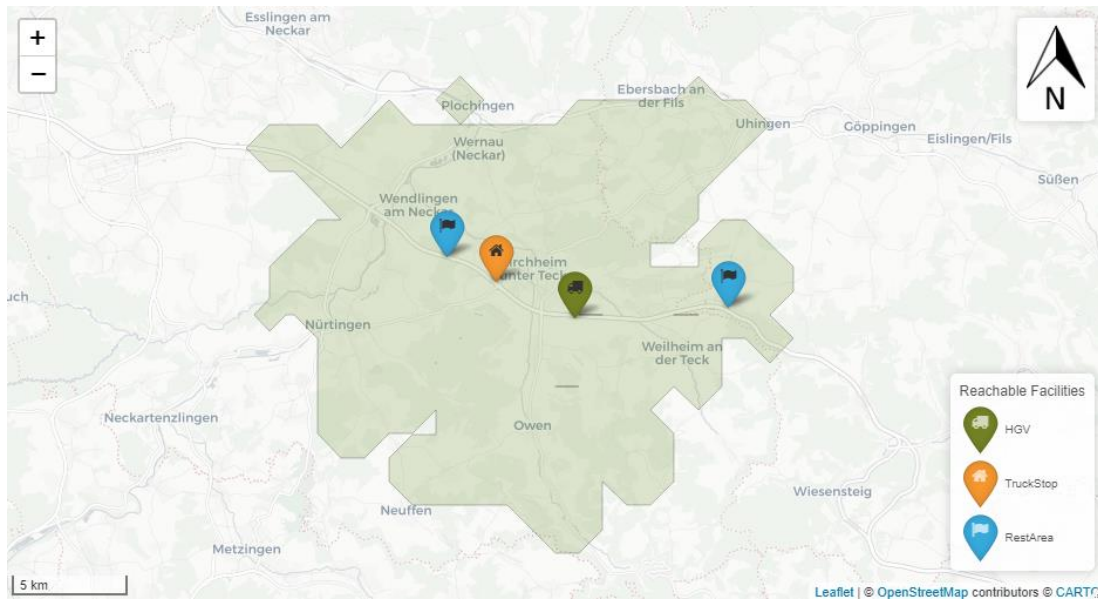
$$Q_{i,t} = \frac{S_{i,t}}{n(D_{i,t})} \text{ with } n \in [1, \dots, 13180] \quad (11)$$

Equation (11) highlights, how supply and demand are compared in their quotient $Q_{i,t}$. $D_{i,t}$ represents the demand for HGV parking spaces on kilometer i , and $S_{i,t}$ represents the supply of HGV parking spaces on kilometer i . $n(D_{i,t})$ represents the number of polygons (or kilometers) from which the supply $S_{i,t}$ can be reached.²² We thereby assume a uniform distribution of supply on demanders.

Figure 3.7 illustrates an example of reachable parking spaces from a given kilometer i within a 15 km polygon in green color.

²² The number of polygons from where supply can be reached is limited by the total number of analyzed highway kilometers.

Figure 3.7 Driving Distance Polygon



Note: This figure illustrates an example polygon in green color and highway infrastructure facilities assigned with markers in orange and blue color on a German highway. Geospatial data acquired from Google API and OpenStreetMap. The R package was provided by Giraud (2022). The shapefile was taken from the Federal Agency for Cartography and Geodesy (2024).

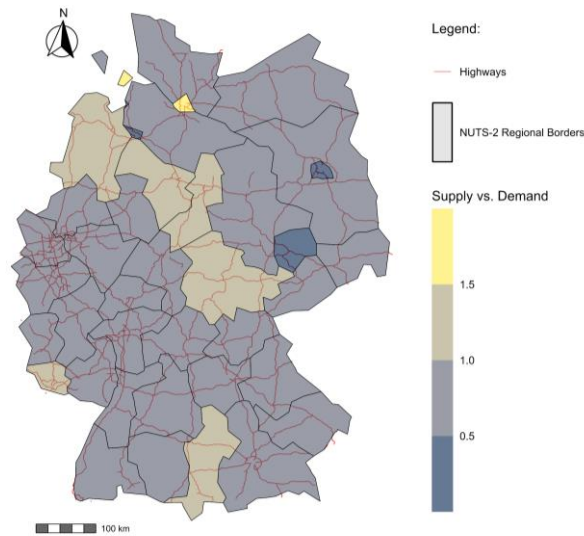
3.5.4.2 Macro View

Equation (10) assumes that an equilibrium ($E_{i,t} \equiv 1$) is achieved when the supply perfectly matches the demand. In other words, each region's parking supply is ideally distributed among the drivers from all regions that can access it. If $E_{i,t} > 1$, it suggests that there is an oversupply in region i , meaning the available parking spaces exceed the demand. Conversely, if $E_{i,t} < 1$, it indicates a shortage, where the demand for parking spaces outstrips the available supply and the need for additional parking facilities.

Figure 3.8 illustrates the average ratio of HGV parking supply to demand aggregated on NUTS-2 regions in Germany, using a color gradient from dark blue to yellow.²³ Regions shaded in gray indicate an undersupply (i.e. $E_{i,t} < 1$), with the parking infrastructure failing to meet the average demand, though not as severely as in regions shaded in dark blue.

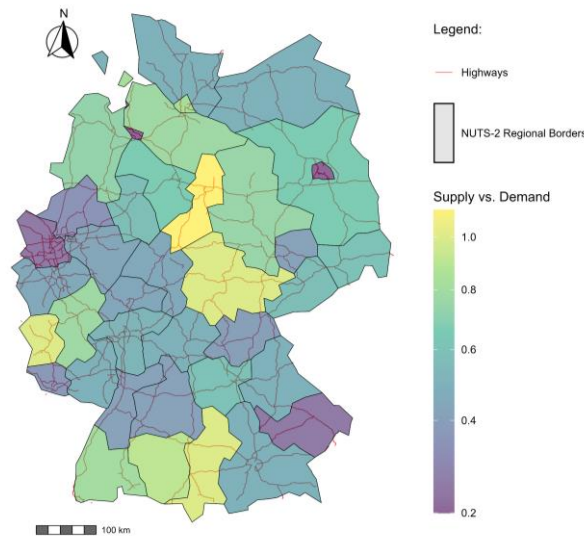
²³ See Table 3.5 for a detailed breakdown.

Figure 3.8 Average Aggregation of Supply and Demand along German Highways



Note: Geospatial data acquired from Google API and OpenStreetMap. The R package was provided by Giraud (2022). The shapefile was taken from the Federal Agency for Cartography and Geodesy (2024).

Figure 3.9 Median Aggregation of Supply and Demand along German Highways



Note: Geospatial data acquired from Google API and OpenStreetMap. The R package was provided by Giraud (2022). The shapefile was taken from the Federal Agency for Cartography and Geodesy (2024).

Figure 3.9 offers a clear depiction of the median supply versus demand ratio for HGV parking aggregated on the level of NUTS-2 regions in Germany, using a color gradient from dark purple (indicating severe undersupply or $E_{i,t} < 1$) to yellow (indicating an exact balance between supply and median demand or $E_{i,t} \equiv 1$). The map reveals that the vast majority of regions are experiencing an undersupply of parking facilities, with many areas shaded in blue to dark purple, indicating ratios as low as 0.2.²⁴

²⁴ See Table 3.5 for a detailed breakdown.

The comparison between the results from average versus median aggregation of supply versus demand ratios demonstrates that, in both scenarios, there is a significant and widespread undersupply of HGV parking across Germany's NUTS-2 regions. Regardless of whether median or average aggregation is applied, the maps consistently show that most regions are shaded in colors indicating undersupply, such as gray, blue, or dark blue.

However, the severity of these shortfalls varies. Bremen, North Rhine, Berlin, and Lower Bavaria show the largest gaps, while other regions – such as parts of Brandenburg and Lower Saxony – appear closer to balance.

We distinguish between three spatially grounded explanatory mechanisms that emerge from visual patterns in the data. The first mechanism, which we refer to as freight corridor concentration, suggests that the most acute mismatches occur along Germany's primary freight routes. In particular, regions such as Lower Bavaria (southeast), North Rhine (west), and Bremen (north) appear to suffer from infrastructure stress not solely due to local traffic volumes, but as a result of cumulative demand from long-distance transit freight. The second mechanism relates to rest cycle timing effects. Some regions, notably Lower Bavaria (southeast) and Hesse (middle west), may experience heightened parking demand due to their position within typical long-haul driving schedules – specifically, locations that fall within 4.5 or 9-hour intervals on common east–west or north–south routes. These points in the journey correspond to mandatory rest breaks, concentrating demand independently of total throughput. The third explanatory mechanism pertains to urban freight bottlenecks. Highly urbanized regions such as Bremen, Dusseldorf (North Rhine), and the Frankfurt Rhine-Main area (Hesse) exhibit persistent undersupply that can plausibly be attributed to spatial constraints, dense last-mile delivery activity and logistical complexity.

3.5.4.3 Location Analysis for Potential Investments

In infrastructure or real estate investments, supply and demand are typically among the key determinants in location analysis. Our methodology operates on a meta-level, making it applicable across a wide range of investment scenarios. For example, in infrastructure analysis – such as ports or passenger vehicle parking – satellite imagery and demand data can be effectively utilized. There is also significant potential for real estate developers, particularly in the logistics sector. Our methodology for measuring truck parking demand is both scalable and applicable beyond the German market. Satellite data is generally available for the entire built environment, though resolution varies by continent and country. In order to meaningfully combine supply and demand data, reliable truck traffic frequency counts are required – data that is typically only available in industrialized

countries. Within Europe, the applied methodology offers a cost-effective and scalable approach to identifying potential undersupply in truck parking infrastructure.

The identified undersupply has significant implications for both specialized real estate developers and policymakers. For developers, the regions experiencing the most severe undersupply represent key opportunities for investment. By leveraging our data, we can precisely identify the polygons – specific areas within these regions – that are most in need of additional HGV parking infrastructure. This targeted approach allows developers to focus their efforts on areas where demand is highest, ensuring that new facilities will meet an urgent need and likely see high utilization.

For policymakers, Figure 3.9 highlights the urgent need to address the infrastructure shortfalls that are widespread across the country. By using the data to pinpoint exactly where the undersupply is highest, policymakers can prioritize regions for funding and development, ensuring that resources are allocated to the areas with the greatest need. This strategic investment could help alleviate parking shortages, reduce illegal parking and enhance road safety for HGV drivers, ultimately leading to more efficient freight transport and economic benefits across Germany. While Figures 3.8 and 3.9 indicate a general trend of undersupply, the ability to pinpoint specific areas of greatest need provides a powerful tool for targeted action and investment. Overall, we show that there is a strong investment case for specialized developers.

3.6 Policy Debate

Our analysis of HGV parking infrastructure along German highways reveals a critical imbalance between available supply and escalating demand, presenting both challenges and opportunities for specialized real estate developers. Despite the Ministry of Transport's five-point plan, which includes initiatives like creating new truck parking options, enhancing telematic parking procedures and optimizing existing space utilization, the gap between current provision and the needs of HGV operators remains significant (Bundesministerium für Digitales und Verkehr, 2020). These governmental measures, while forward-thinking, have not fully addressed the complexity of the issue, particularly when considering the potential role of private sector investment in bridging this gap.

A central factor inhibiting private investment in HGV parking is the current market structure, particularly the dominant position of Tank & Rast²⁵. As the quasi-monopolistic operator of service station on the Autobahn network, Tank & Rast offers free parking

²⁵ Tank & Rast GmbH has a 93 percent market share and is owned by an investor consortium consisting of Allianz, Munchner Ruck, Canada's pension fund OMERS, and the China Investment Corporation (Piller, 2023).

subsidized through ancillary services such as fuel and food sales. This model effectively crowds out competition: private developers must operate on non-federal land and charge for parking to achieve cost recovery, placing them at a structural disadvantage. The absence of price signals in the free parking segment – combined with exclusive access rights granted to Tank & Rast – prevents market-driven capacity expansion in high-demand areas. The German Monopolies Commission and other regulatory bodies have raised concerns that these long-term concession agreements restrict competition and innovation, even in adjacent sectors such as electric vehicle charging (German Council of Economic Experts, 2024). The result is a systemic under-provision of HGV parking, exacerbated by high entry barriers – both institutional and economic – for new market participants. Developers face substantial upfront costs, uncertain demand and inferior locations relative to the Autobahn network.

Importantly, the economic viability of developing new paid parking infrastructure is also limited by HGV drivers' behavioral preferences. Drivers consistently prioritize free parking until it is fully occupied. Only then do they consider alternatives – either paid facilities or, increasingly, informal and often illegal parking. This behavior aligns with discrete choice models under capacity constraints (Ben-Akiva & Lerman, 1985), in which individuals select the highest-utility option given costs, accessibility and availability. Paid parking typically involves both monetary costs and detours off the highway, reducing its relative utility. When enforcement against illegal parking is weak, and the perceived safety risk is low, informal parking becomes a rational, if undesirable, alternative for drivers operating under strict legal rest time constraints.

This behavioral dynamic reflects a deeper market failure (see model in 3.8 Appendix): the absence of enforceable and differentiated pricing mechanisms results in inefficient allocation. Paid infrastructure may remain underused, while free and illegal parking options are chronically oversubscribed. Urban parking economics has demonstrated similar effects, where rigid pricing and insufficient enforcement lead to demand spilling over into unregulated or unauthorized spaces (Arnott & Inci, 2006; Verhoef et al., 1995). In the context of HGV infrastructure, this implies that expanding paid options alone – without corresponding adjustments in pricing, accessibility, or enforcement – is unlikely to resolve the imbalance.

The problem of parking scarcity is not unique to HGVs; urban areas face similar challenges with passenger vehicle parking, driven by legal requirements and the escalating cost of maintaining these spaces (Lehner & Peer, 2019; Yan et al., 2019). However, the aforementioned absence of parking fees for HGVs and the specific demand for exclusive HGV

parking spaces (Malik et al., 2017; Pècheux et al., 2002) further complicate the issue. Technology, particularly real-time information applications on HGV parking availability, has been identified as a potential solution to alleviate some of these challenges (Boris & Johnson, 2015; Martin & Shaheen, 2013; Trépanier, 2010). Nonetheless, land-use policies significantly limit the development of new parking facilities, with jurisdictions often imposing restrictions on HGV parking on roadsides or other spaces (Giuliano et al., 2018; Perry et al., 2017). These high entry barriers compound the challenges pertaining to HGV parking provision.

Urban areas, where land is particularly scarce and expensive, face the most significant challenges. Zoning policies and urban densification targets frequently prohibit the construction of adequate HGV parking lots, presenting a substantial barrier to resolving the parking shortage (Giuliano et al., 2018; Meyer, 1999). Innovative solutions, such as adapting vacant or underutilized urban properties for HGV parking during off-peak hours, have been suggested as viable alternatives (Perry et al., 2017). Tax incentives and the implementation of nominal overnight parking fees could offer financial viability for these initiatives (Fleger et al., 2002).

3.7 Conclusion

The findings of this paper provide a comprehensive analysis of the current state of HGV parking infrastructure in Germany, with a specific focus on the implications for specialized real estate developers. First, we utilize machine learning methods to determine the actual supply of HGV parking spaces along German highways. This approach allows for an accurate and current number that can be updated regularly. We then match our supply-side results with demand determined from traffic volume. The analysis reveals a critical and widespread undersupply of HGV parking spaces, with neither median nor average demand being adequately met across most regions.

The inability to meet demand on both the median and average levels highlight the potential for high returns on investment in the HGV parking sector. This situation presents a unique opportunity for developers to enter a market with minimal competition and significant unmet needs, ensuring that new developments are quickly absorbed by the market and generate stable revenue streams.

The long-term growth potential of the HGV parking sector is another consideration for specialized real estate developers. As Germany remains a central hub in European and global logistics, the demand for HGV parking is expected to grow alongside the expansion of freight transport activities. Developers who can strategically target these underserved

areas stand to benefit from an immediate and sustained demand for parking infrastructure. Moreover, the development of infrastructure facilities improves working conditions for HGV drivers so that they no longer must live on the highway.

Lastly, the paper emphasizes the importance of adopting innovative solutions to effectively address the infrastructure and in particular the parking shortfall. Traditional real estate development strategies may fall short in this complex and regulated market. Developers who can leverage technology – such as real-time parking availability systems – or explore creative land-use strategies, particularly in constrained urban environments, will be better equipped to meet the challenges of the market. Accordingly, further research potential lies in the collection and analysis of locally detailed data on infrastructure demand. Moreover, economic studies on subsidies and regulation are needed to evaluate targeted policy measures addressing the imbalance between highway infrastructure demand and supply.

3.8 Appendix

We model the parking decision of HGV drivers as a discrete utility-maximizing choice between three options: (12) free public parking (typically at rest areas directly along the Autobahn), (13) paid private parking (usually off-network), and (14) illegal parking (e.g., on ramps or industrial roadsides). This extended framework accounts for the empirical observation that many drivers opt for unauthorized parking even when paid options exist, particularly when free facilities are fully occupied, and enforcement is weak.

Let drivers derive utility U from each option as follows:

Utility U_f from free parking:

$$U_f = \theta u_f + (1 - \theta)u_p \quad (12)$$

where θ is the probability of finding an available free spot, and u_f is the utility derived from it. If no free spot is found, the fallback utility u_p reflects a switch to paid parking.

Utility U_p from paid parking:

$$U_p = -C_p - T + \varepsilon_p \quad (13)$$

where C_p denotes the monetary cost, T captures the time and fuel penalty for diverting off the highway, and ε_p is an idiosyncratic error term capturing preference heterogeneity.

Utility U_i from illegal parking:

$$U_i = -R - S + \varepsilon_i \quad (14)$$

where R represents the expected financial penalty from enforcement (if applicable), S is the perceived safety risk (e.g., collisions or theft), and ε_i is an individual-specific shock.

Drivers are expected to choose the option with the highest expected utility. In this framework, illegal parking can dominate paid parking in cases where monetary and detour costs ($C_p + T$) outweigh enforcement risks and perceived safety penalties ($R + S$). This helps explain the widespread persistence of unauthorized truck parking along European freight corridors despite the existence of fee-based alternatives.

The structure aligns with capacity-constrained discrete choice models (Ben-Akiva & Lerman, 1985) and insights from urban parking economics (Arnott & Inci, 2006; Verhoef et al., 1995). Empirical extensions could estimate choice probabilities using a multinomial or mixed logit model and simulate scenarios under varying levels of enforcement, pricing, or capacity expansion. Such a model also supports policy insights: for example, increasing

the perceived risk of enforcement R or lowering the cost of paid parking C_p could reduce illegal parking incidence.

Table 3.5 Overview of Supply, Demand, and Equilibrium

NUTS-2 region	Total supply	Total demand	Average aggregated equilibrium	Median aggregated equilibrium
Freiburg	1643	1540	0.99	0.80
Karlsruhe	1826	3023	0.61	0.42
Stuttgart	2801	4172	0.79	0.42
Tuebingen	828	851	0.84	0.91
Mittelfranken	2812	3520	0.82	0.60
Niederbayern	797	1220	0.60	0.25
Oberbayern	3115	3811	0.79	0.50
Oberfranken	1686	2167	0.68	0.40
Oberpfalz	1423	2159	0.62	0.50
Schwaben	1533	1314	1.26	1.00
Unterfranken	2244	2750	0.83	0.50
Berlin	95	386	0.46	0.20
Brandenburg	3856	4354	1.00	0.67
Bremen	140	466	0.20	0.20
Hamburg	426	696	1.75	0.83
Darmstadt	2264	4011	0.82	0.53
Giessen	917	1762	0.55	0.44
Kassel	2245	2704	0.77	0.46
Mecklenburg-Vorpommern	1729	1902	0.78	0.50
Braunschweig	2330	2110	1.39	1.11
Hannover	2473	2805	1.27	0.67
Lueneburg	3083	2837	0.97	0.78
Weser-Ems	3786	3169	1.09	0.73
Arnsberg	2230	4201	0.65	0.44
Detmold	1608	2186	0.71	0.58
Duesseldorf	1942	4795	0.53	0.25
Koeln	2200	3883	0.80	0.45
Muenster	1630	2984	0.52	0.35

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NUTS-2 region	Total supply	Total demand	Average aggregated equilibrium	Median aggregated equilibrium
Koblenz	1673	2132	0.75	0.78
Rheinessen-Pfalz	1848	2440	0.80	0.50
Trier	424	709	0.88	1.00
Saarland	356	983	1.13	0.38
Chemnitz	1434	1912	0.84	0.57
Dresden	1655	1963	0.80	0.60
Leipzig	430	894	0.42	0.42
Sachsen-Anhalt	4623	4535	0.95	0.75
Schleswig-Holstein	1798	2634	0.89	0.50
Thuringen	3440	3184	1.08	1.00

3.9 References

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4 The Price of Politics: A County-Level Analysis of Political Uncertainty and German House Prices

4.1 Abstract

This study examines the linkage between political uncertainty and housing market purchasing behavior in Germany. We measure politically related uncertainty using the media-based Uncertainty Perception Indicator, which captures domestic political uncertainty more comprehensively than conventional economic policy-focused measures, and examine its effects on housing markets using transaction data covering all 400 counties in Germany. Applying spatial regression techniques to address neighborhood spillover effects, we identify county-level house and condominium prices to be negatively associated with increased political uncertainty. The negative effect is further increased in counties with higher unemployment rates, with house prices showing greater sensitivity than condominium prices. Our results suggest that political uncertainty has a significant impact on homebuyer activity and housing market purchasing behavior, with implications for housing supply development in Germany.

Keywords: Homebuyer activity, Political uncertainty, Spatial spillover, Spatial regression, Housing

4.2 Introduction

“When policies and rules are subject to repeated changes at the hands of politicians largely eyeing short-term political gains, it becomes increasingly difficult to make economic decisions and plan for the future.” (Luo et al., 2022)

Frequent policy changes, shifts of political power, or unclear political intentions result in uncertainty over political outcomes. Over the last decade, Germany and many other countries experienced higher than usual uncertainty over political outcomes, largely driven by exogenous shocks such as migration, the COVID pandemic and the war in Ukraine.²⁶ Market participants take these uncertainties into account when making decisions that affect their economic outcomes. These reactions differ individually, but also among sectors.

The housing sector serves as a prime case in point; its purchases are long-lived and partially irreversible, making it particularly sensitive to uncertainty. Few other sectors are as heavily regulated as housing in Germany: while housing can be viewed as a private good with significant externalities (e.g., urban planning and social stability; see Glaeser & Gyourko, 2008), it is often treated as a social good in policy contexts. Additionally, energy-efficiency requirements have been expanded in recent years, while energy-efficient housing is still subject to political discourse. These features distinguish the German market from more market-oriented systems, like the U.S. or UK, where regulations are less pervasive and tenant protections weaker (for example, there exist no nationwide rent caps), making Germany an ideal laboratory to examine how political uncertainty amplifies regulatory risks and affects homebuyer activity across diverse regional markets. Because housing is a long-lived and illiquid asset, expectations about the regulatory environment are capitalized on current prices. Political uncertainty therefore affects housing not only through realized policy changes but also through anticipatory adjustments in property valuation. Furthermore, initial findings indicate that German reactions to (domestic) political uncertainty are more pronounced than average by international standards. This is particularly evident in rising household savings rates (Giavazzi & McMahon, 2012), declining private investment, and reduced consumer spending (Mueller et al., 2025) during periods of heightened political uncertainty. These features make Germany a compelling case to study how political uncertainty shapes homebuyer activity and pricing behavior.

²⁶ The German Economic Policy Uncertainty (EPU) Index rose sharply during major geopolitical and social shocks over the past decade. The index reached unprecedented peaks during the European migration crisis (2015–2016), the COVID-19 pandemic (2020), and following the Russian invasion of Ukraine (2022), reflecting heightened uncertainty over fiscal, energy, and housing policy. These spikes illustrate how exogenous shocks have translated into persistently elevated political and economic uncertainty in Germany.

In general, housing market outcomes depend on overall economic conditions, such as household income, economic growth, interest rates and demographics as well as regulatory settings. While variation in homebuyer activity can to a certain extent be explained by sensitivity to these fundamentals and market cycles (e.g., Knoll et al., 2017; Zhang & Wan, 2024), a significant share of unexplained variation persists. This remaining variation can be attributed, at least in part, to shifts in political or regulatory uncertainty, as shown by prior works linking political uncertainty to real estate activity (e.g., Luo et al., 2022) and by studies demonstrating that regulatory constraints, such as planning restrictions or building codes, increase the sensitivity of house prices to shocks in constrained markets (Hilber & Vermeulen, 2016; Gyourko & Molloy, 2015).

Recent studies identify negative effects of election uncertainty on construction activity in the U.S. (see Luo et al., 2022 and Canes-Wrone & Park, 2014). According to Antonakakis et al. (2015) and André et al. (2017), political uncertainty exerts negative effects on house prices. Choudhry (2020) finds similar results for the UK. Most of these studies rely on the Economic Policy Uncertainty (EPU) Index by Baker et al. (2016), which captures policy-related uncertainty once political developments have produced measurable economic repercussions. However, EPU primarily reflects realized policy-related uncertainty, and may miss earlier, perception-driven stages of political instability.

The Uncertainty Perception Indicator (UPI) on German Politics, developed by Rieger et al. (2023), captures broader perceived political uncertainty – including ambiguity about future government actions and institutional reliability – before these perceptions translate into economic consequences. Unlike other uncertainty measures, the UPI German Politics is not compiled based on a predefined dictionary; instead, uncertain narratives are dynamically adapted to current events. The index is thus continuously adjusted over the observation period and reflects political developments, for instance in relation to rent control or building regulations. To date, the index is only available for German media. Using the UPI German Politics therefore allows us to test whether German housing markets respond to the anticipation of political instability itself rather than to its realized macroeconomic effects. This distinction is particularly relevant for homebuyers, where long holding periods make perception-based uncertainty especially influential. Homebuyers in Germany typically make few purchases, often only once in their lifetime. This is also reflected in the low homeownership rate of 45 percent by international standards (Kaas et al., 2021). Analyzing

homebuyer activity in Germany, we focus on the two most popular forms of home ownership: houses and condominiums.²⁷

We are not aware of prior studies that have investigated how broad, perception-based political uncertainty influences homebuyer activity in Germany. This gap potentially arises from both the scarcity of granular data and the dominant focus on Anglo-Saxon markets. Our analysis leverages county-level transaction data and spatial econometric techniques to examine how political uncertainty, measured through the UPI German Politics, shapes regional housing prices and purchasing behavior. We find that house prices and condominium prices decrease when political uncertainty increases. Furthermore, we demonstrate that housing prices in regions with higher unemployment are particularly responsive to an increase in political uncertainty, with house prices reacting more sensitively than condominium prices. Our findings complement previous research on the negative impact of political uncertainty on residential real estate prices and homebuyers' purchasing behavior. Studies by Antonakakis et al. (2015), El-Montasser et al. (2016), André et al. (2017), and Choudhry (2020) reveal negative impacts of primarily economic policy uncertainty on residential real estate prices. Luo et al. (2022) provide initial evidence of a negative impact of party-political uncertainty on housing construction. However, there is little evidence of political uncertainty, that is not necessarily economically driven, influencing purchasing behavior and housing prices. This study contributes to the literature in three ways. First, we extend existing findings on policy-related uncertainty by demonstrating that perceived political uncertainty (UPI German Politics) affects housing prices even before it manifests in economic policy uncertainty (EPU). This highlights an anticipatory channel whereby expectations about political instability are priced into housing markets. Second, we identify important market heterogeneity: uncertainty effects vary by local economic conditions and property types, with houses in high-unemployment regions showing the strongest sensitivity. Third, we apply spatial econometric techniques to all 400 German counties using transaction data, explicitly accounting for spatial dependencies inherent in housing markets.

The remainder of the paper is organized as follows: Section 4.3 reviews related literature and provides a theoretical background on uncertainty in the real estate sphere. In Section 4.4, we present the methodology, namely our data and empirical design. Section 4.5 reviews the results of our spatial regressions and Section 4.6 concludes.

²⁷ In the context of this study, a condominium is defined as property ownership of a unit in a multi-family building combined with sharing undivided ownership of common areas with other unit owners in a cooperative association (Rosen & Walks, 2013).

4.3 Uncertainty in Real Estate

The relationship between uncertainty and economic outcomes has been extensively documented. Uncertainty surrounding economic, fiscal, monetary, or regulatory policies exerts broad adverse effects on the real economy. Studies show that heightened uncertainty can depress economic growth (Bloom et al., 2018), have adverse impacts on the labor market (Ferrara & Guérin, 2018) and reduce production levels as well as output (Basu & Bundick, 2017). As with uncertainty in general, the reasons for adverse effects of political uncertainty are among others: postponement of major purchases, resulting price volatility and corresponding risk premiums²⁸ as well as transaction costs that ultimately distort the allocation of capital resources.

4.3.1 Theoretical Framework of Uncertainty in Real Estate

Real estate purchases possess three critical features that make them particularly sensitive to uncertainty: irreversibility, timing flexibility and high capital intensity (Dixit & Pindyck, 1994). These characteristics create a framework where uncertainty significantly alters optimal purchasing behavior through several key economic mechanisms.

Real options concepts, early applied to real estate by Titman (1985) in his work on urban land prices and later formalized into a comprehensive theoretical framework by Dixit and Pindyck (1994), provide the primary theoretical foundation for understanding purchases under uncertainty. When purchases are irreversible – as is typically the case with housing – uncertainty increases the option value of waiting. The homebuyer holds a "call option" on the opportunity, and exercising this option eliminates the possibility of waiting for new information. Political uncertainty increases this waiting option's value by expanding the potential range of future outcomes. Mathematically, the option value of waiting increases with the variance of property valuations, which political uncertainty directly amplifies (Bulan et al., 2009). This creates a zone of inaction, where purchases remain unexecuted as homebuyers rationally wait for uncertainty resolution (Geltner et al., 2007).

Political uncertainty also affects housing purchases through financial channels. The risk premium component increases as uncertainty raises the perceived volatility of rental income and property values (Pástor & Veronesi, 2013; Baker et al., 2016). Simultaneously, credit markets tighten – lenders reduce loan-to-value ratios and increase spreads, while existing leveraged owners face refinancing risks that can trigger distressed sales (Gissler et al., 2016; Brunnermeier & Sannikov, 2014). These financing constraints particularly impact

²⁸ It should be noted that uncertainty is not comparable to risk. Unlike risk, when it comes to uncertainty, outcomes are unknown, and thus assigning probabilities to future states is not feasible.

housing because of its high leverage ratios and external financing dependence (Ling & Naranjo, 2015).

Housing markets are substantially regulated, making them particularly sensitive to political uncertainty through the regulatory channel. Uncertainty about future regulations regarding zoning, rent control, property taxation, or environmental requirements directly affects property valuation. Anticipated changes in regulatory frameworks create uncertainty about future compliance costs, which are often substantial in real estate development (Gyourko & Molloy, 2015). This regulatory channel is especially pronounced in housing markets due to their social importance and consequent political salience (Hilber & Vermeulen, 2016).

4.3.2 Review of Empirical Literature

The empirical literature on political uncertainty can be categorized into three distinct strands: studies examining political uncertainty's impact on general capital allocation, research specifically addressing real estate transactions and analyses of political uncertainty's effects on asset prices including housing. Due to the focus of our analysis on the housing sector, we analyze literature that addresses homebuyer behavior, transactions and pricing of housing real estate.

The effect of uncertainty on real estate is amplified by the sector's illiquid nature. Buildings are durable, site-specific and expensive to modify or repurpose. Once construction begins, sunk costs cannot be fully recovered if future conditions worsen (Dixit & Pindyck, 1994). Most empirical studies confirm a negative impact of uncertainty on housing transaction activity. Using election-based uncertainty measures, Canes-Wrone and Park (2014) find that political uncertainty during elections leads to delayed transactions, with this effect being more pronounced in competitive electoral races with significant policy differences between candidates. Similarly, Luo et al. (2022), using the EPU as well as partisan conflict indices, establish that political uncertainty negatively impacts residential construction activities, leading to a decline in building permits.

Political uncertainty exerts downward pressure on housing prices through several channels. Christou et al. (2017) find that heightened uncertainty reduces household willingness to make major purchases, particularly for owner-occupied housing. This demand reduction is amplified by housing purchases' substantial leverage, making households more sensitive to uncertainty about future income (Ngai & Sheedy, 2020). Also, political uncertainty reduces market liquidity as both buyers and sellers adopt a wait-and-see approach, increasing the liquidity premium in transaction prices (Clayton et al., 2008).

The uncertainty impact on housing supply operates primarily through investment decisions. Developers delay or cancel projects during heightened political uncertainty, reducing new housing supply (Luo et al., 2022). This effect is particularly strong because real estate development involves substantial sunk costs and long-time horizons (Bulan et al., 2009). Existing homeowners and developers may, furthermore, delay listing properties during uncertain periods (Ngai & Tenreyro, 2014).

These supply-side effects have significant implications for housing affordability. As Luo et al. (2022) demonstrate, political uncertainty leads to reduced construction activity, exacerbating housing shortages in supply-constrained markets. The combination of price and supply effects creates a feedback loop: reduced development activity constrains housing supply, putting upward pressure on prices once uncertainty resolves, potentially triggering further political interventions (Hilber & Vermeulen, 2016).

Regarding specific effects on housing prices, Choudhry (2020) obtains long- and short-term negative effects of economic policy uncertainty on housing prices in England and Wales, using the EPU Index. El-Montasser et al. (2016) suggest a bi-directional causality between policy uncertainty and housing prices, indicating that uncertainty regarding future economic fundamentals can lead to increased housing price volatility, amplifying financial cycles. André et al. (2017) uncover a causal relationship between EPU and real housing returns in the US, demonstrating that high EPU may lead to lower housing prices especially during downturns. Antonakakis et al. (2015), similarly, find that economic policy uncertainty has a significant negative impact on housing prices and market returns in the US from 1984 to 2012. Table 4.1 gives an overview of uncertainty-related housing literature. This overview shows that the existing literature deals predominantly with the negative impact of economic policy uncertainty on house prices and focuses mainly on Anglo-Saxon housing markets.

Fewer findings are available on the influence of other types of political uncertainty on house prices. Hilber and Vermeulen (2016) find negative effects of uncertainty on policy reforms on house prices in the UK, analyzing a panel data set of 35 years. Choi (2023) as well as Van Nguyen and Vergara-Alert (2023) isolate negative house price effects of election uncertainty in the US.

Anticipating the concept of real options theory for purchasing decisions under uncertainty, the high degree of political regulation of the housing market and the evidence to date on the impact of mainly economic policy uncertainty on real estate prices, a significant negative association between media-perceived generic political uncertainty and housing prices is to be expected. Given the lack of evidence to the contrary, it is furthermore

expected that perceived political uncertainty has a negative impact on both house and condominium prices. However, the heterogeneity of regions in Germany is likely to cause local differences in the impact of political uncertainty on housing prices.

Table 4.1 Overview of Related Literature

Study	Aspect of housing market	Uncertainty measure	Data	Methodology
Clayton et al. (2008)	Homebuyer activity	Market liquidity	US (1984-2003)	Error-correction model
Canes-Wrone & Park (2014)	Homebuyer activity	Election uncertainty	US survey data (2008)	Probit regression
Ngai & Tenreiro (2014)	House prices	Economic uncertainty	UK and US (1996-2012)	Poisson regression
Antonakakis et al. (2015)	House prices	EPU	US (1987-2014)	Time varying correlation measure
El-Montasser et al. (2016)	House prices	EPU	CA, FR, GER, IT, ES, UK, US (2001-2013)	Bootstrap panel causality test
Hilber & Vermeulen (2016)	House prices	Policy reforms	England (1974-2008)	Panel regression
André et al. (2017)	Housing returns	EPU	US (1953-2014)	(Vector) Autoregressive models
Ongan & Gocer (2017)	Home prices	EPU	US cities (1991-2016)	Unit root and cointegration tests
Choudhry (2020)	House prices	EPU	Regions in UK	Cointegration tests
Christou et al. (2017)	Housing returns	EPU	OECD countries (2003-2014)	Panel regression
Luo et al. (2022)	Building permits	Partisan conflict index	US states (1981-2017)	Panel regression
Choi (2023)	House price growth	Election uncertainty	US counties (1994-2018)	Panel regression
Van Nguyen & Vergara-Alert (2023)	House price growth, transactions, permits	Gubernatorial elections	US states (1982-2018)	Difference-in-difference analysis
[our work]	House and condominium prices	UPI German Politics & EPU	Germany (2013-2022)	Spatial autoregressive regression (SAR)

Note: This table gives a systematic overview of literature on housing markets and political uncertainty.

4.4 Data

4.4.1 Measuring Political Uncertainty

Researchers have conceptualized political uncertainty in different ways, each approach capturing distinct aspects of this multifaceted phenomenon. Baker et al. (2016) developed the Economic Policy Uncertainty Index, which requires articles to simultaneously contain terms from three categories: economy (for example, "economic," "economy"), policy (e.g., "regulation," "deficit"), and uncertainty (e.g., "uncertain," "uncertainty"). This narrow intersection captures uncertainty once it manifests in economic policy discourse. Election-based measures (Julio & Yook, 2012; Canes-Wrone & Park, 2014) use electoral cycles and competitiveness as proxies, focusing on uncertainty about future policy directions.

For our analysis, we utilize the German Politics category of the Uncertainty Perception Indicator developed by Rieger et al. (2023). Unlike EPU's restrictive three-category requirement, the UPI measures generic political uncertainty by identifying any political content in articles containing uncertainty terms, making it particularly suitable for analyzing real estate markets, where political decisions impact investment conditions through multiple channels beyond economic policy.

The UPI employs Rolling-LDA (Rolling Latent Dirichlet Allocation), a dynamic topic modeling approach that maintains temporal consistency while allowing topics to evolve. This contrasts with EPU's static keyword counting. Using a corpus of three leading German newspapers – Sueddeutsche Zeitung (center-left), Die Welt (center-right), and Handelsblatt (business-focused) – the system processes articles containing uncertainty-related terms and identifies political content through unsupervised clustering rather than predetermined categories.²⁹

Crucially, the topic-specific words update quarterly through machine learning, ensuring the index captures contemporary political concerns. While EPU misses uncertainty that has not yet entered economic policy vocabulary, UPI detects emerging political uncertainties before they crystallize into policy debates. The German Politics UPI encompasses uncertainty surrounding structural reforms, legislative processes, and electoral outcomes – a broader scope than EPU's economic policy focus. Applying the UPI to the German housing market thus allows us to examine the effects of political uncertainty that are not necessarily economic in nature. National political uncertainty encompasses not only economic uncertainty, but also social policy uncertainty in the context of tenant protection

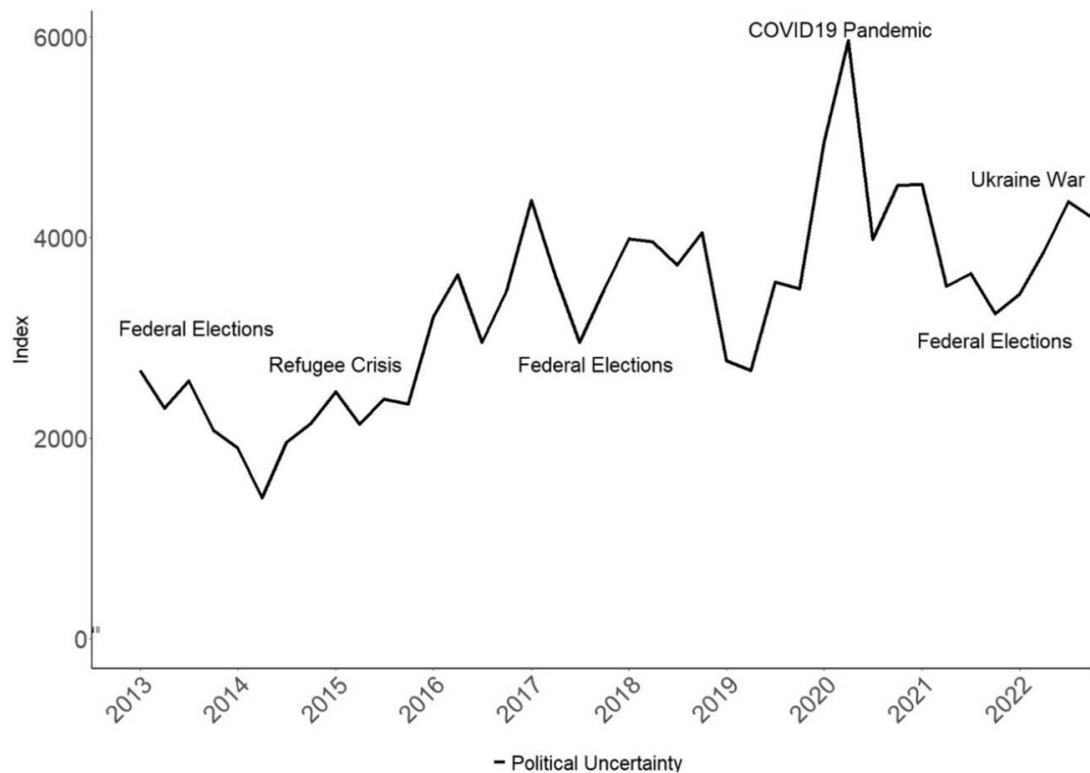
²⁹ The index does not separately report which underlying medium accounts for what share of the total number of media analyzed. It therefore cannot be ruled out that individual media contribute disproportionately to the overall score.

or social welfare, as well as domestic political uncertainty about public safety or social order. The various aspects of the political spectrum and the associated uncertainty covered by the UPI enable insights that go beyond economic policy contexts.

Figure 4.1 illustrates the index development over time, showing clear spikes during major political events. It is worth mentioning that the UPI, unlike the widely used EPU, does not show high peaks during federal elections. The only moderate correlation between the two measures, reported in Table 4.3, underscores the difference in the type of political uncertainty that both indices reflect.³⁰ The monthly UPI data is aggregated into quarterly means to align with our market data frequency. Table 4.2 provides summary statistics, while Appendix Table 4.12 presents an example of the dynamically selected words in 2021Q1.

³⁰ The conceptual lead-lag relationship, that is the UPI capturing political uncertainty before it crystallizes into the EPU's economic-policy vocabulary, is theoretically motivated by the broader semantic scope and the dynamic Rolling-LDA construction. A formal empirical test of the temporal precedence (e.g. via Granger causality between the two indices) is beyond the scope of this analysis and is left for future research. The complementary orthogonalized residual UPI_EPU_RES (Section 4.5) addresses the overlap concern by isolating UPI variation that is uncorrelated with EPU.

Figure 4.1 Development of UPI German Politics Indicator 2013-2022



Note: This chart illustrates the UPI Indicator, developed by Rieger et al. (2023), over time in level values.

4.4.2 Homebuyer Activity and Prices

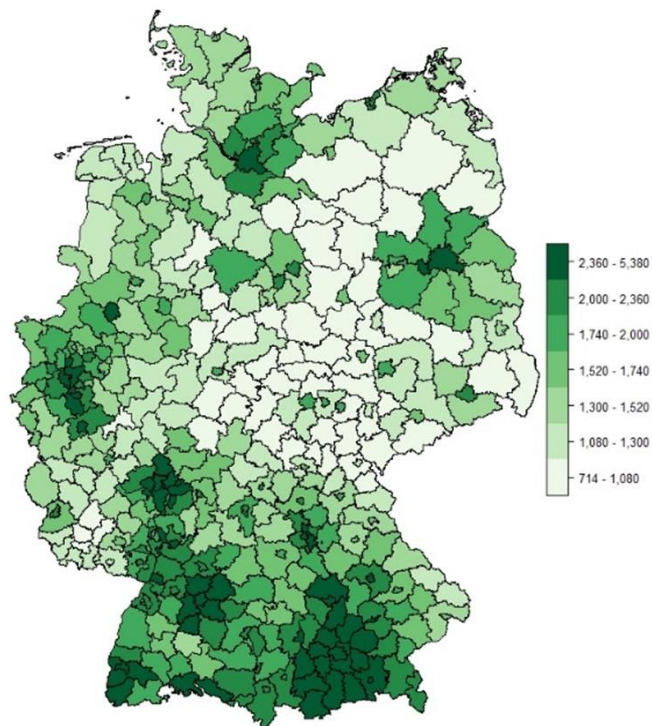
Homebuyer activity can be measured through several indicators, for instance, building permits, construction activity, transactions, or listings. As building permits or constructions do not adequately represent real estate purchasing decisions since they come with inconsistent delays to the decision of, for example, applying for a permit, transaction or offer data better represents actual purchasing decisions. Even though transactions might not cover the whole scope, as new buildings are only captured after construction, transactions offer the most accurate representation of investment sentiment (Fisher et al., 2007).

As mentioned earlier, since local German housing markets are heterogeneous and might exhibit varying market features, we allow for regional differences and control for spatial dependencies by gathering panel data for all 400 German counties. County-specific transaction data is provided by Verband Deutscher Pfandbriefbanken (2023). About 590 regional and national member banks report accompanied transactions, making it the largest German transaction database. Our obtained data includes quarterly median per square meter transaction prices for condominiums and detached houses, covering each county over the period from 2013Q2 to 2022Q1. The sample consists of one median-price observation for each of the 400 counties in Germany over a period of 36 quarters, totaling

14,400 data points. We construct two different segments, namely transactions of detached houses as well as transactions of condominiums. Transactions prices (normalized by the floor space) for each county and quarter represent the housing prices in our panel. Transactions are available for each county and quarter in the house price data set, eliminating the need for data adjustment. However, because of limited transaction activity of condominiums in rural counties, median prices for 247 counties over 36 quarters remain in the dataset for condominiums, totaling 8,892 observations. Figures 4.2 and 4.3 illustrate sample averages as well as data availability for German counties.

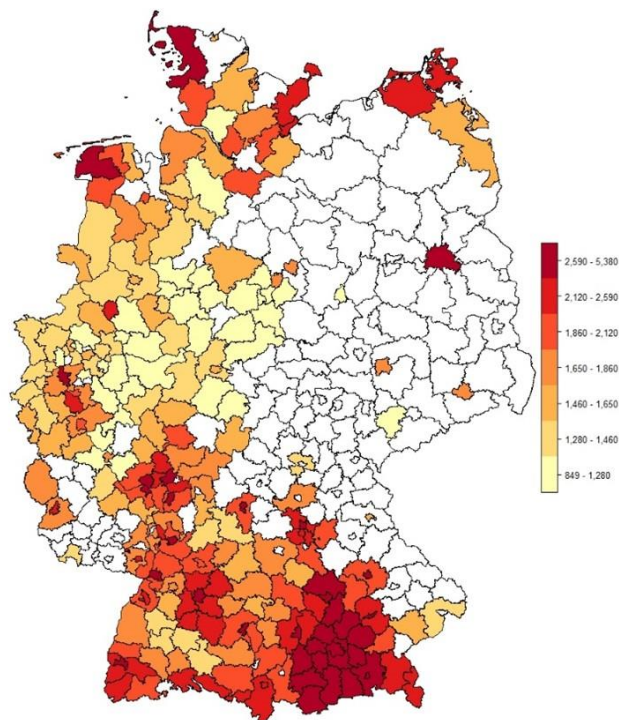
Housing prices and homebuyer activity depend on the supply and demand in individual housing markets. Since demand for housing is primarily reflected in socioeconomic and demographic control variables, it is crucial to look at supply to explain price variations (Grimes & Aitken, 2010; Anenberg & Ringo, 2024). The panel dataset is therefore enriched by the quarterly total number of all property listings on Germany's largest online real estate platform "Immobilienscout24", derived from RWI and ImmobilienScout24 (2023). The total number of listings thereby serves as control variable. Analogously, we distinguish between condominiums and detached houses. While this approach is suboptimal, as it captures mostly private selling intentions rather than actual housing stock, it allows us to represent the supply side of the private housing market (Kolbe et al., 2021). In combination with transaction prices, we apply both measures to isolate the effects of generic political uncertainty on housing markets.

Figure 4.2 Average House Prices 2013-2022 (in €)



Note: This figure illustrates sample-averages of transaction house prices in Germany, in euros, per square meter. Darker color denotes higher prices, while brighter color denotes lower prices. Data source: VDP (2023).

Figure 4.3 Average Condominium Prices 2013-2022 (in €)



Note: This figure illustrates sample-average condominium transaction prices, in euros, per square meter. Darker color denotes higher prices, while brighter color denotes lower prices. Uncolored parts of the map symbolize missing data not included in the data set subsample for condominium prices. Data source: VDP (2023).

4.4.3 Further Control Variables

Our analysis bases on a comprehensive dataset of quarterly data for all 400 German counties between April 1, 2013, and March 31, 2022.³¹ Broader macroeconomic conditions are controlled by including regional determinants of housing supply and demand, such as mortgage interest rates, unemployment and land prices. The interest rate variable denotes real interest rates on secured mortgages, which are most common for residential property financing, and are derived from the German Federal Bank.³² The unemployment rate serves as economic indicator and is derived from the Federal Employment Agency.³³ Land prices are normalized per square meter and serve as real estate market indicator. We collect land price data from the Federal and State Statistical Offices.³⁴

In addition, demographic variables like age-coefficients, population density and migration³⁵ are included. All demographic variables serve as local housing demand indicators and are derived from the Federal and State Statistical Offices.³⁶ Table 4.2 reports descriptive statistics for our data set. If feasible, control variables come at quarterly- and county-level. If county-level data is not available, the next best is chosen, i.e. federal state-level or national-level. Table 4.3 reports pairwise correlations. It is worth mentioning that political uncertainty is negatively correlated with house and condominium prices.

³¹ The condominium sample consists of data for 247 counties.

³² See [German Federal Bank Database](#) for details on residential mortgages.

³³ See [Federal Employment Agency Database](#) for details on unemployment data.

³⁴ See [Federal and State Statistical Offices Database](#) for details on land prices.

³⁵ The migration variable is normalized by 10,000 inhabitants.

³⁶ See [Federal and State Statistical Offices Database on Population](#) for details regarding demographics.

Table 4.2 Descriptive Statistics

	Obs.	Mean	Std. dev.	25%	50%	75%
House prices	14,400	1,733.02	820.93	1,181.60	1,552.66	2,083.34
Condominium prices	8,892	1,918.00	931.75	1,257.40	1,707.70	2,361.20
House listings	14,400	409.00	364.65	163.00	307.00	544.00
Condominium listings	8,892	361.99	1,120.26	87.75	167.00	339.00
Political uncertainty	14,400	3,303.00	947.23	2,544.00	3,469.00	3,886.00
Unemployment rate	14,400	5.46	2.53	3.50	5.00	6.83
Population density	14,400	532.60	700.92	115.70	199.80	674.60
Population age	14,400	44.97	1.95	43.70	44.70	46.10
Interest rate	14,400	1.74	0.47	1.30	1.75	1.90
Land prices	14,400	159.56	231.10	48.89	91.08	180.72
Migration per 10,000 inhabitants	14,400	66.06	61.39	28.70	57.10	93.33
EPU Index	14,400	229.90	116.72	147.70	191.50	256.40
Political uncertainty_EPU_RES	14,400	56.56	837.35	-627.46	42.62	556.60

Note: This table presents summary statistics for the house prices and condominium prices data set. Variables are printed in levels and before transformations to give a brief overview of the applied data sets.

Table 4.3 Pairwise Correlations

	House prices	Condo- minium prices	House listings	Condo- minium listings	Political uncertainty	Un- employment rate	Population density	Population age	Interest rate	Land prices	Migration per 10,000 inhabitants	EPU Index	Political uncer- tainty_ EPU_RES
House prices	1												
Condominium prices	0.763***	1											
House listings	-0.213***	-0.303***	1										
Condominium listings	-0.274***	-0.298***	0.616	1									
Political uncertainty	-0.026***	-0.035***	-0.099***	-0.086***	1								
Unemployment rate	-0.297***	-0.304***	0.036***	0.076***	-0.005*	1							
Population density	0.405***	0.182***	-0.013**	-0.001***	0.000	0.401***	1						
Population age	-0.547***	-0.246***	-0.033***	-0.084***	-0.004	0.257***	-0.446***	1					
Interest rate	0.110***	0.129***	-0.179***	-0.207***	-0.071***	-0.029***	0.002	0.019**	1				
Land prices	0.799***	0.620***	-0.090***	-0.100***	-0.007	-0.178***	0.593***	-0.665***	0.046***	1			
Migration per 10,000 inhabitants	0.103***	-0.037***	0.068***	0.139***	0.022***	-0.080***	0.022***	-0.183***	0.082***	0.138***	1		
EPU Index	0.121***	0.147***	-0.118***	-0.127***	0.470***	-0.070***	0.002	0.024***	0.087***	0.045***	0.092***	1	
Political uncertainty_ EPU_RES	-0.063***	-0.080***	-0.075***	-0.059***	0.969***	0.014***	0.000	-0.011	-0.102***	-0.020**	-0.002	0.236***	1

Note: This table presents the correlation matrix of the applied data set. Significance levels are indicated by *** p<0.01, ** p<0.05, and * p<0.10.

4.5 Empirical Analysis

This section presents the empirical findings on the relationship between political uncertainty and homebuyer activity in Germany. We first conduct preliminary tests, then present our main regression results, followed by a detailed analysis of regional heterogeneity in the effects of political uncertainty on housing markets. Finally, we conduct several robustness checks.

4.5.1 Political Uncertainty and Economic Fundamentals

The preliminary analysis of our data reveals non-stationarity in political uncertainty measures and interest rates applying a panel unit root test. Non-stationarity of economic fundamentals and interest rates is a common issue in economic research, as this data underlies trends or shocks (see, for example, Rapach & Weber, 2004 and Kim, 2018). However, it comes not as a surprise to observe similar behavior for political uncertainty measures. The Uncertainty Perception Indicator and other uncertainty measures amplify whenever uncertainty arises or decreases. As illustrated in Section 4.4.1, the perception of uncertainty rises sometimes suddenly and sometimes shows trending behavior. Observing both variables, interest rates and uncertainty perception measures, at the same time, reveals a causal relationship operating through multiple channels. Interest rates are driven by monetary policy and market expectations, with risk premiums rising when political uncertainty increases. Whenever political uncertainty arises, influencing market expectations, interest rates show a time-delayed reaction. Both variables, additionally, respond to common economic fundamentals that affect monetary conditions and political stability. This observation is in line with the evidence of Hartzmark (2016), proving a robust relation between real interest rates and market uncertainty. The studies of Amisano and Tristani (2019) on uncertainty shocks and long-term interest rates and Wang and Boatwright (2019) on financial markets reaction on political uncertainty further prove the fundamental relation between interest rates and political uncertainty measures.

Given this theoretical relationship and the identified non-stationarity of both variables, we test for cointegration. We employ the Johansen test on cointegration, developed by Johansen (1991), to isolate a potential long-term relationship between these measures. The test results indicate a highly significant cointegration relationship between both variables, allowing us to isolate an error correction term.³⁷ This error correction term is

³⁷ The cointegration finding confirms that German mortgage rates and political uncertainty move together in the long run, consistent with the risk premium channel where sustained political uncertainty becomes priced into credit markets.

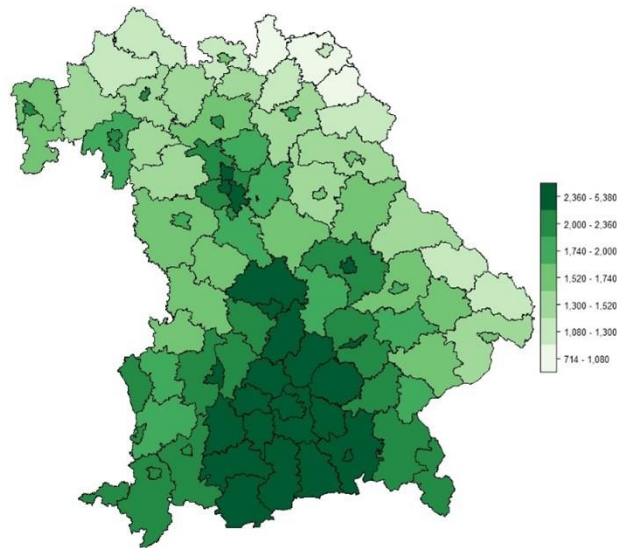
included in all regression specifications to obtain unbiased short-term effects. Furthermore, we use first differences of the Uncertainty Perception Indicator as well as of the interest rate variable to prevent biases resulting from the identified non-stationarity in levels.

4.5.2 Spatial Regression Methodology

While working with a georeferenced price data set, it becomes evident that emerging price dynamics overcome geographical borders of analyzed German counties. The visual presentation of sample-average values in Figure 4.2 and Figure 4.3 indicates spatial clustering of converging prices printed in darker color. An examination of the illustrative map excerpts of sample-average house prices in the federal state of Bavaria (Figure 4.4) and of sample-average condominium prices in the federal state of Baden-Wurttemberg (Figure 4.5) strengthens this impression. Spatial clustering of higher and lower prices across several counties, visualized through darker and lighter color, respectively, becomes apparent. The analytical assessment of this observation based on Morans' I test on spatial autocorrelation, first developed by Moran (1950), further strengthens the graphical perception. The test statistics appear highly significant for every time period of the sample (see Appendix Table 4.13). This spatial dependence (i.e., spatial autocorrelation) is particularly pronounced in metropolitan areas and their surrounding counties, highlighting the importance of accounting for spatial effects in our analysis.

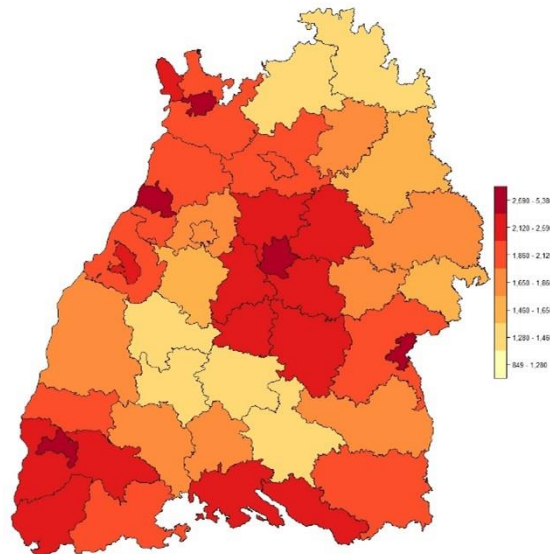
The evidence of previous studies analyzing residential real estate prices in Germany further supports our approach. Otto and Schmid (2018) prove spatial autocorrelation of county-level real estate prices in Germany. Ehlert et al. (2024) find county-level property prices to be spatially clustered based on socioeconomic factors. Deppner and Cajias (2022), furthermore, find evidence for improved hedonic valuation accuracy when accounting for spatial dependencies in German property data. Braun and Lee (2021) prove significant spatial spillover effects when analyzing German land and house prices. Multiple other studies incorporate spatial autocorrelation when dealing with georeferenced real estate data to avoid omitted variable bias and violations of regression assumptions (see Helbich et al., 2014; Fuess & Koller, 2016; or Conway et al., 2010).

Figure 4.4 Average House Prices in the State of Bavaria 2013-2022 (in €)



Note: This figure illustrates sample-average house transaction prices, in euros, per square meter, in the federal state of Bavaria. Darker color denotes higher prices, while brighter color denotes lower prices. Data source: VDP (2023).

Figure 4.5 Average Condominium Prices in the State of BW 2013-2022 (in €)



Note: This figure illustrates sample-average condominium transaction prices, in euros, per square meter, in the federal state of Baden-Württemberg. Darker color denotes higher prices, while brighter color denotes lower prices. Data source: VDP (2023).

To address identified spatial autocorrelation, we set up a neighborhood matrix based on decreasing influences with increasing geographical distance. We employ a maximum impact distance of 300 kilometers.³⁸ This allows us to capture influences that can be observed across several county boundaries. Aiming to isolate the effect political uncertainty exerts on housing transaction activity and prices in German counties, a panel

³⁸ Otto and Schmid (2018) prove that spatial dependencies in German real estate markets become negligible beyond 200-300km. Our distance-based weights gradually capture spatial dependencies up to 300km.

regression analysis is conducted. To address general spatial autocorrelation as well as spillover effects emerging from counties into neighboring counties, we apply spatial regression techniques. The properties of neighboring counties are thereby included in the regression equation. The weight with which neighboring counties influence each other is based on the distance-based weight matrix. In contrast to common queen neighborhood matrices, counties do not necessarily have to share a common border to express spatial dependency in terms of real estate prices.

The application of a panel model makes it possible to examine the time series of each county collectively to isolate general and average effects of political uncertainty on housing markets. Furthermore, a panel model allows for controlling unobserved time-invariant regional heterogeneity. Combining panel characteristics with spatial attributes also allows us to separate spatial spillover effects from temporal developments during the observation period. Nevertheless, the present model does not distinguish between short-term and long-term effects of political uncertainty on housing prices. A vector autoregressive model could have identified short-term and long-term differences. André et al. (2017) use a similar methodology to isolate the effect of economic policy uncertainty on house prices. However, such a model would have become very complex given the large number of counties analyzed. Using cross-sectional models would have been another way of estimating the impact of political uncertainty on housing prices. The application of these models would have enabled the comparison of selected time periods or the modeling of events with, for instance, particularly high political uncertainty measured by the proxy variable. Nonetheless, a cross-sectional analysis would have provided temporary insights, which are particularly sensitive to extreme values or unobserved heterogeneity. Compared to a panel model, a cross-section model offers less variation in the data and therefore no possibility to adjust for dynamic effects (Elhorst, 2014). The impact of political uncertainty on housing prices could have also been estimated using seemingly unrelated regressions based on the available data. This estimation method, however, would not have allowed for an interpretation of direct and indirect spatial impacts, as it only reflects spatial correlations in the errors. The spatial autoregressive panel regression model used is particularly sensitive regarding the weighting of the neighborhood matrix and does not allow the coefficients to be interpreted as marginal effects without calculating spatial impacts (Anselin, 2022). However, given the available data structure and the identified spatial autocorrelation, it appears suitable for isolating the impact of political uncertainty on housing transaction prices.

Developed by Elhorst (2010) and LeSage (2014) among others, this regression model allows us to compute global spillover effects of spatial neighbors depicted in a

neighborhood matrix. The equally well-known spatial error model (SEM) would have been appropriate to include local spillover effects. However, as shown in Figures 4.2 and 4.3, the identified spatial dependencies appear across several county borders and are therefore classified rather global than local. We employ the following baseline regression equation:

$$\log(\text{Price}_{i,t}) = \rho \sum_{j=1}^N W_{i,j} \log(\text{Price}_{j,t}) + \beta \text{UPI}_{t-1} + \gamma C_{i,t-1} + \text{ECTerm}_{t-1} + \mu_i + \delta_y + \varepsilon_{i,t} \quad (15)$$

$$i, j = 1, \dots, N \quad (16)$$

where the indices i or j and t refer to counties and quarters within our panel, respectively. $\log(\text{Price}_{i,t})$ denotes the logarithmized transaction price per square meter of condominiums or houses within a county and quarter.³⁹ Standard errors are computed using the Newey–West approach to ensure robustness to heteroskedasticity and within-county autocorrelation. The sum of $W_{i,j} \log(\text{Price}_{j,t})$ refers to the spatial spillover effects of neighboring counties. W is a spatial weights matrix inversely based on distances between two respective counties, where $W_{i,j}$ is the i, j -th weight for counties i and j . ρ measures the spatial response factor with neighboring counties. UPI_{t-1} denotes our proxy for political uncertainty lagged by one quarter, whereas β refers to the estimated coefficient.⁴⁰ $C_{i,t-1}$ is a $1 \times K$ vector of one quarter lagged control variables with γ denoting the estimated parameter. The control variables include real residential mortgage interest rate, unemployment rate, population density, mean age of a counties population, building land prices per square meter, migration per 10,000 inhabitants as well as the number of house listings and condominium listings, respectively.⁴¹ Descriptive statistics are reported in Table 4.2. ECTerm_{t-1} refers to the one quarter lagged error correction term⁴² controlling for the identified long-term relation between interest rate and political uncertainty measure. All independent variables are lagged by one quarter to account for market adjustment periods. μ_i and δ_y denote the county and year fixed effects included to control for unobserved heterogeneity in all model specifications. Lastly, $\varepsilon_{i,t}$ refers to the identically and independently normally distributed error term.

³⁹ We apply natural logarithms of transaction prices per square meter to ensure linearity.

⁴⁰ We mean-scaled the UPI variable for ease of interpretation.

⁴¹ We mean-scaled the house and condominium listings for ease of interpretation and logarithmized building land prices to ensure linearity.

⁴² The error correction term represents residuals from the cointegrating regression between interest rates and political uncertainty, capturing deviations from their long-run equilibrium. Including this term ensures that our political uncertainty coefficients reflect direct effects on housing prices rather than indirect effects through disequilibrium in credit markets.

4.5.3 Main Regression Results

We apply the regression model detailed in Section 4.5.2 on our two panel data sets for house prices and condominium prices, respectively. The applied sample consists of 14,400 observations for house prices and 8,892 observations for condominium prices within a time span from 2013Q2 to 2022Q1. The estimated regression results are presented in Table 4.4. In columns (1) and (3), we report the results for regressions without control variables, whereas in columns (2) and (4), all mentioned control variables are applied. Our results reveal a consistent and statistically significant negative relationship between our political uncertainty proxy and housing transaction prices. The coefficient ρ on the spatial response factor is highly significant and positive in all model specifications, indicating strong spatial spillover effects for transaction prices. Other variables behave as expected throughout all regression models. Transaction prices, for example, appear higher in denser populated counties and prices decline in counties where listings increase. However, the estimated coefficients of spatial autoregressive models (SAR) cannot be interpreted as marginal effects without considering spatial impact analysis. Therefore, we report the spatial impact analysis for the regression estimates of Table 4.4 in Table 4.5. Direct impacts refer to the effect of a covariate on the dependent variable within a county. Indirect impacts present the spillover effects of all neighboring counties properties on the dependent variable in a specific county. The sum of direct and indirect impacts equals the reported total impact, which again can be interpreted as marginal effect. Figure 4.6 gives an overview of the methodological framework of spatial impacts within a spatial regression application. The national UPI German Politics Indicator has a direct impact on house and condominium prices in a given county. Additionally, there exist spatial dependencies between prices in neighboring counties (see Section 4.5.2). These result in spillover effects that transfer the influence of the national UPI German Politics Indicator on prices in the given county to all neighboring counties, and the price effects in all neighboring counties to the given county. Each county is part of a complex neighborhood network where external effects, such as a change in the national UPI German Politics Index, spread. Our analysis suggests that approximately 40 to 50 percent of the total effect of political uncertainty on housing markets results from spatial spillovers, highlighting the importance of considering spatial dependencies when analyzing real estate markets. The significant influence of spatial spillover effects also shows that the interconnection of habitats extends beyond county boundaries. This interdependence proves that both positive and negative externalities do not affect real estate markets in isolation, but rather across regions. Shared infrastructure, commuting behavior and geographical proximity render subordinate regions interdependent, like pieces of a puzzle. Whenever one piece of the puzzle is

affected by external factors, such as increased political uncertainty, all other pieces are also affected by spatial transmission effects. This also demonstrates that diversification can be crucial in minimizing asset risk from a geographic perspective. It furthermore appears plausible that national political uncertainty has a transregional impact on housing markets and does not merely result in local price reductions. These may, however, be tempered by local circumstances.

In economic terms, our regression results indicate that a one-standard-deviation increase in the political uncertainty proxy results in a decrease of house prices of approximately 2.19 percent, on average; and a decrease of condominium prices of approximately 2.42 percent, on average, respectively, *ceteris paribus*. To contextualize these values, we employ a numerical example for a hypothetical political uncertainty shock, comparable to the COVID-19 pandemic, where the uncertainty measure increases by approximately 2.8 standard-deviation-units within one quarter. Applying our estimated values, this political uncertainty shock would result in a drop in house prices by on average 6.13 %, and a drop in condominium prices by on average 6.78%, respectively, *ceteris paribus*. To summarize, our spatial regression results provide empirical evidence for the significant negative effect of political uncertainty, proxied by the UPI German Politics Indicator, developed by Rieger et al. (2023), on housing prices in German counties. While condominium prices appear to react slightly stronger on increases of political uncertainty, the overall negative relationship indicates significant explanatory power of housing transaction prices in Germany.

Table 4.4 Political Uncertainty and Transaction Prices

	House prices (log)		Condominium prices (log)	
	(1)	(2)	(3)	(4)
Political uncertainty	-0.0085*** (0.0027)	-0.0133*** (0.0030)	-0.0092** (0.0041)	-0.0138*** (0.0042)
Interest rate	-0.0007 (0.0198)	0.0232 (0.0215)	-0.0276 (0.0280)	-0.0191 (0.0290)
Error correction term	-0.0050 (0.0036)	-0.0124*** (0.0038)	-0.0003 (0.0055)	-0.0084 (0.0060)
Unemployment rate		0.0046 (0.0034)		0.0186*** (0.0055)
Population density		0.0011*** (0.0002)		0.0008*** (0.0002)
Population mean age		-0.0341*** (0.0108)		0.0470*** (0.0170)
Land prices (log)		0.0397*** (0.0066)		0.0354*** (0.0087)
Migration		-0.0003*** (0.0001)		-0.0001 (0.0001)
House listings		-0.0026 (0.0020)		
Condominium listings				-0.0006 (0.0037)
Spatial parameter (ρ)	0.4016*** (0.0276)	0.4016*** (0.0276)	0.4836*** (0.0266)	0.4436*** (0.0276)
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
Observations	14,400	14,400	8,892	8,892
Counties	400	400	247	247
Sigma	0.1773	0.1747	0.2109	0.2091
AIC	-35,652	-36,015	-19,062	-19,116
BIC	-35,554	-35,871	-18,970	-18,982

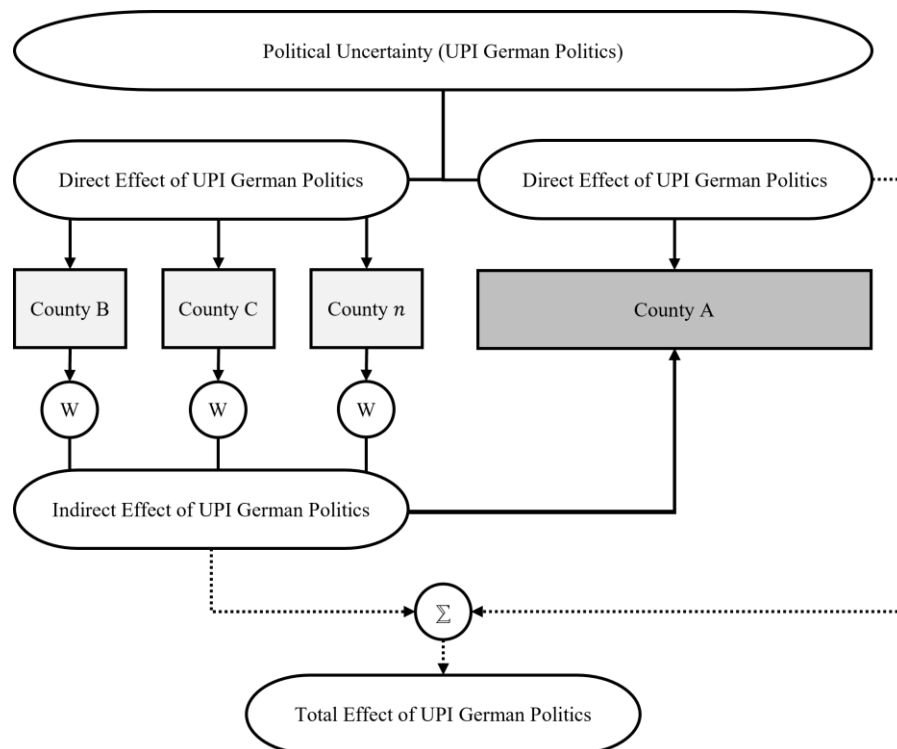
Note: This table presents the results of spatial autoregressive regressions analyzing the impact of political uncertainty, proxied by the UPI Indicator by Rieger et al. (2023), on house prices and condominium prices. The dependent variables are logarithmized median house prices and condominium prices per square meter, respectively. Independent variables are lagged by one quarter. The sample period is 2013Q2 to 2022Q1. Newey-West robust standard errors are in parentheses. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 4.5 Spatial Impacts for Political Uncertainty and Transaction Prices

	House prices (log)		Condominium prices (log)	
	(1)	(2)	(3)	(4)
Direct impact				
Political uncertainty	-0.0086*** (0.0027)	-0.0132*** (0.0029)	-0.0094** (0.0041)	-0.0135*** (0.0043)
Indirect impact				
Political uncertainty	-0.0069*** (0.0023)	-0.0087*** (0.0022)	-0.0088** (0.0039)	-0.0106*** (0.0035)
Total impact				
Political uncertainty	-0.0156*** (0.0051)	-0.0219*** (0.0050)	-0.0182** (0.0084)	-0.0242*** (0.0080)

Note: This table presents the results of spatial autoregressive regressions analyzing the impact of political uncertainty, proxied by the UPI Indicator by Rieger et al. (2023), on house prices and condominium prices. The dependent variables are logarithmized median house prices and condominium prices per square meter, respectively. The independent variable reported is mean-scaled UPI Indicator. For brevity, we only report coefficients of interest. The given coefficients refer to direct, indirect and total spatial impact measures, respectively. Newey-West robust standard errors are in parentheses. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Figure 4.6 Flow Chart on the Mechanism of Spatial Impacts



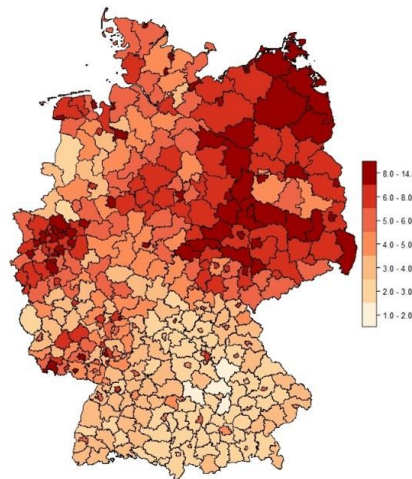
Note: This figure illustrates the mechanism of the direct and indirect effects of the independent variable of interest, UPI German Politics, in spatial regression. The sum of the indirect effects, weighted by the spatial weight matrix (W), and the direct effect result in the total marginal effect of the independent variable of interest, UPI German Politics, on the dependent variable, logarithmized median house prices and condominium prices per square meter, respectively.

4.5.4 Political Uncertainty and Local Economies

Based on the identified negative relationship between political uncertainty and housing prices, we analyze the local exposure to political uncertainty effects on housing prices in this subsection. As previous studies have found evidence for local economic indicators influencing the magnitude of uncertainty effects on financial outcomes and property related variables (Francis et al., 2014; Waisman et al., 2015; or Luo et al., 2022), we expect to find similar evidence analyzing German county-level housing prices. Local housing markets with stronger economic environments may appear rather robust against political uncertainty, while economically underdeveloped regions may show higher vulnerability to political uncertainty. This expectation aligns with the evidence of Feng (2022) and Hwang and Quigley (2006) on real estate market variance being dependent on economic surroundings.

To empirically test the moderation effect of political uncertainty and local economic conditions, we include the interaction between the UPI German Politics (referred to as political uncertainty) as proxy for political uncertainty and the county unemployment rate in our regression approach. Figure 4.7 illustrates sample averages of county unemployment rates. Spatial clusters of high unemployment rates are visible, especially in the rural northeastern and the former industrial western part of Germany, and marked in darker color. We report on the results of the spatial regression approaches with unemployment interactions in Table 4.6. The coefficient on the interaction term is negative and highly significant for house prices, indicating a stronger impact of political uncertainty in counties where unemployment rates are higher. However, we find no significant effect for the interaction term on condominium prices. The differential impact likely reflects differences between house and condominium markets in economically stressed regions. Houses could represent discretionary purchases dominated by risk-averse owner-occupiers, who are directly exposed to local unemployment risk and can delay purchases when uncertainty rises. In contrast, condominiums tend to serve essential housing needs and attract private investors besides owner-occupiers, who value stable rental yields. In high-unemployment areas, Germany's social safety net – including housing allowances – creates a floor under rental demand, ensuring stable yields, making condominiums resilient assets that generate steady income even during uncertain times. Consequently, while house markets in high-unemployment counties exhibit price effects that amplify uncertainty effects, condominium markets maintain relative stability through their necessity-driven demand and professional investor base, making them less sensitive to the interaction between local economic stress and political uncertainty.

Figure 4.7 Average Unemployment Rate 2013-2022 (in Percentage)



Note: This figure illustrates sample-average unemployment rates in German counties in percentage. Higher unemployment rates are denoted by darker color, while lower unemployment rates are denoted by brighter color. Data source: Federal Employment Agency Database (2024).

Table 4.6 Spatial Heterogeneous Effects of Political Uncertainty on Transaction Prices

	House prices (log)		Condominium prices (log)	
	(1)	(2)	(3)	(4)
Political uncertainty × unemployment rate	-0.0067** (0.0033)	-0.0062* (0.0032)	-0.0010 (0.0051)	-0.0022 (0.0051)
Political uncertainty	-0.0104*** (0.0028)	-0.0132*** (0.0030)	-0.0124*** (0.0042)	-0.0136*** (0.0043)
Unemployment rate	0.0086** (0.0036)	0.0045 (0.0034)	0.0183*** (0.0055)	0.0185*** (0.0055)
Spatial parameter (ρ)	0.4380*** (0.0271)	0.3969*** (0.0278)	0.4706*** (0.0270)	0.4423*** (0.0276)
Controls	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
Observations	14,400	14,400	8,892	8,892
Counties	400	400	247	247
Sigma	0.1772	0.1746	0.2104	0.2091
AIC	-35,667	-36,014	-19,073	-19,115
BIC	-35,553	-35,862	-18,966	-18,973

Note: This table presents the results of spatial autoregressive regressions analyzing the impact of political uncertainty, proxied by the UPI Indicator by Rieger et al. (2023), on house prices and condominium prices. The dependent variables are logarithmized median house prices and condominium prices per square meter, respectively. Independent variables are mean-scaled UPI Indicator, unemployment rate and the interaction term between mean-scaled UPI Indicator and unemployment rate. Independent variables are lagged by one quarter. For brevity, we report only coefficients of interest. The sample period is 2013Q2 to 2022Q1. Newey-West robust standard errors are in parentheses. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

4.5.5 Robustness Checks

To ensure validity and generalizability of our findings on the relationship between political uncertainty and housing markets, we conduct several robustness checks. These checks examine whether our results hold across different model specifications, regional and temporal subsamples, as well as uncertainty measures.

Baker et al. (2016) developed a proxy measure for economic policy uncertainty based on newspaper archive analysis applying uncertainty-related dictionaries. Even though our analysis does not focus on economic policy uncertainty but refers to generic political uncertainty, a comparative analysis of the Economic Policy Uncertainty Index (EPU) and the Uncertainty Perception Indicator (UPI German Politics) appears appropriate. Media coverage might not separate both aspects of political uncertainty as strictly as we try to, and both indices rely at least partly on similar uncertainty key words. Furthermore, the EPU is available in a version focused solely on Germany.

While we identify only moderate positive correlation between EPU and UPI used in the main regression (see Table 4.3 for pairwise correlations), we use EPU as an alternative uncertainty measure. Doing so, we replace the UPI German Politics Indicator by the EPU Index in our baseline regression, depicted in equation (15), and run the regression on house and condominium prices again.⁴³ The results are reported in Table 4.7. The estimated coefficients in columns (1) and (2), as well as (5) and (6), are weakly significant and positive for the effect of the EPU Index on house prices, and insignificant for the effect of EPU on condominium prices. The contrasting results – negative for UPI, weakly positive for EPU – diverge from international evidence, where EPU typically shows negative effects on real estate. Several factors may explain this divergence. First, the measures capture different uncertainty dimensions: UPI's broader scope includes political uncertainties before they translate into economic policy concerns, while EPU focuses specifically on policy-related uncertainty. This suggests that market participants may respond differently to generic versus policy-specific uncertainty. Second, Germany's institutional context differs fundamentally from Anglo-Saxon markets studied in most EPU literature. The German market's heavily regulated nature, strong tenant protections and historical perception as a 'safe haven' (Kofner, 2014) may create different transmission mechanisms. When uncertainty becomes policy-specific (EPU), German real estate's stable rental yields and

⁴³ We mean-scale the EPU Index and lag it by one quarter to ensure comparability to the main regression applying the UPI Indicator. The cointegration process, as described in Section 4.5.1, is redone applying the EPU Index.

regulatory framework may attract capital seeking refuge from more volatile – a pattern less likely in liberalized markets.

However, to rule out potential overlapping between both indices, we run a variance decomposition process by regressing the EPU Index on the UPI German Politics Indicator, considering the interest rate and an error correction term calculated as described in Section 4.5.1. The residuals of this regression, named UPI_EPU_RES, are again included in the baseline regression model stated in equation (15).⁴⁴ The resulting variable appears filtered for potential impacts that might result from economic policy uncertainty. The regression results applying the UPI_EPU_RES variables are reported in Table 4.7, in columns (3) to (4) and (7) to (8). All coefficients remain highly significant and negative, indicating that the filtered political uncertainty proxy has a significant negative impact on house prices and condominium prices. The spatial impacts of the mentioned regressions are reported at the bottom of Table 4.7. In economic terms, a one-standard-deviation increase of UPI_EPU_RES decreases house and condominium prices by, on average, approximately 2.66 and 2.95 percent, respectively, *ceteris paribus*. These estimates are slightly higher than the ones of the main regression, reported in Table 4.4, and equally significant.

⁴⁴ Descriptive statistics for the resulting variable are illustrated in Table 4.2. The UPI_EPU_RES variable is mean-scaled and lagged by one quarter to ensure comparability to the previous regressions.

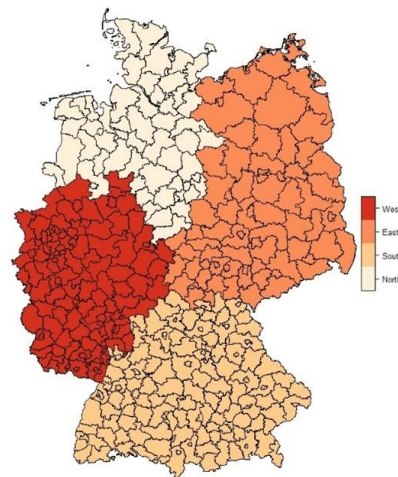
Table 4.7 Robustness Checks of Political Uncertainty and Economic Policy Uncertainty

	House prices (log)				Condominium prices (log)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EPU	0.0112** (0.0048)	0.0112** (0.0048)			0.0131* (0.0071)	0.0134* (0.0070)		
UPI_EPU_RES			-0.0108*** (0.0026)	-0.0162*** (0.0029)			-0.0111*** (0.0040)	-0.0165*** (0.0042)
Spatial parameter (ρ)	0.4475*** (0.0269)	0.4064*** (0.0276)	0.4373*** (0.0272)	0.3900*** (0.0280)	0.4893*** (0.0264)	0.4462*** (0.0275)	0.4759*** (0.0269)	0.4337*** (0.0279)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,000	14,000	14,000	14,000	8,892	8,892	8,892	8,892
Counties	400	400	400	400	247	247	247	247
Sigma	0.1773	0.1748	0.1777	0.1746	0.2111	0.2092	0.2107	0.2089
AIC	-35,650	-36,003	-35,659	-36,022	-19,058	-19,114	-19,068	-19,123
BIC	-35,551	-35,859	-35,560	-35,878	-18,965	-18,979	-18,975	-18,988
Spatial impacts								
Direct impact								
EPU	0.0113** (0.0049)	0.0115** (0.0049)			0.0127* (0.0074)	0.0137* (0.0072)		
UPI_EPU_RES			-0.0108*** (0.0026)	-0.0163*** (0.0029)			-0.0111*** (0.0040)	-0.0168*** (0.0043)
Indirect impact								
EPU	0.0091** (0.0039)	0.0078** (0.0341)			0.0119* (0.0070)	0.0109* (0.0056)		
UPI_EPU_RES			-0.0083*** (0.0022)	-0.0103*** (0.0021)			-0.0099*** (0.0039)	-0.0127*** (0.0035)
Total impact								
EPU	0.0205** (0.0098)	0.0193** (0.0089)			0.0245* (0.0161)	0.0246* (0.0145)		
UPI_EPU_RES			-0.0191*** (0.0050)	-0.0266*** (0.0049)			-0.0210*** (0.0079)	-0.0295*** (0.0080)

Note: This table presents the results of spatial autoregressive regressions analyzing the impact of political uncertainty, proxied by the UPI Indicator by Rieger et al. (2023), on house prices and condominium prices. The dependent variables are logarithmized median house prices and condominium prices per square meter, respectively. Independent variables are mean-scaled EPU Index by Baker et al. (2016) and UPI_EPU_RES. Independent variables are lagged by one quarter. For brevity, we report only coefficients of interest. The sample period is 2013Q2 to 2022Q1. Newey-West robust standard errors are in parentheses. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Another robustness test is conducted to rule out potential biases resulting from regional disparities within our data sample.⁴⁵ Therefore, we split our samples for house prices and condominium prices into four subsamples each. Figure 4.8 illustrates the apportionment based on the four main geographical regions in Germany. We then run our baseline regression, depicted in equation (15), again. Table 4.8 reports the results for subsample regressions. The coefficient on political uncertainty proxied by the UPI German Politics index comes out negative and highly significant for house prices. Eastern German counties, which experienced significant political and economic transformations following reunification, show the strongest sensitivity of house prices to political uncertainty. This heightened sensitivity might stem from the region's historical experience with political instability and economic restructuring. In contrast, Western German counties, with their longer history of stable market economies, exhibit a somewhat lower sensitivity to political uncertainty. However, coefficients for UPI impact on condominium prices are negative but partly insignificant. The northern and eastern subsamples include too few observations because of missing data, and their coefficients can therefore not be soundly interpreted. To sum up, the effect of political uncertainty on housing prices seems to vary slightly across spatial regions but is robustly negative and significant for all interpretable subsamples.

Figure 4.8 Spatial Regions of Germany



Note: This figure illustrates the apportionment of Germany in four spatial regions. Northern, southern, eastern and western parts are depicted in different colors.

⁴⁵ The four-region partition (North, West, South, East) follows the established North–South and East–West gradient in German economic geography and balances spatial granularity against subsample size given the panel's overall dimension. Substantial regional heterogeneity in German housing markets is well-documented (Brausewetter et al., 2024). The aim is to verify whether the estimated effect of political uncertainty is robust across major geographical sub-markets rather than driven by particular sub-regions. We acknowledge that coverage is uneven, with the apartment East subsample comprising of fewer counties.

Table 4.8 Robustness Checks of Spatial Regions

	House prices (log)				Condominium prices (log)			
	(North)	(West)	(South)	(East)	(North)	(West)	(South)	(East)
Political uncertainty	-0.0119** (0.0046)	-0.0151*** (0.0040)	-0.0109** (0.0043)	-0.0340*** (0.0115)	-0.0083 (0.0125)	-0.0161** (0.0072)	-0.0101* (0.0052)	-0.0192 (0.0351)
Interest rate	0.0200 (0.0323)	0.0206 (0.0295)	0.0111 (0.0276)	0.0731 (0.0834)	-0.0581 (0.0850)	0.0003 (0.0480)	-0.0210 (0.0359)	-0.2086 (0.1648)
Error correction term	-0.0113* (0.0062)	-0.0159** (0.0059)	-0.0137** (0.0057)	-0.0253 (0.0154)	0.0015 (0.0185)	-0.0135 (0.0102)	0.0026 (0.0076)	0.0040 (0.0417)
House listings	-0.0012 (0.0034)	-0.0117*** (0.0036)	0.0011 (0.0027)	-0.0083 (0.0057)				
Condominium listings					-0.0039 (0.0090)	-0.0021 (0.0074)	0.0094** (0.0045)	-0.0225 (0.0221)
Spatial parameter (ρ)	0.4464*** (0.0502)	0.3886*** (0.0502)	0.3696*** (0.0374)	0.0791 (0.0658)	0.2251*** (0.0639)	0.3565*** (0.0551)	0.4522*** (0.0408)	-0.0716 (0.0638)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,268	4,356	5,040	2,736	1,620	3,384	3,636	252
Counties	63	121	140	76	45	94	101	7
Sigma	0.1122	0.1379	0.1441	0.2823	0.2582	0.2167	0.1672	0.2402
AIC	-7,697	-12,931	-14,544	-4,169	-2,759	-6,975	-9,460	-450
BIC	-7,588	-12,810	-14,420	-4,056	-2,656	-6,858	-9,342	-383
Spatial impacts								
Direct impact								
Political uncertainty	-0.0125** (0.0048)	-0.0152*** (0.0038)	-0.0108** (0.0043)	-0.0348*** (0.0117)	-0.0085 (0.0122)	-0.0164** (0.0071)	-0.0101* (0.0051)	-0.0186 (0.0329)
Indirect impact								
Political uncertainty	-0.0096** (0.0043)	-0.0097*** (0.0030)	-0.0062** (0.0026)	-0.0033 (0.0028)	-0.0025 (0.0030)	-0.0093** (0.0043)	-0.0083* (0.0044)	-0.0014 (0.0051)
Total impact								
Political uncertainty	-0.0218** (0.0093)	-0.0249*** (0.0069)	-0.0170** (0.0069)	-0.0380*** (0.0132)	-0.0111 (0.0164)	-0.0257** (0.0118)	-0.0184* (0.0101)	-0.0199 (0.0373)

Note: This table presents the results of spatial autoregressive regressions analyzing the impact of political uncertainty, proxied by the UPI Indicator by Rieger et al. (2023), on house prices and condominium prices. The dependent variables are logarithmized median house prices and condominium prices per square meter, respectively. The data sets are divided into spatial regions, as described in Section 4.5.5, for robustness tests. Independent variables are lagged by one quarter. For brevity, we report only coefficients of interest. The sample period is 2013Q2 to 2022Q1. Newey-West robust standard errors are in parentheses. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 4.9 Robustness Checks for Urbanity

	House prices (log)		Condominium prices (log)	
	(Urban)	(Rural)	(Urban)	(Rural)
Political uncertainty	-0.0132*** (0.0046)	-0.0101*** (0.0038)	-0.0165*** (0.0052)	-0.0151** (0.0068)
Interest rate	0.0142 (0.0272)	0.0143 (0.0269)	-0.0042 (0.0343)	-0.0378 (0.0431)
Error correction term	-0.0140** (0.0062)	-0.0061 (0.0052)	-0.0135* (0.0074)	-0.0025 (0.0097)
Spatial parameter (ρ)	0.1662*** (0.0372)	0.4331*** (0.0320)	0.3690*** (0.0317)	0.2779*** (0.0372)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
Observations	6,192	8,208	4,572	4,320
Counties	172	228	127	120
Sigma	0.1790	0.1683	0.1823	0.2334
AIC	-15,106	-21,161	-11,074	-8,277
BIC	-14,978	-21,028	-10,952	-8,156
Spatial impacts				
Direct impact				
Political uncertainty	-0.0132*** (0.0048)	-0.0101*** (0.0038)	-0.0166*** (0.0053)	-0.0149** (0.0068)
Indirect impact				
Political uncertainty	-0.0027** (0.0011)	-0.0077*** (0.0030)	-0.0095*** (0.0030)	-0.0056** (0.0023)
Total impact				
Political uncertainty	-0.0159** (0.0059)	-0.0179*** (0.0068)	-0.0260*** (0.0088)	-0.0205** (0.0097)

Note: This table presents the results of spatial autoregressive regressions analyzing the impact of political uncertainty, proxied by the UPI Indicator by Rieger et al. (2023), on house prices and condominium prices. The dependent variables are logarithmized median house prices and condominium prices per square meter, respectively. The data sets are divided into subsamples, containing urban and rural regions, respectively. The subsampling is detailed in Section 4.5.5 and performed for robustness tests. Independent variables are lagged by one quarter. For brevity, we report only coefficients of interest. The sample period is 2013Q2 to 2022Q1. Newey-West robust standard errors are in parentheses. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

In addition, we address potential urban and rural differences in the effect of political uncertainty on residential real estate prices, because the population density significantly influences housing markets within our baseline regression approach (see Table 4.4). We split our samples into an urban and rural subsample each.⁴⁶ Then we rerun the main regression, as stated in equation (15), to identify potential differences in political uncertainty perception based on settlement structure. The results are reported in Table 4.9.

Urban counties show a stronger negative response to political uncertainty compared to rural counties. This pattern may reflect the greater integration of urban real estate markets with national and international economic trends, making them more responsive to political

⁴⁶ We define counties with a population density above 250 inhabitants per square kilometer as urban and all other counties as rural.

developments. Additionally, urban housing markets typically have higher price levels and greater investor participation, potentially amplifying the effects of uncertainty. The stronger effect of political uncertainty in urban areas may also be explained by the higher valuation levels in urban areas. Whenever political uncertainty leads to an increase in the discount rate, real estate values in urban, and thus more expensive regions, are more severely affected than less expensive regions, which are more likely to be in rural areas. However, the negative relationship between political uncertainty and housing prices remains significant even though population settlement shows some moderating effect.

Furthermore, we conduct robustness checks on temporal biases within our data. Spanning from 2013 to 2022, our data set includes the duration of the COVID-19 pandemic. This major external shock is found to have substantial impact on real estate markets across the globe.⁴⁷ Qian et al. (2021) find empirical evidence for declining house prices in China during the COVID-19 pandemic. Gluszak and Belniak (2020) report similar effects analyzing house prices in UK. In contrast, Gamber et al. (2023) as well as Zhang et al. (2023) find evidence for increasing house prices resulting from an increasing demand meeting limited supply analyzing US data. To further address the potential impact of the COVID-19 pandemic on the effect of political uncertainty perception analyzing housing prices, we split our samples into pre- and post-COVID-19 subsamples each.⁴⁸ We then rerun the regression, stated in equation (15), on the data subsamples. Table 4.10 reports the results. The coefficients on political uncertainty remain negative and highly significant in all outcomes. However, we observe a small decline in coefficients in the post-COVID-19 samples compared to the pre-COVID-19 samples. This likely reflects constant higher levels of political uncertainty (see Figure 4.1 for illustration) and eventuating familiarization effects.

⁴⁷ We preliminary checked our data for structural breaks and found no indication for the occurrence.

⁴⁸ The COVID-19 disease was declared a pandemic by the World Health Organization (WHO) on March 11, 2020. Accordingly, we define the pre-COVID-19 samples spanning from 2013Q2 to 2019Q4 and the post-COVID-19 samples spanning from 2020Q1 to 2022Q1.

Table 4.10 Robustness Checks for COVID-19

	House prices (log)		Condominium prices (log)	
	(Pre COVID19)	(Post COVID19)	(Pre COVID19)	(Post COVID19)
Political uncertainty	-0.0173*** (0.0049)	-0.0140*** (0.0033)	-0.0152** (0.0075)	-0.0163*** (0.0045)
Interest rate	-0.0190 (0.0229)	0.2734*** (0.0379)	-0.0438 (0.0321)	0.2374*** (0.0509)
Error correction term	-0.0172*** (0.0058)	-0.0073 (0.0060)	-0.0086 (0.0085)	-0.0004 (0.0097)
Spatial parameter (ρ)	0.2941*** (0.0361)	0.3818*** (0.0505)	0.4315*** (0.0327)	0.3474*** (0.0585)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
Observations	10,400	4,000	6,422	2,470
Counties	400	400	247	247
Sigma	0.1859	0.1112	0.2274	0.1248
AIC	-24,637	-13,605	-12,721	-7,828
BIC	-24,521	-13,530	-12,613	-7,756
Spatial impacts				
Direct impact				
Political uncertainty	-0.0172*** (0.0048)	-0.0139*** (0.0035)	-0.0154* (0.0079)	-0.0164*** (0.0044)
Indirect impact				
Political uncertainty	-0.0072*** (0.0024)	-0.0086*** (0.0028)	-0.0115* (0.0062)	-0.0088*** (0.0031)
Total impact				
Political uncertainty	-0.0244*** (0.0070)	-0.0226*** (0.0059)	-0.0269* (0.0139)	-0.0252*** (0.0072)

Note: This table presents the results of spatial autoregressive regressions analyzing the impact of political uncertainty, proxied by the UPI Indicator by Rieger et al. (2023), on house prices and condominium prices. The dependent variables are logarithmized median house prices and condominium prices per square meter, respectively. The data sets are divided into subsamples, with sample periods from 2013Q2 to 2019Q4 and from 2020Q1 to 2022Q1, respectively. The subsampling is detailed in Section 4.5.5 and performed for robustness tests. Independent variables are lagged by one quarter. For brevity, we report only coefficients of interest. Newey-West robust standard errors are in parentheses. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

To rule out potential biases in estimated coefficients due to applied spatial weight matrices, we apply modified versions of the spatial weights matrix described in Section 4.5.2. The spatial weights matrix used in the main regressions is based on Otto and Schmid's (2018) findings on regional interdependencies in the German housing market, reaching up to 300 km. To ensure that estimated coefficients are not solely based on a particular specification of the matrix, alternative matrices with neighborhood distances of up to 100 km and up to 200 km were applied. Furthermore, a simplified Queen Matrix is integrated, considering only first-order neighboring counties. We then rerun the regression, shown in equation (15), with the described variations of the neighborhood matrices. Table 4.11 compares the estimated results of all variations in neighborhood matrices for transaction prices of houses and condominiums. The coefficients on the impact of political uncertainty, proxied by UPI German Politics, remain significantly different from zero and negative. The size of the

estimated coefficients on political uncertainty varies slightly across the scenarios described. However, the indirect effects, presented in the lower part of Table 4.11, show that negative effects of political uncertainty are widespread in housing prices. The spatial parameter ρ , which increases with the expansion of the spatial weighting matrix, supports the findings of Otto and Schmid (2018) on large-scale neighborhood relationships of housing prices in Germany. Thus, a large-scale consideration of the interdependence of housing prices between counties appears to be better suited to reflect the effects of political uncertainty than smaller-scale analyses.

Table 4.11 Robustness Checks of Neighborhood Matrices

	House prices (log)			Condominium prices (log)		
Neighborhood matrix	Inv. dist. 100km	Inv. dist. 200km	Queen first-order	Inv. dist. 100km	Inv. dist. 200km	Queen first-order
Political uncertainty	-0.0169*** (0.0030)	-0.0148*** (0.0030)	-0.0172*** (0.0030)	-0.0186*** (0.0042)	-0.0163*** (0.0042)	-0.0199*** (0.0043)
Interest rate	0.0222 (0.0214)	0.0224 (0.0215)	0.0203 (0.0214)	-0.0266 (0.0290)	-0.0221 (0.0291)	-0.0252 (0.0291)
Error correction term	-0.0149*** (0.0041)	-0.0135*** (0.0041)	-0.0152*** (0.0041)	-0.0094 (0.0060)	-0.0093 (0.0060)	-0.0103* (0.0060)
Spatial parameter (ρ)	0.1686*** (0.0144)	0.2989*** (0.0224)	0.1309*** (0.0125)	0.1994*** (0.0168)	0.317*** (0.0226)	0.1440*** (0.0135)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,400	14,400	14,400	8,892	8,892	8,892
Counties	400	400	400	247	247	247
Sigma	0.1745	0.1746	0.1745	0.2092	0.2092	0.2093
AIC	-35,951	-35,985	-35,926	-19,021	-19,068	-18,997
BIC	-35,807	-35,841	-35,782	-18,887	-18,933	-18,862
Spatial impacts						
Direct impact						
Political uncertainty	-0.0170*** (0.0032)	-0.0150*** (0.0031)	-0.0171*** (0.0031)	-0.0187*** (0.0048)	-0.0167*** (0.0048)	-0.0203*** (0.0048)
Indirect impact						
Political uncertainty	-0.0034*** (0.0007)	-0.0063*** (0.0015)	-0.0025*** (0.0005)	-0.0045*** (0.0013)	-0.0076*** (0.0023)	-0.0033*** (0.0009)
Total impact						
Political uncertainty	-0.0204*** (0.0038)	-0.0212*** (0.0044)	-0.0197*** (0.0036)	-0.0232*** (0.0060)	-0.0244*** (0.0070)	-0.0236*** (0.0056)

Note: This table presents the results of spatial autoregressive regressions analyzing the impact of political uncertainty, proxied by the UPI Indicator by Rieger et al. (2023), on house prices and condominium prices. The dependent variables are logarithmized median house prices and condominium prices per square meter, respectively. Models differ in terms of applied neighborhood spatial weights matrices. The model set up is detailed in Section 4.5.5 and performed for robustness tests. Independent variables are lagged by one quarter. For brevity, we report only coefficients of interest. The sample period is 2013Q2 to 2022Q1. Newey-West robust standard errors are in parentheses. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

We also perform robustness tests for the impact of political uncertainty on the total number of listings of houses and condominiums in Germany, which we use as explanatory variables in the price regressions (see Table 4.4). However, no significant relationships were

found. While the number of real estate listings in some model specifications explains part of the variance in housing prices, and thus serves as a control variable, we do not find any significant influence of political uncertainty on the number of real estate listings themselves. Potential explanations for this disparity could lie in the timing and transaction costs of housing real estate. Prices may respond faster to political uncertainty than sales intentions, for instance, for buildings already under construction. Furthermore, listings do not reflect actual transactions. Listings may remain active even though transactions have already taken place, or sales intentions have changed in the meantime.

Conducting several robustness tests to address potential biases within our sample or variable definitions, we empirically prove stable and significant negative effects of generic political uncertainty on housing prices in German counties.

4.6 Conclusion

This study examines how generic political uncertainty affects housing markets in Germany. Using the UPI German Politics that captures a broader spectrum of political uncertainty than commonly used indicators like the EPU, making it well-suited for Germany's heavily regulated housing markets where political decisions directly impact homebuyer conditions, we prove a non-negligible linkage between political actions and housing markets.

Germany provides an ideal setting for this research because of its extensive housing regulations and recent experiences with significant political uncertainty from migration, the COVID-19 pandemic and geopolitical tensions. Our analysis uses a dataset covering all 400 German counties over the timespan of 2013-2022, allowing us to capture local market variations while controlling for local conditions. Our spatial econometric approach addresses the inherent neighborhood dependencies in housing markets, with findings showing that 40-50% of political uncertainty's effect results from spatial spillovers. Robustness checks reveal stronger negative effects in Eastern Germany and economically underdeveloped counties, with intensified impacts before the COVID-19 pandemic emerges. Our results show that generic political uncertainty leads to lower housing prices, as homebuyers may adopt a wait-and-see approach. This uncertainty-induced delay constrains housing supply, potentially worsening affordability challenges. Therefore, alongside conventional measures, clear and consistent policy frameworks that minimize uncertainty could help stimulate homebuyer activity and address housing shortages. However, the price discounts due to political uncertainty identified may also represent opportunities for homebuyers willing to take risks. The systematic monitoring of political

outcomes and related expectations may complement market analysis and offer potential for countercyclical buying opportunities.

While we rely on a nation-wide political uncertainty measure, developing regional-specific political uncertainty indices at the county or municipal level could capture local variations and provide more granular insights. In addition to national political uncertainty, there is also local and supra-regional political uncertainty. This arises, for example, as a result of building regulations, citizens' initiatives, funding allocations, or local representative elections, and would need to be measured individually on a local basis. Despite this limitation, our primary interest was first understanding how generic nation-wide political uncertainty unfolds regionally in housing markets. Our analysis period (2013-2022) may not capture longer-term market cycles, suggesting value in extended timeframe studies. Additional research could explore uncertainty's differential impacts across property types, price segments and homebuyer categories, while comparative studies across countries with different regulatory environments would provide valuable insights into how institutional contexts mediate uncertainty's effects on housing markets. In addition, a detailed analysis of narratives surrounding uncertainty may provide further insight into which specific political events or subcategories of political uncertainty exert a stronger, or weaker, impact on housing markets.

4.7 Appendix

UPI Dictionary

The UPI Indicator is based on a corpus of three leading nation-wide German newspapers: Sueddeutsche Zeitung (center left), Die Welt (center right) and Handelsblatt (business). Following a number of preprocessing steps, an issue-specific analysis corpus is produced by applying a rather open query “uncertainty” OR “uncertain” OR “uncertainties” to the sub-categories that are defined through specific words. Matches that count towards the uncertainty index are articles that both contain an uncertainty-word and a category-specific word while meeting safeguards. The category-specific words are dynamically obtained through clustering and are adjusted every quarter (Rieger et al., 2023). Table 4.12 presents an example of the top 30 words in 2021Q1 contributing to index construction.

Table 4.12 UPI Dictionary in 2021Q1

Words	Words (continued)
federal government	merkel
federation	cdu
companies	chancellor
business	laschet
worker	merz
schools	spd
employees	dreyer
subsidies	party
home office	angela
rapid test	union
tests	soeder
spahn	roettgen
law	prime minister
heil	prime ministers
affected	gruenen
trade union	malu
regulation	armin
altmaier	fdp
coworker	habeck
opening	federal parliament
measures	chancellery
steel	federal chancellor
incidence	coalition
staff	merkels
additional	csu
relaxations	kretschmann
critics	mistake
CEO	votes
called	easter rest
judgement	friedrich

Note: This table presents the top 30 words applied to construct the UPI Indicator in 2021Q1. These words represent the most cited words referring to the political environment in Germany. We translated the words into English language, as they were initially conducted in German. Some of the listed words are names of politicians, ministries or political parties. For details on how the UPI Indicator is constructed, refer to Rieger et al. (2023).

Table 4.13 Moran's I Test Statistics for Transaction Prices

Quarter	(House prices)	(Condominium prices)
2013Q2	29.8625***	17.8688***
2013Q3	29.3458***	22.3868***
2013Q4	29.7262***	21.1091***
2014Q1	26.2963***	19.3714***
2014Q2	29.3760***	20.0418***
2014Q3	34.3999***	23.1655***
2014Q4	33.6439***	23.4442***
2015Q1	32.3567***	20.8979***
2015Q2	31.1530***	22.9666***
2015Q3	29.9520***	20.5148***
2015Q4	30.0597***	22.0858***
2016Q1	37.2093***	21.2695***
2016Q2	34.5000***	20.7549***
2016Q3	33.6619***	22.7749***
2016Q4	32.0204***	20.1865***
2017Q1	32.5533***	20.7324***
2017Q2	33.7658***	21.4744***
2017Q3	32.2547***	23.7140***
2017Q4	33.4172***	21.7603***
2018Q1	35.3577***	21.1411***
2018Q2	30.1494***	19.5894***
2018Q3	32.6997***	21.7918***
2018Q4	36.0511***	23.7758***
2019Q1	32.9722***	22.2392***
2019Q2	33.3483***	21.9526***
2019Q3	34.4006***	22.9917***
2019Q4	34.3672***	23.0578***
2020Q1	34.7579***	23.2211***
2020Q2	35.7641***	22.9806***
2020Q3	36.4477***	23.7616***
2020Q4	35.1603***	23.7154***
2021Q1	33.3808***	21.5115***
2021Q2	34.8515***	23.1942***
2021Q3	35.0476***	23.2839***
2021Q4	34.5137***	22.7861***
2022Q1	35.3621***	24.1517***

Note: This table presents the results of Moran's I test, developed by Moran (1950), applied on house prices in euros per square meter, and condominium prices in euros per square meter, respectively. A distance-based neighborhood matrix was applied. For detailed information about the neighborhood set up, see Section 4.5.2. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

4.8 References

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5 Conclusion

5.1 Executive Summaries

This section provides a brief overview of each of the three scientific papers that form this dissertation. For each paper, it outlines the central problem and objective, reviews the data and methodology, and concludes with a synopsis of the results and their contribution to scholarship and practice.

Paper 1 | Building Homes for Tax Revenues? Spatial Evidence on the Fiscal Effects of Residential Land Development

Problems and Objective

Housing shortages, soil erosion and municipal budget constraints (Owens & Cowell, 2011; Borrelli et al., 2017) underscore the need for sustainable land-use. In Germany, approximately 500,000 m² of agricultural and undeveloped land is converted for development use each day (Federal and State Statistical Offices, 2025c). Initial approaches to sustainable land-use propose, for example, tradable planning permits to steer land designation (Henger & Bizer, 2010; Henger et al., 2023). Other measures, such as the German Federal Government's Sustainability Strategy, propose fixed quotas for different land-use categories (German Federal Government, 2025). However, decisions on zoning and land consumption are made at the local level. In the absence of alternative incentives, municipalities tend to favor expanding commercial areas to increase business tax revenues (Langer & Korzhenevych, 2018). Given this commercial orientation in spatial planning and the lack of competing arguments, this paper aims to estimate the municipal tax revenues generated by residential land development. To investigate whether residential zoning generates revenue incentives compared to those of commercial zoning, this paper analyzes tax revenues and land-use decisions in German municipalities.

Data and Methodology

We use a comprehensive, self-compiled data set comprising of tax revenues, land-use data and local demographic and economic indicators. This cross-sectional data set spans the period from 2016 to 2022. Covering 10,744 German municipalities, it also includes geographical information on municipal locations and neighboring relationships. This enables both visual and analytical examination of spatial dependencies using Moran's I. The identified spatial correlation in municipal tax revenues is then analyzed using spatial autoregressive regression models. Municipal income tax revenues and total tax revenues serve as dependent variables. Changes in municipal residential areas and overall settlement

areas serve as explanatory variables of interest. A vector of control variables and fixed effects is utilized to address individual heterogeneity. Because previous studies have established a bidirectional relationship between zoning and tax revenues (Song & Zenou, 2006; Chapman & Gorina, 2012; Langer & Korzhenevych, 2018), we combine a spatial autoregressive regression model with an instrumental variable approach. Following Langer and Korzhenevych (2018), we use the vegetated area of a municipality at the beginning of the observation period as a proxy for the maximum potential land development. Methodologically, the analysis proceeds in three steps. First, we estimate the effects of residential areas and settlement expansion on municipal tax revenues to establish a comparative benchmark for tax revenues associated with commercial land development. Second, we examine regional disparities by using interaction terms. Finally, we conduct extensive robustness tests to reduce the risk of biases in model specification and variable selection.

Results and Contribution

The empirical results indicate that municipal tax revenues generated by residential land development are competitive with those associated with commercial zoning. We estimated an average increase in municipal income tax revenue of €47 per square meter of newly created living space in 2016 prices.⁴⁹ At the same time, the estimated average increase in total municipal tax revenues attributable to the expansion of the settlement area is approximately €12 per square meter.⁵⁰ An earlier study by Langer and Korzhenevych (2018) estimated additional municipal business tax revenue of €13 per square meter of commercial building-land designation in Germany in 2010 prices. Although the observation periods, analyzed regions and land-use definitions differ somewhat, the comparison provides a useful relative measure of the additional tax revenues generated by commercial and residential building-land designation. Using average land development, payback periods of five to nine years emerge for the expansion of residential and settlement areas, compared with the seven years previously estimated for commercial areas (Langer & Korzhenevych, 2018). The evidence on revenue gains may therefore be interpreted as indicating a municipal incentive to create housing. Further research, however, is needed to analyze the effects of municipal revenue across building types and local land development costs.

⁴⁹ 2016 serves as the base year of the analysis. Thus, the results have been adjusted for inflation during the observation period. The unadjusted result amounts to €54.

⁵⁰ Without adjusting for inflation, the result equals €14.

Paper 2 | Living on the Highway? Addressing Highway Infrastructure Potential through Object Detection

Problems and Objective

Progressive globalization and the growth of e-commerce are contributing to increasing HGV traffic on European highways. While the number of vehicles can increase in the short term, highway infrastructure develops more slowly, leading to greater wear, structural strain and hazardous working conditions for HGV drivers (Krasniuk et al., 2024; Nevland et al., 2020). Governments and public authorities increasingly recognize the resulting capital requirements and have begun to mandate investment (Federal Ministry of Finance, 2025). However, concerns remain that these funds may be allocated inefficiently or inappropriately (Glaeser & Joshi-Ghani, 2014). Infrastructure site assessment often depends on manual data collection and case study methods due to missing or incomplete data (Kabir et al., 2020). Yet those methods carry the risk of inaccuracy and, ultimately, resource misallocation. Object detection techniques applied to satellite imagery offer a means of collecting previously unavailable infrastructure data and may therefore reduce that risk (Ma et al., 2019; Zhu et al., 2017). This paper consequently aims to propose a large-scale approach to a transferable framework for assessing infrastructure needs, using German highway parking infrastructure as an illustrative case.

Data and Methodology

We use location data from OpenStreetMap and corresponding high-resolution satellite imagery from the Google Maps API to compile a unique dataset on highway infrastructure in Germany. Bounding boxes are created manually to train an algorithm for automated identification of highway infrastructure supply, specifically HGV parking spaces. Approximately 10,000 labeled bounding boxes are then used as a training set for a YOLOv8 object detection algorithm. This refined and calibrated model achieves a detection precision of 88.7 percent. This is subsequently applied to identify and quantify the remaining HGV parking spaces in the German dataset. Because supply data alone provides only limited insight into infrastructure adequacy, automated traffic-count data are collected to estimate associated demand. After cleansing the traffic data, demand for HGV infrastructure is estimated using an economic model developed by Pêcheux et al., (2002) and Patel et al. (2022) based on driving behavior and regulatory compliance. Finally, travel distance polygons, based on the average distance of 15 kilometers that drivers travel to reach infrastructure (Niederrheinische IHK, 2024), are used to compare HGV parking supply and demand. This makes it possible to determine local equilibria between highway infrastructure supply and demand and to compare them after regional aggregation.

Results and Contribution

By combining local traffic data with object detection based estimates of HGV parking supply and applying driving-distance polygons, the results indicate a widespread shortage of highway infrastructure in Germany. However, a regional perspective reveals substantial differences in the degree of imbalance between supply and demand. Urban areas around Berlin and Bremen, for example, exhibit greater deficits than rural transit zones such as Lower Saxony. These findings may help policymakers and practitioners assess infrastructure needs more systematically. Geographical comparison highlights areas requiring particular attention, while spatial analysis may reveal recurring patterns that contribute to existing shortages. The proposed methodology may also prove beneficial for evaluating the effectiveness of implemented measures once the algorithms are rerun using more recent data. More broadly, the framework could be adapted to other infrastructure challenges, including the maintenance and expansion of rail infrastructure or the modernization and extension of energy infrastructure. Lastly, the detection accuracy achieved in this study demonstrates that object detection in satellite imagery offers an innovative approach for evaluating information that was previously unavailable or incomplete.

Paper 3 | The Price of Politics: A County-Level Analysis of Political Uncertainty and German House Prices

Problems and Objective

Real estate is an illiquid asset due to its immobility and high transaction costs, and transactions therefore heavily depend on stakeholder expectations (Huang, 2013; Monfared & Pavlov, 2019). Given the strong interdependence between political outcomes and housing, particularly in the context of affordability constraints and political intervention in markets, real estate purchases are particularly sensitive to expectations about political conditions. Whenever policies and measures change rapidly or become the subject of intense public debate, uncertainty emerges (Luo et al., 2022). This uncertainty impedes forecasting and, in line with real-options theory, provides a rationale for postponing transactions until uncertainty subsides and information improves (Titman, 1985; Dixit & Pindyck, 1994). Previous research has identified discounts associated with rising political uncertainty, coupled with reduced construction activity and lower transaction volumes (Choudhry, 2020; El-Montasser et al., 2016; André et al., 2017; Antonakakis et al., 2015; Luo et al., 2022). Yet, these studies generally define political uncertainty primarily in reference to economic policy. International conflicts, climate change and global trends also shape political activity, and thus generate uncertainty that does not necessarily take the form of economic policy. At the same time, housing market participants, especially homebuyers, consider all available information when making purchasing decisions because of their observed risk aversion (Christou et al., 2017; Ngai & Sheedy, 2020). This paper, therefore, aims to clarify the effect of generic political uncertainty on homebuyer behavior and on resulting housing transaction prices.

Data and Methodology

Our analysis is based on a unique data set of transaction prices for residential properties in German cities and counties. The data spans the period from 2013Q2 to 2022Q1 and is drawn from the transactional database of the Verband Deutscher Pfandbriefbanken (2023), the largest database of real estate transactions in Germany, fed by more than 590 property financing institutions (Verband Deutscher Pfandbriefbanken, 2023). Median price per square meter by quarter and county, for detached houses and condominiums serve as the dependent variables. The Uncertainty Perception Indicator (UPI), developed by Rieger et al. (2023), serves as a proxy for perceived political uncertainty. Using dynamic Rolling-LDA techniques, this index captures the emergence of political uncertainty in major German daily newspapers (Rieger et al., 2023). Additional control variables, including mortgage interest rates, unemployment rates and demographics, are included to account

for economic trends and local characteristics affecting real estate prices. To ensure reliable estimates, preliminary tests are conducted to assess stationarity, spatial and temporal correlations, and variance stability. To account for identified spatial dependencies among adjacent counties, we employ spatial autoregressive (SAR) models to isolate the impact of political uncertainty on German housing prices. In a subsequent step, spatial heterogeneity is examined using interaction terms to explore local differences in housing market sensitivity to rising political uncertainty. Comprehensive robustness checks are additionally performed to reduce the risk of bias arising from geographical or temporal sample selection, the modeling of spatial dependencies, or variable definition.

Results and Contribution

Political uncertainty affects stakeholder expectations and, therefore, influences homebuyer behavior. The results suggest that generic political uncertainty negatively effects transaction prices for both single-family homes and condominiums. House prices decline by 2.2 percent, on average, while condominium prices decline by 2.4 percent, on average, following a one-standard-deviation increase in media-perceived political uncertainty. An uncertainty shock comparable to the COVID-19 pandemic would imply discounts of 6.1 to 6.8 percent for house and condominium prices, respectively. Spatial analysis further indicates that prices in regions with higher unemployment are more sensitive to political uncertainty, with house prices again more affected than condominium prices. These findings may be useful to both policymakers and homebuyers. Policymakers may benefit from insights into how uncertainty affects housing markets when designing policies. Greater awareness of how uncertainty is perceived may create incentives for transparent and unambiguous communication of policy measures and for closer engagement with industry stakeholders. Meanwhile, risk-taking homebuyers may benefit from potential discounts. The results also indicate that political uncertainty need not relate directly to economic issues to exert a negative influence on real estate prices. However, the extent to which political uncertainty affects both homebuyer activity and real estate pricing remains insufficiently understood. Future research might examine which dimensions of political uncertainty most strongly affect housing markets, how long these influences persist, and through which channels political uncertainty is transmitted into market outcomes.

5.2 Final Remarks

Global trends continually confront society with new challenges. In the context of living and working spaces, these include the shortage of adequate housing driven by urbanization, migration and demographic change. A further challenge lies in the lack of suitable infrastructure resulting from the growth of e-commerce, business expansion and past investment backlogs. These and related challenges are global in scope and therefore rank high among the United Nations' Sustainable Development Goals. Overcoming them requires sustained interaction among relevant stakeholders. In the built environment, these stakeholders include investors and, above all else, policymakers and developers. To address the central concerns at the heart of this dissertation, namely the provision of affordable housing and adequate infrastructure, stakeholders need substantive knowledge and reliable information for decision-making. Research and practice alike are therefore challenged to question traditional approaches, adopt modern methods of information gathering and remain attentive to mutual expectations.

Land-use planning marks the start of every development project. Given the persistent challenge of housing development and the growing awareness of the environmental costs of soil sealing, further changes in land-use planning are likely if existing problems are not to worsen. Initial approaches towards sustainable zoning have relied primarily on regulation. Yet, pilot initiatives, such as tradable planning permits or the circular concept of the German Sustainability Strategy, have not gained broad traction (Langer & Korzhenevych, 2018; Henger et al., 2023). Local interests appear to continue dominating spatial planning. Incentivizing decision-makers may help encourage shifts in land-use planning. The findings of the first paper suggest that the designation of residential land generates tax revenues for municipalities that are equal to, or even greater than, those from commercial land. The approach proposed here not only offers a counterargument to planning centered on business tax revenue but also suggests a framework for incorporating spatial dependencies into development planning. More broadly, the results reinforce the value of regionally coordinated spatial planning efforts to foster synergy effects. Planning, however, is merely the first step in addressing housing shortages. Approval, realization and sustainable long-term use are all required if viable solutions are to be achieved.

Infrastructure is the backbone of a functioning economy and society. Given current government efforts to expand infrastructure through special funds (Federal Ministry of Finance, 2025), debate surrounding the location, construction, and financing is expected to play a significant role in policy and practice in the upcoming years. Yet, the greater the

political pressure to deliver infrastructure rapidly, the greater the risk of misallocation (Glaeser & Joshi-Ghani, 2014). Limited public resources for construction and maintenance require sound decision-making. Traditional methods, such as manual data collection and case study analysis, should accordingly be supplemented by technological innovation to reduce the risk of inaccuracies and errors. The findings of this dissertation propose an exemplary approach for the automated identification of infrastructure supply and demand. The second paper not only identifies regions of demand for highway infrastructure in Germany but also demonstrates how machine learning and automated object detection in satellite imagery can be used to record infrastructure facilities. With appropriate adjustments, the methodology could be transferred to other infrastructure issues, such as roads, wind turbines, or railway networks. At the same time, further research is required to determine incentives for infrastructure provision, including whether additional municipal tax revenues might play a role. Innovative methods such as satellite-image classification or generative artificial intelligence may also help identify optimal infrastructure locations and predict future use. Furthermore, the public sector remains dependent on commercial stakeholders for the planning, development and maintenance of infrastructure. An evidence-based dialogue between policymakers and practitioners is essential to ensure efficient processes and avoid distorted incentives.

Another important aspect of analyzing the interaction between policymakers and practitioners in real estate development is mutual expectations. There is considerable evidence that expectations shape stakeholders' decision-making in real estate markets. The findings of this dissertation draw on this insight and indicate not only that expectations are reflected in real estate prices but also, that political uncertainty, in particular, triggers adverse expectations, thereby depressing housing prices. Given the most recent developments in global politics, namely the ongoing war in Ukraine, security tensions in the Middle East and international tariff disputes, the Economic Policy Uncertainty Index (EPU) has reached its highest level since its introduction⁵¹ (Davis, 2016). Noticeable impacts on real estate and housing markets can be expected. Under such conditions, the importance of aligning expectations to avoid inefficiency and resource misallocation becomes even clearer. When policy and industry stakeholders must devote attention to navigating uncertainty, their capacities may be diverted away from overarching challenges, such as affordable housing and adequate infrastructure. From an economic perspective, it is therefore vital to minimize uncertainty and promote mutual understanding. Further

⁵¹ Unfortunately, a comment on the current development of the UPI Indicator used in the third paper of this dissertation is no longer possible, as the index has not been updated since 2023.

research should seek to pinpoint the consequences of uncertainty and insufficient dialogue and explore incentives to mitigate both.

This dissertation highlights three aspects of the interplay between political and real estate stakeholders in a spatial context: residential land-use planning, highway infrastructure provision and uncertainty perception in housing markets. The first paper estimates additional tax revenue in response to the initial research question regarding municipal incentives to designate residential building land. The second proposes satellite image analysis to address the initial problem of balancing supply and demand for highway infrastructure, particularly parking facilities. The third offers insight into the tangible effects of political uncertainty on housing markets, and thus addresses the original research question of how uncertainty matters for homebuyers. However, looking at the big picture, these studies are small-scale examples within a much-larger network of countless links and nodes. Other issues of equal relevance to the real estate industry and researchers worldwide include the transformation of inner cities, the design of future workplaces and the decarbonization of the built environment.

The studies presented here are intended to encourage data-driven decision-making and stimulate further research. While the findings presented are based on specific historical circumstances, they nevertheless offer useful approaches to contemporary problems. The conclusions drawn in this dissertation are limited by the observation periods under study and by the geographical focus on Germany. In addition, the time lag inherent in the collection and publication of official statistics limits the availability of recent demographic and economic data. Future research will need to determine whether these findings remain valid or change over time. The transferability of findings to other periods and geographical regions is limited and must always be considered when applying them.

Finally, the fundamental challenges of affordable housing and infrastructure provision are likely to persist on the global agenda. Researchers and practitioners alike will continue grappling with them for generations to come. Analyzing the interactions among political and commercial stakeholders emphasizes the interdisciplinary nature of real estate development. Although this aspect remains relatively unexplored, the findings of this dissertation suggest substantial scope for further research. Mutual expectations and incentives, innovative methods of data analysis and the role of uncertainty may all shape the next generation of research on real estate development. However, given the exposure of real estate markets to broader global change, the issues that will preoccupy both scholarship and practice in the future may not yet be foreseen.

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