Essays on Housing Supply and the Monocentric City Model

Von Der Mercator School of Management, Fakultät für Betriebswirtschaftslehre,

der

Universität Duisburg-Essen

zur Erlangung des akademischen Grades

eines Doktors der Wirtschaftswissenschaft (Dr. rer. oec.)

genehmigte Dissertation

von

Eyayaw Beze

aus

Lalibela (**ሹምሹሃ**)

Referent: Prof. Dr. Tobias Seidel
Korreferent: Prof. Dr. Nadine Riedel
Tag der mündlichen Prüfung: 01.07.2024

Cumulative Dissertation - Current Status of Each Chapter

Chapter 1: **Geographic Constraints and the Housing Supply Elasticity in Germany**

A similar version of this chapter has been published as *Beze, E. (2023). Geographic Constraints and the Housing Supply Elasticity in Germany.* Ruhr Economic Papers #1003. *http://dx.doi.org/10.4419/96973169.*

Chapter 2: **The Impact of COVID-19 on Real Estate Markets in Germany** *(joint work with Patrick Thiel)*

A similar version of this chapter has been published as *Beze, Eyayaw and Thiel, Patrick, The Impact of COVID-19 on Real Estate Markets in Germany (January 19, 2024). Available at SSRN: https://ssrn.com/abstract=4700238.*

Chapter 3: **Testing the Gradient Predictions of the Monocentric City Model in Addis Ababa**

This chapter has not been published anywhere yet.

Acknowledgments

This dissertation would not have been possible without the support of my supervisors, colleagues, friends, and family.

First, I am grateful to my supervisor, Prof. Dr. Tobias Seidel, for his consistent support and guidance throughout this journey. I especially appreciate his time and support during the challenging pandemic period. Thank you for the frequent Zoom meetings and timely nudges. His input has been crucial to my research progress. I credit him for the idea behind the first chapter. I also thank my second supervisor, Prof. Dr. Nadine Riedel, for her invaluable feedback on the first chapter and insightful discussions on the other two chapters, which have been highly valuable for my research progress. Thank you for your amazing kindness.

I also thank the Principal Investigators (PIs) of the Research Training Group (RTG) on Regional Disparities & Economic Policy, especially Prof. Dr. Thomas Bauer for his invaluable comments and suggestions. I thank Andreas Mense for his valuable input on the first chapter. I would like to express my special gratitude to my colleagues at the Chair of Economics (VWL), Mercator School of Management (MSM): Sebastian Kunert, Fabian Bald, Philipp Markus, Malte Borghorst, Siegfried Laurus To, Lu Wei, Lorenz Gschwent, Max Perl, Christian Willerding-Möllmann, Cagla Diner, and Klaudia Gil Cespédes. I am grateful to all members of the RTG and the Ruhr Graduate School in Economics (RGS Econ) for the great time together, discussions, and overall support. I would like to thank Helge Braun for his incredible support and kindness during my coursework and for helping me settle in the Ruhr Area. I thank all of the 2019 cohort, especially Dejan, David, Ralf, and Solveig, for their genuine personality and kindness. I would like to extend a special thanks to my dear friend Ioannis Arampatzidis for his incredible friendship and personality. Thank you for riding along on this journey.

I want to thank Gerrit Wegmann for his excellent work as a research assistant and support in the third chapter. I also want to express my strong gratitude to my co-author and colleague, Patrick Thiel, for his invaluable collaboration and discussions.

Above all, I am grateful to my beloved mother, Adina (Etatey), for her unwavering love and lifelong sacrifices to support my education, despite not having the opportunity to attend school herself. I would like to thank my late father (Eyaye), for his amazing personality and love. I would like to thank my siblings, Daniel (Dani-Embum), Tsion (Lastawork), Surafel (Etatu), and Almaz (Gugut), for their love and support. I am deeply grateful to my partner, Erkinai, for her love, presence, support, and unwavering belief in me. Thank you for being an integral part of my journey. You have been an incredible companion during this journey. Thank you for your immense contribution to proofreading this dissertation, your sharpness is incredible. Simply, everything I am, I owe to you. Without you all, this would not have been possible.

Furthermore, I want to thank my friend and dear brother Getnet for his unbelievable friendship and support. I thank my cousins Mulugeta (FNG) and Dejen (DJ) and dear friend Dereje (Kay), for their love and support.

Thank you to my special friends – Akuka, Zhenya, Eldi, and Enri – for making my European time fun and adventurous. I look forward to better days together ahead.

I am thankful to everyone who has been part of my journey, directly or indirectly.

Finally, I am highly grateful for the financial support from the Stiftung Mercator via the RGS Econ.

*To my late father, Teka Beze Gared (**ኡንጉሱ ተካ በዜ**), whom I lost during my Ph.D. journey. I miss you every day.*

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Introduction

The housing market is a key component of the economy. Housing is a fundamental need, accounting for one-third of household consumption expenditure and represents a valuable asset that often exceeds a country's GDP. In Germany, for example, the value of residential housing in 2023 is approximately \$30 trillion, about seven times larger than its annual GDP (Statista, 2024; IMF, 2023). More importantly, the housing market serves as the primary mechanism through which households and firms sort themselves across space, based on their preferences and constraints, shaping the spatial structure of cities and the distribution of key economic variables such as house prices, income, and population density. Accessibility to jobs and amenities varies within and between cities, and understanding these dynamics is crucial for understanding urban spatial structure.

Urban economics has long sought to explain the observed regularities in the spatial structure of cities, such as the dramatic variation in land-use intensity and building heights within and between urban areas. The monocentric city model, which emerged from the seminal works of Alonso (1964), Mills (1967), and Muth (1969) (AMM), provides a rigorous economic framework for understanding these patterns. The key element of the model is the idea that commuting cost differences within a city must be balanced by compensating variations in housing prices. This dissertation applies and extends the insights of this framework to analyze three important aspects of urban spatial structure and housing markets. The first chapter examines how geographic constraints affect the price elasticity of housing supply in Germany, shedding light on the determinants of inter-county differences in house price and supply growth. The second chapter investigates the impact of the COVID-19 pandemic on the German housing market, a significant shock that may have altered the spatial structure of cities relating to the valuation of amenities and housing demand. Finally, the third chapter directly tests the gradient predictions of the monocentric city model in the context of Addis Ababa, extending the model's applicability to rapidly growing cities in developing countries. Together, these chapters leverage the power of the AMM framework to provide new insights into the spatial structure of cities and housing markets in diverse settings.

Chapter 1 examines the price elasticity of the housing supply and the geographic constraints of the housing supply in Germany. The housing supply elasticity is a key parameter in urban economics as it determines the congestion externalities. Cities are physical structures, and the elasticity of housing supply helps determine the extent to which increases in productivity will create bigger cities or just higher wages and more expensive housing (Glaeser et al., 2006). As a key ingredient for quantitative spatial models, housing supply elasticity estimates for Germany have been lacking, and much of the existing evidence on housing supply elasticity comes from the US housing market. The German housing market is not only large but also has peculiar characteristics in contrast to markets in the US and other European countries.

Germany has one of the lowest homeownership rates among OECD countries, with only 44% of households owning their primary residence in 2010 (Kaas et al., 2021). Its housing policies create incentives for tenants rather than homeowners, with a robust social housing sector with broad eligibility requirements, high transfer taxes on house purchases, and no mortgage interest tax deductions for owner-occupiers (Kaas et al., 2021). Legislation that prevents speculative behavior and the low frequency of change in homeownership, as well as low interest and mortgage rates, contribute to the market's stability. Given this context, this chapter analyzes the housing supply in the 2008-2019 time period and presents housing supply elasticity estimates. Using a reduced-form approach, and the Bartik instrument as the source of identification, we estimate, on average, an inelastic supply of floorspace 0.22 across German districts. This study finds that geographic constraints affect the elasticity, with high land development intensity reducing the elasticity. Interestingly, the unavailability of land due to restrictive geography does not significantly impact this elasticity, as the variation in land undevelopability is low across districts. This chapter contributes to the literature by providing robust estimates of the price elasticity of housing supply for Germany and highlighting the role of geographic constraints in shaping housing supply elasticity.

Chapter 2 contrasts the significant "donut effect" observed in the US housing market during the COVID-19 pandemic with the German housing market's resilience. The donut effect refers to the phenomenon where central areas in cities experience rent declines, while suburban areas see high housing demand, forming a donut-shaped pattern. This study draws on the key prediction of the monocentric city model: the rent gradient. House prices or rents are higher in city centers than in the peripheries due to lower commuting costs and higher amenities (Alonso, 1964; Mills, 1967; Muth, 1969). However, following the COVID-19 pandemic outbreak, commuting costs have fallen or been eliminated because of the possibility of working from home (WFH). Additionally, urban consumption amenities were largely inaccessible because of strict lockdown measures. These trends may have reduced the demand for housing in city centers and dense neighborhoods within cities, potentially flattening the rent gradient. Strong evidence for this exists in the US housing market: the pandemic has caused significant population movements away from high population density and central areas to low density and suburban neighborhoods in metropolitan areas (Liu and Su, 2021; Ramani and Bloom, 2021; Gupta et al., 2022).

This chapter approaches that question from the perspective of the German housing market. We used comprehensive zip code-level data on housing prices and rents to examine temporal changes, comparing pre- and post-pandemic periods. Despite expectations, only apartment rents in suburbs and low-density zip codes have slightly increased compared to those in the CBD and high-density zip codes. Furthermore, we analyzed urban and environmental amenities to understand the changes in rents, but we did not find any significant effect. Our amenity data, constructed from OSM, shows that the valuation of both consumption and environmental amenities remains relatively stable. All findings are robust across various CBD definitions and regional subsets, such as big cities versus small cities. Consequently, the findings suggest that the German housing market exhibited resilience during the COVID-19 pandemic, pointing to cultural and structural market differences in contrast to the US. The German housing market's resilience during the pandemic relates to its unique characteristics.

Chapter 3 delves deeper into the monocentric city model and analyzes the gradient predictions of the model in Addis Ababa, an example of a rapidly developing city. It presents new empirical evidence that supports the monocentric city model's predictions in a developing country context. The monocentric city model, a key foundation of urban economics, posits that housing or land values, population density, and building heights decrease with distance from the CBD. While the model has strong theoretical and empirical support in cities in developed countries, evidence from cities in developing countries is limited.

This chapter examines the relevance of the model in Addis Ababa, a rapidly growing prime city in Ethiopia. Using a unique dataset of over 70,000 property listings and satellite-based building footprint data, it provides new empirical evidence on rent and structural density gradients. Specifically, this study finds that the rent gradient estimates for both house prices and rents in Addis Ababa are negative, in both panel and crossectinal settings. The magnitude of the estimates is similar to previous studies such as McMillen (2006) and Liotta et al. (2022). The structural density gradient is also strongly negative, where high-rise buildings are mostly found in the city center. The findings suggest that the monocentric model explains Addis Ababa's urban structure, despite its different growth patterns compared to cities in developed countries. These patterns include the city's lack of planning, land use fragmentation, urban sprawl, limited infrastructure, high rates of informal housing, and rapid population growth.

Additionally, the study demonstrates data generation possibilities in data-scarce environments. It also highlights the potential of leveraging new data sources and methods for urban research in developing countries, where urban data is often limited. By providing a unique real estate dataset for Addis Ababa, this chapter contributes to a better understanding of urban dynamics not only in Addis Ababa but also in other developing country cities.

By examining the interplay between geographic constraints, the impact of the COVID-19 pandemic, and the applicability of the standard urban model in different urban settings, this dissertation contributes to the field of urban economics. Specifically, it contributes to our understanding of the determinants of housing supply and the price elasticity of housing supply and market resilience in the face of global crises. Furthermore, it provides new empirical evidence supporting the standard urban economics model in the context of a developing city. The findings have implications for policymakers, urban planners, and researchers interested in understanding the dynamics of housing markets and cities.

Chapter 1

Geographic Constraints and the Housing Supply Elasticity in Germany

Abstract

The study estimates the housing supply elasticity and the impact of geographic constraints in Germany from 2008 to 2019 using the Bartik instrument. The results indicate that the housing supply is, on average, inelastic, with a floorspace elasticity of 0.22 and a units elasticity of 0.25. The study also reveals that geographical constraints partially affect the housing supply elasticity across districts. High development intensity decreases the elasticity, while the unavailability of land for development due to restrictive geography has no significant impact. The housing supply elasticity estimates may prove useful for calibrating quantitative spatial models in Germany.

JEL codes: R310
Keywords: House prices, housing supply, housing supply elasticity

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A similar version of this chapter has been published as *Beze, E. (2023). Geographic Constraints and the Housing Supply Elasticity in Germany. Ruhr Economic Papers #1003.* http://dx.doi.org/10.4419/96973169.

1.1 Introduction

The price elasticity of housing supply is a key parameter in urban economics because it drives the congestion externalities and governs urban growth dynamics. An inelastic supply of land or housing means that any positive change in housing demand or location due to a positive productivity or amenity shock translates into higher prices—a major source of urban disutility—rather than higher quantities. On the contrary, if housing is supplied more elastically, we might expect smaller price changes and larger adjustments in city sizes. Moreover, inelastic supply aggravates house price differences across regions, affecting inter-regional labor mobility, and may constrain housing affordability in cities and regions, particularly in the big and growing ones. Thus, the housing supply elasticity is central to understanding the long-term development of cities and regions (Combes et al., 2019; Glaeser et al., 2006; Saks, 2008; Lerbs, 2014).

Over the past two decades, house prices have risen in cities worldwide, often due to a combination of strong and growing demand and a limited supply of new housing. Significant variations in the level and growth of house prices across cities and locations within cities and regions have been recorded (Glaeser, 2020; Hilber and Mense, 2021). An unresponsive housing supply can undoubtedly lead to higher house prices. However, examining what limits the housing supply and why may take more work. For example, in the US, house price gaps in rural and urban areas are much larger than the gaps in construction costs which is understood as a reflection of the difficulty of building new houses, especially in dense urban cores (Glaeser, 2020). While building new houses may help reduce house prices and alleviate affordability issues, answering why some cities and regions can build more houses more flexibly than others in response to the growing demand for housing is essential. More precisely, why do changes in demand for housing, triggered by productivity or amenity shocks, increase house prices rather than inducing more construction activities and city growth in some cities and not others?

This study empirically examines these questions by analyzing the growth of housing supply and house prices between 2008-2019 across the 401 German districts.[1] More precisely, I estimate the price elasticity of housing supply from a productivity or amenity shock induced response in housing supply. The main source of variation exploited for identifying the housing supply elasticity parameter is a Bartik (1991) labor demand shock, which has been widely used in the literature (for example, Saiz (2010) and Baum-Snow and Han (2019)) as a proxy for demand. As such, average housing supply elasticity estimates reflect variations in housing demand shocks due to changes in labor demand over time across districts.

However, construction costs or productivity, existing land development, and land use regulations may also influence housing supply differences. These factors can also mediate the responsiveness of the housing supply to changes in housing demand. Housing supply variations across districts are high due to differences in existing development intensity and land availability constraints. Therefore, parameterizing the housing supply elasticity with these observed housing supply heterogeneities allows us to get elasticity estimates at the district level and captures the importance of these factors in mediating the relationship between housing quantity and price.

Much of the existing evidence on the housing supply elasticity comes from the US housing market, but the literature is limited for other countries due to data availability, particularly for Germany. To my knowledge, only Lerbs (2014) estimated the housing supply elasticity for Germany, using a dynamic panel data model from new construction permits of single-family homes for 2004-2010. By adopting the recent approaches in the literature (Saiz, 2010; Hilber and Vermeulen, 2016; Baum-Snow and Han, 2019), this paper presents the German housing market's peculiarities regarding the

[1]There are 401 districts ("Kreise" in German) according to the 2019 end-of-the-year (31.12.2019) administrative structure breakdown.

housing supply elasticity.[2] For doing so, I leverage a detailed unique house price dataset by RWI and ImmobilienScout24 (2020) covering the whole of Germany available for 2007 onward. Furthermore, in line with the housing production literature, I use total residential floorspace over housing units as the main measure of housing quantity as it better captures the true level of housing supply (Baum-Snow and Han, 2019; Epple et al., 2010).[3]

Using a reduced form approach, I recover the housing supply elasticity as the impact of housing demand-induced growth in house prices on residential floorspace growth over 2008-2019. Following the housing production literature, I derive a housing supply function incorporating local variations in construction costs or productivity and land availability. This allows writing the housing supply elasticity as a function of the same factors. Finally, I estimate the housing supply elasticity via a two-stage least squares (2SLS) estimation using predicted employment growth as an instrument for house price growth.

The data show that most districts in Germany have experienced substantial growth in house prices, an about 32% change between 2008 and 2019, on average. Urban districts, in particular, have experienced slightly higher growth than rural districts, but there is little difference in price growth between the West and East German districts. In contrast, the housing supply growth has been weak across German districts, about 7%, on average. New construction permits and completions have been continuously declining since 1995, gradually rising after 2009, yet the 2008-2019 levels remain far below the late 1990s and early 2000s.

[2]The German housing market is known for its stability, pro-tenant rental laws, moderate rental income taxes, low interest and mortgage rates, recent fundamental supply shortages, and stiff land use regulations (German Property Market Outlook 2021, Deutsche Bank AG, accessed August 10, 2022, Global Property Guide, accessed August 12, 2022). Moreover, it was one of the few housing markets that experienced less house price volatility during the 2008-2009 financial crisis. Because of these unique features (subtle nuances), studying this market, particularly concerning housing supply and elasticity differences across districts, would be a great addition to the literature.

[3]In the literature, housing supply has been measured or proxied by several variables, including housing units (stock), new construction permits, completions, and starts, and the number of households (e.g., Saiz (2010)).

Consequently, districts, on average, have been supply-inelastic. According to the baseline results, on average, a district has about 0.22 elasticity in floorspace, 0.25 in units. That means, over the 2008-2019 period, a 10% increase in house prices has generated a 2.2% growth in residential floorspace, on average, keeping other things constant. These estimates are similar to what Lerbs (2014) found for 2004-2010 (a short-run elasticity of 0.25 and a long-run value of 0.4).[4] Baum-Snow and Han (2019) also found housing supply elasticity estimates in a similar range for census tracts in the US for 2000-2010.[5]

The baseline specification obscures district heterogeneity since it does not allow the housing supply elasticity to vary across districts. Instead, the main specifications allow housing supply elasticities to vary across districts as a function of housing supply constraints. This is achieved by interacting price growth with fractions of already developed land and land that cannot be developed because of steep slopes and water bodies. According to the results, only land development intensity significantly constrains the housing supply elasticity in German districts, while land undevelopability due to restrictive geography has no significant impact. Land development intensity lowers the housing supply elasticity by about 0.46. Moving in the interquartile range of existing development intensity (5.4%, 23.0%) reduces the floorspace elasticity by 0.08, from 0.285 to 0.204.

Finally, this paper provides robust housing supply elasticity estimates for Germany from 2008-2019. These estimates may prove useful for calibrating quantitative urban or regional models in Germany, which previously relied heavily on estimates for other markets. In addition, the study's utilization of supply constraints in Germany, precisely the measurement of undevelopable land constructed from elevation and land cover data, can

[4]Apart from the time periods, however, estimates in this paper may be different from Lerbs (2014) estimates due to differences in the empirical methods employed. First, permits are used as a housing quantity measure, as opposed to the residential floorspace used in this paper. Second, the price data used in the two papers are different.

[5]The authors estimate the housing supply elasticity to be in a range of 0.3-0.5 aggregated to the Metropolitan Statistical Area (MSA) level (see (3) and (8) columns of Table 6 and Table 11 in the Appendix of their paper).

be valuable for other studies examining the housing supply constraints in Germany.

1.2 Literature Review

This study builds on a growing body of literature examining the determinants of housing supply. The existing literature presents strong evidence regarding the impact of supply constraints on house prices and the housing supply elasticity in the US housing market (Glaeser and Gyourko, 2005; Saiz, 2010; Paciorek, 2013; Baum-Snow and Han, 2019). In other markets, the literature is somewhat limited, except for a few notable studies, such as Hilber and Vermeulen (2016) and Büchler et al. (2021), which looked at the UK and Swiss markets, respectively. Much of the existing work looks at differences between cities concerning spatial scale. Few studies take on within cities and regions, such as neighborhoods, at a granular spatial scale, for example, Baum-Snow and Han (2019).

Glaeser and Gyourko (2005), Saiz (2010), Paciorek (2013), Hilber and Vermeulen (2016), and Baum-Snow and Han (2019) explore the relationship between housing prices and various factors such as regulatory approval, geography, and land availability. Glaeser and Gyourko (2005) argues that changes in house prices in the US appear to result from a changing regulatory regime that has made large-scale development increasingly difficult in expensive regions of the country. Saiz (2010) uses a variation of the Alonso-Mills-Muth model to show that land-constrained metro areas should have more expensive housing and higher amenities or productivity. Most areas widely regarded as supply inelastic were found to be severely land-constrained by their geography, and highly regulated areas were found to be geographically constrained. Paciorek (2013) focuses on the relationship between supply constraints and house price volatility and indicates that permit delays and marginal costs of new investment explain much of the observable differences in elasticity across markets. Hilber and Vermeulen (2016) finds regulatory constraints to be the causal impact of various long-run supply constraints on house prices in England. Finally, Baum-Snow and Han (2019) provides a comprehensive characterization of housing supply elasticities for residential neighborhoods in 306 US metro areas and finds that distance from urban centers, initial development density, topography, and zoning regimes are among the most important determinants of local housing supply.

In summary, the literature on the impact of supply constraints on house prices and supply is extensive in the US but limited for other countries (Hilber and Vermeulen, 2016). There is strong evidence emphasizing that both geographical constraints (see Saiz, 2010; Paciorek, 2013) and regulatory constraints (see Glaeser and Gyourko, 2005; Paciorek, 2013; Gyourko et al., 2021; Glaeser, 2020) explain much of the rapid house price growth across cities and markets in the US, as well in the UK (Hilber and Vermeulen, 2016). In most of the US studies, the Wharton Residential Land Use Regulatory Index (WRLURI 2006 or 2018) has been exclusively used as a measure of regulatory restrictiveness. In contrast, Hilber and Vermeulen (2016) used a dataset that includes direct information on actual planning decisions to measure regulatory restrictiveness. Regarding geographic constraints, mainly the degree of land development and unavailability, measures constructed from digital elevation models and land cover classes have been used. In the literature, housing supply is measured by several variables, including housing units (stock), construction permits, completions or starts, and household size. The housing production literature (see Epple et al., 2010; Combes et al., 2021) suggests using housing services, which can be proxied by floorspace, as a better measure, as used in Baum-Snow and Han (2019). Bartik (1991) is widely used as a main source of variation for identifying the housing supply elasticity parameter.

This study extends the analysis period of Lerbs (2014) to 2008-2019, providing a more recent assessment of the price elasticity of housing supply in Germany. Unlike the previous study, which focused on single-family homes using construction permits for 2004-2010, this study uses residential floorspace, including for single-family homes, construction permits, and completion, providing a more comprehensive measure of housing supply. Additionally, by examining the impact of geographic constraints on housing supply elasticity at the district level, this study captures the heterogeneity in housing supply across districts, which has not been explored in the literature.

1.3 Method

I begin with a simple theoretical derivation of the supply of housing on a fixed plot of land and a simple aggregation to the district level. Then, the empirical implementation subsection discusses how the housing supply elasticity is estimated using the Bartik (1991) shocks as an instrument for housing demand.

1.3.1 Model

This subsection demonstrates the derivation of the local housing supply function, following the housing production function literature (Epple et al., 2010; Combes et al., 2021). Importantly, the model demonstrates how the local housing supply and housing supply elasticity can be written as a function of supply determinants, in particular geographical or physical constraints.

1.3.1.1 Housing supply

A simple model of district housing supply

A competitive developer combines a fixed amount of land $\overline{T}$ and non-land inputs K, which I simply call capital, to produce housing H via a Cobb-Douglas technology:

$$H = H(A, \overline{T}, K) = A\overline{T}^{\alpha} K^{1-\alpha}, \tag{1.1}$$

where $\alpha \in (0, 1)$. A captures supply heterogeneity across parcels due to local labor costs, productivity, geography, or ease of construction differences.[6]

A representative builder maximizes profit by choosing capital K over a fixed parcel of land $\overline{T}$

$$\Pi = P(x) \cdot H - R - P^K \cdot K,$$

where R denotes the endogenous price of land of size $\overline{T}$, and P^K is the price of capital which is assumed to be invariant across parcels and locations and normalized to unity. The price of a unit of housing developed on a parcel of size $\overline{T}$ is given by P and depends on x, a vector of observed or unobserved parcel or location characteristics that reflect the housing demand on the parcel.[7]

Builder's profit maximization delivers the factor demand for capital K.[8]

$$K^* = \Big((1-\alpha)AP(x)\Big)^{\frac{1}{\alpha}}\overline{T} \equiv K^*(P(x), \overline{T}, A)$$

By substituting the factor demand equation for capital back into the housing production function Equation 1.1, the per parcel supply function can be written as:

$$H(A, \overline{T}, K^*(P(x), \overline{T}, A)) = \mu A^{\frac{1}{\alpha}} P(x)^{\frac{1-\alpha}{\alpha}} \overline{T} \equiv H^S(P(x), A), \quad \text{with } \mu = (1-\alpha)^{\frac{1-\alpha}{\alpha}}.$$

In log-linear form,

$$\ln H^S(P(x), A, \overline{T}) = \ln \mu + \frac{1}{\alpha} \ln A + \underbrace{\Big(\frac{1-\alpha}{\alpha}\Big)}_{\varepsilon} \ln P(x) + \ln \overline{T}. \tag{1.2}$$

This shows that the supply of housing developed on a parcel depends on local supply heterogeneity A, local housing demand conditions captured by $P(x)$, and on the size of the parcel $\overline{T}$.

[6] K captures a composite of all inputs for housing production other than land, which can broadly be labor and materials.

[7] The full detail of this section is delegated to the Appendix; see Section 1.A.

[8] Since land is fixed, the developer chooses capital to maximize profit.

Following Baum-Snow and Han (2019), aggregation of the housing supply on a parcel in Equation 1.2 over all developed parcels in the district delivers the total supply of housing in the district. Let $\mathcal{L}_i$ denote the total (developable) land endowment of district i and $\Lambda_i(P_i)$ the fraction of partitioned parcels that are developed in i, then the stock of developed land in i is defined as $\mathcal{T}(P_i) = \Lambda_i(P_i) \cdot \mathcal{L}_i$. The implicit district-level aggregate housing supply function $S_i(P_i(x))$ can then be defined as the product of the (average) housing supply per parcel and the stock of developed land:

$$\begin{aligned} S_i(P_i) &= H_i^S(P_i, A_i) \cdot \mathcal{T}_i(P_i) \\ \ln S_i(P_i) &= \left[\ln \mu_i + \frac{1}{\alpha} \ln A_i + \varepsilon \ln P_i\right] + \left[\ln \Lambda_i(P_i) + \ln \mathcal{L}_i\right] \end{aligned} \tag{1.3}$$

Differentiating Equation 1.3 with respect to $\ln P$ delivers the housing supply elasticity,

$$\varepsilon_i^S \equiv \varepsilon + \frac{\partial \ln \Lambda_i(P_i)}{\partial \ln P_i}, \tag{1.4}$$

where the first term captures the intensive margin of development (floorspace per parcel) and the second reflects the extensive margin (parcel development).

Districts with more developable (more flat or less rugged) land, low initial level of development density, and unrestrictive regulation may respond more along the extensive margin, increasing the level of land development. In contrast, districts that have a high level of existing development (high built-up) or are restricted by their geography or by restrictive land regulation may respond along the intensive margin, increasing floorspace per parcel.

1.3.1.2 Housing demand

The canonical housing demand is derived from a utility maximization problem of a representative household living in district i that consumes final goods C priced at 1 and a unit of housing H_i priced at $P_i(x)$.

$$\max_{C,H} U(C,H) = \theta H_i^{\beta} C_i^{1-\beta}$$
$$\text{s.t.} \quad w_i = C_i + P_i(x) \cdot H_i \,,$$

where w_i denotes average wage or productivity in i.[9] The first order condition for utility maximization with respect to H delivers the housing demand function

$$H_i^*(P_i(x), w_i) = \beta \frac{w_i}{P_i(x)} \equiv H_i^d(P_i(x), w_i).$$

Assuming that locations within district i are perfect demand substitutes for given values of parcel characteristics, then P_i representing the average price of housing in the district, summing up over the housing consumption of all the residents N of i, the log aggregate housing demand function for district i can be written as

$$\ln P_i = \ln \beta + \ln w_i - \ln H_i^d + lnN_i. \tag{1.5}$$

The housing demand function in Equation 1.5 shows how exogenous productivity (w_i) changes can be used as demand shifters for identifying the housing supply elasticity.[10]

1.3.2 Empirical implementation

Fundamental to recovering the housing supply elasticity ε is finding an exogenous shifter that comes from the housing demand function Equa-

[9]For simplicity, I assume that market imperfections are minimal such that workers earn wages equal or proportional to their productivity.

[10]Higher levels of productivity are associated with higher levels of economic development and income, which can lead to increased demand for housing by attracting more people to an area (Glaeser and Gottlieb, 2009; Glaeser, 2008). This increased demand can drive up local house prices, as people are willing to pay more for housing in areas with strong job market opportunities and higher wages. Home builders will react to the increased demand and higher prices by building new houses, other things held constant.

tion 1.5. This shifter can be used as an instrument for house prices provided it is uncorrelated with supply shifters (such as construction costs or productivity).

The main estimation equation is the aggregate housing supply function Equation 1.3 in discrete changes

$$\Delta \ln H_i^S = a_i^S + \varepsilon_i^S \Delta \ln P_i + \boldsymbol{\beta} \mathbf{X}_i^S + u_i^S, \tag{1.6}$$

where i indexes districts across Germany and changes are computed from long (log) differences between 2008-2019, and $\mathbf{X}$ includes a set of district controls.[11] The parameter vector of interest is $\varepsilon_i^S = \mathbf{Y}_i \varepsilon$. Following Saiz (2010) and Baum-Snow and Han (2019), such a setup allows us to compute an elasticity estimate for each district i. For doing so, ε_i^S can be defined as a function of observed district supply characteristics $\mathbf{Y}_i$ such as undevelopable fraction of land, level of existing land development (developed fraction), and regulation. First, as a baseline specification, and following Saiz (2010), I start with a common price elasticity of housing supply across all districts, i.e., $\varepsilon_i^S = \varepsilon^S \ \forall i$, which corresponds to ε in the aggregate housing supply function in Equation 1.3. Then, I consider estimating the housing supply elasticity levels that vary across districts as a function of these observed district supply conditions.

1.3.2.1 The housing supply elasticity as a function of supply constraints

In this section, I demonstrate how land unavailability (due to geographical constraints), the level of existing land development, and restrictive land use regulations impact the housing supply elasticity. I follow the reasoning by Saiz (2010) and Baum-Snow and Han (2019) as to why these constraints mediate the impact of growth in house prices on housing supply.

[11] The control variables include construction and labor costs, housing supply constraints, and dummy variables for whether the district is urban and in West Germany. Depending on the variable type, controls are either in levels or logarithms.

As districts are inherently different, they will respond differently if they receive the same amount of housing demand shock. More precisely, the same level of demand shock will produce different results in housing supply growth because of differences in factors that affect housing supply. For instance, districts that are more flat, growing, and less regulated are expected to react more to a given change in housing demand, other things held constant. Therefore, the extent to which changes in housing demand translate into more construction rather than higher prices depends on physical and regulatory factors. More land availability (for instance, through rezoning) shifts the supply curve outward. The question is whether land and regulatory constraints also impact the housing supply elasticity, i.e., whether ε_i^S is a function of land availability, regulation, and development intensity.

The first hypothesis I test is whether districts that have a high level of existing development, measured by the fraction of land that is already developed (*Developed*), have more inelastic housing supply than newer or physically growing districts, i.e., ε_i^S is a function of development intensity:

$$\Delta \ln H_i^s = \varepsilon^S \Delta \ln P_i + \beta^{Developed} \Delta \ln P_i \times \text{Developed}_i + \boldsymbol{\beta X}_i^S + u_i^S , \qquad (1.7)$$

where $\beta^{\text{Developed}} \leq 0$. Then, we have district-specific housing supply elasticities that incorporate development intensity: $\varepsilon_i^S = \varepsilon^S + \beta^{\text{Developed}} \times \text{Developed}_i$.

Second, I test whether districts that are land-constrained due to geography (measured by *Unavail*) have more inelastic housing supply than relatively unconstrained districts, i.e., ε_i^S is a function of land unavailability:

$$\Delta \ln H_i^s = \varepsilon^S \Delta \ln P_i + \beta^{\text{Unavail}} \Delta \ln P_i \times \text{Unavail}_i + \boldsymbol{\beta X}_i^S + u_i^S , \qquad (1.8)$$

where $\beta^{\text{Unavail}} \leq 0$. Then, the elasticity is given by $\varepsilon_i^S = \varepsilon^S + \beta^{\text{Unavail}} \text{Unavail}_i$.

Third, I combine the above two cases and test the importance of both variables (developed and unavailable land fractions) in affecting the response of supply growth to price growth, i.e., ε_i^S is a function of both developed land and land unavailability:

$$\begin{aligned}\Delta \ln H_i^s = \varepsilon^S \Delta \ln P_i + \beta^{\text{Developed}} \Delta \ln P_i \times \text{Developed}_i + \\ \beta^{\text{Unavail}} \Delta \ln P_i \times \text{Unavail}_i + \boldsymbol{\beta X}_i^S + u_i^S ,\end{aligned} \tag{1.9}$$

where $\beta^{\text{Developed}} \leq 0$, $\beta^{\text{Unvail}} \leq 0$.Then, the elasticity is given by $\varepsilon_i^S = \varepsilon^S + \beta^{\text{Developed}}\text{Developed}_i + \beta^{\text{Unavail}}\text{Unavail}_i$.

1.3.2.2 Constructing the Bartik instrument

Since, in equilibrium, housing quantity and price are jointly determined, the classic endogeneity problem needs to be addressed to correctly identify ε_i^S in Equation 1.6. Solving this problem requires an exogenous shifter, sourced from the demand equation in Equation 1.5, that generates exogenous housing demand changes across locations. Ideally, this shock then causes a shift in the housing demand curve so the housing supply curve can be traced out and the parameter ε_i^S is identified. The Bartik (1991) instrument, also known as the shift-share instrument, has been widely used in the literature for identification (see, for example, Saiz (2010), Hilber and Vermeulen (2016), Baum-Snow and Han (2019)), as a proxy for or source of variation in housing demand. Below I explain how the Bartik instrument has been constructed and used for identification in this study.

The Bartik instrument or shock is a labor demand shock that is constructed from predicted industry employment growth (Goldsmith-Pinkham et al., 2020; Blanchard and Katz, 1992; Bartik, 1991). By construction, local employment growth is the weighted mean of local industry growth rates, where the weights are local employment shares of the industries,

$$g_{it} = \sum_k z_{ikt} \cdot g_{ikt},$$

where the subscripts i, k, and t index district, industry, and time (year), respectively. z_{ikt} denotes industry k's employment share in district i's total employment L_{it}, and g_{ikt} denotes industry k's employment growth in i from

$t-1$ to t.

The local industry growth rate g_{ikt} can be decomposed into a national industry growth rate g_{kt} and an idiosyncratic local industry growth rate $\tilde{g}_{ikt}$ components:

$$g_{ikt} = g_{kt} + \tilde{g}_{ikt}.$$

The Bartik instrument uses the national industry growth rate g_{kt} and local industry composition at some base or initial time period to predict the local industry employment growth g_{ikt}. Following Bartik (1991), "predicted employment growth" can be written as

$$\widehat{g_{it}} = \sum_{k=1}^{K} z_{ikb} \cdot g_{kt}$$
$$\text{with } g_{kt} = \frac{L_{kt} - L_{kt-1}}{L_{kb}},$$

where L represents the actual level of employment, b denotes some initial time period, variables without index i represent values at the national level, and variables without index k are aggregates over industries. g denotes the growth rate of employment from $t-1$ to t as a proportion of the base year value. L_{kt} can be calculated for each i from leave-one-out aggregate of L_{ikt}, denoted $L_{(i')kt}$.

From the data, I constructed seven (hence $K = 7$) broad industry classes.[12] Moreover, following the Bartik instrument convention, I take the first period of the study as the initial period (i.e., $b = 2008$).

The Bartik instrument used in the estimation is the predicted change in the logarithm of employment between the base period (2008) and the last

[12]The industry classification follows the German Classification of Economic Activities, Edition 2008 (WZ_2008). I aggregate the district and national industry employment data that I used for constructing the Bartik instrument to 7 broad industry classes: (1) agriculture, forestry, and fishing, (2) mining and quarrying, energy, and water, sewage, and waste, (3) manufacturing, (4) construction, (5) trade, transport, hospitality, and information and communication, (6) finance and insurance, and real estate, (7) public and other services, education, and health.

(2019), $\widehat{\Delta \ln L_i} = \sum_k z_{ik_2008} \left(\ln L_{(i')k_2019} - \ln L_{(i')k_2008}\right)$.

1.4 Data

I construct a house price index from a granular and rich set of house price data. The housing stock and floorspace, population, and employment data are all obtained from the German Regional Statistical Offices Database.

1.4.1 House prices

I use the RWI-GEO-Real Estate Data of the FDZ Ruhr at RWI (RWI and ImmobilienScout24, 2020) to construct quality-adjusted house prices.[13] The data are highly detailed (at a scale of 1km^2 grid), cover all of Germany, and have been available since 2007. Moreover, the data come with a rich set of property characteristics, enabling us to compute a hedonic price index to quality-adjust house prices.

I construct a mix-adjusted house price index from the following panel hedonic regression

$$\ln P_{hit} = \delta_{it} + \mathbf{X}_{hit}\boldsymbol{\beta} + e_{hit}, \tag{1.10}$$

where h indexes houses, i districts and t years 2008-2019, P price of houses in euros per m^2, δ_{it} denotes district-year fixed effects that are of main interest to estimate, and $\mathbf{X}$ includes a set of house characteristics.[14] In Equation 1.10, the estimated intercepts $\widehat{\delta}_{it}$ represent the quality-adjusted prices for each district i in every year t. After estimating Equation 1.10 with fixed effects, the hedonic price index is given by $\widehat{\delta}_{it} = \ln P_{hit} - \mathbf{X}\widehat{\boldsymbol{\beta}}$.

[13]The original data is provided by *ImmobilienScout24*, Germany's largest online platform for listing real estate (for both selling and renting houses and apartments). The house prices are self-reported offer prices by the respective home seller or agent and may therefore differ from the actual transaction prices.

[14]House attributes included in the hedonic regression are: floorspace, plot area, number of rooms, number of floors, number of bedrooms, number of bathrooms, type of the house, type of heating, years of construction and renovation, condition and facilities of the property, whether the property has a basement, a guest washroom, is or in a protected building, and is usable as a holiday house. The mix-adjusted house price index computation is based on the method described by Ahlfeldt et al. (2020).

1.4.2 Housing quantity

Housing quantity is measured by housing units (stock) and housing services proxied by total residential floorspace. As houses vary in both observable and unobservable characteristics, they need to be standardized to account for these differences. In fact, the housing production literature views houses as only differing in the housing services they provide, which are homogeneous and perfectly divisible (Epple et al., 2010; Combes et al., 2021).

In light of that, this paper uses total residential floorspace as the main measure of housing quantity, as a stock count of houses or buildings may not accurately reflect the true level of housing supply in a city or region. Moreover, using housing units as a measure of housing supply does not account for differences in size or other attributes. For example, newly built or renovated houses are often larger and better equipped with features than older houses, which units may not capture. Data on housing quantity variables such as residential units, floorspace, and construction activities (i.e., permits and completions) were obtained from the Regional Atlas of Germany.

1.4.3 Geographic data

I use geographical data to construct land development intensity, land unavailability, and terrain ruggedness index (TRI) measures.[15]

From the Digital Elevation Model (DEM) of Germany at 200 × 200 meter resolution, I calculated slope to extract the share of land corresponding to steep slopes, which makes up the undevelopable land (along with land covered by wetland and water bodies) measure.[16] An area exhibiting steep

[15]TRI is an objective measure of terrain heterogeneity. I computed TRI according to Riley et al. (1999), which calculates TRI by comparing changes in elevation between a central pixel and its eight neighbors as the square root of the squared sum of these elevation differences. Grid cell level TRI values were then averaged across grid cells within districts for TRI value at the district level. TRI is derived from the same DEM data.

[16]Digitales Geländemodell Gitterweite 200 m (DGM200)

slopes (for example, above 15% in the US context) is considered unsuitable for construction (Saiz, 2010).

From the Corine Land Cover (CLC) Germany, compiled by the German Remote Sensing Data Center (DFD) of DLR and the Federal Agency for Cartography and Geodesy (BKG), I calculated the exact share of land covered with wetlands and water bodies to measure land unavailability. More, development intensity is constructed from the exact share of "artificial surfaces", a comprehensive land cover class that includes continuous and discontinuous urban fabric, defined by CLC.

1.4.3.1 Undevelopable and developed land

I define undevelopable or unavailable land as land covered by wetlands and water bodies or as potentially developable land with an average slope greater than 15%. Undevelopable land may also include already developed land (an area covered by "artificial surfaces" such as buildings) if we rule out redevelopment through renovation or demolition as a development option. In other words, land already developed may not be regarded as undevelopable as it can be redeveloped. In this paper, already-developed land is not part of the undevelopable land. I use the land cover classes defined by Corine Land Cover (CLC) that are relevant to Germany.

The area with a slope greater than 15% is defined over the district's total "developable stock" of land. I define the developable stock as the district's total administrative area, excluding the area covered with wetlands and water bodies. In other words, areas covered by forests or agriculture make up the developable stock. Note that developable stock does not exclude areas with a slope greater than 15%. The fraction of area with a slope greater than 15% is defined over this quantity, i.e., developable stock as a denominator.

More concisely, denoting the district's total administrative area by T, developed land by $T^{\text{artificial}}$, area covered by wetland by T^{wetland}, water bodies by T^{water}, agriculture by T^{agri}, and forests by T^{forest}, then developable stock

$T^{\text{developable}}$ is given by

$$T^{\text{developable}} = T - T^{\text{artificial}} - T^{\text{wetland}} - T^{\text{water}} = T^{\text{agri}} + T^{\text{forest}}.$$

Then, the fraction of developable land that is lost to steep slopes is defined as $r^{steep} = \frac{T^{steep}}{T^{\text{developable}}}$, where $T^{steep} = T^{\text{developable}} \cdot 1\,[\text{slope} > 15\%]$, the developable area with a slope greater than 15%.

The fraction of undevelopable land is defined as the ratio of the total undevelopable land to the total administrative land of the district. Undevelopable land $T^{\text{undevelopable}}$, is given by

$$T^{\text{undevelopable}} = T^{steep} + T^{\text{wetland}} + T^{\text{water}}.$$

Then, the share of undevelopable land (out of the total land), $r^{\text{undevelopable}} = \frac{T^{\text{undevelopable}}}{T}$. Similarly, the share of "developed land" is $r^{\text{developed}} = \frac{T^{\text{artificial}}}{T}$.

Undevelopable share is this paper's main measure of geographical constraint, with TRI and slope as alternative measures. Finally, the developed share measures the existing level of development intensity.

1.4.4 Bartik shocks: Predicted employment growth

In the main regression analysis, the fundamental source of variation in changes in housing demand is predicted employment, also known as Bartik or local labor demand shock. I use employment data decomposed by seven industries to construct this shock using the 2008 industry employment levels in German districts and the national industry-specific employment growth rates from 2008 to 2019. Labor demand shock is local employment growth in each district that would have resulted, given the district's industry composition in the initial period (2008), had employment in each industry developed over time (2008-2019) in the same way as at the national (Germany) level.

Finally, other controls, including the price of land, population, income, and other socioeconomic control variables used in this study, are all obtained from the Federal Statistical Office and Statistical Offices of the Federal States (2022).

1.5 Results

1.5.1 Descriptive analysis

As shown in Figure 1.1, average prices of houses in Germany have significantly increased over the 2008-2019 time period across districts. In level terms, the average price of houses (of all types) was about €2,563 per m^2 in 2008, which rose by about 32.2% to about €3,388 per m^2 in 2019. Single-family homes followed the same trend; the average price of single-family homes increased by about 28.9%.[17] Variation in average house prices (measured by the standard deviation) across districts has significantly risen over this period. For all homes, the standard deviation of prices in $€/m^2$ has increased by 84%, from about 883 in 2008 to about 1,625 in 2019. For single-family homes, price variation has gone up by 78%, from 991 in 2008 to 1,760 in 2019.

Across space, as shown in Figure 1.2, there has been high variation in the level and the growth of house prices, especially in and around big "city-districts". High-price places in 2008, such as Berlin, Munich, and Hamburg, remained expensive also in 2019 and experienced a higher house value appreciation. Urban districts have experienced relatively higher growth than their rural counterparts. Price levels have risen by about 34.5% in urban and by 28.9% in rural districts, on average, over the 2008-2019 time period. Prices of single-family homes have grown by about 30.7% and 26.2%, in urban and rural districts, respectively. In contrast, there has been little disparity along the West-East divide; house prices have risen by about 32.4% in the West and 30.7% in the East

[17]These house prices are quality-adjusted, i.e., these are the hedonic values (as discussed in Section 1.4.1). Additionally, prices are adjusted for inflation using Germany's 2015 general Consumer Price Index.

districts. However, the growth of prices of single-family homes has been higher in the East German districts, by 32.5%, while in the West districts by 28.3%.

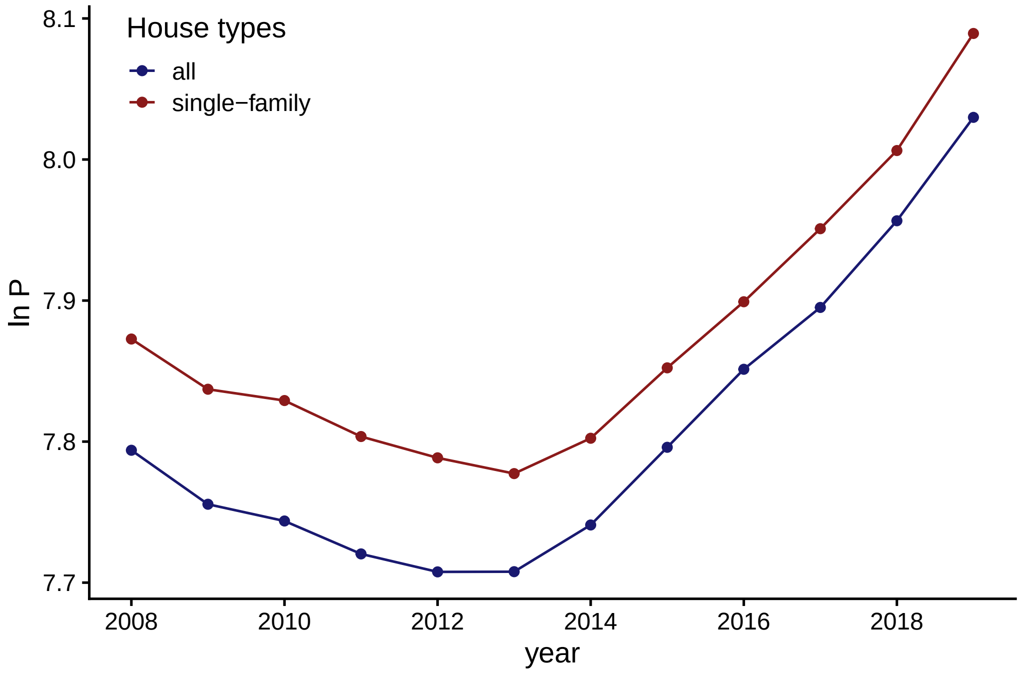


Figure 1.1: The development of house prices in Germany.

Notes: $\ln P$ is the log of average house prices across districts each year. The house type category "all" captures all house types, including "single-family" homes. House prices are in 2015 prices. Data obtained from RWI and ImmobilienScout24 (2020).

In contrast, the growth of the residential housing supply has not been strong in Germany. In the 2008-2019 time period, in the average district, housing supply, measured by the stock of residential buildings, has grown by 6.74%, and about twice higher growth has been recorded for single-family residential homes, 13.09%. Urban districts have experienced relatively higher growth in housing supply, too, about 6.9% in urban and 6.5% in rural districts. For the supply of single-family homes, 14.3% and 11.6% growth have been seen in urban and rural districts, respectively. On average, the housing supply in West German districts has grown by

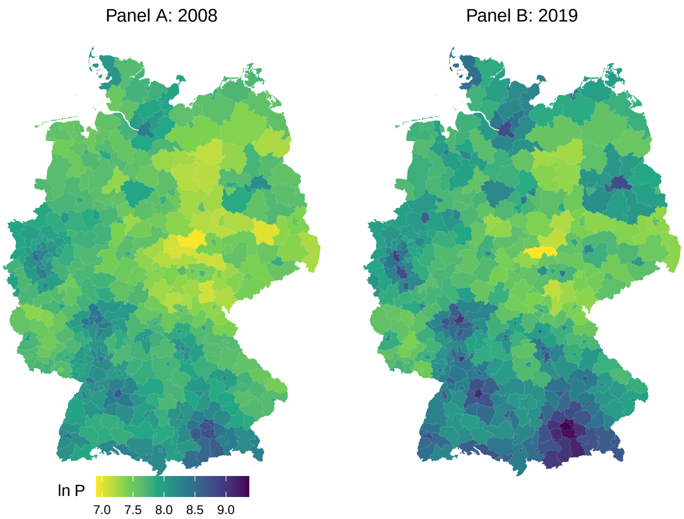
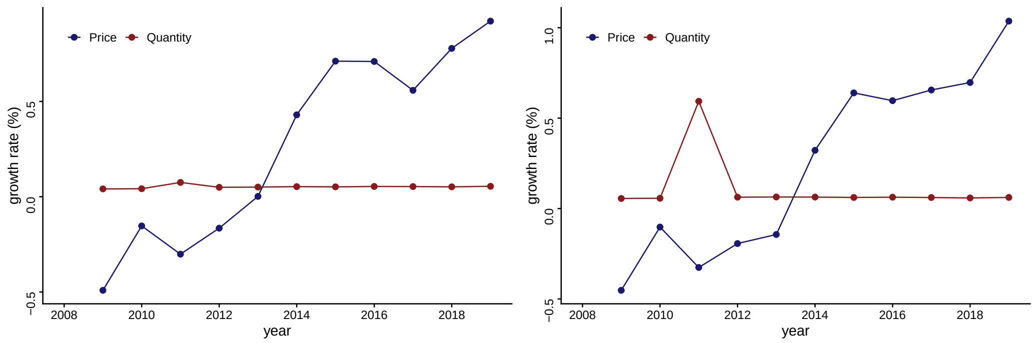


Figure 1.2: Spatial trends: house prices across districts in Germany.

Notes: This figure shows the spatial dynamics of house prices in Germany in 2008 and 2019. $\ln P$ denotes the log of house prices in Euro per m^2. Darker colors represent higher house values. House prices are in 2015 prices. Data obtained from RWI and ImmobilienScout24 (2020).

7%, whereas in East German districts it has grown by 5.7%. The supply of single-family homes in West German districts has grown by 12.7%, while in east districts by 15.1%.

Figure 1.3 compares average log house prices and quantity growth over time. Growth in housing supply has not been stronger than the growth of house prices. Permits and completions data support the slow development of the housing supply. New construction, in terms of permits and completions of residential buildings, as shown in Figure 1.4, has taken a gradual uptick since 2009. However, the levels of this period are far below the 1995-2005 levels. On average, a district in 1995 permitted the construction of 517 residential buildings, of which 477 were completed in the following year. The net addition to housing stock, housing flow—level change in housing stock, was 479. The continuous decline of new building permits and completions from the late 1990s until 2009 might show the increasing difficulty of building new houses in Germany over the decades.



(a) All residential buildings

(b) Single-family buildings

Figure 1.3: The growth of house prices vs housing supply.

Notes: This figure compares the annual growth of the log of average house prices against the log of average housing supply (measured by residential buildings) in Germany by house type. Panel (A) displays growth rates (%) for all types of residential buildings, including single-family buildings, and Panel (B) displays single-family buildings. The 2011 data points appear incorrect due to data inconsistency in connection to the 2011 German Census. The house price data are obtained from RWI and ImmobilienScout24 (2020), and data for housing quantity measures are extracted from Federal Statistical Office and Statistical Offices of the Federal States (2022).

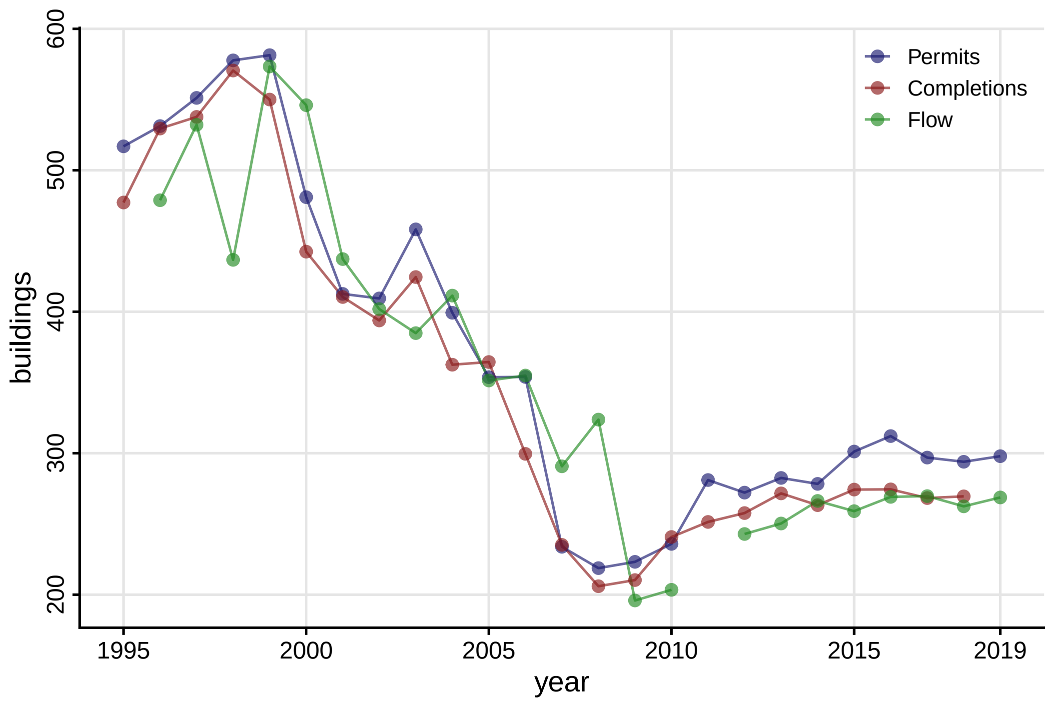


Figure 1.4: Construction activities, residential buildings.

Notes: This figure shows construction activities in residential buildings in the average district. "Flow" is defined as the annual change in the stock of residential buildings. The construction statistics of the 1995-2008 period reveal important details about the growth of new construction in Germany compared to the recent data points this study examines. The 2011 value for flow is discarded due to data issues. The data are obtained from Federal Statistical Office and Statistical Offices of the Federal States (2022).

Table 1.1: OLS Results: Housing Supply Elasticity Estimates

	Floorspace	Units	Permits	Completions
	(1)	(2)	(3)	(4)
$\Delta \ln \mathrm{P}$	0.113^{***}	0.114^{***}	-0.073	0.094
	(0.013)	(0.011)	(0.136)	(0.160)
Developed	-0.114^{***}	-0.065^{***}	-0.852^{***}	-0.723^{***}
	(0.014)	(0.013)	(0.163)	(0.215)
Unavail	-0.055^{**}	-0.034^{*}	-0.658^{***}	-0.466^{**}
	(0.023)	(0.020)	(0.195)	(0.190)
ln Constr. costs	-0.050^{**}	-0.107^{***}	-0.157	-0.464^{*}
	(0.020)	(0.018)	(0.201)	(0.253)
ln Constr. labor	0.005	0.002	0.353^{***}	0.448^{***}
	(0.010)	(0.009)	(0.104)	(0.122)
Urban	0.007	0.004	-0.262^{***}	-0.190^{***}
	(0.005)	(0.005)	(0.056)	(0.067)
West	0.026^{***}	0.014^{*}	0.237^{***}	0.135^{*}
	(0.008)	(0.008)	(0.068)	(0.081)
Constant	-0.167	0.156	4.982^{*}	0.916
	(0.255)	(0.225)	(2.706)	(2.849)
R^2	0.322	0.321	0.332	0.198
Num. obs.	401	401	401	401

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Notes: The dependent variables are changes in the log of total residential floorspace, buildings, permits, and completions. Regressions include the log of construction costs in 2019, the log of construction labor in 2008, urban vs. rural, and west vs. east district classifications as defined by BBSR (2021), and the log of population and household income in 2008. The fraction of land developed (Developed) and unavailable (Unavail) are for 2006. Robust standard errors are in parentheses.

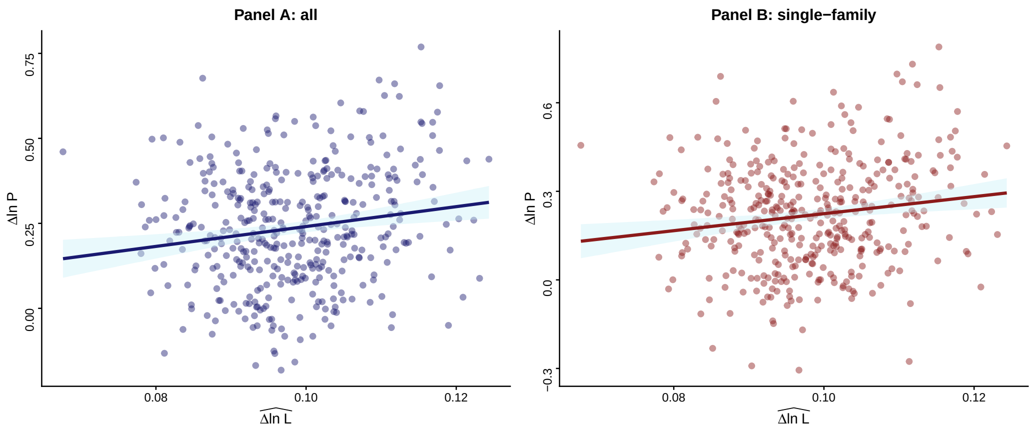
1.5.2 Empirical analysis

Table 1.1 displays the OLS estimates for the housing supply elasticity. These estimates represent equilibrium relationships and appear small due to the endogeneity between house prices and quantity through the housing demand function.[18]

The identification challenge in estimating the housing supply elasticity is isolating the demand-induced change in the housing supply. The Bartik instrument utilized to handle the endogeneity ($\widehat{\Delta \ln L_i}$) meets the relevance requirement very well. The partial correlation between $\Delta \ln P_i$ and $\widehat{\Delta \ln L_i}$ is strong, with an F-statistic well above 10 in the first stage, as shown

[18]According to the OLS results, on average, a 10% growth in house prices over the 2008-2019 time period is associated with a 1.1% increase in floorspace supply. For single-family homes, the estimates are not even statistically significant, see Table 1.B.4 in the Appendix.

in the first-stage results in the Appendix in Table 1.B.1. Note that other observable important housing demand predictors are controlled for. Figure 1.5 shows a strong correlation between the instrument and the growth of house prices.



(a) All residential buildings (b) Single-family buildings

Figure 1.5: The relevance of the Bartik instrument.

Notes: This figure shows the correlation between the endogenous variable ($\Delta \ln P$) and the instrument ($\widehat{\Delta \ln L_i}$), i.e., the relevance condition of the instrument, by house type. Each dot represents a value pair for a district. The house prices data are obtained from RWI and ImmobilienScout24 (2020), and the employment data from Federal Statistical Office and Statistical Offices of the Federal States (2022).

The instrument indicates that in the 2008-2019 time period, all of the districts would have experienced positive overall industry employment growth and hence housing demand had employment in each industry grown the same as at the national level.[19] Of these 401 districts with positive employment growth, 365 of them have seen positive growth in house prices, and 380 in housing supply, and only 348 have experienced positive growth in both.[20] The fact that not all districts that have received positive growth in housing demand have experienced positive growth

[19]In terms of the actual observed level of employment ($\Delta \ln L_i$), 347 out of 401 (86.5%) districts have experienced positive employment growth.

[20]However, of all 401 districts, 365 of them have seen positive growth in house prices, and 380 in housing supply.

in housing supply may imply that changes in housing demand do not necessarily translate into a positive supply response. This demonstrates the relevance of estimating the housing supply elasticity because it helps us know whether demand growth is creating city growth or higher house prices. In other words, looking at the local housing supply conditions is essential to understand the differential outcome of demand growth. In Section 1.5.3, I discuss why a (demand-driven) change in house prices may trigger a differential (positive) growth in housing supply across districts.

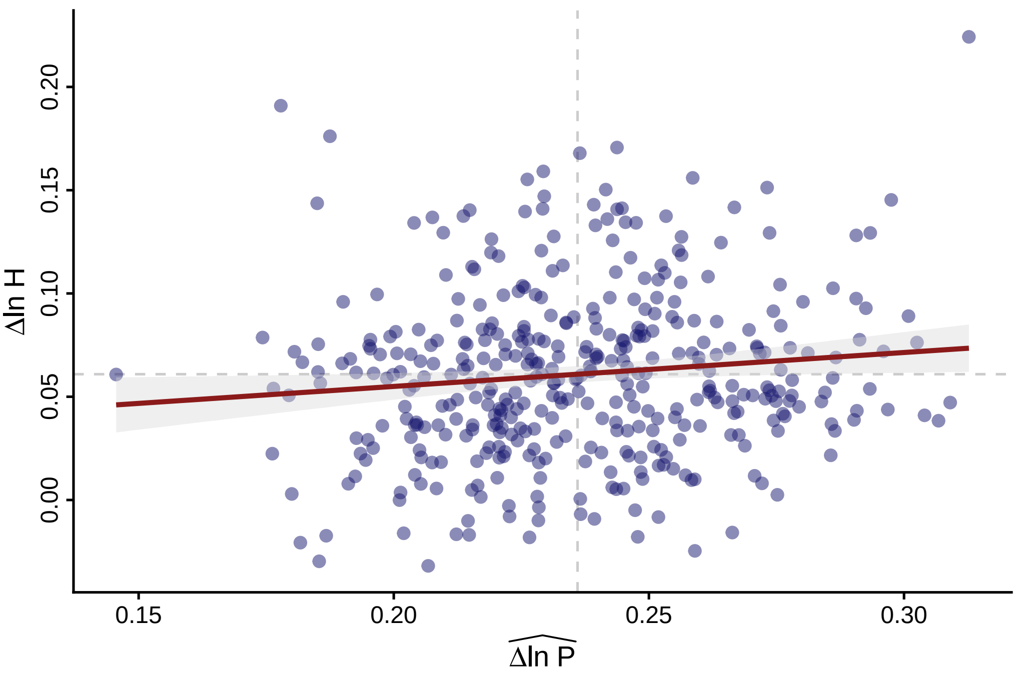


Figure 1.6: The growth of the housing supply vs prices.

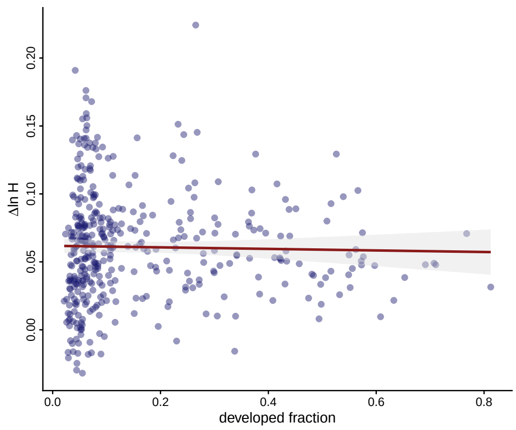
Notes: This figure depicts the housing supply growth against the predicted growth of house prices. $\widehat{\Delta \ln P}$ represents the fitted values from this regression: $\Delta \ln P = \beta_0 + \beta_1 \widehat{\Delta \ln L_i}$, which keeps the variation in $\Delta \ln P$ due to only changes in housing demand. The dotted lines denote the means of the respective variables. Each dot represents a value pair for a district. The house price data are obtained from RWI and ImmobilienScout24 (2020), and data for housing quantity measures are extracted from Federal Statistical Office and Statistical Offices of the Federal States (2022).

Figure 1.6 illustrates the response of housing supply growth to demand-induced price growth. This helps us to inspect the housing supply elasticity visually. First, I regress $\Delta \ln P_i$ on the instrument (and a constant) to net out its importance, i.e., this retains the house price growth caused by demand change. Then, I plot housing supply growth ($\Delta \ln H_i$) against (the netted) price growth $\widehat{\Delta \ln P_i}$. There is a higher variation in price growth than in supply growth. On average, supply growth has been less responsive to price growth; the slope coefficient is 0.14. That means, on average, a 1% price growth is associated with a 0.14% growth in the housing supply, which implies that the housing supply has been inelastic in Germany. This study aims to explore the disparities in the responsiveness of housing supply among districts. The data shows varying growth rates in housing supply and prices among districts. By examining the reasons for this heterogeneity, we can better understand the variation in the housing supply elasticity across districts.

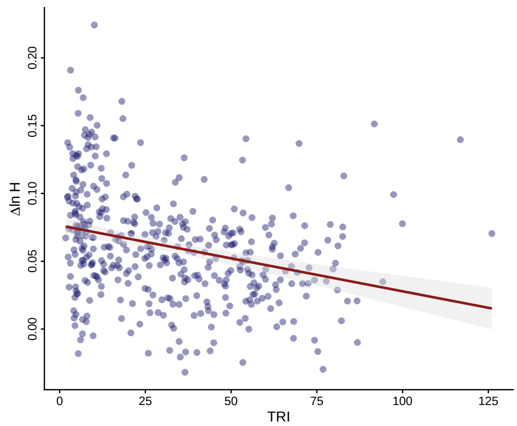
1.5.3 Main results: Housing supply heterogeneity

It is evident that by restricting housing supply, physical or geographical constraints affect the housing supply elasticity. For instance, urban districts or cities have high existing built-ups, i.e., a larger fraction of their land is already developed. This creates a physical constraint for new development or redevelopment. As a result, highly developed or dense cities may not respond, to a certain change in housing demand, as much as growing and scarcely populated rural districts—which usually have relatively lower levels of existing land development (thus have more land for new construction). This is what the data, as well as the empirical results, show. In 2006, the data available close to the initial period of the study (i.e., 2008), the average level of development intensity, measured by the fraction of land that is already developed, was 0.16 (see Section 1.4.3.1). Urban districts had a higher level of land development (0.24), on average, as compared to the rural districts' (0.09) (see Figure 1.B.3). Thus, this development intensity heterogeneity might explain the variation in the housing supply elasticity across districts.

On the other hand, geographical constraints, such as having a rugged terrain or the existence of wetlands, or being surrounded by water bodies, may also be relevant for examining housing supply elasticity differences across districts. As the negative correlation between supply growth and TRI shows in the right panel in Figure 1.7, geographically restricted districts have lower supply growth. However, restrictive geography does not characterize most German districts. Germany is generally a low-elevation country (with an average elevation level of 274 meters or an average slope of 4.87%). Other than a few exceptions in the south close to the Alps and the north close to the coast, land undevelopability is small in most districts. Thus, one may expect this variable to be insignificant in explaining Germany's housing supply elasticity. The average land undevelopability was less than 10% (0.08) in 2006, and about 0.6683292 of the districts have a value below it. A few extreme cases are Berchtesgadener Land and Garmisch-Partenkirchen, Bavarian districts known for ski resorts, with over 60% of their land being undevelopable.



(a) Developed fraction



(b) TRI

Figure 1.7: Housing supply growth vs housing supply constraints.

Notes: This figure shows the correlation between housing supply constraints and housing supply growth. The left panel shows the effect of the 2006 level of land development intensity, and the right panel shows the effect of land unavailability due to terrain ruggedness. Few outliers along the x-axis are removed. Each dot represents a value pair for a district.

Table 1.2: IV Results: Housing Supply Elasticity Estimates

	Floorspace				Units			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\Delta \ln P$	0.221^{***}	0.299^{***}	0.232^{***}	0.310^{***}	0.245^{***}	0.302^{***}	0.248^{***}	0.305^{***}
	(0.043)	(0.052)	(0.041)	(0.050)	(0.041)	(0.044)	(0.039)	(0.043)
$\Delta \ln P \times$ Developed		-0.461^{***}		-0.463^{***}		-0.334^{***}		-0.336^{***}
		(0.063)		(0.063)		(0.051)		(0.052)
$\Delta \ln P \times$ Unavail			−0.114	−0.101			−0.020	−0.012
			(0.099)	(0.111)			(0.097)	(0.102)
Developed	-0.145^{***}		-0.145^{***}		-0.104^{***}		-0.104^{***}	
	(0.019)		(0.020)		(0.019)		(0.020)	
Unavail	−0.032	−0.029			−0.006	−0.003		
	(0.028)	(0.032)			(0.026)	(0.027)		
Constant	0.592^{***}	0.453^{**}	0.598^{***}	0.459^{**}	1.057^{***}	0.958^{***}	1.063^{***}	0.964^{***}
	(0.194)	(0.193)	(0.194)	(0.192)	(0.185)	(0.175)	(0.185)	(0.176)
R^2	0.206	0.128	0.209	0.137	0.095	0.099	0.091	0.094
Num. obs.	401	401	401	401	401	401	401	401

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Notes: Regressions include the log of construction costs in 2019, the log of construction labor in 2008, urban vs. rural, and west vs. east district classifications as defined by BBSR (2021), and the log of population and household income in 2008. The fraction of land developed (Developed) and unavailable (Unavail) are for 2006. Robust standard errors are in parentheses.

Table 1.2 presents the main results from the IV estimation, for floorspace and units, for all houses.[21] As mentioned above, shifts in housing demand are proxied by predicted employment growth. As discussed in Section 1.3.2.1, I run the estimation in iterative steps. First, I estimate the elasticity that does not vary across districts; this can be regarded as the estimate for the average district and corresponds to ε^S (without index i) in Equation 1.6. The controls included in the first or second stages are log population, construction costs, household income, and dummy variables for West German and urban districts.

The first column in Table 1.2 presents the baseline floorspace elasticity estimate for ε^S. It is highly statistically significant and equals 0.22. This estimate indicates that, on average, the responsiveness of housing supply to a 1% change in house prices across districts in Germany between 2008 and 2019, is 0.22%, holding other factors constant. However, this average estimate masks potential variations across districts, which will be accounted

[21]Results for single-family houses are provided in the Appendix, see Table 1.B.5.

for in subsequent steps.

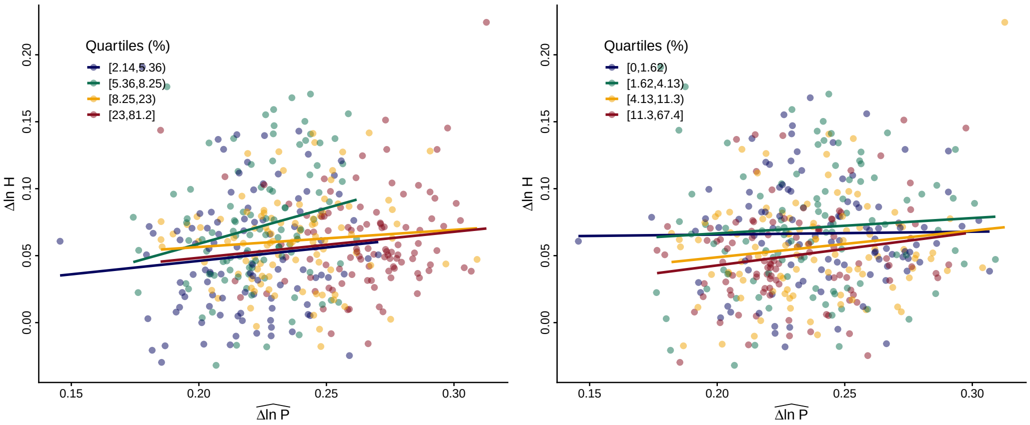
Land development intensity

In this step, I examine how development intensity, measured by the fraction of developed land in the initial period, affects the housing supply elasticity. As discussed in Section 1.5.3, districts differ in their development intensities; while some are already highly built-up, some others are growing. A high level of existing land development may limit new development or make redevelopment difficult or costly. Thus, highly built-up districts may have low supply responses as they do not have vacant land for constructing new houses, regardless of the size of the demand shock, keeping other things constant. In this case, we may expect demand growth to create price growth instead of quantity growth. In Figure 1.8, we can see that the slope of the supply curve gets flatter for higher quartiles of development intensity. In the second column of Table 1.2, I control for districts' levels of development intensity in 2006 by interacting it with $\Delta \ln P$. For the average development intensity of 16.08%, the housing supply elasticity is 0.22. Moving within the interquartile range of development intensity (5.4%-23.0%), lowers the floorspace elasticity from 0.27 to 0.19[22], that is a 42% difference in the housing supply elasticity.

Land unavailability

In this step, I examine the impact of restrictive geography on the housing supply elasticity, measured by the fraction of unavailable land. The housing supply elasticity should be lower in districts where land unavailability is relatively high. According to the results, the housing supply elasticity in Germany is not significantly impacted by land unavailability. This is shown by the statistically insignificant coefficient $\widehat{\beta}^{\text{Unavail}}$ (see column (3) of Table 1.2 and Figure 1.8). Controlling for the level of land unavailabil-

[22]That is computed as ($\widehat{\varepsilon}_i = \widehat{\varepsilon} + \widehat{\beta}^{\text{Developed}} \cdot \text{Developed}_i = 0.3 - 0.46 \cdot \text{Developed}_i = (0.27, 0.19)$).



(a) Developed land

(b) Undevelopable land

Figure 1.8: Housing supply constraints and housing supply elasticity.

Notes: This figure shows the relationship between housing supply growth and prices for the quartiles of the supply constraints. The left panel shows the effect of the 2006 level of land development intensity, and the right panel shows the effect of land unavailability due to terrain ruggedness. Each dot represents a value pair for a district.

ity (Unavail), the estimated floorspace elasticity does not change, 0.232.[23] As compared to the constant elasticity case ($\widehat{\varepsilon} = 0.221$), the difference is negligible (-0.011). This may imply that land unavailability does not lower the housing supply elasticity. This is consistent with the low variation in land unavailability across districts; the average land unavailability (0.08) is small. Thus, there is no clear pattern that land unavailability lowers the housing supply elasticity in Germany.

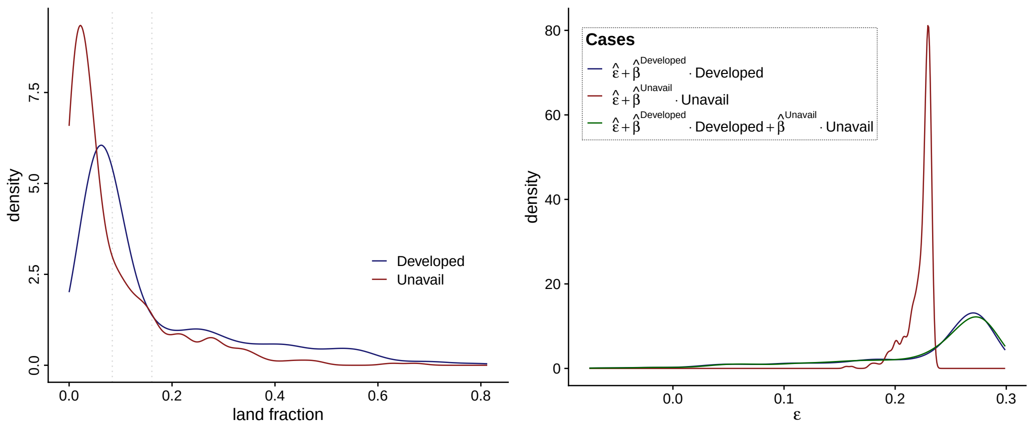
Finally, the above two steps are combined, corresponding to estimating ε_i in Equation 1.9 and amplifying both constraints' impact on the housing supply elasticity. As shown in column (4) of Table 1.2, at the mean value of Developed, the estimate for the housing supply elasticity is 0.235[24], which is not quantitatively different from the estimates in the above three cases

[23]This is computed as $\widehat{\varepsilon}_i = \widehat{\varepsilon} + \widehat{\beta}^{\text{Unavail}} \cdot \text{Unavail}_i = 0.23$, because $\widehat{\beta}^{\text{Unavail}}$ is insignificant.

[24]Since $\widehat{\beta}^{\text{Unavail}}$ is insignificant, the coefficient on $\Delta \ln P \cdot \text{Unavail}$ is ignored and the housing supply elasticity estimate is computed as ($\widehat{\varepsilon}_i = \widehat{\varepsilon} + \widehat{\beta}^{\text{Developed}} \cdot \text{Developed}_i = 0.31 - 0.46 \cdot \text{Developed}_i = 0.24$).

(0.221, 0.225, and 0.223, respectively), which reaffirms the insignificance of land unavailability in impacting the housing supply elasticity.

The above cases show that only land development intensity significantly constrains the housing supply elasticity, while land undevelopability due to restrictive geography has no significant impact. Comparing the estimated coefficients on the respective interaction terms (see Table 1.2) shows that development intensity has an about 0.46 negative impact in mediating the response of housing supply growth to price growth ($\widehat{\beta}^{\text{Developed}} = -0.46$). Land development intensity ranges between (0.02, 0.81), as a result, the housing supply elasticity estimate ranges between (0.3, -0.07). As the left panel in Figure 1.9 shows, the higher variation in the share of developed land (with a standard deviation of 0.16) translates into variations in the housing supply elasticity.



(a) Housing supply constraints (b) Housing supply elasticity

Figure 1.9: Housing supply constraints and elasticity heterogeneities.

Notes: This figure shows the distributions of the housing supply constraints (left panel) and the housing supply elasticity estimates (right panel) across districts. The cases in the right panel correspond to the estimation equations Equation 1.7, Equation 1.8, and Equation 1.9) in Section 1.3.2.1 and the respective results in Table 1.2.

1.6 Conclusion

While the existing literature presents strong evidence about the impact of housing supply constraints on house prices and housing supply elasticities in the US housing market, the literature needs to be more comprehensive about other markets. Therefore, this paper attempts to highlight the unique characteristics of the German housing market concerning housing supply constraints and elasticity.

According to the data, house prices grew by more than 5 times higher than that of housing supply, 32.2%, 6.74%, respectively, in the 2008-2019 period. Although this period has seen a growth in new housing construction, the levels are far below those of the early 1990s. As this growth imbalance suggests, Germany's housing supply is quite inelastic. Moreover, housing supply constraints tend to lower the housing supply elasticity, consistent with the literature, despite the small variations of topological constraints across districts. More precisely, districts with less built-up, and more flat and developable land, have a less inelastic housing supply. Land use regulations are a crucial component of supply constraints. The strong negative impact of these regulations on housing supply and elasticity is well-documented (see Glaeser and Gyourko (2005), Saiz (2010), Baum-Snow and Han (2019)). However, this paper's supply constraints are limited to topographical constraints due to the need for administrative land use regulation data. Future research could help us understand the stringency of land use regulation in Germany and its impact on house prices and housing supply.

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Appendix

1.A Derivation of the housing supply function

A competitive developer combines a fixed amount of land $\overline{T}$ and non-land inputs K, which I simply call capital, to produce housing H via a Cobb-Douglas technology:

$$H = H(A, \overline{T}, K) = A\overline{T}^{\alpha} K^{1-\alpha}, \tag{1.11}$$

where $\alpha \in (0, 1)$. A captures supply heterogeneity across parcels due to local labor costs, productivity, geography, or ease of construction differences. For simplicity, the district index i and parcel identifier l are dropped. Note that K captures a composite of all inputs for housing production other than land, which can broadly be labor and materials.

A representative builder maximizes profit by choosing capital K over a fixed parcel of land $\overline{T}$

$$\begin{aligned}\Pi &= P(x) \cdot H - P^T \cdot \overline{T} - P^K \cdot K \\ &= P(x) \cdot H - R - K,\end{aligned}$$

where R denotes the endogenous price of land of size $\overline{T}$, and P^K is the price of capital assumed to be invariant across parcels and locations and normalized to unity. Note that although capital K is the only variable factor, hence the total capital cost is given by $C(H(K)) = P^K \cdot K = K$ represents the total variable cost. I assume that the total capital cost also includes labor costs and fixed development costs such as development permits and land preparation costs. Thus it captures more than just the variable cost of capital, i.e., all other non-land costs.

The price of a unit of housing developed on a parcel of size $\overline{T}$ is given by P and depends on x, a vector of observed or unobserved parcel or location characteristics that reflect the demand for housing on the parcel, and may for example include measures of accessibility to public goods and local amenities. However, these characteristics are assumed to be uncorrelated with the level of capital investment K (Combes et al., 2021).

Since land is fixed, the builder chooses capital to maximize profit. Therefore, the builder's profit maximization delivers the factor demand for capital K.

$$\begin{aligned}
\frac{\partial \Pi}{\partial K} &= P(x)\frac{\partial H}{\partial K} - 1 = 0 \\
\implies P(x)\frac{(1-\alpha)A\overline{T}^{\alpha}}{K^{\alpha}} &= 1 \\
\implies K^{*} &= \Big((1-\alpha)AP(x)\Big)^{\frac{1}{\alpha}}\overline{T} \equiv K^{*}(P(x), \overline{T}, A)
\end{aligned}$$

By substituting the factor demand equation for capital back into the housing production function, I can then define the per parcel supply function as follows:

$$\begin{aligned}
H(K^{*}(P(x), \overline{T}, A)) &= A\overline{T}_{i}^{\alpha}\Big(K^{*}(P(x), \overline{T}, A)\Big)^{1-\alpha} \\
&= A\overline{T}^{\alpha}\left(\Big((1-\alpha)AP(x)\Big)^{\frac{1}{\alpha}}\overline{T}\right)^{1-\alpha} \\
&= \underbrace{(1-\alpha)^{\frac{1-\alpha}{\alpha}}}_{\mu} A^{\frac{1}{\alpha}} P(x)^{\frac{1-\alpha}{\alpha}}\overline{T} \\
&= \mu A^{\frac{1}{\alpha}} P(x)^{\frac{1-\alpha}{\alpha}}\overline{T} \equiv H^{S}(P(x), A)
\end{aligned}$$

In log-linear form,

$$\ln H^{S}(P(x), A, \overline{T}) = \ln \mu + \frac{1}{\alpha}\ln A + \underbrace{\Big(\frac{1-\alpha}{\alpha}\Big)}_{\varepsilon}\ln P(x) + \ln \overline{T}. \tag{1.12}$$

Thus, the supply of housing developed on a parcel depends on local supply heterogeneity A, local housing demand conditions captured by $P(x)$, and the size of the parcel $\overline{T}$.

Following Baum-Snow and Han (2019), to get the total housing supply at the district level, I aggregate the housing supply on a parcel in Equation 1.12 over all developed parcels in the district. Denoting the total (developable) land endowment of district i by $\mathcal{L}_i$ and the fraction of partitioned parcels that are developed in i by $\Lambda_i(P_i)$, then the stock of developed land in i is defined as $\mathcal{T}(P_i) = \Lambda_i(P_i) \cdot \mathcal{L}_i$. Then, the implicit **district-level aggregate housing supply function** $S_i(P_i(x))$ can be defined as the product of (average) **housing supply per parcel** and the **stock of developed land:**

$$\begin{aligned} S_i(P_i) &= H_i^S(P_i, A_i) \cdot \mathcal{T}_i(P_i) \\ \ln S_i(P_i) &= \left[\ln \mu_i + \frac{1}{\alpha} \ln A_i + \varepsilon \ln P_i\right] + \left[\ln \Lambda_i(P_i) + \ln \mathcal{L}_\mathrm{i}\right] \end{aligned} \tag{1.13}$$

Now I can derive the housing supply elasticity,

$$\begin{aligned} \varepsilon_i^S \equiv \frac{\partial \ln S_i\,(P_i)}{\partial \ln P_i} &= \frac{d \ln H_i^S\,(P_i)}{\partial \ln P_i} + \frac{\partial \ln \mathcal{T}_i\,(P_i)}{\partial \ln P_i} \\ &= \varepsilon + \frac{\partial \ln \Lambda_i(P_i)}{\partial \ln P_i}, \end{aligned} \tag{1.14}$$

where the first term captures the intensive margin of development (floorspace per parcel) and the second reflects the extensive margin (parcel development).

1.B Additional tables and figures

This section includes extra tables and figures that support the main findings of the paper. The main results focus on all types of houses including single-family homes. Here, I show results specifically for single-family homes, including OLS, first-stage, and IV results. Additionally, the housing supply elasticity estimates for permits and completions are included. Permits and completions are commonly used as proxies for housing supply in research (for example, see Lerbs (2014)).

Table 1.B.1: First-stage Results

	All homes	**Single-family homes**
	(1)	(2)
Bartik	3.781***	3.146***
	(0.916)	(1.115)
ln Pop	−0.002	−0.006
	(0.014)	(0.016)
ln HH income	0.673***	0.635***
	(0.080)	(0.087)
Urban	−0.014	−0.017
	(0.020)	(0.023)
West	−0.103***	−0.150***
	(0.024)	(0.025)
Constant	−6.619***	−6.116***
	(0.810)	(0.880)
R^2	0.181	0.141
Num. obs.	401	401
F statistic	17.415	12.917

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.
Notes: The dependent variable is the change in the log of house prices (of all-type, including single-family homes) in the first column, and of only single-family homes in the second column. Regressions include urban vs. rural and west vs. east district classifications as defined by BBSR (2021), the log of population and household income in 2008. Robust standard errors are in parentheses.

Table 1.B.2: IV Results: Housing Supply Elasticity Estimates (Permits)

	Housing Supply Growth: $\Delta\ln(H)$ (Permits)			
	(1)	(2)	(3)	(4)
$\Delta\ln P$	−0.690	−0.085	−0.441	0.161
	(0.447)	(0.524)	(0.441)	(0.521)
$\Delta\ln P$ × Developed		-2.710^{***}		-2.745^{***}
		(0.648)		(0.650)
$\Delta\ln P$ × Unavail			-2.876^{***}	-2.789^{***}
			(0.941)	(0.840)
Developed	-0.763^{***}		-0.772^{***}	
	(0.184)		(0.191)	
Unavail	-0.779^{***}	-0.747^{***}		
	(0.216)	(0.202)		
Constant	−1.486	−1.790	−1.497	−1.820
	(1.915)	(1.925)	(1.930)	(1.921)
R^2	0.277	0.251	0.258	0.246
Num. obs.	401	401	401	401

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Notes: Regressions include the log of construction costs in 2019, the log of construction labor in 2008, urban vs. rural, and west vs. east district classifications as defined by BBSR (2021), and the log of population and household income in 2008. The fraction of land developed (Developed) and unavailable (Unavail) are for 2006. Robust standard errors are in parentheses.

Table 1.B.3: IV Results: Housing Supply Elasticity Estimates (Completions)

	Housing Supply Growth: $\Delta \ln(H)$ (Completions)			
	(1)	(2)	(3)	(4)
$\Delta \ln P$	0.533	1.319^{**}	0.640	1.422^{***}
	(0.446)	(0.517)	(0.440)	(0.513)
$\Delta \ln P \times$ Developed		-3.555^{***}		-3.572^{***}
		(0.699)		(0.704)
$\Delta \ln P \times$ Unavail			-1.324^{*}	-1.225^{*}
			(0.750)	(0.740)
Developed	-0.991^{***}		-0.994^{***}	
	(0.240)		(0.244)	
Unavail	-0.352^{*}	-0.315		
	(0.205)	(0.212)		
Constant	1.670	1.252	1.635	1.209
	(2.159)	(2.192)	(2.167)	(2.189)
R^2	0.159	0.121	0.151	0.121
Num. obs.	401	401	401	401

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Notes: Regressions include the log of construction costs in 2019, the log of construction labor in 2008, urban vs. rural, and west vs. east district classifications as defined by BBSR (2021), and the log of population and household income in 2008. The fraction of land developed (Developed) and unavailable (Unavail) are for 2006. Robust standard errors are in parentheses.

Table 1.B.4: OLS Results: Housing Supply Elasticity Estimates

	Floorspace	Units	Permits	Completions
	(1)	(2)	(3)	(4)
Δ ln P–single-family	0.023^{*}	0.014	−0.129	0.059
	(0.013)	(0.015)	(0.147)	(0.145)
Developed	0.062^{***}	0.113^{***}	-1.234^{***}	-1.133^{***}
	(0.015)	(0.018)	(0.197)	(0.248)
Unavail	0.012	0.032	-0.689^{***}	-0.400^{*}
	(0.022)	(0.024)	(0.225)	(0.206)
Urban	0.017^{***}	0.014^{**}	-0.282^{***}	-0.156^{**}
	(0.006)	(0.006)	(0.066)	(0.073)
West	-0.024^{**}	-0.038^{***}	0.199^{**}	0.103
	(0.010)	(0.010)	(0.077)	(0.097)
ln Constr. costs	-0.124^{***}	-0.181^{***}	−0.262	−0.462
	(0.021)	(0.022)	(0.225)	(0.294)
ln Constr. labor	0.001	−0.003	0.428^{***}	0.534^{***}
	(0.010)	(0.012)	(0.123)	(0.135)
Constant	−0.287	−0.026	6.232^{**}	1.403
	(0.286)	(0.294)	(3.011)	(3.384)
R^2	0.301	0.396	0.379	0.239
Num. obs.	401	401	401	401

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Notes: The dependent variables are changes in the log of total residential floorspace, buildings, permits, and completions, all for single-family homes. Regressions include the log of construction costs in 2019, the log of construction labor in 2008, urban vs. rural, and west vs. east district classifications as defined by BBSR (2021), and the log of population and household income in 2008. The fraction of land developed (Developed) and unavailable (Unavail) are for 2006. Robust standard errors are in parentheses.

Table 1.B.5: IV Results: Housing Supply Elasticity Estimates (single-family homes)

	Floorspace				Units			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\Delta \ln P$	0.274^{***}	0.267^{***}	0.259^{***}	0.253^{***}	0.298^{***}	0.262^{***}	0.276^{***}	0.242^{***}
	(0.055)	(0.067)	(0.056)	(0.068)	(0.060)	(0.078)	(0.061)	(0.079)
$\Delta \ln P$ × Developed		0.024		0.022		0.176		0.174
		(0.116)		(0.114)		(0.146)		(0.143)
$\Delta \ln P$ × Unavail			0.220	0.216			0.321^{*}	0.307^{*}
			(0.155)	(0.152)			(0.177)	(0.172)
Developed	0.008		0.007		0.051		0.050	
	(0.029)		(0.028)		(0.032)		(0.032)	
Unavail	0.051	0.050			0.076^{**}	0.072^{**}		
	(0.032)	(0.032)			(0.036)	(0.036)		
Constant	1.244^{***}	1.247^{***}	1.254^{***}	1.257^{***}	1.684^{***}	1.742^{***}	1.696^{***}	1.754^{***}
	(0.225)	(0.218)	(0.223)	(0.217)	(0.245)	(0.243)	(0.244)	(0.242)
R^2	−0.446	−0.436	−0.463	−0.454	−0.353	−0.409	−0.374	−0.424
Num. obs.	401	401	401	401	401	401	401	401

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Notes: Regressions include the log of construction costs in 2019, the log of construction labor in 2008, urban vs. rural, and west vs. east district classifications as defined by BBSR (2021), and the log of population and household income in 2008. The fraction of land developed (Developed) and unavailable (Unavail) are for 2006. Robust standard errors are in parentheses.

Table 1.B.6: IV Results: Housing Supply Elasticity Estimates

	Housing Supply Growth: $\Delta \ln(H)$ (Permits–single-family)			
	(1)	(2)	(3)	(4)
$\Delta \ln P$	-0.889^{*}	0.139	−0.643	0.370
	(0.529)	(0.600)	(0.534)	(0.605)
$\Delta \ln P$ × Developed		-4.730^{***}		-4.733^{***}
		(0.922)		(0.903)
$\Delta \ln P$ × Unavail			-3.479^{***}	-3.272^{***}
			(1.106)	(0.960)
Developed	-1.189^{***}		-1.191^{***}	
	(0.207)		(0.212)	
Unavail	-0.790^{***}	-0.737^{***}		
	(0.233)	(0.220)		
Constant	−0.687	−1.992	−0.834	−2.140
	(1.812)	(1.918)	(1.825)	(1.906)
R^2	0.307	0.236	0.299	0.249
Num. obs.	401	401	401	401

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Notes: Regressions include the log of construction costs in 2019, the log of construction labor in 2008, urban vs. rural, and west vs. east district classifications as defined by BBSR (2021), and the log of population and household income in 2008. The fraction of land developed (Developed) and unavailable (Unavail) are for 2006. Robust standard errors are in parentheses.

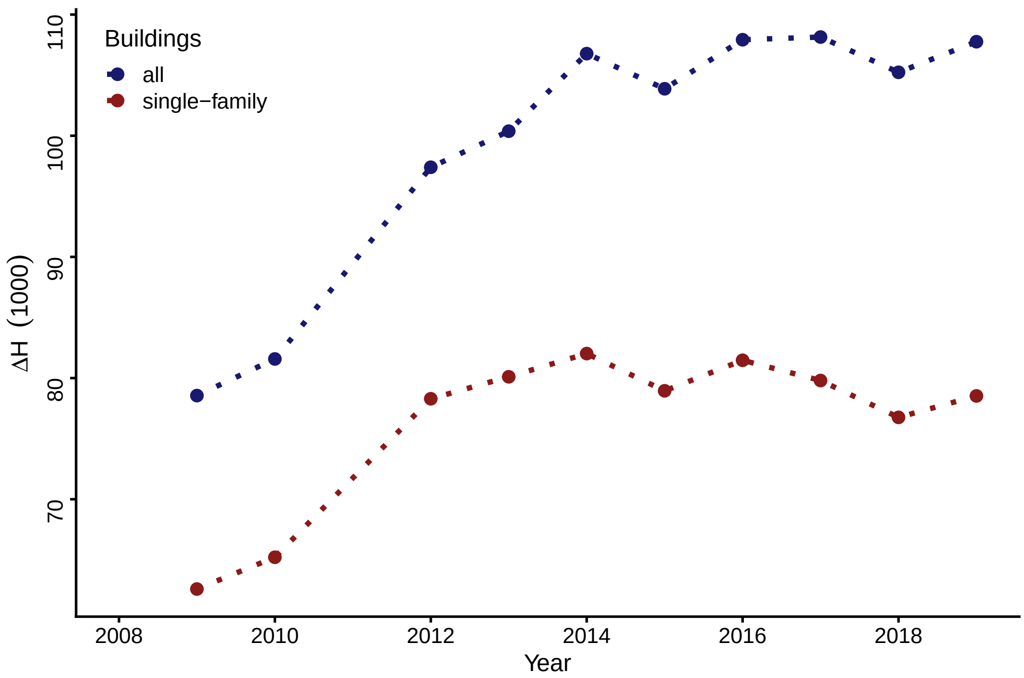

Figure 1.B.1: The total building stock in Germany (annual change).

Notes: This figure shows the total building flow (annual change in stock) in Germany in the 2008-2019 period. The house type category "all" captures all house types, including "single-family" homes. The data are obtained from Federal Statistical Office and Statistical Offices of the Federal States (2022).

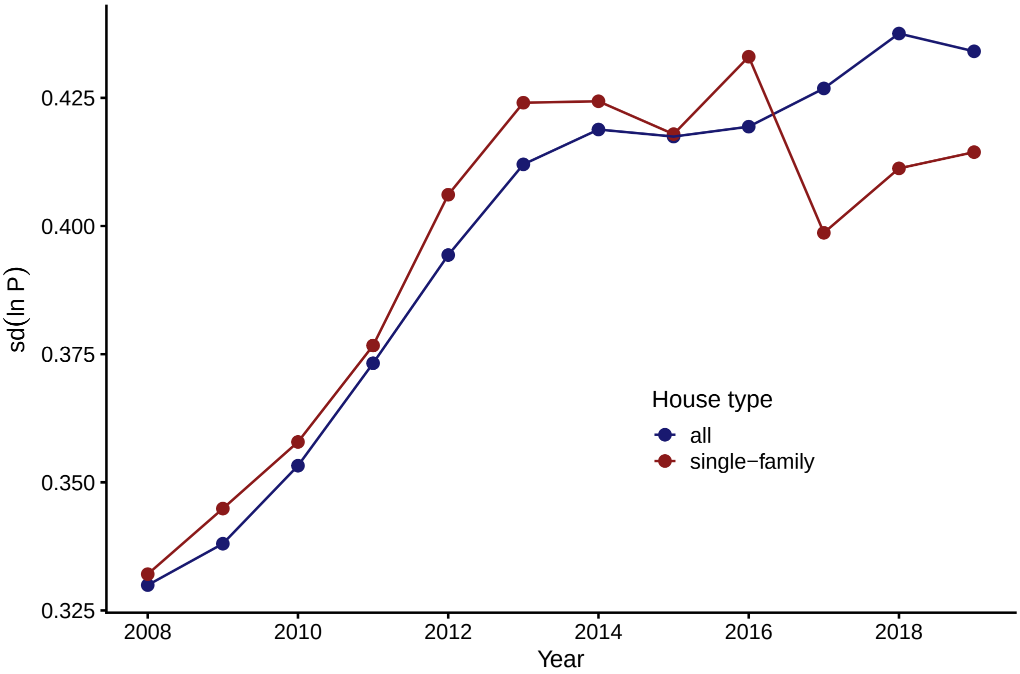

Figure 1.B.2: The house price variability across districts in Germany.

Notes: This figure shows the house price variation across districts in Germany over time. The house price variation is measured by the standard deviation of $\ln P$ across districts yearly. The house type category "all" captures all house types, including "single-family" homes. The data are obtained from RWI and ImmobilienScout24 (2020).

Table 1.B.7: IV Results: Housing Supply Elasticity Estimates

	Housing Supply Growth: $\Delta \ln(H)$ (Completions–single-family)			
	(1)	(2)	(3)	(4)
$\Delta \ln P$	0.476	1.684^{***}	0.574	1.772^{***}
	(0.492)	(0.566)	(0.492)	(0.568)
$\Delta \ln P \times$ Developed		-5.552^{***}		-5.562^{***}
		(0.950)		(0.945)
$\Delta \ln P \times$ Unavail			−1.444	−1.219
			(0.906)	(0.934)
Developed	-1.379^{***}		-1.381^{***}	
	(0.270)		(0.273)	
Unavail	−0.316	−0.260		
	(0.215)	(0.237)		
Constant	0.782	−0.737	0.703	−0.809
	(2.231)	(2.404)	(2.227)	(2.392)
R^2	0.201	0.117	0.199	0.123
Num. obs.	401	401	401	401

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Notes: Regressions include the log of construction costs in 2019, the log of construction labor in 2008, urban vs. rural, and west vs. east district classifications as defined by BBSR (2021), and the log of population and household income in 2008. The fraction of land developed (Developed) and unavailable (Unavail) are for 2006. Robust standard errors are in parentheses.

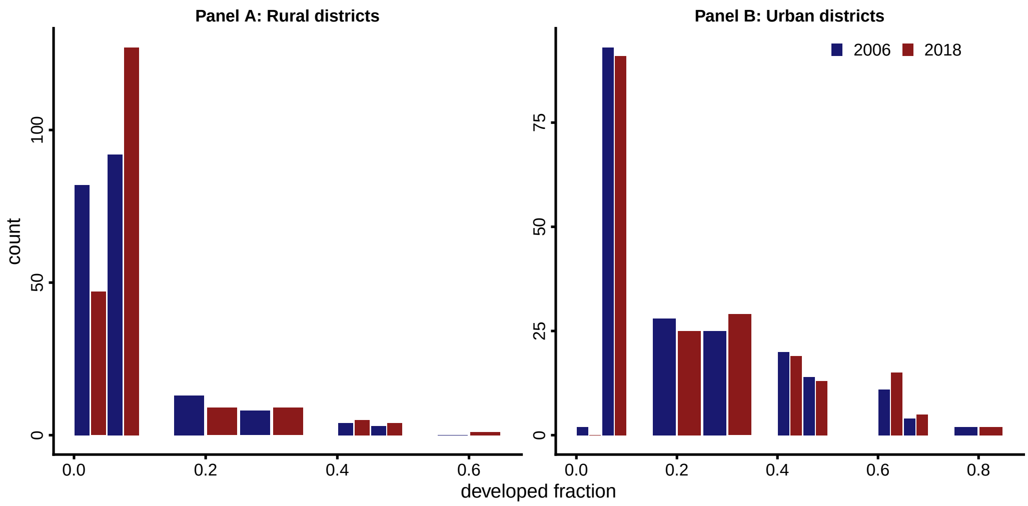

Figure 1.B.3: Land development in rural vs urban districts.

Notes: This figure shows the difference in the land development intensity between the urban and rural districts for 2006 and 2018. The land development is higher in the urban districts, as expected, as they have a higher population density and more developed land.

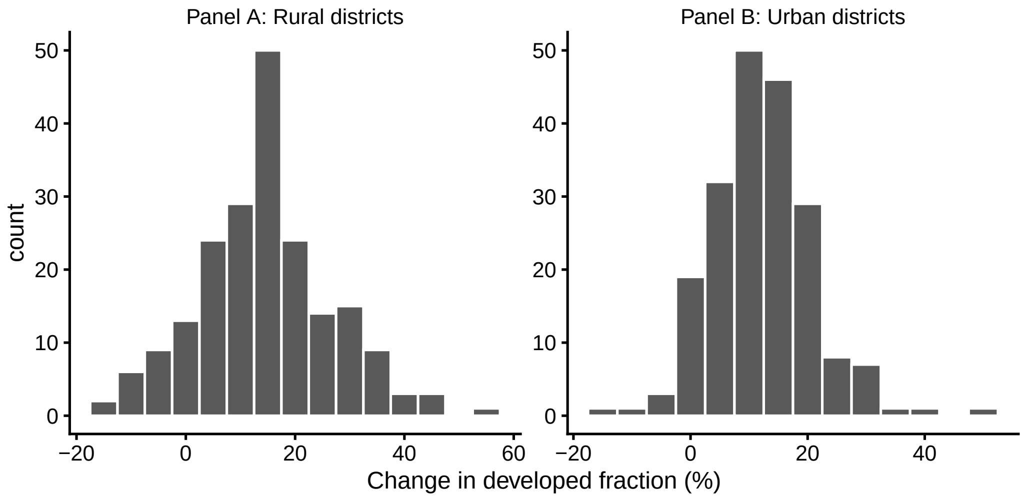

Figure 1.B.4: The distribution of land development growth: 2006-2018.

Notes: This figure shows the distribution of the growth of land development for urban and rural districts over the 2006-2018 period. Land development growth is higher in rural districts, partly because the rural districts had lower land development and more developable land in 2006 than the urban districts.

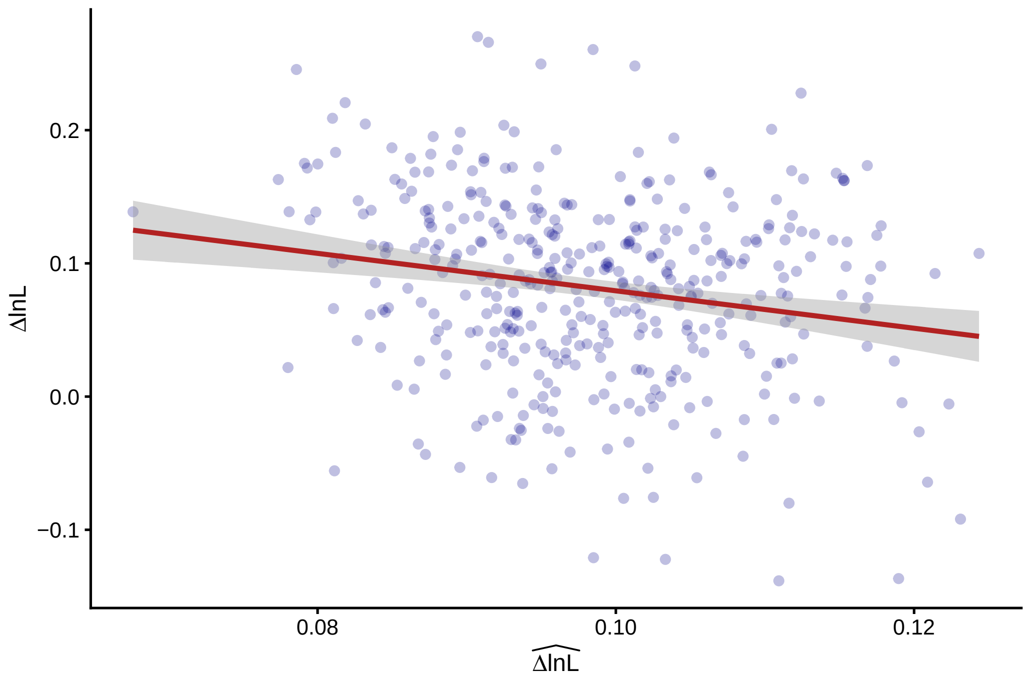

Figure 1.B.5: Correlation between the predicted and the actual employment growth.

Notes: The figure compares the labor demand shock predicted from local employment (the Bartik instrument) to the actual employment growth. The labor demand shock on the x-axis helps identify the price elasticity of housing supply in the study. Employment data are sourced from Federal Statistical Office and Statistical Offices of the Federal States (2022).

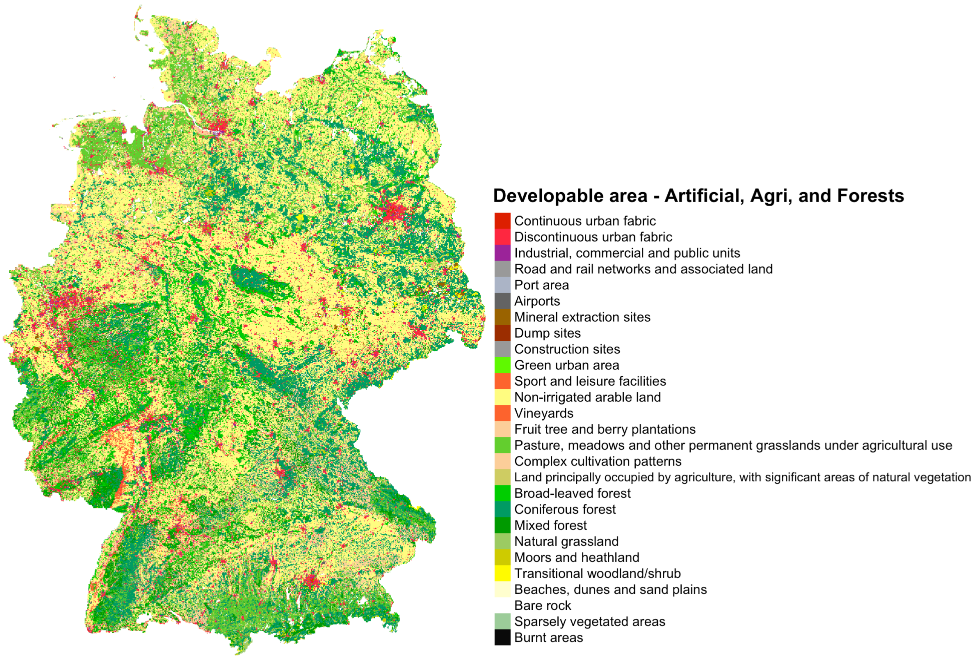

Figure 1.B.6: Developable land in Germany.

Notes: This figure shows the distribution of developable land in Germany. The developable land comprises the area covered by agriculture, forests, or artificial surfaces (see Section 1.4.3.1). Areas covered with artificial surfaces are part of the developable stock as they can be redeveloped through renovation or demolition. The data are extracted from Corine Land Cover (CLC) Germany, compiled by the German Remote Sensing Data Center (DFD) of DLR and the Federal Agency for Cartography and Geodesy (BKG).

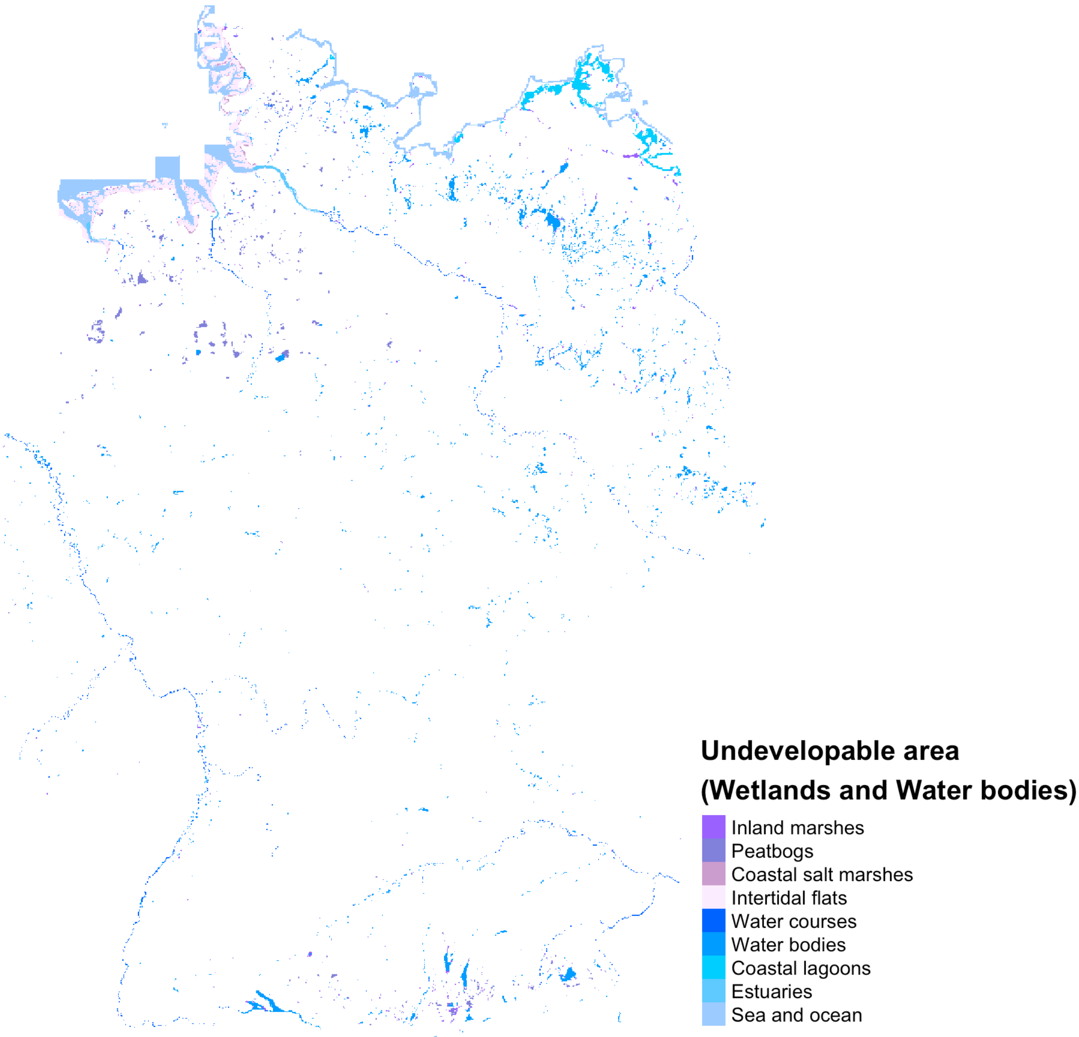

Figure 1.B.7: Undevelopable land.

Notes: This figure shows the distribution of undevelopable land in Germany. The undevelopable land comprises wetlands and water bodies (see Section 1.4.3.1). The data are extracted from Corine Land Cover (CLC) Germany, compiled by the German Remote Sensing Data Center (DFD) of DLR and the Federal Agency for Cartography and Geodesy (BKG).

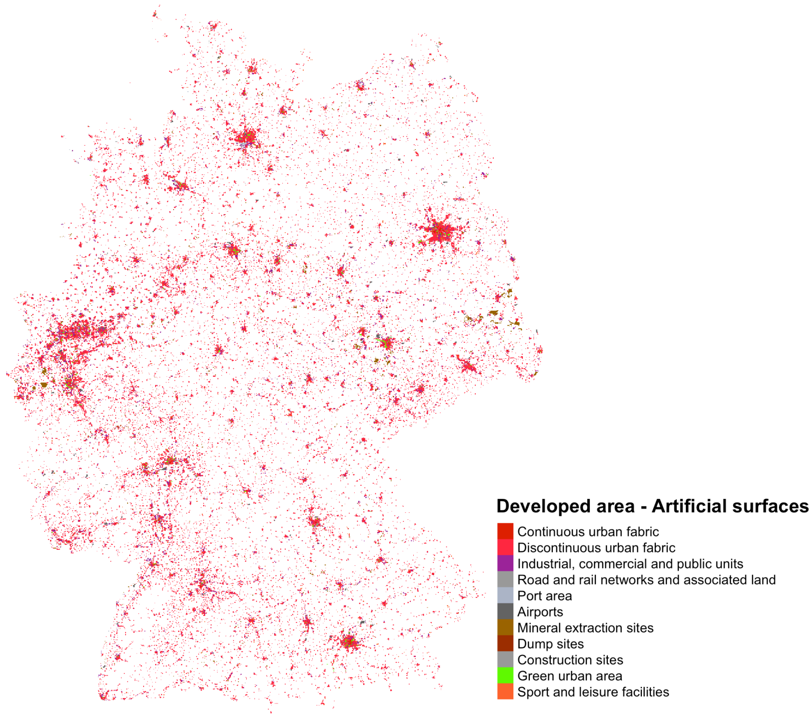

Figure 1.B.8: Developed land.

Notes: This figure shows the distribution of developed land in Germany. The developed land comprises areas already covered with artificial surfaces such as buildings. The data are extracted from Corine Land Cover (CLC) Germany, compiled by the German Remote Sensing Data Center (DFD) of DLR and the Federal Agency for Cartography and Geodesy (BKG).

Chapter 2

The impact of COVID-19 on real estate markets in Germany

Abstract

The COVID-19 pandemic has disrupted established urban patterns. Research on the US housing market shows a significant increase in suburban demand, resulting in higher suburban prices (the ”donut effect”). However, the German market did not experience such drastic changes. We examined price and rent adjustments, using detailed housing data, and found little evidence supporting the US donut effect. Apartment rents increased in suburbs, while house prices remained unchanged. Examining amenities, we found no explanation for the price and rent differences between the CBD and suburbs. The difference may be attributed to cultural and structural factors. Our analysis, including population and migration data, reveals that residents in Germany exhibit a slower-moving trend. Our findings remain robust across diverse settings and city subsets.

JEL codes: R23, R31
Keywords: House prices, Rent gradient, COVID-19, Donut effect, Urban amenities

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This chapter is coauthored with Patrick Thiel. A similar version has been published on SSRN https://ssrn.com/abstract=4700238

2.1 Introduction

The key prediction of the Alonso (1964), Mills (1967), Muth (1969) (AMM) model is the rent gradient, which establishes a negative relationship between house prices or rents and distance from the city center. Lower commuting costs, higher amenities, and other agglomeration benefits justify higher prices in city centers than in the suburbs (Brueckner, 1987). However, following the outbreak of the COVID-19 pandemic, commuting costs have fallen or been eliminated because of the possibility of working from home (WFH), and urban consumption amenities were largely inaccessible because of strict lockdown measures. This may have reduced the demand for housing in city centers and dense neighborhoods within cities. Furthermore, there is strong evidence that the pandemic has caused significant population movements away from these areas to suburbs and low-density neighborhoods. However, much of the existing literature exclusively studies the US housing market (see, for example, Gupta et al., 2022; Liu and Su, 2021; Ramani and Bloom, 2021; and Duranton and Handbury, 2023). In this paper, we study how the COVID-19 pandemic and urban amenities affected real estate markets within and across German cities. In addition to adding the German experience to the current literature, our contribution is emphasizing the role of amenities. In the US literature, the WFH channel is championed as a potential explanation for changes in the housing market during the pandemic. The discussion of amenities is less detailed, although it is considered as a potential mechanism. We focus on house prices and apartment rents comparing them before and after the pandemic to document changes in the housing market.

We develop a simple spatial equilibrium model to analyze the impact of the COVID-19 pandemic on housing demand in densely-populated central locations versus low-density suburban areas within cities. Our model builds upon previous research by Liu and Su (2021), Ramani and Bloom (2021), and Duranton and Handbury (2023), which primarily focuses on commuting costs and remote work's impact on housing demand in high-density central locations. However, the literature is limited on how the pandemic may have affected people's preferences for local amenities and its subsequent impact on housing demand. This paper aims to highlight the pandemic's impact on housing demand through the revaluation of amenities between consumption and environmental amenities. The model shows how commuting costs and amenities determine the spatial distribution of housing prices in an equilibrium setting. It predicts that housing demand will shift from the CBD to the suburbs due to the increased value of suburban amenities, decreased value of consumption amenities, and the fall of commuting costs due to the rise of remote work arrangements during the pandemic. The shift in the importance of amenities is expected to lead to a decline in CBD prices and an increase in suburban prices. Our empirical strategy follows these predictions of housing demand reallocations. To test these predictions, we utilize data on house prices and apartment rents from the German housing market and amenities data from OpenStreetMap (OSM).

We find that, from March 2020 to March 2021, the slopes of the gradients have changed by 0.005 and 0.010 for prices and rents, respectively. Although the positive changes in the slopes show a flattening of the gradients, the magnitudes are small to suggest that the pandemic has caused the same clear and strong flattening of gradients in Germany as observed in the US. For comparison, Gupta et al. (2022) found the change in slope for price 0.012, and the slope change for rents 0.032, from December 2019 to December 2020, for the US. Put differently, while for the US the decrease in the slopes of the price and rent gradients are 11.65% and 100.00%, for Germany, they are 9.38% and 22.40%. Thus, it is not evident that the pandemic has caused the same strong flattening of gradients in Germany as observed in the US. There appear to be only minor adjustments to the slopes of the gradients.

Overall, our results show little evidence of the flattening of the bid-rent curve in the German housing market. This result is robust to spatial subdivision into large, medium, or small cities. Amenities, our main mechanism, do not explain the donut effect. Based on our data, we do not observe a significant shift in the importance of consumption amenities towards environmental amenities, especially at the monthly level. We also find that residents in Germany did not move more than before the pandemic. We did not observe population movements within and between cities during the pandemic. Overall, according to our results, the German housing market has not been as disrupted as in the US by the COVID-19 pandemic. The differences may be attributed to institutional and cultural differences. The German housing market has proven to be fairly stable and resistant to disruption, as detailed in the Appendix.

The remainder of the paper is structured as follows. Section 2.2 provides a summary of the literature on the impact of the pandemic on housing markets and highlights key findings. Section 2.3 presents a simple theoretical model that guides our empirical strategy. Section 2.4 discusses the data sources and presents stylized facts. Section 2.5 presents our main findings, and Section 2.6 concludes the paper.

2.2 Literature Review

Our work expands on the increasing volume of research exploring the intersection of the COVID-19 pandemic, remote work practices, amenities, and real estate markets. Several studies demonstrate that the pandemic has induced a redistribution of housing demand, population, and economic activities within cities, shifting from city centers and densely populated areas to suburban and less dense regions (Gupta et al., 2022; Liu and Su, 2021; Ramani and Bloom, 2021). Duranton and Handbury (2023) complement these studies by providing a comprehensive review of the effects of the pandemic and the rise of work from home (WFH) in cities, employing a version of the monocentric city model. The authors highlight the "commuting dividend" and "home office tax" effects of WFH, noting short-term downtown housing price drops, subsequent rebounds, and continued suburban price rises. They connect the pandemic and WFH trends to changes in housing prices and commuting patterns and discuss potential challenges for maintaining vibrant downtown economies due to the loss of daytime workers and the potential impact on agglomeration benefits.

These studies collectively show how the pandemic flattened the bid rent curve in US metropolitan areas, causing house prices and rents in city centers to decrease while increasing in the suburbs. This led to a population shift from central urban areas to suburban locales. These changes in housing demand and population are most noticeable in metropolitan regions characterized by a high proportion of remote workers, strict lockdown measures, and inelastic housing supply (Gupta et al., 2022). The decrease in demand in densely populated and central urban neighborhoods is attributed to the diminished need for proximity to jobs that can be done remotely and the reduction in the appeal of urban amenities (Liu and Su, 2021; Ramani and Bloom, 2021).

This urban-to-suburban shift, dubbed the "donut effect" by Ramani and Bloom (2021), is not observed in smaller cities or movements across cities. The intercity relocations from larger, denser cities to smaller or less populated ones are less substantial, attributed in part to the emergence of hybrid work patterns in the post-pandemic period (Liu and Su, 2021; Ramani and Bloom, 2021).

The literature strongly supports a positive relationship between population density and the potential for WFH and the movement of workers with high WFH potential away from the CBD during the pandemic in the US Althoff et al. (2022). Therefore, the question is how significant is WFH in the German context. Overall, the COVID-19 pandemic had a greater impact on the labor markets of major German cities compared to other regions, which experienced a faster recovery(Hamann et al., 2023). Thus, similar to the US, the effects seem to be present in large cities in Germany. Furthermore, Alipour et al. (2023) shows that about 56% of jobs in Germany can be performed (at least partially) from home, although there is great heterogeneity across occupational groups. The increase in WFH has also led to a shift in consumption patterns away from the CBDs to the suburbs, where people now also work from (Alipour et al., 2022). However, WFH is a much less valued job attribute than other job benefits. German workers report that they are willing to give up about 5% of their income for the opportunity to work from home two days a week. The effects for other job benefits, such as additional paid days off, are two to three times greater (Nagler et al., 2022).

The other channel discussed for explaining the changes in real estate markets during the pandemic, albeit to a lesser extent, is the change in the valuation of (urban) amenities. The literature generally documents a positive impact of amenities on rents and prices (see, for example, Cho et al., 2006; Conway et al., 2010; Schäfer and Hirsch, 2017; Kolbe and Wüstemann, 2015). This applies to both environmental amenities, such as green spaces and water bodies, and consumption amenities, like fancy restaurants, cafes, and tourist attractions. However, these studies also show that the effect of amenities on house prices is typically smaller than the effect of structural variables such as the unit's size or the building's age. The key question for our study is whether the valuation of amenities changed with the pandemic. However, the literature is rather limited on this specific question. van Vuuren (2023) finds that house prices in amenity-rich areas decreased during the pandemic (compared to less amenity-rich areas) and that there is a reduction in willingness to pay for such amenities. Cheung and Fernandez (2021) examines the impact of amenities on house prices in Auckland (New Zealand) and finds that the premium paid for the enjoyment of amenities is reduced or even negative after the pandemic. They attribute this finding to changes in perceptions of open space, which may signal some risk following the experience of COVID-19. Another study by Batalha et al. (2022) shows that prices and rents in Lisbon and Porto, Portugal, decrease in tourist areas. However, tourist attractions may be a special type of amenity, as they are also typically associated with business activities. Overall, the evidence so far, however limited, points to a negative change in amenities due to the pandemic.

To the best of our knowledge, no study explicitly addresses the potential changes in the valuation of amenities during the pandemic in Germany. Therefore, this study emphasizes this second channel to explain changes in the housing market during the pandemic. An open question with respect to both WFH and amenities is whether developments during the pandemic caused population movements that led to structural changes in the German housing market. We investigate this question by analyzing post-pandemic population levels using county-level migration statistics.

2.3 Methodology

This section presents a simple spatial equilibrium model that guides our expectations of the impact of the COVID-19 pandemic on housing demand in densely populated central locations versus low-density remote locations. Our model closely follows prior work by Liu and Su (2021), Ramani and Bloom (2021), and Duranton and Handbury (2023). While the literature focuses on the mediating role of commuting costs and the prevalence of WFH on demand for housing in high-density central locations, there is a lack of understanding regarding how the pandemic may have changed people's preferences for local amenities and its subsequent impact on housing demand.

We aim to contribute to the literature by emphasizing the impact of the pandemic on housing demand through the channel of amenity revaluation. We study this with two components of amenities: environmental amenities, such as green spaces and water bodies, and consumption amenities, such as cafes, bars, museums, etc. (see Section 2.4.3 for the details). This paper investigates the impact of changes in the accessibility of local amenities caused by the pandemic on house prices and rents. The theoretical model supports our empirical approach by providing predictions on housing demand reallocation, which we verify using house price data from the German housing market and amenities data from OpenStreetMap (OSM).

2.3.1 Model

Following Duranton and Handbury (2023), we consider a city that produces its consumption good in its downtown, often called the central business district (CBD), where all jobs are concentrated. Residents derive utility from the consumption good, denoted q, sold at a fixed price of one, and housing, denoted h. Every location in the city is indexed by d, representing the distance to the CBD. Housing is supplied competitively across the city from the CBD (where $d = 0$) to the urban fringe (where $d = \bar{d}$). We take the housing supply and its distribution across the city as given.

Residents' preferences are represented by a utility function $u(h, q, A(d))$, where A represents local amenities, which is a function of d. We assume that utility is increasing in all three arguments and is strictly quasi-concave.

A resident living at a distance d from the CBD incurs a commuting cost of td^{τ}, where $\tau < 1$. This implies that commuting costs increase disproportionately with distance.[1] Let $r(d)$ denote the rental price of floorspace per unit of housing at a distance d from the CBD. The resident's budget constraint can be expressed as $w - td^{\tau} = r(d)h + q$, where w represents income.

We assume a Cobb-Douglas form for the utility function:

$$u(h, q, A) = h^{\alpha} q^{1-\alpha} A(d), \tag{2.1}$$

where α reflects the importance of housing in utility, with $\alpha \in (0, 1)$.

Solving the utility maximization problem subject to the budget constraint yields the demand functions for housing and the consumption good:

[1]Following Duranton and Handbury (2023), we adopt the assumption that commuting costs increase non-linearly with distance to the CBD d. This specification aligns with the real-world commuting data, which indicates that households' distance to work and total vehicle-kilometers driven increase less than proportionately with the distance to the CBD.

$$h^* = \alpha \frac{w - td^\tau}{r(d)}, \quad q^* = (1 - \alpha)(w - td^\tau) \tag{2.2}$$

Note that these solutions do not include the effect of amenities A directly. In this simplified model, amenities affect utility but do not directly affect the budget constraint. Thus, they do not appear in the optimal choice of consuming h and q. However, they affect the location choice of the resident and thus the price of housing $r(d)$, which indirectly affects housing and consumption choices.

2.3.1.1 Spatial equilibrium

Assuming that all residents in the city are homogeneous in incomes and preferences and are freely mobile within the city, the concept of "spatial equilibrium" states that they should attain the same level of utility, represented by $\bar{u}$, throughout the city. Quantitatively, this can be expressed as:

$$u(h, q, A(d)) = h^\alpha q^{1-\alpha} A(d) = \bar{u} \tag{2.3}$$

That means, residents that live in the CBD $d = 0$ and in the suburb $d = \bar{d}$, enjoy the same level of utility:

$$u_{\text{cbd}} = u_{\text{suburb}} \tag{2.4}$$

The spatial equilibrium condition implies that residents have no utility gains by moving from one location to another within the city. Therefore, the total derivative of utility with respect to distance must be zero.

We obtain the equilibrium price difference between the CBD and the suburb by inserting the respective distances and using the optimal choice values in Equation 2.2.

$$
\begin{aligned}
h_{\text{cbd}}^{\alpha} \cdot q_{\text{cbd}}^{1-\alpha} \cdot A(0) &= h_{\text{suburb}}^{\alpha} \cdot q_{\text{suburb}}^{1-\alpha} \cdot A(\bar{d}) \\
\frac{h_{\text{cbd}}^{\alpha}}{h_{\text{suburb}}^{\alpha}} \frac{q_{\text{cbd}}^{1-\alpha}}{q_{\text{suburb}}^{1-\alpha}} &= \frac{A(\bar{d})}{A(0)} \\
\left(\frac{w}{w - t\bar{d}^{\tau}} \frac{r(\bar{d})}{r(0)} \right)^{\alpha} \left(\frac{w}{w - t\bar{d}^{\tau}} \right)^{1-\alpha} &= \frac{A(\bar{d})}{A(0)} \\
\left(\frac{r(\bar{d})}{r(0)} \right)^{\alpha} &= \frac{w - t\bar{d}^{\tau}}{w} \frac{A(\bar{d})}{A(0)} \\
\implies \frac{r(\bar{d})}{r(0)} &= \left(\frac{w - t\bar{d}^{\tau}}{w} \frac{A(\bar{d})}{A(0)} \right)^{\frac{1}{\alpha}}
\end{aligned}
$$

Taking the logarithm yields the equilibrium percentage difference between the CBD and the suburb prices:

$$
\ln\left(\frac{r(0)}{r(\bar{d})}\right) = \frac{1}{\alpha} \ln\left(\frac{w}{w - t\bar{d}^{\tau}}\right) + \frac{1}{\alpha} \ln\left(\frac{A(0)}{A(\bar{d})}\right) \tag{2.5}
$$

This equation shows that the relative commute cost and amenity levels determine the price difference. Higher amenities or lower commuting costs for the suburb (due to lower t) increase the price in the suburb relative to the CBD, and the price difference decreases, all else being equal.

2.3.1.2 Introducing amenity shock

The COVID-19 pandemic has caused a WFH shock and a potential revaluation of amenities. Since the beginning of the pandemic, access to consumption amenities has been largely restricted due to strict lockdown and social distancing measures. Moreover, the virus has been spreading rapidly, resulting in higher infection and death rates in high-density central locations within cities. It is crucial to capture these local shocks to amenities to understand the effects of the pandemic on housing demand.

We build upon the above part by providing more specific information about amenities to introduce an amenity shock. In the pre-pandemic time, amenity enters the utility of a representative resident as $U(h, q, A(d)) = h^a \cdot q^{1-\alpha} \cdot (\kappa A_c + \varepsilon A_e)$ where A_c and A_e denote consumption and environmental amenities. The parameters κ and ε are weights that represent the relative importance placed by the resident on each type of amenity, respectively. During the pandemic, the relative importance of consumption and environmental amenities may change due to factors such as the closure of establishments in the CBD or the increased preference for open spaces in the suburb. We consider this shift by modifying the utility function during the pandemic to U', which now has $\kappa' A_C + \varepsilon' A_E$ in the amenity component, where $\kappa' < \kappa$ represents the decreased weight of consumption amenities in the CBD due to closures and restrictions, and $\varepsilon' > \varepsilon$ represents the increased weight of environmental amenities in the suburb due to greater emphasis on open space and nature during lockdowns or WFH periods. The utility maximization problem now involves comparisons between altered utilities of living in or close to the CBD and further away. Residents reevaluate their preferences based on these changes in amenities and other considerations such as moving and commuting costs. As a result, we may observe a shift in housing demand from the CBD towards the suburb during the pandemic period.

Furthermore, it is important to highlight that consumption amenities, such as access to fancy restaurants, shops, and entertainment venues, are highly concentrated in the CBD, and their availability is limited in the suburbs. In contrast, environmental amenities, such as open space, clean air, and quieter neighborhoods, are scarce in the CBD but more abundant in the suburbs. The amenity function, as defined below, captures this heterogeneity:

$$A(d) = A_c(d) + A_e(d) = a_c \cdot e^{-bd} + a_e \cdot e^{\phi d}, \tag{2.6}$$

where a_c and a_e represent the maximum (minimum) consumption (environmental) amenity levels in the city at the CBD, and the parameters b and ϕ determine how fast each amenity type changes with distance from the CBD.

For simplicity, suppose $A_c(0) \equiv A_e(\bar{d}) = a_e e^{\phi \bar{d}}$. That means that the highest level of consumption amenities is equivalent to the highest level of environmental amenities. Plugging the amenity function into Equation 2.5, we get

$$\begin{aligned}
\ln \frac{r(0)}{r(\bar{d})} &= \frac{1}{\alpha}\left(\ln \frac{w}{w - t\bar{d}^{\tau}} + \ln \frac{\kappa \cdot a_c + \varepsilon \cdot a_e}{\kappa \cdot a_c \cdot e^{-b\bar{d}} + \varepsilon \cdot a_e \cdot e^{\phi \bar{d}}}\right) \\
&= \frac{1}{\alpha}\left(\ln \frac{w}{w - t\bar{d}^{\tau}} + \ln \frac{\kappa \cdot e^{\phi \bar{d}} + \varepsilon}{e^{\phi \bar{d}}(\kappa \cdot e^{-b\bar{d}} + \varepsilon)}\right).
\end{aligned} \tag{2.7}$$

Equation 2.7 indicates that the price difference is a function of the weights residents give to amenities. Specifically, the price difference is smaller when residents place greater importance on environmental amenities. In addition, as residents move farther from the CBD, the availability of consumption amenities decreases while the availability of environmental amenities increases.

Taking derivatives of the left-hand side of the equation with respect to κ and ε provides the change in the price differential as a function of a change in the weights assigned to consumption and environmental amenities, respectively.

Specifically, we have:

$$\begin{aligned}
\partial \ln \frac{r(0)}{r(\bar{d})} &= \frac{1}{\alpha}\left(\frac{e^{\phi \bar{d}}}{\kappa \cdot e^{\phi \bar{d}} + \varepsilon} - \frac{e^{-b\bar{d}}}{\kappa \cdot e^{-b\bar{d}} + \varepsilon \cdot e^{\phi \bar{d}}}\right) \cdot \partial \kappa \\
&= \frac{1}{\alpha}\left(\frac{1}{\kappa + \varepsilon} - \frac{e^{\phi \bar{d}}}{\kappa \cdot e^{-b\bar{d}} + \varepsilon \cdot e^{\phi \bar{d}}}\right) \cdot \partial \varepsilon
\end{aligned}$$

These equations describe how a small change in the relative importance of consumption or environmental amenities affects the log price/rent differential between the CBD and the suburb. If $\kappa' < \kappa$ (i.e., the relative importance of consumption amenities decreases), then $\partial \ln(r(0)/r(\bar{d}))/(\partial \kappa) < 0$, indicating that the price/rent differential will decrease. On the other hand, if $\varepsilon' > \varepsilon$ (i.e., the relative importance of environmental amenities increases), then $\partial \ln(r(0)/r(\bar{d}))/(\partial\varepsilon) < 0$, similarly indicating that the price/rent differential will decrease. Thus, these results suggest that a pandemic-induced decrease in the relative importance of consumption amenities (along with a simultaneous increase in the relative importance of environmental amenities) will decrease the price/rent differential between the CBD and the suburb. This supports the intuitive concept of the "donut effect", where housing demand may shift from the CBD to the suburbs during a pandemic as people prioritize environmental amenities more.

This simple model demonstrates how commuting costs and amenities determine residential choices and the spatial distribution of housing prices in an equilibrium setting. It predicts that housing demand will shift from the CBD to the suburbs due to the increased value of suburban amenities, decreased value of consumption amenities, and the rise of remote work arrangements during the pandemic. This shift is expected to cause a decline in CBD prices and an increase in suburban prices. Before the pandemic, when remote work was not prevalent, commuting costs were high, and there was a strong preference for consumption amenities, CBD house prices and rents were higher. However, during the pandemic, with widespread remote work and a greater preference for suburban amenities, the price and rent differences between CBD and suburbs become smaller, resulting in declining CBD prices and rents and increasing suburban prices and rents.

2.3.2 Empirical Strategy

The model's theoretical prediction in Section 2.3.1 suggests that changes in commuting costs, central location attractiveness, and suburban amenities value lead to a reallocation of housing demand. There is a high concentration of consumption amenities near the CBD, while suburbs offer abundant environmental amenities. Due to the rapid spread of the COVID-19 virus in high-density areas during the pandemic, strict lockdown policies were enforced, limiting access to consumption amenities. Consequently, people may have started valuing consumption amenities less since they are inaccessible and placing more importance on suburban amenities, causing high demand for suburban housing. This study aims to empirically examine if this holds true for the German housing market.

We test these predictions by analyzing changes in price and rent gradients following the pandemic. In line with the "flattening the curve" literature for the US, we expect house prices and rents to fall in central locations and rise in suburbs during the pandemic in Germany, at least in big cities. To do so, we estimate the slope of the price and rent gradients for each month from 2017 to 2021.

To identify the impact of the pandemic on property prices in the CBD versus suburbs, like Gupta et al. (2022), we specify the following regression equation:

$$\ln p_{it} = \mathbf{x}_i'\boldsymbol{\beta} + \delta_t(t \times \ln dist_i) + \alpha_t + \alpha_i + e_{it}, \tag{2.8}$$

where $\ln p_{it}$ is the logarithm of average hedonic price or rent (described in Section 2.4.1) in zip code i, at time (i.e., month-year) t, $\ln dist_i$ is the logarithm of the (Euclidean) distance between the centroid of the zip code i and its CBD.[2] We control for zip code level cross-sectional characteristics $\mathbf{x}_i$.[3] Finally, time and LMR fixed effects α_t and α_i are included to capture time trends and unobserved regional characteristics.

δ_t, the coefficient of the interaction term between time t and distance, esti-

[2]We define the CBD as the geographical center in the labor market region, as defined by Kosfeld and Werner (2012), weighted by the number of inhabitants. For more details, refer to Section 2.4.2.

[3]The zip code controls are the logarithm of the total purchasing power, average household size, the share of households with German background, and the share of households aged 18-45 years old. These controls represent pre-pandemic levels in 2019, based on data from RWI and Microm (2022). They remain constant throughout our estimations and do not vary over time.

mates the slope of the gradient for each month. We anticipate the estimates for this coefficient to be negative, as the AMM model predicts, and the magnitude to decrease in absolute terms during the pandemic, indicating a flattening of the gradient. The cutoff period for the pandemic is March 2020, corresponding to the time when the first lockdown was imposed in Germany.

Alternatively, to analyze the growth of house prices and rents over time, we divided the zip codes into CBD and suburb groups and estimated the following regression equation:

$$\ln p_{it} = \mathbf{x}_i'\boldsymbol{\beta} + \alpha_t + \alpha_i + e_{it}. \tag{2.9}$$

In this equation, our coefficients of interest are the time fixed effects α_t, which capture the growth of the hedonic values over time. The controls and individual fixed effects remain the same as before. We run this regression analysis separately for each group of zip codes.

Lastly, we specify the following regression equation to investigate the role of amenities, our main explanation channel for the donut effect.

$$\ln p_{it} = \mathbf{x}_i'\boldsymbol{\beta} + \beta_a AI_i + \delta_t(t \times AI_i) + \alpha_t + \alpha_i + e_{it}, \tag{2.10}$$

where AI_i represents an index of consumption or environmental amenities, all other elements remain the same as before. The coefficient of interest is δ_t, the interaction between time and amenity indices. This interaction captures the effect of changes in the valuation of consumption or environmental amenities on house prices and rents following the pandemic. We expect the coefficient to be negative for consumption amenities and positive for environmental amenities, as predicted in Section 2.3.1.2.

2.4 Data

We use real estate data from RWI-GEO-Real Estate Data (RWI-GEO-RED) of the FDZ Ruhr at RWI (RWI and ImmobilienScout24 (2022b) and RWI and ImmobilienScout24 (2022a)), and amenity data from OpenStreetMap (OSM).

2.4.1 Rents and house prices

We construct house price and rental indices using a comprehensive and detailed dataset on housing RWI-GEO-RED (RWI and ImmobilienScout24, 2022b,a). The dataset includes a wide range of property characteristics, enabling us to calculate hedonic indices.

To create a quality-adjusted index, we employ panel hedonic regression as follows:

$$\ln p_{hijt} = \mathbf{x}'_{hijt}\boldsymbol{\beta} + \alpha_{ijt} + e_{hijt}, \tag{2.11}$$

where h,i,j, and t index properties, zip codes, municipalities, and times (i.e., month-year), respectively. The variable p denotes rent or price in euros per m^2, α_{ijt} denotes zip code-municipality-time fixed effects, and $\mathbf{x}'_{hijt}$ includes a set of property characteristics.[4] Our zip code-level quality-adjusted prices (or rents) are the estimates of the fixed effects in Equation 3.11: $\widehat{\alpha}_{ijt} = \widehat{\ln p}_{hijt} - \mathbf{x}'_{hijt}\widehat{\boldsymbol{\beta}}$.

[4]The hedonic regressions include the following property characteristics: floorspace, number of rooms, floors, bedrooms, and bathrooms; house or apartment dummy; home type; apartment type; type of heating; years of construction and renovation; condition and facilities of the property; whether the property has a basement; whether it has a guest washroom; whether it is in or is a protected building; and whether the property is usable as a holiday house.

2.4.2 Zip Codes, Labor Market Regions (LMRs), and Central Business Districts (CBDs)

Our zip code data come from the Postleitzahlen Deutschland and covers all zip codes in Germany. The data contains information on zip code boundaries and associated towns and cities.

Kosfeld and Werner (2012) define 141 labor market regions (LMRs) in Germany, based on commuting flows. The delineation of these regions is based on combining one or more administrative regions at the county level to create self-contained labor markets. The boundaries of local labor markets are defined so that commuting flows within labor market regions are relatively large compared to commuting between regions, with an upper limit of 45-60 minutes for commuting time.

We use these LMRs to define the CBDs as the geographical center of each LMR, weighted by the number of inhabitants at the 1x1 km grid-cell level.[5] The information on the number of inhabitants comes from RWI and Microm (2022). Figure 2.1 shows the constructed CBD locations and the respective distance between the CBD and the center of each zip code.

For a categorical classification of CBD and suburb, we rely on a data-driven definition of groups by using percentiles of the distance to the CBD. Locations within the 10^{th} percentile are considered to belong to the CBD area ($P_{10\%} \approx 6.1km$). We classify locations above this threshold but below the median distance as suburban areas. For a more detailed analysis, we split the suburban areas into two rings: ring 1 with distances up $P_{30\%} \approx 12.4km$; ring 2 with distances up $P_{50\%} \approx 18.3km$. Zip codes with larger distances to the CBD lay outside the core area and are not further considered in this classification.

[5]Other weighting variables, such as the number of residential buildings and households, are also used to determine the central points in the LMRs. However, the results remain unchanged. We also used the unweighted centers of the LMRs, and the most populous municipality in the county as the CBD location (see Figure 2.B.1 for the comparison).

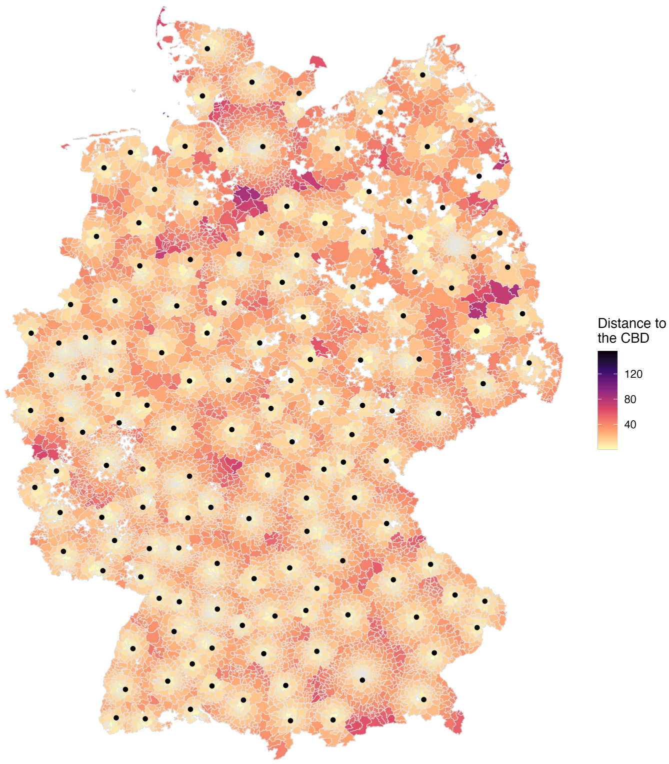


Figure 2.1: CBD locations and distance to the CBD.

Notes: The distance is calculated as the Euclidean distance between the geographical center of the zip code and the CBD based on the LMR definition.

2.4.3 Amenities

We distinguish between two types of amenities — consumption amenities and environmental amenities. To model the presence of amenities in urban areas accurately, we rely on OpenStreetMap (OSM) data, which we extract for the period 2017 to 2021.[6] Consumption amenities combine places to eat, places for education, and places for entertainment. We categorize green spaces and water bodies as environmental amenities.[7]

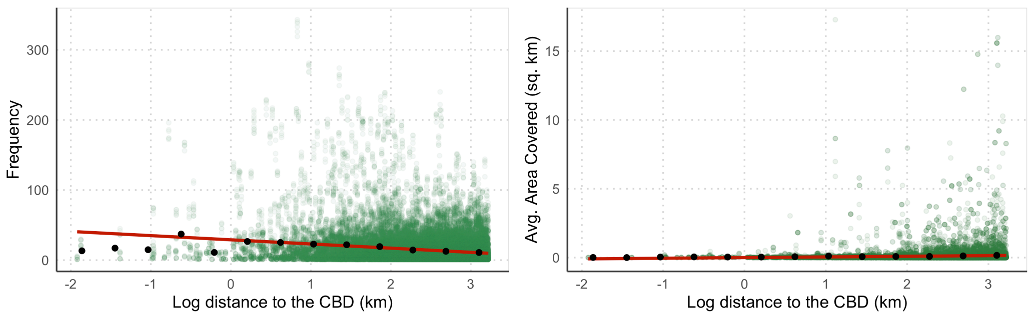
The consumption amenities data are collected as point data. It is possible that we list multiple buildings belonging to an amenity. For example, even though a city may have only one university, its buildings may be scattered throughout the city, resulting in multiple data points in our sample. The environmental amenities data are collected as polygon data.

Figure 2.2 shows the distribution of consumption amenities (left panel) and environmental amenities (right panel) relative to the distance to the CBD for all zip codes. We report consumption amenities based on frequency, as these are represented by points in space. Environmental amenities are reported in terms of the area covered relative to the size of the zip code, as these are represented as polygons. The figure shows that consumption amenities have a higher frequency closer to the CBD, as indicated by the decreasing slope of the trend line. The pattern is less clear for environmental amenities. Here, the slope of the trend line is close to zero, indicating evenly distributed amenities. However, the stylized facts below (Section 2.4.4) show locations further away from the CBD benefit, on average, from larger environmental areas. The trade-off between consumption and environmental amenities may influence households' decisions on where to live. Those prioritizing consumption amenities may reside closer to the CBD, while those who value environmental amenities may prefer

[6]We use a snapshot of OSM at the end of each year.

[7]For consumption amenities, we classify restaurants, bars, cafes, pubs, and ice cream stores as food locations, cinemas, and theaters as places of entertainment, and colleges, universities, kindergartens, schools, and libraries as education opportunities. For environmental amenities, we combine lakes, rivers, streams, canals, parks, gardens, and nature reserves.

suburban locations.



(a) Consumption amenities

(b) Environmental amenities

Figure 2.2: The gradient of amenities (raw values) as a function of the distance to the CBD.

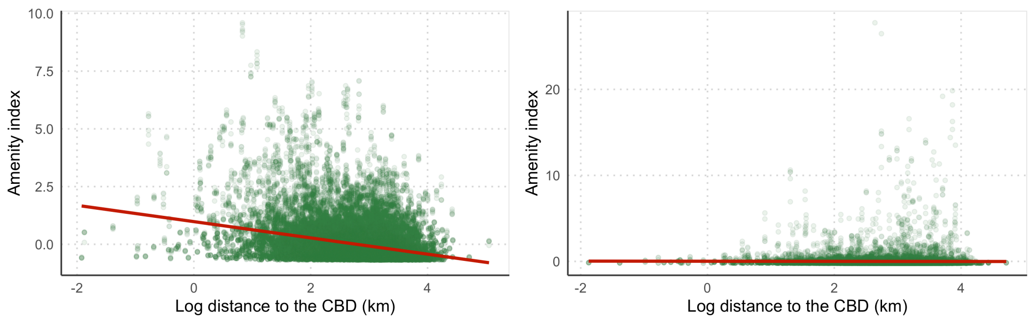
Notes: Both panels illustrate the relationship between amenities and their distance to the CBD, with data points coded green representing zip code values and darker points representing averages within a 2 km distance bins.

We transform the raw data into a zip code dataset to make consumption and environmental amenities usable in the analysis. We use the frequency of consumption amenities and the area covered by environmental amenities, which are normalized into an index using z-score normalization.[8] Following this strategy has the advantage that the resulting indices have a mean of zero and a standard deviation of one, making them comparable despite having different units.[9]

Figure 2.3 shows the distribution of the constructed index for consumption amenities (left panel) and environmental amenities (right panel). The plot looks almost identical to the raw data plot (Figure 2.2), which is intended as we only normalize the scales but keep the underlying patterns. It again shows a high frequency of consumption amenities in the CBD and an evenly distributed presence of environmental amenities across space.

[8] z-score normalization follows the formula: $\frac{x - mean(x)}{SD(x)}$

[9] The resulting indices have negative values for low counts of consumption amenities and small areas covered for environmental amenities.



(a) Consumption amenities (b) Environmental amenities

Figure 2.3: The gradient of amenities (indices) as a function of the distance to the CBD.

2.4.4 Stylized Facts

Stylized Fact 1: Consumption amenities are more prevalent in the CBD, while environmental amenities cover larger areas in the suburbs. Table 2.1 shows the average number of amenities and the area covered by environmental amenities, based on our definition of CBD and suburbs. The number of consumption amenities decreases with distance to the CBD. On average, the CBD (within a distance of 6.1 km from the center location) has approximately 22 consumption amenities (such as restaurants, schools, etc.). In the suburban ring 1 (6.1 – 12.4 km), there are only about 16 such facilities, and in the suburban ring 2 (12.4 – 18.3 km), there are about 13 facilities. For environmental amenities, on average, the area covered by these amenities increases from the CBD to the suburbs, ranging from 0.07 to 0.14 square kilometers.

Overall, this indicates that urban dwellers can avail themselves of consumption facilities more frequently, but they must also share a narrower range of environmental resources with their neighbors. Conversely, suburban residents have access to larger expanses of greenery and aquatic features, although they may have to undertake longer journeys to access consumption amenities.

Stylized Fact 2: While consumption amenities are negatively associated with the distance to the CBD, environmental amenities are positively associated.

Equation 2.6 demonstrates that the consumption amenities parameter b exhibits a negative sign while the environmental amenities parameter ϕ exhibits a positive one. Empirical evidence supporting this theoretical relationship can be ascertained through regression of the constructed amenity indices against the distance from the CBD.

The results in Table 2.2 indicate a significant negative effect of distance to the CBD on consumption amenities. The coefficient for environmental amenities (measured as the area covered) is significant and positive, but it is not significant for the index.

Table 2.1: Descriptive statistics on amenities

	Consumption amenities		Environmental amenities	
Ring	N	SD	Covered area (km^2)	SD
CBD	21.86	31.78	0.07	0.49
Suburb Ring 1	15.76	20.46	0.09	0.32
Suburb Ring 2	12.63	16.55	0.14	0.81
Outside	10.21	14.17	0.19	0.84

Notes: The table shows the average number of consumption and the average area covered by environmental amenities for the CBD and the suburban locations. Source: Authors' table.

Stylized Fact 3: The valuation of consumption and environmental amenities remains relatively constant in Germany during and after the pandemic.

Figure 2.4 shows the relationship between hedonic prices (rents) and the amenity indices in the top (bottom) panels. The relationship between hedonic values and amenities appears almost identical for both prices and rents. While the price trend for environmental amenities is flat in 2020 and 2021, the slope of the 2021 line for consumption amenities is slightly

Table 2.2: Estimates for the parameters b and ϕ

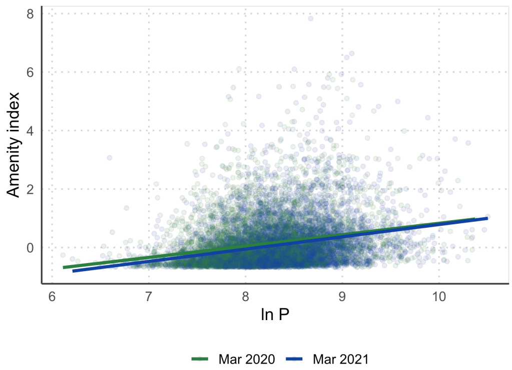
Type	Consumption amenities		Environmental amenities	
	ln count	index	ln area km^2	index
	(1)	(2)	(3)	(4)
Constant	4.323***	0.9777***	-6.538***	0.0169
	(0.0117)	(0.0508)	(0.0320)	(0.0485)
ln dist	-0.2468***	-0.3508***	0.1669***	-0.0063
	(0.0050)	(0.0166)	(0.0132)	(0.0183)
Observations	65,830	8,478	65,830	3,800
R^2	0.03564	0.08925	0.00231	3.13×10^{-5}

Notes: The table shows the estimates for the parameters b and ϕ from Equation (2.6), which represent the relationship between amenities and the distance to the CBD. The estimation uses amenity data for 2019. The number of observations for the indices represents zip codes. In the raw data, the number of observations counts the amenity object.

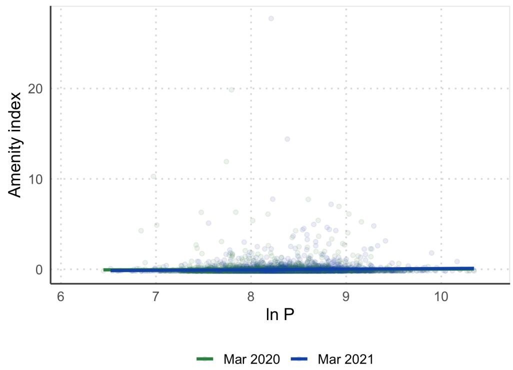
steeper than in 2020 (compare panels (a) and (b)). This implies that the valuation of consumption amenities with regard to house prices has increased in 2021. This minor change may be attributed to the pandemic and the closure of amenities such as high-end restaurants and cafes due to lockdown and social distancing measures. The (partial) reopening of these establishments and improved pandemic coping strategies may have enhanced the appreciation of local amenities. In contrast, the assessment of both facilities in relation to rental rates shows minimal variation between the onset of the pandemic in March 2020 and March 2021.

2.5 Results

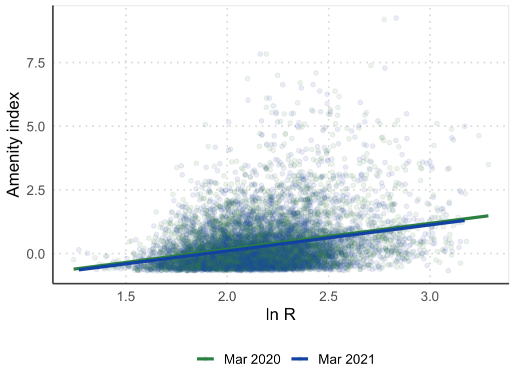
While the pandemic appears to be affecting the trend of apartment rents in Germany, average house prices have remained unaffected, as shown in Figure 2.5. In Germany, average rents started decreasing at the beginning



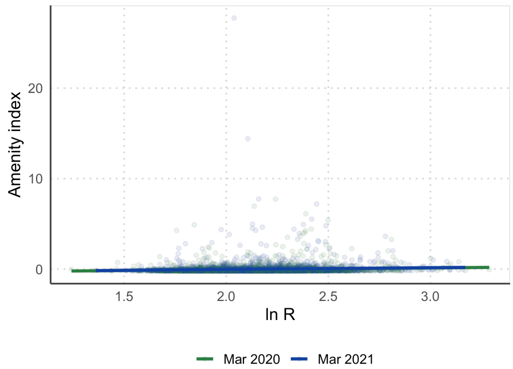
(a) Prices: Consumption amenities



(b) Prices: Environmental amenities



(c) Rents: Consumption amenities



(d) Rents: Environmental amenities

Figure 2.4: Correlation between prices/rents and amenities in March 2020 and 2021.

of 2020, coinciding with the onset of the pandemic. Rents recovered to the pre-pandemic (late 2019) levels in late 2020. However, the trend repeats starting in January 2021, with rents falling throughout 2021, albeit at a lower rate, paralleling the second wave of the pandemic. Since increasing rents by landlords is highly unlikely due to rental controls in Germany, the downturn in rents may have been triggered by the decline in demand, especially in major German cities and high-density areas.

With respect to house prices, no clear downturn is visible in the trend. House prices remained relatively stable throughout 2020 and 2021. This may be due to several factors. House prices are forward-looking, and home buyers likely anticipate a recovery from the pandemic by 2021. In addition, low interest rates may have supported demand for houses, and housing supply constraints on new construction may have limited the availability of homes for purchase.

Overall, the trends suggest that while the pandemic directly impacted apartment rents, house prices were more resilient, likely due to a combination of demand, supply, and financial factors. The divergence in trends for rents versus prices warrants further research to better understand the dynamics at play.

A key finding in the literature is that suburban housing prices and rents increased while those in the CBD locations decreased during the pandemic in the US (see, for example, Gupta et al. (2022)). However, according to our results, this pattern is not strongly observed in the German housing market. Figure 2.6 shows the relationship between hedonic prices (left panel) and hedonic rents (right panel) and the distance to the CBD for March 2020 and March 2021. Both price and rent gradients have a negative slope, consistent with the key prediction of the AMM model that prices or rents decrease with the distance to the CBD.

However, we do not observe any effects of the pandemic leveling the bid-rent curves, at least not in terms of prices. The price curves appear equally parallel in March 2020 and March 2021 (Figure 2.6 left panel). The slope

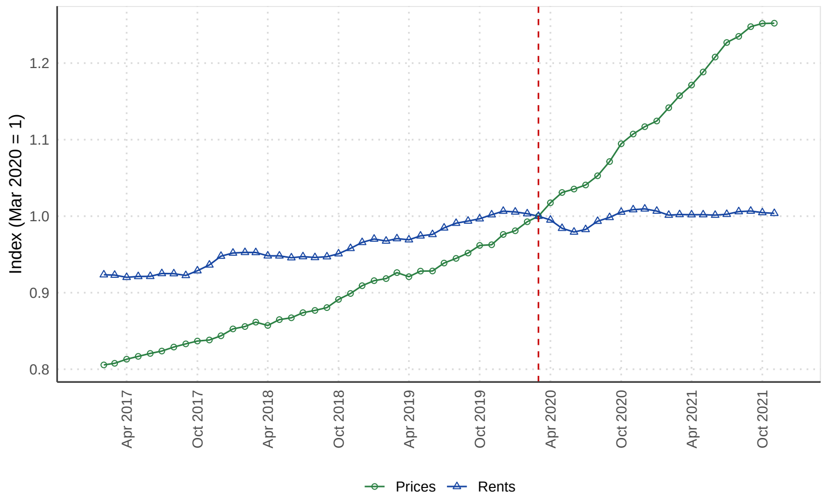
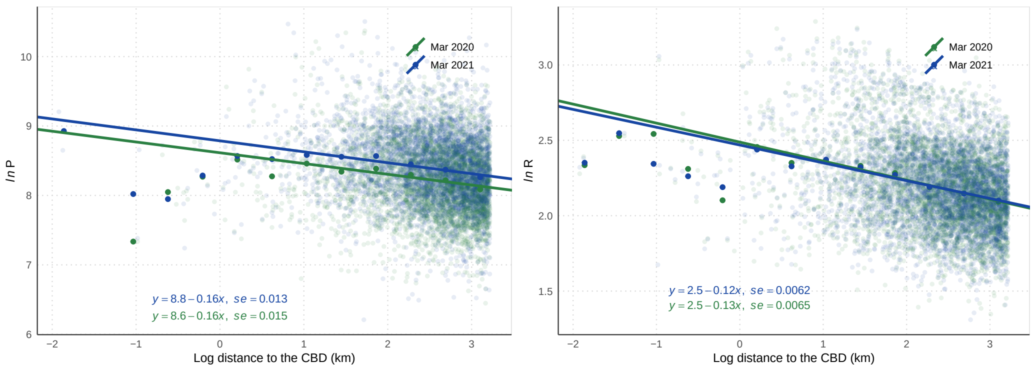


Figure 2.5: Trends of house prices and rents relative to March 2020.

Notes: Note that the data is smoothed using a 3-month moving average.

is slightly flatter for the rent gradient in March 2021 than in March 2020, although the difference is marginal. We also provide additional evidence that strengthens this finding in the Appendix by plotting the change in house prices and rents against the distance to the CBD and comparing the pandemic levels with pre-pandemic values (see Figure 2.B.2 and Figure 2.B.3). We expect suburban areas to experience positive growth in both prices and rents as suburban housing or rental demand increases due to the pandemic. However, there is no clear evidence that this is the case for the German housing market.

The story remains the same when comparing prices before and during the pandemic. Those areas where prices or rents were high pre-pandemic (mostly central and high-density zip codes) should experience less growth during the pandemic than those where prices or rents were lower (mostly the suburban areas), as Gupta et al. (2022) found for the US. As the downward-sloping curves in Figure 2.B.3 indicate, expensive zip codes before the pandemic have shown lower or negative growth, while less expensive zip codes have experienced positive growth in both rents and prices, albeit the patterns are not as strong.



(a) Prices (b) Rents

Figure 2.6: The price and rent gradients for March 2020 and 2021.

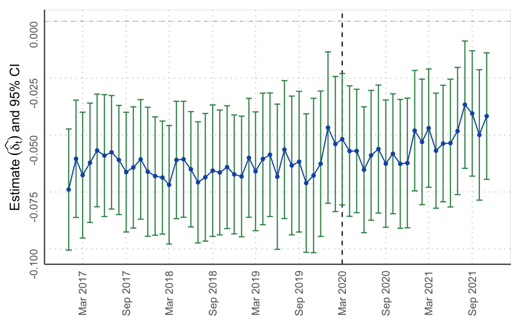
Notes: The figure illustrates the relationship between the distance to the CBD, house prices, and apartment rents, comparing the pre-pandemic (March 2020) and pandemic (March 2021) periods. As expected, in both periods, the gradients are negatively sloping, indicating that prices and rents decrease as the distance from the CBD increases. Lighter points represent zip code values, whereas darker points represent averages within a 2 km distance bins.

Figure 2.8 displays the estimates of the slopes of the gradients specified in Equation 2.8 for each month. The slope of the price gradient shows greater fluctuations in the point estimates but maintains a similar trend as the pre-pandemic time. In contrast, the slope of the rent gradient exhibits a smoother gradual increase over time, starting in late 2019, suggesting that the rent gradient has become flatter during the pandemic.

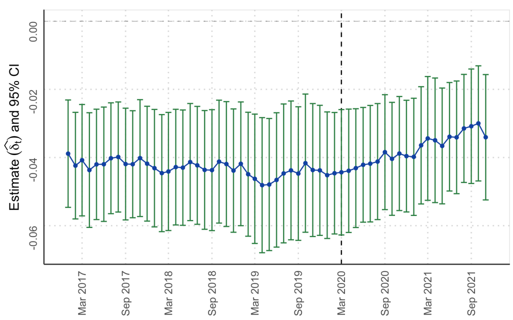
Quantitatively, our estimation results show that the estimated slopes of the gradients are: $(\hat{\delta}_t, \hat{\delta}_{t+1}) = [(-0.052, -0.047); (-0.044, -0.034)]$, where t = March 2020, $t+1$ = March 2021, for prices and rents, respectively. See Table 2.B.1 for the full set of estimates.

That means, from March 2020 to March 2021, the slopes of the gradients have changed by: $\Delta\hat{\delta} = \hat{\delta}_{t+1} - \hat{\delta}_t = (0.005, 0.010)$ for prices and rents, respectively. The positive changes in the slopes show the flattening of the gradients. However, these values are economically insignificant to suggest that the pandemic has caused the same clear flattening of gradients in Germany as observed in the US. For the US, Gupta et al. (2022) found the change in slope for price ($\hat{\delta}$ = .012), and the slope change for rents ($\hat{\delta}$ = 0.032), from December 2019 to December 2020.[10]

Overall, the changes in slope estimates during the pandemic appear small: the decreases in the gradients' slopes are 9.38% and 22.40% for house prices and rents, respectively. This might suggest that the pandemic has led to a flattening of gradients in Germany, but not as clearly and strongly as observed in the US.



(a) Prices



(a) Rents

Figure 2.8: Estimates for the price and rent gradients.

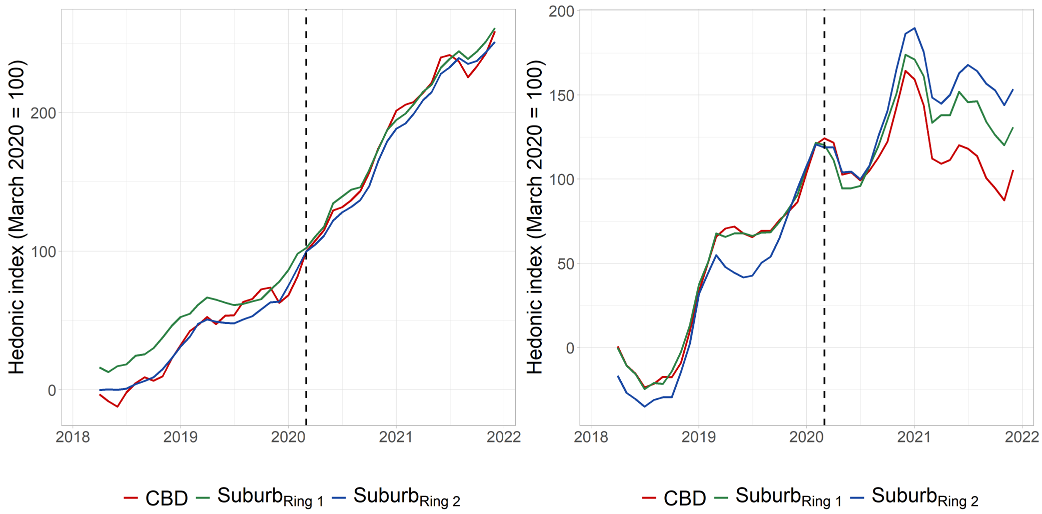
Notes: This figure shows the estimated slopes of the price and rent gradients, which were obtained from the regression in Equation 2.8. $\ln P$ and $\ln R$ are regressed on $\ln \text{dist} \times \text{time}$, with time and LMR fixed effects. The zip code controls include the logarithm of purchasing power, the share of males aged 18-45, and the share of individuals with a German background.

Another approach, as used by Ramani and Bloom (2021), for identifying the donut effect involves dividing the data into CBD and suburban regions and examining the growth of house prices and rents, as specified in Equation 2.9. Figure 2.10 shows the evolution of prices for the CBD (in red) and the two suburban rings (in green/blue) estimated for the full sample.

[10]Gupta et al. (2022) for the US found that the elasticity of house prices to distance decreased from −0.103 in December 2019 to −0.090 in December 2020, with a slope change of ($\hat{\delta}$ = 0.012), resulting in a 37.5% decrease in the steepness of the gradient. Similarly, the elasticity of rents to distance decreased from −0.032 in December 2019 to −0.0001 in December 2020, with a slope change of ($\hat{\delta}$ = 0.032), leading to a 100% decrease in the steepness of the gradient.

The plot shows that the evolution of rents breaks with the onset of the pandemic (right panel Figure 2.10). While rents increased before March 2020, they stagnated shortly after the start of the pandemic. Rents increased again in the summer of 2020 but then decreased for all three groups. At the beginning of 2021, rents in CBDs appear to fall more sharply than in locations further away from the city center. This suggests a delayed donut effect, at least partially and less strongly than in the US.

The evolution for prices is even less pronounced (left panel Figure 2.10). Here, all three groups move in the same direction and show a continuous increase over time.



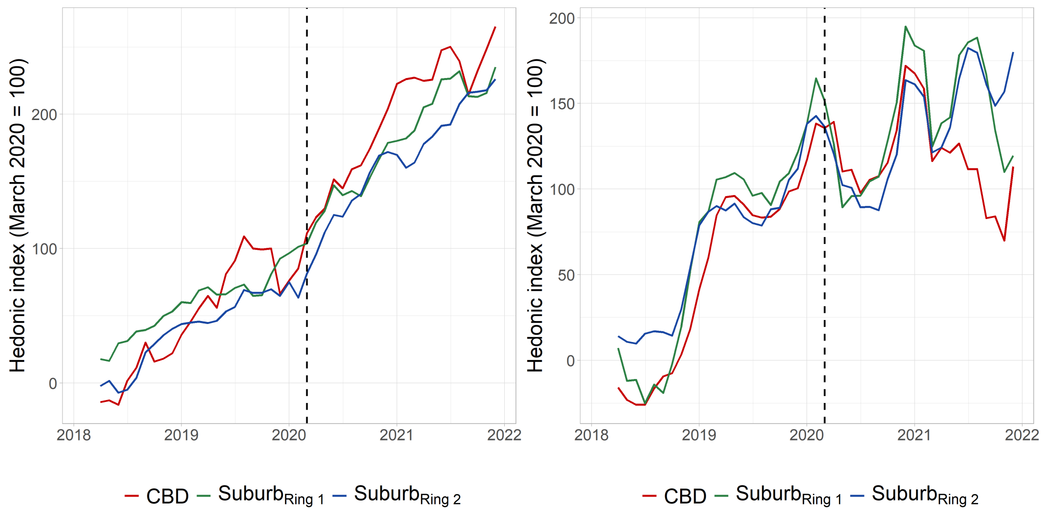
(a) Prices

(a) Rents

Figure 2.10: The donut effect for the full sample.

Notes: The vertical dotted line indicates March 2020, the start of the pandemic.

The donut literature observes that the effect is most prominent in big cities. We test this prediction by re-estimating Equation 2.9 only for the 15 largest German cities with approximately 500,000 residents or more. Figure 2.12 shows that all lines are more volatile for both rents (right panel) and prices (left panel) across all areas. The partial donut effect for rents from the full sample also disappears. Thus, we cannot confirm that the donut effect is strongest in the largest cities in Germany. The indicated donut effect in the full sample comes from medium-sized cities with a population of at least 100,000 but less than 500,000, as shown in Figure 2.B.9 in the Appendix. We also do the same exercise for small cities (below 100,000 in population) and find no evidence of the donut effect (see Figure 2.B.11 in the Appendix).



(a) Prices (a) Rents

Figure 2.12: Donut effect for the 15 largest cities.

Notes: The vertical dotted line indicates March 2020, the start of the pandemic.

The disparities in the pandemic's donut effects on the US and German housing markets can be attributed to institutional and cultural differences between the two markets. The German housing market is characterized by a high degree of stability, a low frequency of home resales, and a high proportion of renters. We discuss these peculiarities in more detail in the Appendix (see Section 2.A), but overall, the German housing market is quite stable and robust, making rapid and potentially short-term changes during the pandemic unlikely.

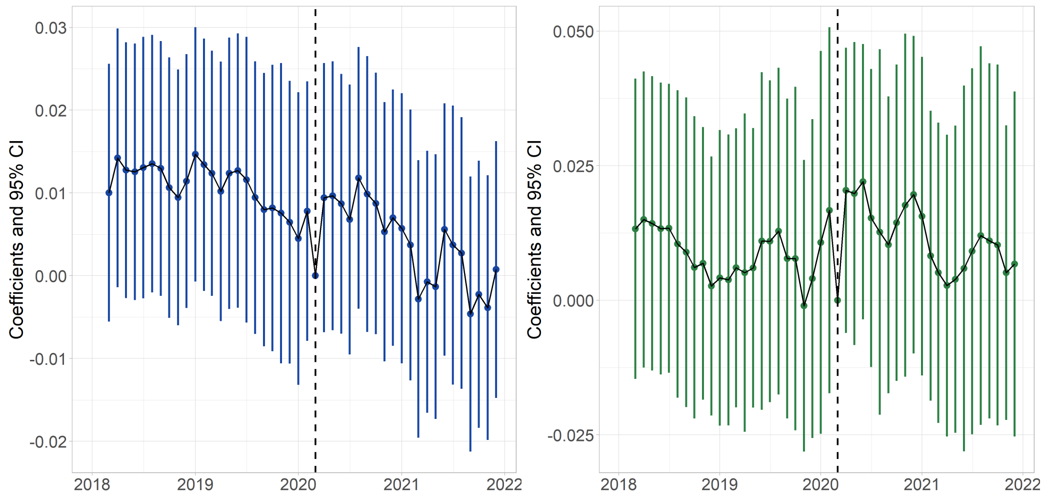
In addition, there is no dramatic change in population levels in either the CBD or the suburbs. We analyzed the population information offered by RWI and Microm (2023), and observed minimal population changes compared to the pre-pandemic levels in 2019 (see Figure 2.B.7 in the Appendix). We also used information on migration across city boundaries provided by Federal Statistical Office (2023). The data shows a very stable pattern of movement into or out of German cities for the years 2017 to 2021 (see Table 2.B.2 in the Appendix). While this data considers movement across cities rather than within cities, which is our focus here, it provides suggestive evidence that residents in Germany do not tend to move frequently and probably less so in uncertain times.

2.5.1 The role of amenities

The literature identifies WFH and amenities as potential channels to explain the housing market results. Due to data limitations and since WFH seems to be weakly valued in Germany (see, for example, Nagler et al. (2022)), we focus on the second channel — the change in the valuation of (urban) amenities.

To assess the valuation of amenities, particularly the potential change during the pandemic, we run Equation 2.10, which includes a continuous time measure with effects relative to March 2020. Figure 2.14 shows the plotted interaction effects for each month for prices and Figure 2.16 shows the effects for rents without spatially restricting the sample. Regardless of the type of dwelling and the amenity considered, there seems to be a slight decreasing trend in the value of amenities after the pandemic, but almost all interactions are insignificant. There is little to no evidence that the value of amenities changed during the pandemic. We have also tested the same analysis for CBD and suburbs in the Appendix, with the same result.

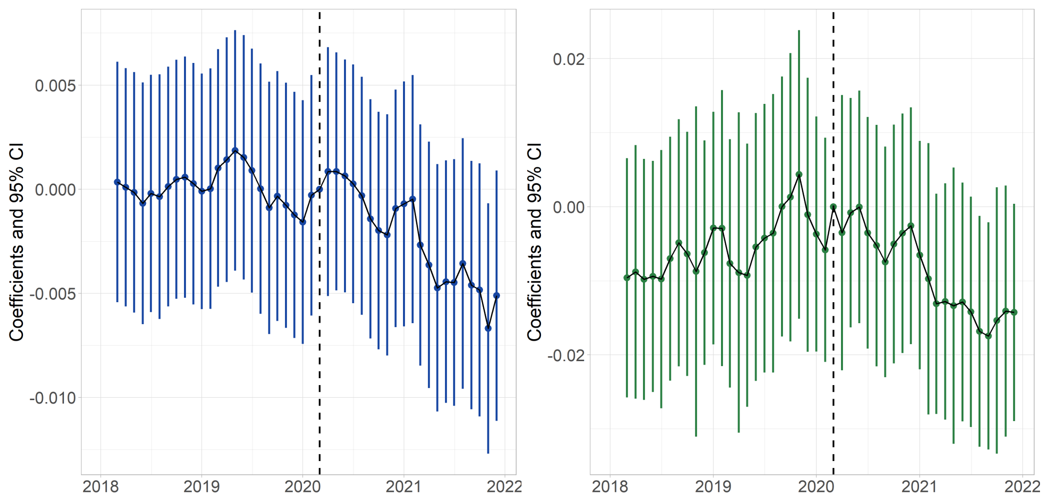
Overall, the results suggest that bid-rent curves in Germany have not flattened, except for rents, where there is only slight evidence. This conclusion is reasonable because WFH is not seen as a compelling job attribute in Germany, the value of amenities remains unchanged, and there is little population movement during the pandemic.



(a) Consumption amenities (a) Environmental amenities

Figure 2.14: Amenities' values vs prices over time - Full sample.

Notes: The vertical dotted line indicates March 2020, the start of the pandemic.



(a) Consumption amenities (a) Environmental amenities

Figure 2.16: Amenities' values over time with respect to rents - Full sample.

Notes: The vertical dotted line indicates March 2020, the start of the pandemic.

2.6 Conclusion

The COVID-19 pandemic has weakened a fundamental tenet of urban economics: the inverse relationship between proximity to the city center and housing prices. However, this conclusion appears to apply mostly to the US housing market and less so to the German housing market, as indicated by the findings of this study.

We used comprehensive zip code-level data on housing prices and rents to examine temporal changes, comparing pre- and post-pandemic periods. We found no strong evidence for the flattening of the bid-rent curve. The absence of the donut effect on prices, consistent with the existing literature, is connected to its forward-looking nature. However, we discovered that during the pandemic, rents in suburbs and low-density zip codes have slightly increased compared to those in the CBD and high-density zip codes.

We analyzed urban amenities to explain the impact of the pandemic on rents, but we did not find any significant effect. Our amenity data, constructed from OSM, shows that the valuation of consumption and environmental amenities remains relatively stable. All findings are consistent across various city center definitions and regional subsets, such as big cities versus small cities.

This leads us to conclude that institutional and structural differences between Germany and the US may contribute to the stability of the German housing market. The German housing market is characterized by extensive governmental support, a large renter population, tax legislation restricting speculative behavior, and low interest rates. Our analysis of population and migration data suggests that residents in Germany are less responsive to location changes related to the pandemic.

Therefore, while the COVID-19 pandemic has undeniably posed challenges globally, its impact on the German housing market, as explored in this study, seems to be less disruptive compared to other countries such as the US. This resilience underlines the effectiveness of the existing structures and policies in Germany's housing market. Further research may be beneficial to fully understand the long-term implications of the pandemic on real estate markets.

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Appendix

2.A The German housing market

The German housing market has a unique structure in Europe. It is characterized by high governmental support, which relies on tools like housing benefits (“Wohngeld”) or the construction of social housing (“sozialer Wohungsbau”). Housing benefits already implemented in 1965 apply to tenants and property owners who use their property themselves. These benefits aim to guarantee a stable living arrangement by lowering the burden of living costs, especially for low-income households. Around 1.5 percent of German households received housing benefits in 2020 (see Federal Ministry for Housing, Urban Development and Building (BMWSB) (2023a), Federal Ministry of Justice (FMJ) (2008)). The government supports the construction of social housing by offering credits with low interest rates. Low-income households can then rent the newly built living space. The government plans to spend one billion Euros annually between 2020 and 2024 for this program (see Federal Ministry for Housing, Urban Development and Building (BMWSB) (2023b)).

The German housing market is characterized by a large rental market, with a high percentage of renters. Over 50 percent of the population rents their living space, the highest value within the European Union (see Federal Statistical Office) (2022)).

In addition, as required by law, sellers of homes who have owned the home for less than ten years must take a significant tax cut on their profit when reselling the home (Federal Ministry of Justice (FMJ), 2023). The legislation aims to prevent speculative behavior that would drive up housing prices even more. It also contributes to a low frequency of change of ownership in the housing market.

The German housing market is remarkably stable, with increasing prices over the last decades. The reasons for this development include the fact that the supply and demand of housing are detached from each other, and the interest rates for mortgages are rather low (see Voigtländer (2022), Deutsche Bank) (2022)).

2.B Additional tables and figures

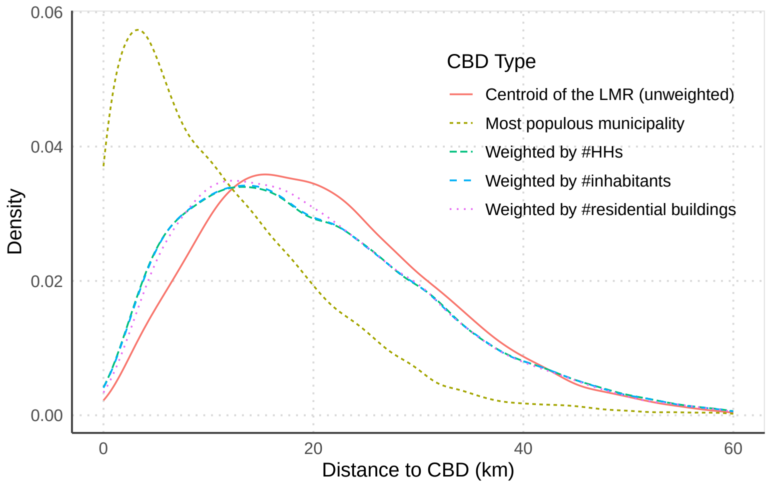


Figure 2.B.1: Density of distance to the CBD by CBD types.

Notes: The figure illustrates the density of distances to the CBD by different types of CBDs. The CBDs are defined based on the geocentroid of the LMR (unweighted), weighted by the number of inhabitants, the number of residential buildings, and the number of households. The fourth type is based on the most populous municipality's centroid in the county, similar to Ahlfeldt et al. (2020).

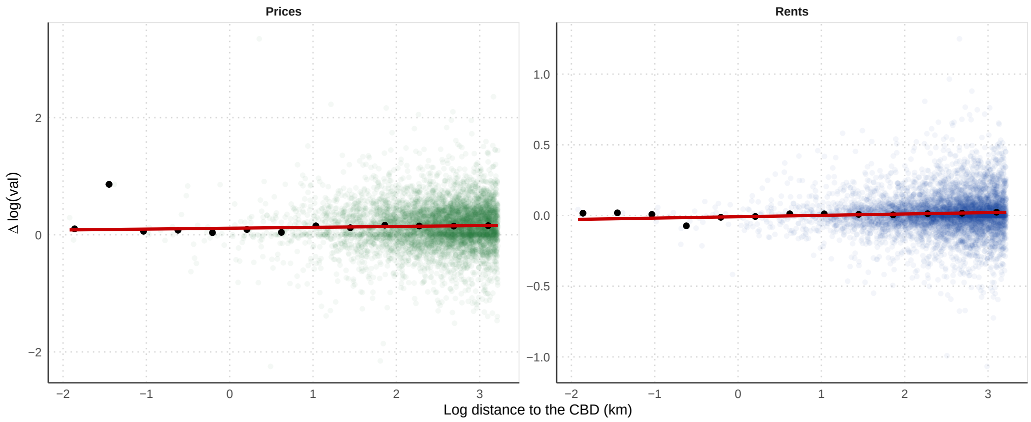


Figure 2.B.2: Changes in prices/rents against distance to the CBD.

Notes: The figure illustrates the relationship between the distance to the CBD and changes in log house prices and apartment rents from the pre-pandemic (March 2020) to the pandemic (March 2021) periods. The expected pattern is upward-sloping curves, indicating that prices and rents tend to increase as the distance from the CBD increases. However, this pattern cannot be observed here, as the curves appear to be almost horizontal. Lighter points represent zip code values, whereas darker points represent averages within a 2 km distance bins.

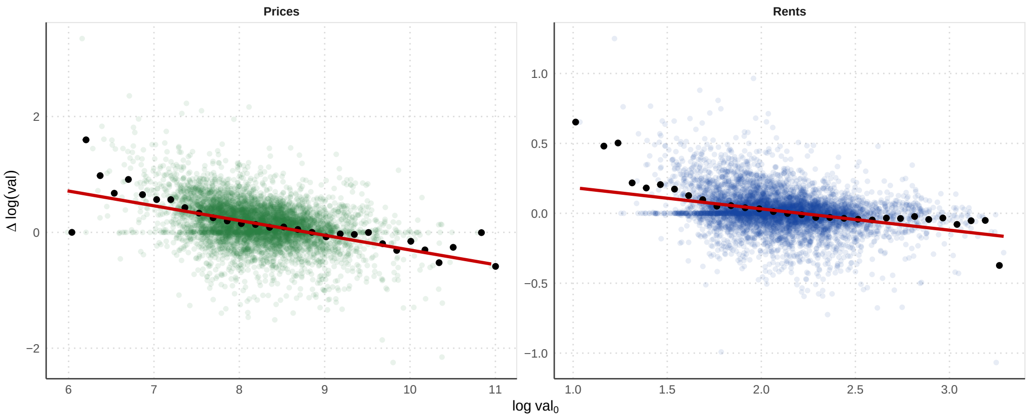


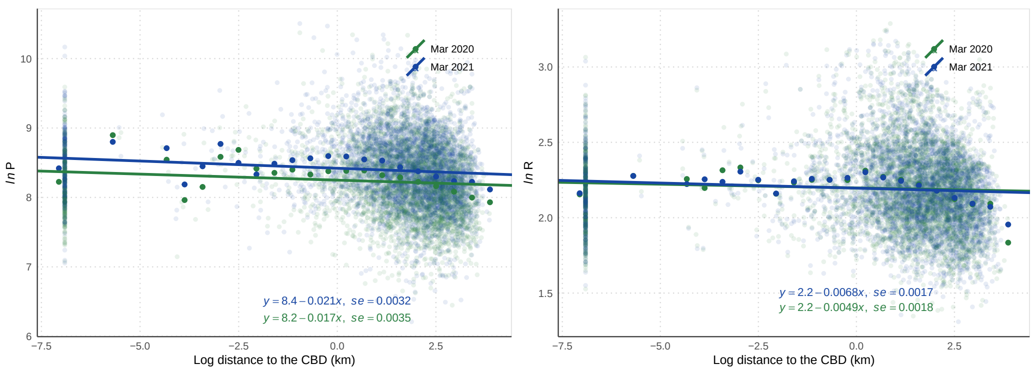
Figure 2.B.3: Changes in prices/rents against the pre-pandemic levels.

Notes: The figure illustrates the relationship between pre-pandemic levels and changes in log house prices and apartment rents from the pre-pandemic period (March 2020) to the pandemic period (March 2021). The expected trend is a downward slope, indicating that zip codes with high prices and rents before the pandemic would experience lower or negative changes. This pattern is evident in the graph, with fitted lines sloping downwards for both prices and rents. Lighter points represent zip code values, whereas darker points represent averages within a 2 km distance bins.

Table 2.B.1: Slope estimates of the housing price and rent gradients.

	$\ln P$ (1)	$\ln R$ (2)
Jan2019 × ln dist	-0.0682*** (0.0134)	-0.0418*** (0.0092)
Feb2019 × ln dist	-0.0600*** (0.0132)	-0.0449*** (0.0092)
Mar2019 × ln dist	-0.0659*** (0.0132)	-0.0462*** (0.0096)
May2019 × ln dist	-0.0586*** (0.0137)	-0.0479*** (0.0098)
Jul2019 × ln dist	-0.0564*** (0.0153)	-0.0447*** (0.0103)
Aug2019 × ln dist	-0.0634*** (0.0154)	-0.0438*** (0.0103)
Sep2019 × ln dist	-0.0617*** (0.0156)	-0.0447*** (0.0099)
Nov2019 × ln dist	-0.0678*** (0.0172)	-0.0437*** (0.0099)
Feb2020 × ln dist	-0.0539*** (0.0150)	-0.0446*** (0.0090)
Apr2020 × ln dist	-0.0570*** (0.0145)	-0.0439*** (0.0092)
May2020 × ln dist	-0.0570*** (0.0137)	-0.0431*** (0.0088)
Jul2020 × ln dist	-0.0589*** (0.0144)	-0.0418*** (0.0086)
Aug2020 × ln dist	-0.0562*** (0.0142)	-0.0412*** (0.0086)
Sep2020 × ln dist	-0.0625*** (0.0141)	-0.0384*** (0.0085)
Oct2020 × ln dist	-0.0582*** (0.0133)	-0.0404*** (0.0084)
Nov2020 × ln dist	-0.0626*** (0.0143)	-0.0388*** (0.0085)
Dec2020 × ln dist	-0.0623*** (0.0144)	-0.0396*** (0.0083)
Jan2021 × ln dist	-0.0481*** (0.0134)	-0.0398*** (0.0087)
Apr2019 × ln dist	-0.0605*** (0.0146)	-0.0481*** (0.0100)
Jun2019 × ln dist	-0.0683*** (0.0161)	-0.0466*** (0.0100)
Oct2019 × ln dist	-0.0711*** (0.0154)	-0.0416*** (0.0103)
Dec2019 × ln dist	-0.0626*** (0.0162)	-0.0438*** (0.0097)
Jan2020 × ln dist	-0.0467*** (0.0168)	-0.0452*** (0.0094)
Mar2020 × ln dist	-0.0518*** (0.0146)	-0.0443*** (0.0093)
Jun2020 × ln dist	-0.0652*** (0.0140)	-0.0421*** (0.0085)
Feb2021 × ln dist	-0.0530*** (0.0139)	-0.0364*** (0.0087)
Mar2021 × ln dist	-0.0469*** (0.0131)	-0.0344*** (0.0092)
Apr2021 × ln dist	-0.0569*** (0.0128)	-0.0349*** (0.0092)
May2021 × ln dist	-0.0537*** (0.0129)	-0.0366*** (0.0086)
Jun2021 × ln dist	-0.0535*** (0.0142)	-0.0339*** (0.0081)
Jul2021 × ln dist	-0.0482*** (0.0141)	-0.0341*** (0.0084)
Aug2021 × ln dist	-0.0367** (0.0141)	-0.0315*** (0.0080)
Sep2021 × ln dist	-0.0405*** (0.0139)	-0.0308*** (0.0085)
Oct2021 × ln dist	-0.0500*** (0.0145)	-0.0300*** (0.0085)
Nov2021 × ln dist	-0.0417*** (0.0140)	-0.0340*** (0.0093)
Observations	253,828	235,270
R^2	0.76713	0.80604
Within R^2	0.21043	0.32698
LMR fixed effects	✓	✓
Time fixed effects	✓	✓

Notes: We control for the share of males aged 18-45, the share of German background, and the logarithm of total purchasing power at the zip code level. The estimates for 2017 and 2018 are not shown to fit the table. The standard errors are clustered at the level of the LMR.



(a) Prices

(b) Rents

Figure 2.B.4: The price and rent gradients for March 2020 and 2021.

Notes: The figure illustrates the relationship between the distance to the CBD, house prices, and apartment rents, comparing the pre-pandemic (March 2020) and pandemic (March 2021) periods. The CBD is the most populous municipality in the county. As expected, in both periods, the gradients are negatively sloping, indicating that prices and rents decrease as the distance from the CBD increases. Lighter points represent zip code values, whereas darker points represent averages within a 2 km distance bins.

Table 2.B.2: Average moving statistics across German cities

Year	Move-in	Move-out	Net migration
2017	494.72	460.90	33.83
2018	496.25	462.55	33.70
2019	501.92	473.17	28.75
2020	455.52	434.12	21.39
2021	469.87	439.44	30.43

Notes: The table shows the average number of move-in and move-out statistics for German cities from 2017 to 2021. The difference between both columns is listed as net migration in the last column.

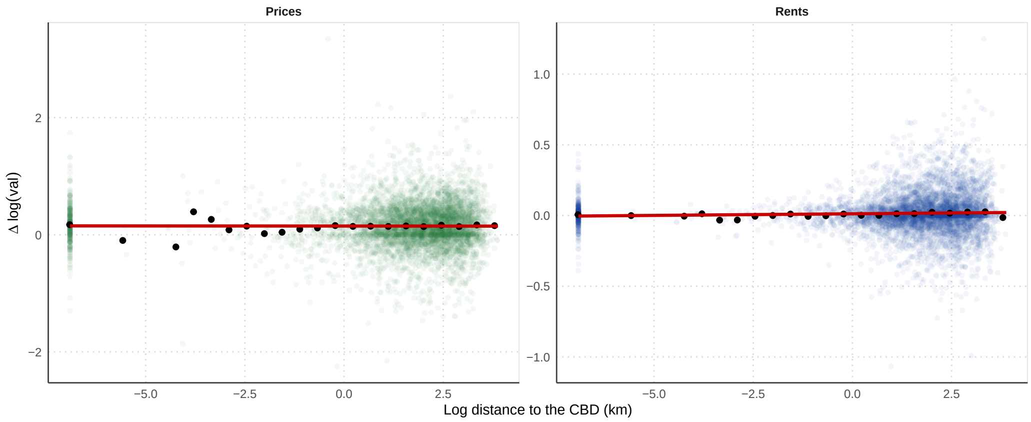
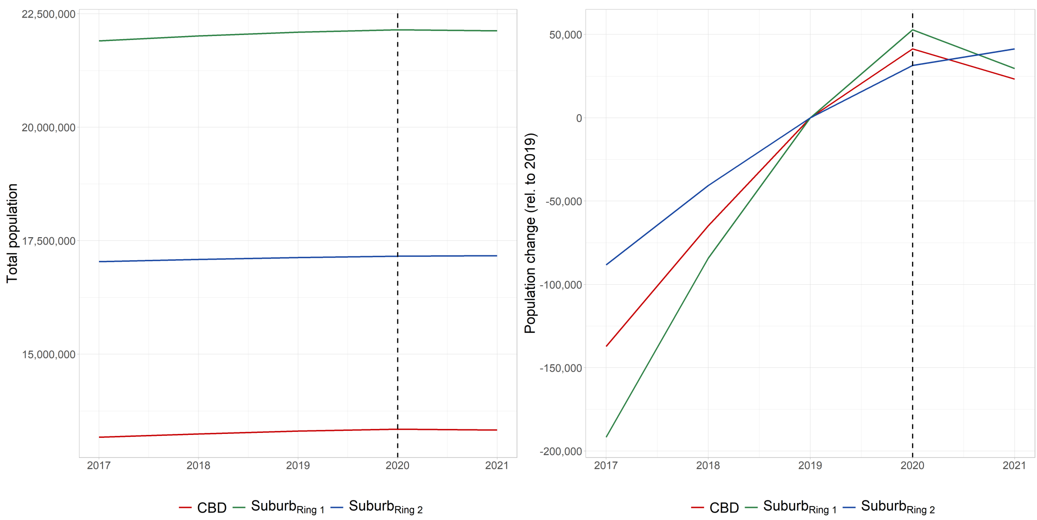


Figure 2.B.5: Changes in prices/rents against distance to the CBD.

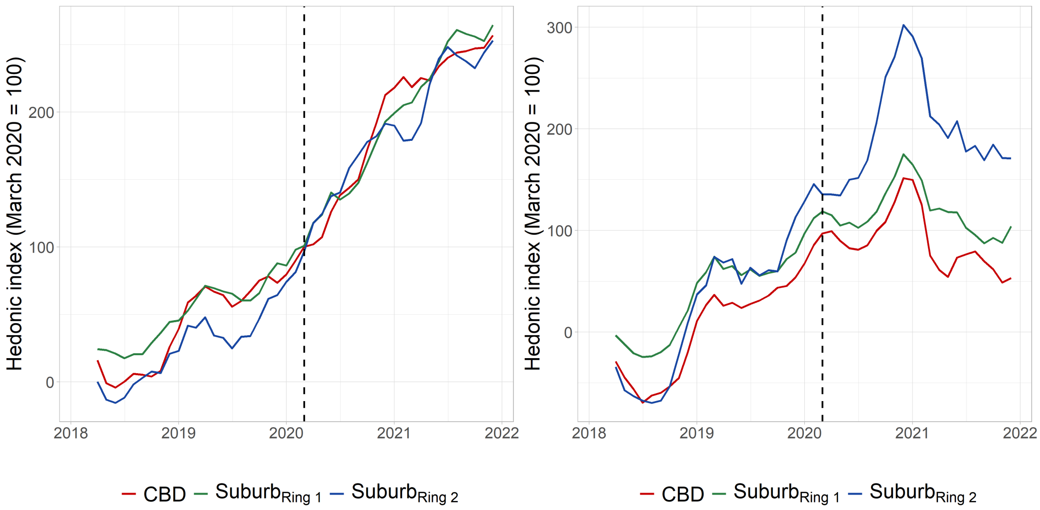
Notes: The figure illustrates the relationship between the distance to the CBD and changes in log house prices and apartment rents from the pre-pandemic (March 2020) to the pandemic (March 2021) periods. The CBD is the most populous municipality in the county. The expected pattern is upward-sloping curves, indicating that prices and rents tend to increase as the distance from the CBD increases. However, this pattern cannot be observed here, as the curves appear to be almost horizontal. Lighter points represent zip code values, whereas darker points represent averages within a 2 km distance bins.



(a) Total population (a) Population change

Figure 2.B.7: Population levels across CBD and suburban areas.

Notes: The figure shows the total population for the CBD and suburban locations from 2017 to 2021 (left panel) and the population change relative to 2019 (right panel).

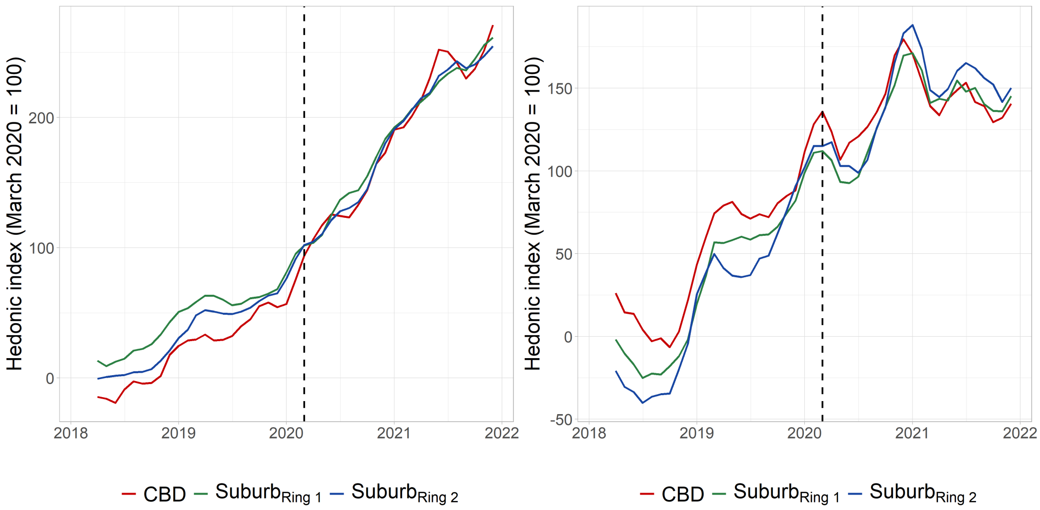


(a) Prices

(a) Rents

Figure 2.B.9: The donut effect for medium-sized cities.

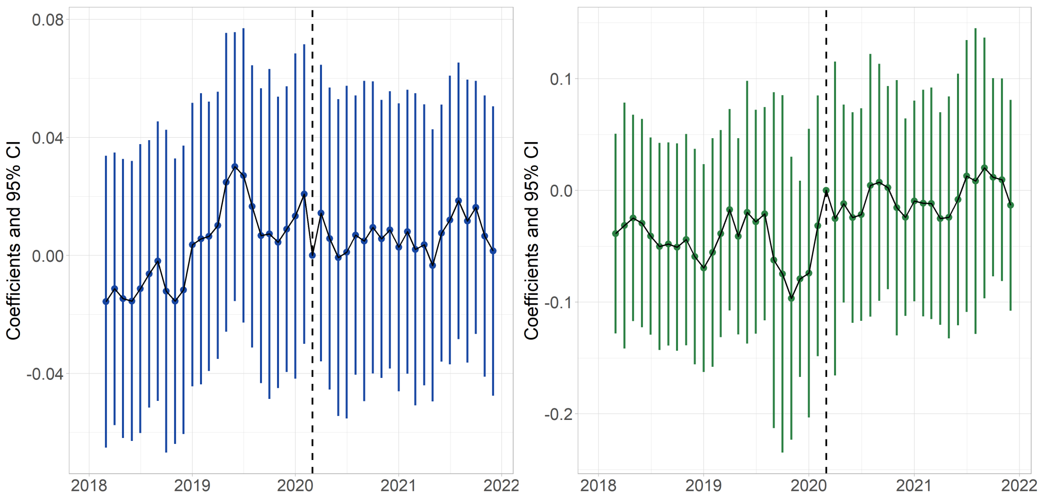
Notes: Medium-sized cities are classified as having a population between 100,000 and 500,000. The vertical dotted line indicates March 2020, the start of the pandemic.



(a) Prices   (a) Rents

Figure 2.B.11: The donut effect for small cities.

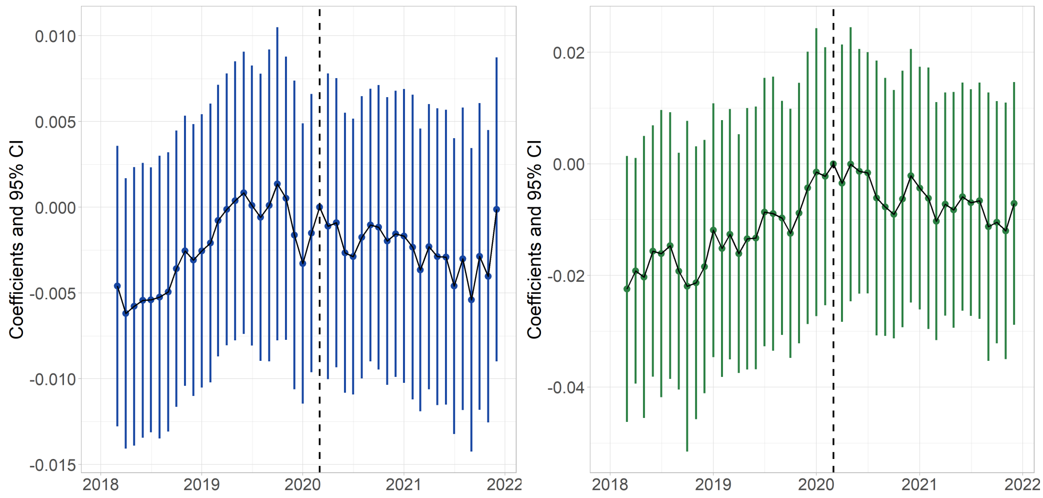
Notes: Small cities have a population of 100,000 or less. The vertical dotted line indicates March 2020, the start of the pandemic.



(a) Consumption amenities   (a) Environmental amenities

Figure 2.B.13: Amenities' values vs prices over time - CBD locations.

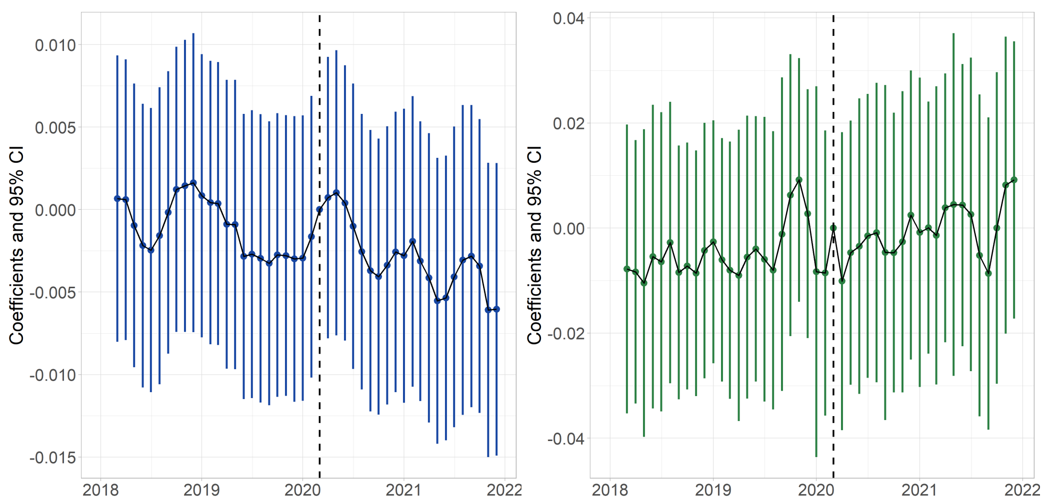
Notes: The vertical dotted line indicates March 2020, the start of the pandemic.



(a) Consumption amenities (a) Environmental amenities

Figure 2.B.15: Amenities' values over time with respect to rents - CBD locations.

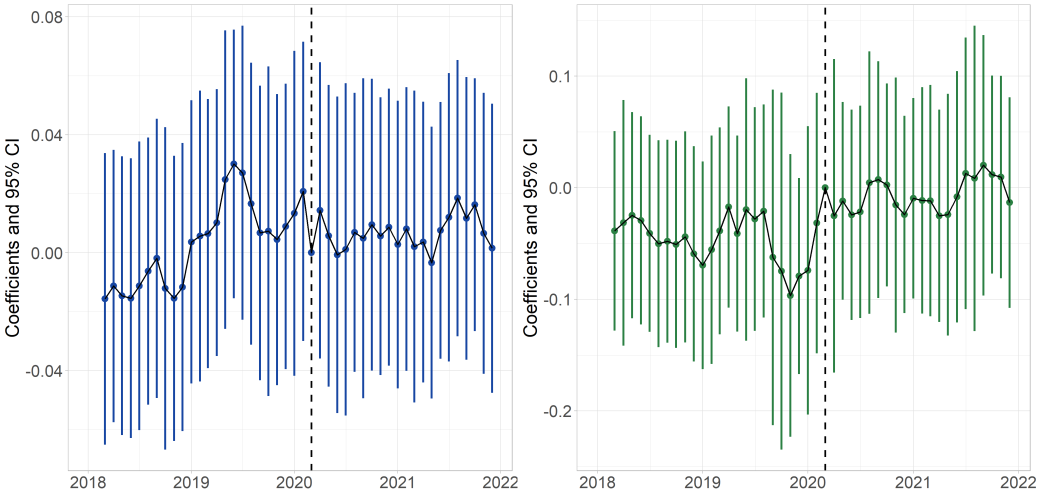
Notes: The vertical dotted line indicates March 2020, the start of the pandemic.



(a) Consumption amenities (a) Environmental amenities

Figure 2.B.17: Amenities' values over time with respect to rents - Suburban Ring 1.

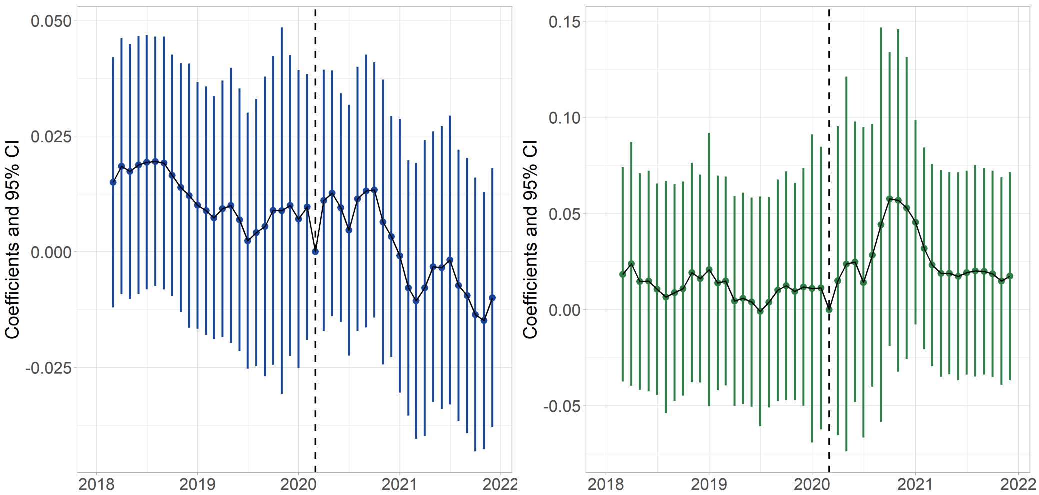
Notes: The vertical dotted line indicates March 2020, the start of the pandemic.



(a) Consumption amenities (a) Environmental amenities

Figure 2.B.19: Amenities' values vs prices over time - CBD locations.

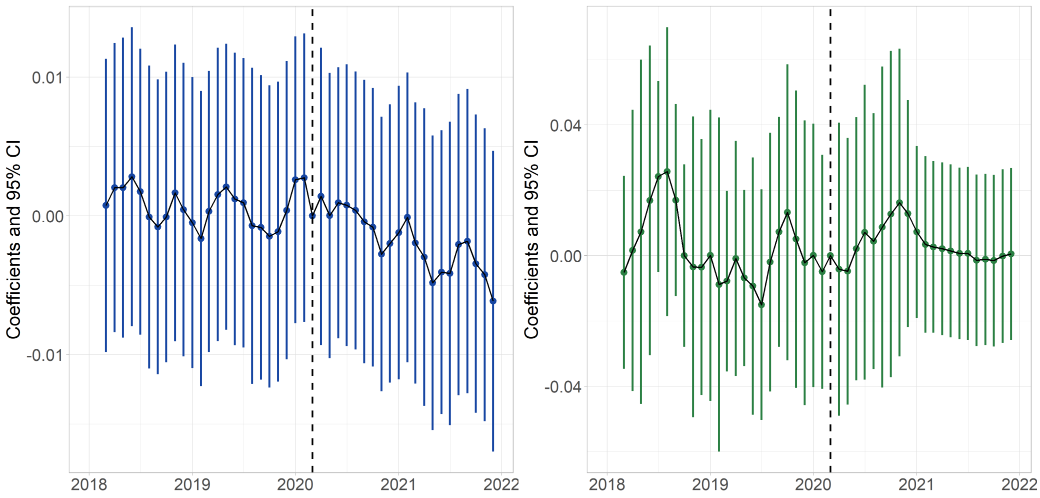
Notes: The vertical dotted line indicates March 2020, the start of the pandemic.



(a) Consumption amenities (a) Environmental amenities

Figure 2.B.21: Amenities' values vs prices over time - Suburban Ring 2.

Notes: The vertical dotted line indicates March 2020, the start of the pandemic.



(a) Consumption amenities

(a) Environmental amenities

Figure 2.B.23: Amenities' values over time with respect to rents - Suburban Ring 2.

Notes: The vertical dotted line indicates March 2020, the start of the pandemic.

Chapter 3

Testing the Gradient Predictions of the Monocentric City Model in Addis Ababa

Abstract

This study presents new empirical evidence for the monocentric city model in a developing country, using unique real estate data for Addis Ababa in 2017-2024 time period. The findings confirm two key predictions of the model: the negative rent and negative structural density gradients. Both house prices and rents decrease as one moves away from the center of Addis Ababa. Using building footprint datasets, the study also shows that the structural density, measured by building height, significantly decreases with distance from the Central Business District (CBD). This study provides a comprehensive georeferenced real estate dataset for Addis Ababa, the first of its kind.

JEL codes: R14
Keywords: Monocentric city model, Rent gradient, Structural density gradient, Housing data, Addis Ababa

3.1 Introduction

The monocentric city model, also known as the AMM, developed by Alonso (1964), Mills (1967), and Muth (1969) is a foundational model in urban economics that effectively explains the spatial structure of cities.[1] It has been extensively used to study the internal features of cities in terms of the spatial distribution of housing prices, incomes, population density, land use, and other urban variables. The model makes several key predictions, including that land and property values, population density, and building heights should decline with distance from the city center.

Despite the model's widespread theoretical use, research on its empirical relevance is less advanced. This is partly due to limited data availability in the past, as noted by Duranton and Puga (2015) (see also Liotta et al. (2022)). Moreover, most empirical studies focus on American cities, with little known about cities in other countries. The empirical relevance of the model, especially in the context of rapidly growing cities in the developing world, remains an open question.

Addis Ababa provides an interesting case study to test the model's applicability in cities in developing countries. Addis Ababa, the capital and the largest city of Ethiopia has experienced rapid population growth and spatial expansion in recent decades.[2] Empirically analyzing the monocentric model's predictions requires granular spatial data on land and property prices, population density, and other outcomes of interest. Obtaining administrative urban data in developing countries is challenging, especially

[1]It is also often called the Standard Urban Model (SUM). The monocentric city model remains a workhorse model in urban economics for analyzing the spatial structure of cities. Since the late 1960s, the model has undergone several improvements and extensions to capture the realities of cities. The original version of the model has several simplifying assumptions and limitations. However, the model's latest iteration allows for heterogeneous preferences and incomes, endogenous housing consumption, polycentric cities, nonlinear commuting costs, and other improvements. See Brueckner (1987) and Duranton and Puga (2015) for a review.

[2]Addis Ababa is a typical developing city, considering its rapidly growing physical and population sizes, and its social and economic relevance for Ethiopia. See Section 3.A in the Appendix for background information on Addis Ababa.

in Ethiopia. The most recent census in Ethiopia dates back to 2007.

This study provides new evidence on the empirical relevance of the monocentric city model in Addis Ababa using a unique urban dataset. The AMM model has five gradient predictions: property and land prices, structural and population density decrease with distance to the Central Business District (CBD), while dwelling size increases (Brueckner, 1987; Duranton and Puga, 2015). These predictions are well-supported in the US and the empirical evidence is less established in other contexts. This study generates data to validate some of these predictions and provides evidence for the AMM model in a developing country context, a topic not previously explored.

Based on the data, we find empirical support for the house price and rent gradients. House prices and rents strongly decrease as the distance from the central business district (CBD) increases. Our rent gradient estimates are similar to those of Liotta et al. (2022), who provide average estimates for a global sample of cities, including Addis Ababa. However, their Addis Ababa estimates are inconclusive due to data limitations, with a sample size of 400 observations. This paper presents reliable rent gradient estimates for Addis Ababa using panel and cross-sectional settings, from 2017 to 2024, based on more than 72,665 unique property listings. In addition, the results show that the rent gradient is steeper for rents than for house prices, suggesting that rent is more sensitive to distance to the CBD than home purchases. This phenomenon likely stems from the city's inadequate public transport system, which causes congestion and longer commutes, thereby increasing the demand for rentals near the CBD.

For analyzing the gradient predictions of the model, this study generates real estate data for Addis Ababa on house prices and rents, using web scraping from online real estate providers. The study is the first to create a detailed georeferenced dataset of property prices for Addis Ababa. The dataset provides information on house and apartment prices and rents, with the standard property characteristics for 2017-2024 time period. The study documents the process of generating data in a data-sparse environment such as Addis Ababa which can serve as a valuable resource for future research. Additionally, it leverages building footprint datasets to compute building characteristics (such as height, volume, area, and count) to analyze the structural density gradient in Addis Ababa.

Another key prediction of the model is the structural density or (the capital intensity in housing) gradient. This prediction has not been studied in comparison to house price and population density gradients (McMillen, 2006). Satellite-based building footprint datasets offer a promising approach to analyzing structural density gradients at a finer scale. For example, the German Aerospace Center (DLR) offers global-scale building footprint datasets called World Settlement Footprint (WSF) 3D and WSF 2019v1 that can be utilized to study building density gradients in cities. In addition, Google recently released the Open Buildings dataset, containing polygons that describe buildings' footprints on the ground in cities across Africa, South and Southeast Asia, Latin America, and the Caribbean.

Leveraging these datasets, this study provides new evidence on the structural density and dwelling size gradients in Addis Ababa. The study finds that structural density, using building height, strongly decreases with distance to the CBD, consistent with the prediction of the model. The data shows taller buildings are highly clustered in the city center. Alternatively, using building volume or count, from both WSF and Open Buildings datasets for the latter, shows the same pattern. For dwelling size, we use the building area (floorspace) as a proxy. The dwelling size gradient, that we should observe that wider buildings farther from the CBD, is negative, contradicting the prediction of the model. Unlike cities in developed countries where suburban housing demand is higher among high-income households, in Addis Ababa they live in central areas of the city, while the suburbs remain underdeveloped. These central areas feature larger residential properties. Consequently, the inverted dwelling size gradient may be a characteristic of Addis Ababa. To better understand this gradient, the study emphasizes the importance of analyzing the distribution of high-income and low-income residents within the city.

To summarize, the monocentric model is well-supported theoretically and empirically, especially in cities in developed countries. This study explores its relevance in Addis Ababa, a rapidly developing city, offering new evidence on rent and structural gradients, based on a unique dataset. The results align with the monocentric model and studies in developed countries. They indicate that the model effectively explains Addis Ababa's urban structure, despite its different form and growth patterns compared to cities in the developed world.

The rest of the paper is organized as follows: Section 3.2 offers a review of empirical studies related to the gradient predictions of the monocentric city model. Section 3.3 presents a simple conceptual framework to derive the gradients that can be examined using the data. The process of data generation and the resulting descriptive results are detailed in Section 3.4. Section 3.5 is dedicated to the econometric estimation of the gradients. Finally, Section 3.6 concludes the paper.

3.2 Literature Review

Several key studies since the 1970s have empirically examined the spatial variation of property prices within urban agglomerations, predominantly in the US. The evidence on the negative rent gradient varies across cities due to factors such as polycentricity (the presence of multiple business centers), local amenities, and dwelling attributes. Generally, rent or land price gradients tend to be negative, aligning with the AMM model. Yet, in some polycentric cities, gradients can be flat or positive, challenging the model's assumptions.

Yinger (1979) discovered a negative gradient in Madison, which was not present in St. Louis due to its polycentric structure. McDonald and Bowman (1979) observed a negative land price gradient near Chicago's CBD, but a positive gradient further away, which contradicts the prediction of the monocentric city model. They attributed this to factors like polycentricity, racial segregation, and disamenities, including pollution and congestion. McMillen (1996) demonstrated that until 1960, the distance to the CBD was a strong determinant of Chicago's land values. However, the subsequent establishment of O'Hare Airport introduced a polycentric aspect.

In addition to accessibility, location-specific amenities and dwelling characteristics significantly impact rents and land values, altering the gradient shape. Cheshire and Sheppard (1995) emphasized their role in determining rents in Reading and Darlington in the UK. This is also iterated by Ahlfeldt (2011) which shows that considering structural, neighborhood amenities, and gravity-based employment accessibility measures enhanced the monocentric model's performance in polycentric Berlin, more details are provided below.

Rappaport (2014) extends the monocentric model by incorporating leisure into the utility function, while assuming a fixed labor supply from workers, to amplify the marginal disutility associated with longer commutes. The study uses a numerical model calibrated to Portland, Oregon, showing that this approach can closely match observed commute times, the geographic distribution of workers' residences, and various gradients of population density, land price, and house price. The findings suggest that despite the criticisms of monocentric models, such as their failure to include leisure explicitly or to account for non-centralized employment patterns, they remain a valuable tool for understanding urban land use.

Among the few non-US studies is Ahlfeldt (2011), which empirically evaluates employment accessibility as a determinant of urban land prices in Berlin. The study found that the monocentric model can still perform satisfactorily when accounting for structural and neighborhood characteristics. However, gravity-based employment accessibility measures provide a more comprehensive explanation of residential land price gradients. These measures capture the dispersed nature of employment centers in modern cities, overcoming the monocentric assumption. The log-linear form of the negative CBD-land-gradient becomes insignificant when gravity variables are introduced. The study shows that a 1% improvement in employment accessibility generated by individual or public transport raises land prices by about 0.22% or 0.04%, respectively.

A recent study by Schmidt et al. (2021) examines the monocentric city model's relevance in explaining urban spatial patterns in German metropolitan areas, traditionally recognized for their polycentric urban forms, regional disparities, and instances of urban shrinkage. The study uses data from 92 metropolitan areas in 2000 and 2014, in both cross-sectional and panel settings to assess the model's validity in Germany. Results show that similar to observations in the US, the monocentric model works well in Germany, showing a strong link between population and urban area size. However, findings on personal income, land prices, and transportation costs are mixed. This research suggests that while the monocentric model is useful for analyzing urban spatial structures in Germany, adjustments are needed due to regional differences and urbanization factors.

Other studies emphasize the need to account for city-specific factors. Analyzing urbanization gradients in Vienna and Amsterdam, Suarez-Rubio and Krenn (2018) found that while both cities exhibit negative population density gradients and monocentric structures, the specific spatial patterns differ. Liu (2019) examines housing price gradients in US cities from 1985-2013 and finds that price appreciation was greater in city centers than suburbs over time, suggesting the steepening of house price gradients in both markets over time. The house price gradient increased in slope fastest in big cities with high GDP and large population. Kulish et al. (2012), focusing on Australian cities, provides evidence that the monocentric model is consistent with empirical regularities observed in large Australian cities. The study examines urban structure including density, the price of land and housing, suggesting that the model's predictions align with the patterns seen in these cities.

Recent studies have empirically tested the gradient predictions of the monocentric city model in broad cross-sections of global cities. Liotta et al. (2022) analyzes a unique dataset of 192 cities and finds that all exhibit the expected negative density gradient and 87% exhibit the expected negative rent gradient with respect to distance from the city center. Quantitatively, a 1% decrease in income net of transportation costs leads to a 21% decrease in densities and a 3% decrease in rents per square meter. The study also observes that cities tend to expand when they are wealthier and more populated, and when transportation or farmland is cheaper. These results suggest that the model captures well the inner structure of many cities worldwide.

The sample of studies reviewed above strongly support the monocentric model empirically, demonstrating its relevance across diverse urban settings and its effectiveness in explaining city structures. The model's ability to explain the spatial distribution of population densities, rents, and housing prices across different cities and over time shows its enduring relevance in urban economics.

This study contributes to this large body of literature by examining Addis Ababa's urban context, presenting new evidence on the model's relevance in a developing city by constructing a unique dataset for this purpose. This study estimates the rent gradient for house prices and rents. Additionally, it provides empirical estimates for the structural density gradient, which represents the decline in capital intensity in housing (building heights). The structural density gradient has not been as extensively analyzed as population densities or land values (McMillen, 2006).

3.3 Conceptual Framework

The study of land use is crucial in economic theory and originated in the form of the theory of agricultural rent presented by David Ricardo and J.H. von Thünen in the 19th century. Ricardo proposed that the rental difference between highly fertile and less fertile land equals their revenue difference. The most fertile land is used first, with less fertile land utilized as agricultural demand rises, and land near the market incurs lower transport costs. Using a simple farming model, von Thünen further developed the theory of location differential rent. He showed that crops requiring less transport are grown farther from the marketplace, while crops with higher transport costs are cultivated closer. Different agricultural land uses compete for land around the marketplace, with land going to the highest bidder. Rent for each crop is based on transportation cost savings compared to distant sites, and remote lands yield no savings and no rent (Alonso, 1964; Duranton and Puga, 2015).

These early insights not only advanced the study of land use but also continued to influence present-day analysis, serving as the foundation for modern land use theory in urban economics. The modern urban land use theory originates from the seminal works of Alonso (1964), Mills (1967), and Muth (1969), forming what is known in the urban economics literature as the Alonso-Mills-Muth (AMM) model. The model provides a comprehensive framework for understanding the spatial structure of cities, focusing on variables such as property prices, population density, and structural density. The model is built on the premise that commuting cost differences within an urban area must be balanced by differences in the price of living space, leading to spatial variation in urban land use and building heights. This model integrates urban transportation, land use, and population patterns to explain urban structures. It highlights the significance of the CBD in shaping residential areas. At its core, the model predicts that housing prices or rents are decreasing functions of distance to the CBD. As Glaeser (2008) notes, the rent gradient is the key prediction of the model. Structural and population density are also negatively associated with distance to the CBD.

Brueckner (1987) presents a unified treatment of the monocentric city model. The author explains the power of this foundational urban economics framework to explain the observed regularities in urban areas, such as the concentration of taller buildings in city centers and the spatial variation in building heights both within and across cities. This model is pivotal in understanding the economic forces shaping urban spatial structures, particularly how commuting costs and the price of housing interact to determine the distribution of building heights and urban density. Key to the AMM model is the concept that commuting costs create a compensating differential in house prices, which in turn influences the spatial structure of cities. The model suggests that higher commuting costs for suburban residents are offset by lower prices for housing, thereby determining the density and height of buildings in different parts of a city. This framework has been instrumental in explaining the gradient of building heights from urban centers to suburban areas and the differences in urban structures between larger and smaller cities. With a review of subsequent studies that adapt and expand the model's assumptions to capture more nuanced and realistic aspects of urban spatial dynamics, the paper underscores the model's enduring relevance and adaptability in urban economic research.

A recent work of Duranton and Puga (2015) also offers a comprehensive overview of the urban land use theory of the model, highlighting the model's adaptability to account for polycentricity and various forms of urban heterogeneity. Their analysis underscores key empirical implications for urban development patterns, with empirical insights from Paris.

3.3.1 A simple version of the AMM model

Based on Brueckner (1987) and Duranton and Puga (2015), we derive the AMM model's gradients relevant to the analysis in this paper, house price, rent, and structural density gradients. The motivation for doing so is to demonstrate quantitatively, with simple equations, the relationship between these urban variables and the distance to the CBD, given the assumptions, parameters, and the other variables of the model.

The simplest version of the model has several simplifying assumptions, such as a monocentric city, homogeneous residents, and linear commuting costs. In the city, all production and consumption happen at one point in the CBD. This central point pins down all other locations, with x representing the distance to the CBD. All residents are employed and commute to the CBD for work, incurring commuting costs that increase linearly with x: τx, $\tau > 0$. All residents are identical in all aspects; they have identical preferences, earn equal wages w, and are freely mobile within the city.

Residents consume housing h, measured in floorspace in square meters, and a composite non-housing good q to maximize utility $V(h, q)$. The price of housing varies across locations $p(x)$, while the price of the consumption good is constant throughout the city and is normalized to one.

Let's represent the preferences of residents with a Cobb-Douglas utility function:

$$V(q, h) = q^{1-\alpha} h^{\alpha},$$

where $\alpha \in (0, 1)$. Each resident chooses housing and consumption subject to its budget constraint: $q + \tau \cdot x + p(x)h = w$.

By substituting for q using the budget constraint, we can turn the utility maximization problem of the resident into a univariate problem of h:

$$\max_{\{h\}} V(h) = (w - \tau x - p(x)h)^{1-\alpha} h^{\alpha}. \tag{3.1}$$

Solving this problem yields the demand functions for h and q:

$$\begin{aligned} \frac{dV}{dh} &= -V_q \cdot p(x) + V_h = 0 \\ \implies p(x) = \frac{V_h}{V_q} &= \frac{\alpha}{1-\alpha} \frac{w - tx - p(x)h}{h} \end{aligned} \tag{3.2}$$

where V_q and V_h are the marginal utilities of q and h, respectively.

$$\begin{aligned} h(p(x), w) &= \frac{\alpha(w - tx)}{p(x)}, \\ q(w) &= (1-\alpha)(w - tx). \end{aligned} \tag{3.3}$$

The choice of a residential location is implicitly part of the utility maximization problem because commuting costs and housing prices vary with

x. Residents will choose a location that gives them the maximum utility according to the demand functions. Since residents are identical and freely mobile within the city, all residents derive the same level of utility at any location within the city.[3] The spatial variation in $p(x)$ is the key to utility equalization throughout the city. This is the **spatial equilibrium** condition, which implies that residents have no utility gains from moving from one location to another within the city, as changes in price and commuting costs exactly offset each other.

Using the demand functions in Equation 3.3, denoting the equilibrium utility level in the city by $\overline{V}$, we can write the indirect utility function as:

$$V\,(w,\tau,x,p) = \Big(w - \tau x - p(x)\cdot h(p(x),w)\Big)^{1-\alpha} h(p(x),w)^{\alpha} \equiv \overline{V} \tag{3.4}$$

Solving Equation 3.4 for $p(x)$, we get the equilibrium price in location x:

$$p(x,\overline{V}) = \alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}}\Big(\frac{w-\tau x}{\overline{V}}\Big)^{\frac{1}{\alpha}}. \tag{3.5}$$

Equation 3.5 is the equilibrium bid rent function: the maximum price a resident is willing to pay for a house in location x given the utility level $\overline{V}$.

By substituting the value of $p(x,\overline{V})$ into the housing demand function in Equation 3.3, we can write the optimal level of housing a resident that lives in x consumes:

$$h(x,\overline{V}) = \Big((1-\alpha)(w-\tau x)\Big)^{\frac{\alpha-1}{\alpha}}\,\overline{V}^{\frac{1}{\alpha}}. \tag{3.6}$$

By the spatial equilibrium condition, the total derivative of utility with

[3]However, residents' optimal baskets may differ, as they can freely combine the housing and consumption good.

respect to distance to the CBD x must be zero.

$$\begin{aligned} \frac{dV}{dx} &= V_h \frac{dh}{dp}\frac{dp}{dx} + V_q \frac{dq}{dx} = 0 \\ \implies \frac{dp}{dx} &= \underbrace{-\frac{V_q}{V_h}}_{V_q\ p(x) \text{ by } 3.2} \overbrace{\frac{dq}{dx}}^{-t} \frac{dp}{dh} \\ \implies \frac{dp}{dx} &= \frac{-t}{h} < 0. \end{aligned} \tag{3.7}$$

Equation 3.7 is the housing price gradient, also known as the **Alonso-Muth condition**, which implies that housing prices decrease with distance from the CBD.

Residents react to the lower housing price by consuming more housing (i.e., living in larger houses) farther away from the CBD. Quantitatively, we can show this by taking the derivative of the housing demand function in Equation 3.3 (or Equation 3.6) with respect to x:

$$\frac{dh(p(x), w)}{dx} = \frac{dh}{dp}\frac{dp}{dx} > 0. \tag{3.8}$$

Equation 3.8 is the positive **housing consumption gradient** which shows that dwelling size (floorspace) increases with distance from the CBD x.[4]

To derive the **structural density gradient**, we need to define the supply side of the housing market as it is the developer's choice. A competitive developer combines a fixed amount of land $\overline{T}$ and non-land inputs K, simply called capital, to produce housing H via a Cobb-Douglas technology:

$$H = H(\overline{T}, K) = \overline{T}^{\beta} K^{1-\beta}, \tag{3.9}$$

[4]The housing gradient dh/dx is positive, because the slope of the housing demand curve dh/dp is negative, and the house price gradient $dp/dx < 0$ as shown in Equation 3.7.

where $\beta \in (0,1)$.[5]

The developer maximizes profit by choosing capital K over the fixed parcel $\overline{T}$

$$\Pi = p(x) \cdot H - R(x) - P^K \cdot K,$$

where $R(x)$ denotes the endogenous price of land of size $\overline{T}$, which varies across locations in the city, and P^K is the price of capital which is assumed to be invariant in the city and normalized to unity. Recall that the price of a unit of housing is given by $p(x)$.

The developer's profit maximization delivers the factor demand for capital K.[6]

$$\begin{aligned} K &= \Big((1-\beta)P(x)\Big)^{\frac{1}{\beta}}\overline{T} \equiv K^*(P(x), \overline{T}) \\ \implies \frac{K}{\overline{T}} &= \Big((1-\beta)P(x)\Big)^{\frac{1}{\beta}} \equiv k(P(x)) \end{aligned} \tag{3.10}$$

The capital-land ratio $k(P(x))$ is the amount of capital the developer uses on $\overline{T}$. The zero profit condition delivers the price of land $R(x) = p(x) \cdot H(K, \overline{T}) - K$. Recalling that the price of a unit of house $p(x)$ is given by Equation 3.5, we can write the capital intensity and price of land as a function of the parameters from the demand side.

The partial derivative of the **structural density** with respect to x can be shown to be negative:

$$\frac{\partial k}{\partial x} = \frac{\partial k}{\partial p}\frac{\partial p}{\partial x} < 0,$$

because $\partial k / \partial p > 0$ in Equation 3.10.

For the derivation of the remaining gradients and further details on the gradients and other implications of the AMM model, please refer to Duranton and Puga (2015) and Brueckner (1987). These studies offer a de-

[5] K captures a composite of all inputs for housing production other than land, which can broadly be labor and materials.

[6] Since land is fixed, the builder chooses capital to maximize profit.

tailed guide on solving the AMM model using the Marshallian, Bidrent, and Hickian approaches, and explain its implications and interpretations. These methods are thoroughly covered in Appendix A of Zenou (2009).

To summarize, the AMM model has five gradient predictions (Brueckner, 1987; Duranton and Puga, 2015). The first is the negative *housing price gradient* (also known as the rent gradient). This is the key prediction of the model, and the rest of the results follow directly or indirectly from it (Glaeser, 2008, p. 20). Housing prices decrease with the distance to the CBD. Quantitatively, commuting costs and the level of housing consumption determine the magnitude of the fall in housing prices. The second prediction is the positive *housing consumption gradient*, implying that dwelling sizes increase with distance to the CBD, as a substitution effect of a decrease in the housing price. The negative *land price gradient* is the third prediction of the model, which is reflected in the lower housing prices further away from the CBD. The fourth prediction, resulting from the negative land price gradient, is the *structural density gradient*. This suggests that houses are built with a lower capital-to-land ratio, indicating the presence of low-rise houses in the city's periphery. Finally, the fifth prediction is the negative *population density gradient*, which suggests that population density increases with proximity to the CBD.[7] Overall, the AMM model predicts that property prices, structural and population density are all decreasing functions of distance to the CBD, with dwelling size being an increasing function of distance.

Constrained by data availability, this study empirically tests the gradients of housing price, rent, dwelling size, and structural density in Addis Ababa. Future research should address land price and population density gradients. It is worth looking at the Global Human Settlement Layer (GHSL) population layer of the European Commission, which provides a spatial

[7]Far away from the CBD, buildings are shorter and have larger units, leaving less space for new construction, and therefore, fewer people can be accommodated per unit of land. The population density is a joint result of consumer and producer decisions. As consumers substitute in favor of housing and producers in favor of land as distance increases, the population density decreases (Brueckner, 1987).

raster dataset on the distribution of residential population expressed as the number of people per cell Schiavina et al. (2023).[8] The next section discusses the unique data utilized for testing these gradients and presents descriptive results.

3.4 Data

This section describes the data generation process, including scraping, cleaning, and geocoding, to prepare a unique dataset that can be used to analyze the spatial distribution and temporal evolution of real estate prices in Addis Ababa. The data generation process involves several steps. Firstly, we scrape property listings from online real estate platforms. The raw data go through a comprehensive cleaning, and property addresses are geocoded. Additionally, we use the building footprint datasets from Google and the German Aerospace Center (DLR) to construct building variables. The dataset offers sale and rent listings for houses and apartments. Subsections below detail the steps taken to maintain data quality and readiness for analysis, establishing a strong foundation for studying urban housing market dynamics in Addis Ababa.

3.4.1 Data collection, cleaning, and preparation

In the past few years, the digital market in Ethiopia has gained momentum, leading to an increase in the opening of online marketplaces, including real estate. These platforms allow brokers, homeowners, and real estate agents to post and cross-post advertisements. They are especially beneficial for reaching the Ethiopian diaspora, who are potential property buyers. Moreover, these platforms offer a valuable opportunity to gather data on property prices and other characteristics. Even so, social media platforms like Telegram and Facebook are highly utilized for property and other consumer product advertisements. These platforms can be leveraged to collect

[8] We are also aware of the WorldPop gridded population data of the world, but the estimates for Ethiopia might be uncertain because of its outdated census.

data on property prices and other characteristics. Future research could explore the potential of these platforms for data collection.[9]

While promising, on these platforms, only a small fraction of properties are currently advertised, and the advertised properties may be limited to high-end ones. Consequently, the data constructed from these platforms may not fully reflect the housing market in Addis Ababa. The differences between advertised and actual prices may also be large. Scraped data may misrepresent the actual market realities, and a validation dataset of actual transactions may help. Previous research has revealed the misrepresentation of scraped online data through fieldwork and real market data (Harten et al., 2021). Without alternative data, information from these platforms can still be valuable for studying the housing market in Addis Ababa despite these concerns.

In Addis Ababa, there is no dominant online real estate platform like Zillow in the US or Immobilienscout24 in Germany. There is a growing number of online real estate platforms, each with an increasing market share. The most popular ones are Jiji, Qefira, AfroTie, and Loozap, which constitute a large fraction of the number of listings (see Table 3.B.1). However, listings are highly cross-posted across platforms, and most of the platforms are generic marketplaces for advertising consumer products such as cars, electronics, and clothing. This study extracts data from all the dominant available online real estate platforms. After meticulous cleaning, we produce a housing price and rent dataset with a rich set of property characteristics.

To create a property prices dataset, we gathered real estate advertisements from the websites of these online providers. We extracted the prices of properties, as well as the available structural and locational characteristics

[9]However, unlike websites, advertisements on social media platforms can pose challenges for systematic data collection due to their lack of structure and style consistency. Verifying the authenticity of properties advertised on these platforms also proves difficult. Despite these challenges, a significant amount of data can be gathered from these platforms, as they are extensively used for posting advertisements in Ethiopia.

of the properties.[10] More precisely, the data includes information on the price, size, address, listing and property types, number of bedrooms and bathrooms, the publication date, and other features of properties such as furnishing status, balcony, garden, etc. Importantly, the title and description of the advertisement contain highly relevant information that can be leveraged to fill any missing relevant characteristics with the help of regular expressions and Retrieval Augmented Generation (RAG) techniques, if applicable.[11]

The steps we have taken to clean the data, including removing misclassifications, inaccuracies, inconsistencies, and duplicates, are discussed below. The process involves standardizing currency and property size units, ensuring accurate categorization of listings and property types, and addressing missing or erroneous values. Special attention was given to the temporal and spatial aspects of the data, recognizing the importance of accurate time and spatial information for longitudinal analysis.

Cleaning the raw data is challenging because most providers fail to format their input boxes correctly, leading to encoding errors and mistyped information. Users might enter the price in the size box and vice versa. This especially complicated the geocoding process due to the presence of extra details unrelated to the address. For further details, please refer to the GitHub repository for this study.[12] Properties are geocoded to determine the exact location, which is an important component of an urban dataset.

Given the diverse nature of real estate listings, outlier detection and removal are crucial to maintaining data quality. We removed outliers in prices and sizes, within the categories of the properties (sale vs. rent, house

[10]The list of online real estate platforms where we scraped data and other active providers is provided in Table 3.B.4.

[11]However, the Natural Language Processing (NLP) and data cleaning tools currently available perform highly for only Latin characters and languages, with less support for Ethiopic texts used in advertisements For instance, regular expressions, even with Unicode support, do not function well with Ethiopic texts, such as word boundaries.

[12]The GitHub repository for this study is available at https://github.com/eyayaw/the-monocentric-city-gradients-addis-ababa. It includes the scripts for scraping, cleaning, analyzing, and visualizing the data.

vs. apartment). Based on the data distribution, we set specific thresholds for property values to regroup misclassified advertisements, but there are very few of them. For instance, if a house or an apartment is priced over 150,000.00 Birr and listed as “for rent”, it is changed to “for sale”. Conversely, if it is priced below 500,000.00 Birr and labeled as “for sale”, it is corrected to “for rent”. Properties priced over 500,000,000.00 Birr are considered outliers and excluded, and those with high prices but small sizes are also removed. For the analysis in this study, data points with prices between (2,500.00, 150,000.00) Birr/m^2 for sale and between (25.00, 500.00) Birr/m^2 for rent, and sizes between (25.00, 500.00) m^2 are used.

Table 3.B.1 shows the number of properties extracted from eleven different providers, classified by listing types “for sale” and “for rent” and property types: houses and apartments. The table reveals that the majority of listings are for sale: 58,442 (for sale), and 14,228 (for rent). In terms of property type, the listings are comparable: 36,877 (apartment), and 35,793 (house), excluding other types. The table also shows that the number of listings varies by provider. Furthermore, the data spans from 2016 to 2024, as shown in Table 3.1. Advertisements before 2020 are scarce, but there is a significant increase in advertisements from 2020 onwards, making the data more reliable.

3.4.2 Geocoding property addresses

The scraped data, essential for urban economics spatial analysis, lacked precise geospatial coordinates for advertised properties. This required geocoding to convert descriptive addresses into precise latitudes and longitudes. Most providers require users to manually input property addresses because they don’t offer autocomplete suggestions from a predefined list of addresses. These addresses present challenges for geocoding due to the variability of the Ethiopic script, the usage of transliteration, common typographical errors, and the presence of extraneous details. Addressing these issues required a comprehensive data cleaning process, which is outlined in the property_address_cleaning_helpers.R and

Table 3.1: Property listings by year, listing, and property types

	For Rent			For Sale			
Year	Apartment	House	Other	Apartment	House	Other	**Total**
2016	-	-	-	-	5	-	**5**
2017	101	111	23	112	176	61	**584**
2018	221	523	45	74	423	95	**1381**
2019	279	258	30	472	1174	323	**2536**
2020	764	548	100	1808	6111	1207	**10538**
2021	1409	697	113	4599	3303	1047	**11168**
2022	2572	1249	151	7003	5171	1769	**17915**
2023	3092	1364	150	12369	9716	2588	**29279**
2024	563	477	15	1439	4487	168	**7149**
Total	**9001**	**5227**	**627**	**27876**	**30566**	**7258**	**80555**

clean_property_addresses.R scripts.

An important step was normalizing the Ethiopic script. Its characters, having multiple visually distinct but phonetically similar representations, presented a significant challenge. For instance, "**ቦሌ መድኃኒዓለም**" (Bole Medhanialem) could variably be written as "**ቦሌ መድ(ሀ|ሃ|ሐ|ሓ)ኒ(ዓ|አ|ኣ)ለም**" due to the interchangeable use of characters like "**ሀ**", "**ሐ**", and "**ኀ**", and "**አ**", "**ዐ**", "**ኣ**", "**ዓ**". Standardizing these variations to a uniform representation was crucial for geocoding APIs to recognize addresses. Common typographical errors and standardized transliterated address variations are corrected to ensure consistent geocoding results.

Another step is removing extraneous information in the addresses. Addresses were often cluttered with irrelevant details that mislead geocoding APIs. Using regular expressions, we isolated and removed irrelevant information, keeping the relevant part of the address. For example, verbose descriptions such as "500 meters from Bole Airport in a beautiful residential neighborhood" to "Bole" or "Bole Airport" needed to be cleaned for accurate geocoding.

In addition, many property addresses lack details and accuracy, with some not including the address in the designated field. For example, "Bole" is a large neighborhood in Addis Ababa that is not precise enough for geocoding. To resolve this issue, we manually reviewed and corrected addresses by utilizing information from the advertisement description.

The thorough cleaning process was crucial in preparing the dataset for accurate geocoding. By effectively managing these challenges, property addresses are accurately geocoded. This georeferenced dataset can now be used for the spatial analysis of the housing market in Addis Ababa, in this study and future research.

Table 3.2 displays the frequency of property listings within subcities. It shows that most listings are coming from Lemi Kura and Bole subcities. Bole, a central and affluent subcity, has high housing demand. Lemi Kura, a new subcity formed in October 2020 from parts of Bole and Yeka, attracts real estate development because of its abundant vacant land. Consequently, numerous advertisements originate from this subcity. It is important to note that we use the new boundary definition of Addis Ababa for geocoding. Thus, advertisements predating the establishment of Lemi Kura are assigned to it if they fall within its boundaries.

Table 3.2: Property listings by subcity and listing types

	For Rent			For Sale			
Subcity	Apartment	House	Other	Apartment	House	Other	**Total**
-	68	71	4	232	2237	189	**2801**
Addis Ketema	35	47	13	203	301	94	**693**
Akaki Kality	90	92	42	662	2491	545	**3922**
Arada	297	131	32	908	381	218	**1967**
Bole	3338	1635	173	7025	4297	1420	**17888**
Gulele	44	49	17	360	352	154	**976**
Kirkos	2131	422	69	3632	1629	673	**8556**
Kolfe Keranio	50	79	33	318	1390	285	**2155**
Lemi Kura	1272	1066	67	8758	10187	1805	**23155**
Lideta	468	619	47	1165	831	250	**3380**
Nifas Silk-Lafto	355	366	66	2535	3472	622	**7416**
Yeka	853	650	64	2078	2998	1003	**7646**
Total	**9001**	**5227**	**627**	**27876**	**30566**	**7258**	**80555**

3.4.3 Constructing hedonic house values

Before using the property price data in any analysis, it is crucial to first compute the hedonic values, accounting for both structural and locational characteristics of properties. More importantly, adjusting the raw property prices for their structural features and neighborhood characteristics is important to avoid skewing the gradient estimates, which could result in an unwarranted dismissal of the AMM model (Cheshire and Sheppard, 1995; Ahlfeldt, 2011).

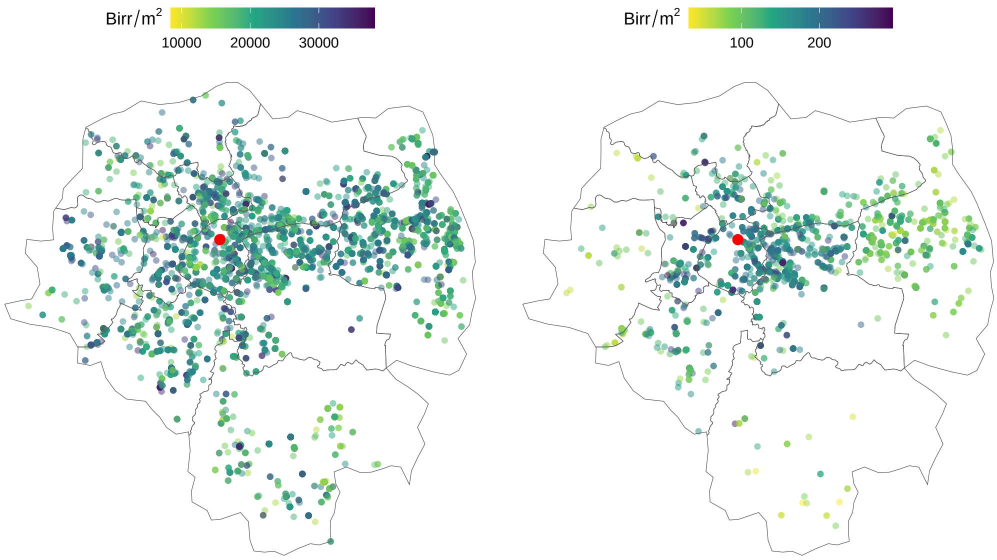
We construct hedonic house prices and rental values of the properties using a wide range of property characteristics available in the dataset through a panel hedonic regression as follows:

$$\ln p_{hit} = \mathbf{x}'_{hit}\boldsymbol{\beta} + \alpha_{it} + e_{hit}, \tag{3.11}$$

where h, i, and t index property, subcity, and time (i.e., month-year), respectively. The variable p denotes the price or rent of the property in Birr per m^2, adjusted for inflation using the Consumer Price Index (CPI) of Ethiopia, with December 2016 as the base period. Subcity and time fixed effects are denoted by α_{it}. The subcity fixed effects control the locational characteristics of properties, including amenities and other unobserved neighborhood features. $\mathbf{x}'_{hit}$ includes a set of property characteristics.[13] The subcity-level quality-adjusted prices are the estimates of the fixed effects in Equation 3.11: $\widehat{\alpha}_{it} = \widehat{\ln p}_{hit} - \mathbf{x}'_{hit}\widehat{\boldsymbol{\beta}}$, where the predicted values $\widehat{\ln p}_{hit}$ are the hedonic values for individual properties. This way of identifying the hedonic house value is also used in Ahlfeldt (2011). The estimation results for Equation 3.11 are provided in Table 3.B.3 in the Appendix. The

[13] The hedonic models control for basic property characteristics: floorspace size in square meters, number of bedrooms and bathrooms, property type (house or apartment), condition, and binary variables for various features of the property such as furnishing status, garden, parking, balcony, elevator, etc. The hedonic regressions also include subcity and time fixed effects to control for unobserved subcity and country level factors that may affect property prices. See Table 3.B.3 in the Appendix for the full list of hedonic attributes.

coefficients of the hedonic attributes overall are in line with expectations.



(a) Price

(b) Rent

Figure 3.1: The spatial distribution of property prices in Addis Ababa, 2023.

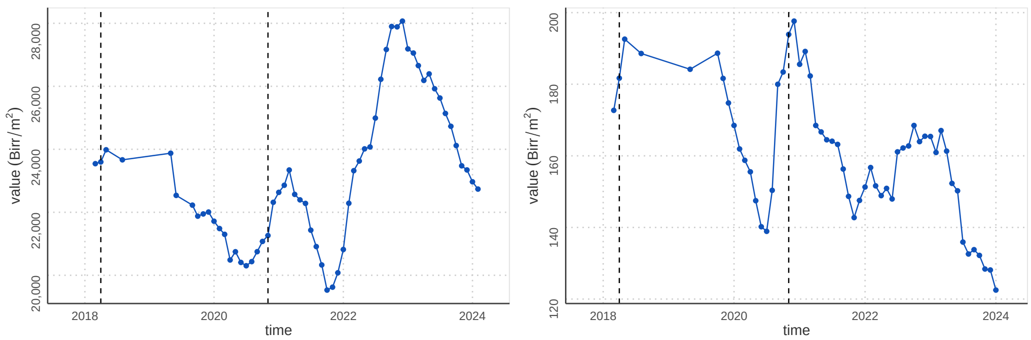
Notes: The map illustrates the average house prices and rents in Birr per square meter in 2023. Lighter colors indicate lower prices. The red point indicates the CBD, Meskel Square. Properties with missing location data are excluded from the map.

The spatial distribution of property prices is mapped in Figure 3.1 for 2023, and Figure 3.B.3 in the Appendix shows all data points combined. The concentration of darker shaded points near the CBD, indicated by the red dot, suggests higher property prices, which gradually decrease away from the center. This pattern is more pronounced for rents than for house prices, indicating the sensitivity of rents to distance.

Figure 3.2 illustrates the trend of hedonic values for house prices and rents in Addis Ababa over time. The left panel displays the monthly average of house prices, which is trending upward. The right panel shows the trend in the average rental prices. Both trends exhibit large fluctuations. Over the past five years, the country's macroeconomic condition has been volatile. This period has seen political instability, negatively affecting the economy and the real estate market. The main drivers of these fluctuations include high inflation rates, the devaluation of the Birr, and a scarcity of foreign currency reserves, making it difficult for developers, other firms, and buyers to access financing (presidio, 2020). Rental prices have fluctuated, with a continuous drop starting in late 2020, likely due to the conflict in the Tigray region and the COVID-19 pandemic. These events caused economic disruptions, low tourism and foreign direct investment (Bundervoet et al., 2020; International Trade Administration, 2024).

Moreover, our data shows that most rental advertisements target tourists and expats, who were scarce during these times, likely impacting the rental market. COVID-19 restrictions on the movement of foreign workers impacted the rental market, particularly for high-end housing, resulting in decreased demand and lower prices (presidio, 2020). Additionally, our data shows fewer observations in the months before 2020 compared to those after. For accurate temporal analysis, we recommend focusing on the later months (see Table 3.1).

Furthermore, the Addis Ababa City Administration has repeatedly suspended and partially resumed land and property transaction services over the past five years (Addis Fortune, 2022b,a; Capital Ethiopia, 2022). In September 2022, property transactions through designated persons (power of attorney rights), were suspended (Addis Fortune, 2022c). The city administration further suspended the transfer of fixed assets and real estate properties, including land in December 2022 (Capital Ethiopia, 2022). These suspensions may have impacted the real estate market in Addis Ababa, leading to fluctuations in property prices and rents. All these factors indicate the high sensitivity of Addis Ababa's real estate market to local and external factors.



(a) Price (b) Rent

Figure 3.2: Average house and rental prices in Addis Ababa.

Notes: The figure shows trends in the average house and rental prices in Addis Ababa over time. The left panel depicts the trends in price, while the right panel shows rent, for houses and apartments combined. These values are the estimated fixed effects from the hedonic models in Equation 3.11. The property values are in Birr per square meter, adjusted for inflation using Ethiopia's CPI, with December 2016 as the base period. The first dashed line marks the beginning of Abiy Ahmed's time as Prime Minister of Ethiopia (April 2018), and the second dashed line indicates the start of the Tigray conflict (November 2020). Months with fewer than 55 advertisements (a minimum of 5 per subcity monthly), are omitted. The series is smoothed with a 4-month moving average for clarity.

3.4.4 Building footprint datasets

The structural density and housing consumption gradients require granular building data. The building variables are extracted from two sources: the German Aerospace Center (DLR) and Google. DLR offers the World Settlement Footprint (WSF) 3D Esch et al. (2022) and WSF 2019v1 Marconcini et al. (2021) datasets. WSF 3D provides detailed data on building height, volume, area, and building distribution globally at a 90m resolution. WSF 2019v1 is a 10m resolution binary mask showing human settlements worldwide with high accuracy. The dataset is utilized for calculating the number of buildings within grid cells.

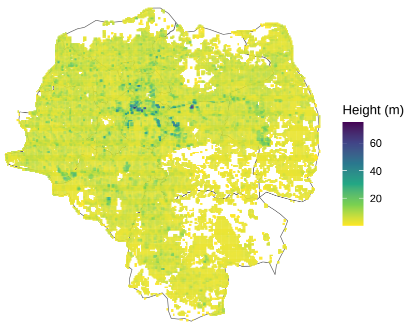
Google recently released a dataset called Open Buildings, which contains building footprints for countries in Africa, South and Southeast Asia, Latin America and the Caribbean (Sirko et al., 2021). This dataset includes building footprints as polygons, which enables us to calculate individual building sizes and total counts within an area such as grid cells.

Unlike the Google dataset, which includes the exact location of the building, the DLR dataset is defined at a higher resolution (around 90m around the equator). To reconcile this, we created $100m \times 100m$ grid cells within which building summary statistics are computed. First, we identify the buildings that intersect with each grid cell. Then, we extract the values for buildings that fall within each grid cell and calculate summary statistics such as average or maximum building height, total area coverage of buildings, and the count of built-up areas, for each grid. Note that in the open buildings dataset, buildings with a confidence level below 0.75 are dropped in this study.

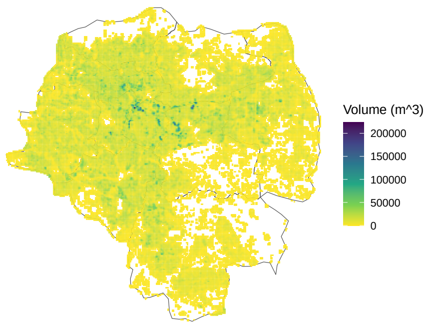
WSF 3D dataset directly contains the average building height within the built-up area. Thus, to construct building height at the grid level, we calculate the average and maximum building height within each grid cell. The building volume and area are calculated similarly. The fraction of the built-up area within each grid cell is also computed. From WSF 2019v1, we computed building counts and area coverage within grid cells similarly.

All these measures enable us to proxy structural density and building size flexibly.

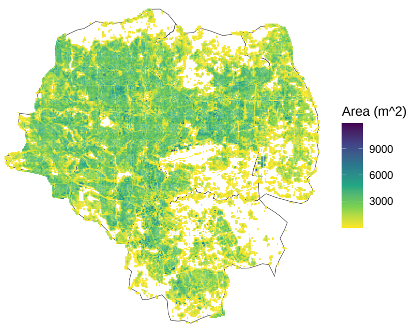
The building characteristics are visualized in Figure 3.3. The figure shows the distribution of building height, volume, area, and number and fraction of the built-up area in Addis Ababa. The building height, volume, and area are higher in the central parts of the city, while the fraction of the built-up area is higher in the periphery. The building characteristics are crucial for estimating the structural density gradient in Addis Ababa.



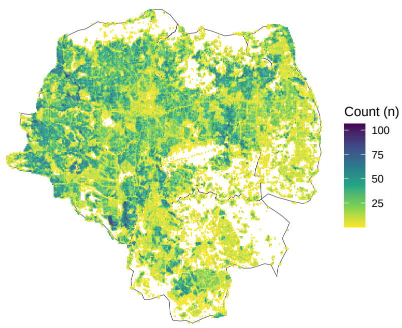
(a) Height (m)



(b) Volume (m^3)



(c) Area (m^2)



(d) Count (n)

Figure 3.3: Building footprint in Addis Ababa.

Notes: The figure displays building height, volume, area, and the number of buildings in Addis Ababa on a $100m \times 100m$ grid scale. The values are aggregated at the grid level. Building height and volume are constructed from the WSF 3D datasets while building area and count are from the Open Buildings dataset.

3.5 Estimating the gradients

Addis Ababa, with its near-circular layout, can be considered a circular city. It is not a polycentric city; only a few of its districts might qualify as CBDs. Meskel Square and the surrounding area, including Biherawi (Legehar), are important historical landmarks in the city center. It is considered the primary CBD of the city. This location is surrounded by headquarters of major local banks, commercial offices, international hotels, entertainment centers and other urban amenities. It also functions as a city transport hub, with nearly all primary road lines intersecting there. Meskel Square borders Bole, an affluent district in the city, which some may consider the center of the city. Another interesting choice is Piassa, once the historical CBD of Addis Ababa but less significant in the modern context. Others might consider Arat Kilo (4 Kilo), home to Addis Ababa University and located near Bete-Mengist (the National Palace) and the Holy Trinity Cathedral, as the city's center. Interestingly, all of these locations are within about 3-kilometer radius of Meskel Square, as shown in Figure 3.4.

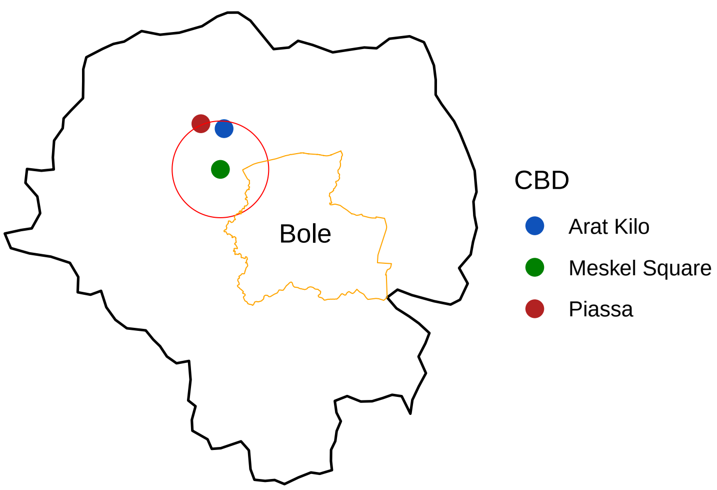


Figure 3.4: Keys CBDs in Addis Ababa.

Notes: The red circle represents a 3 km radius from Meskel Square, the main CBD in this study. The orange line represents the boundary of the Bole subcity.

3.5.1 The rent gradient

Given its level of development and the purchasing power of its residents, Addis Ababa is considered an expensive city.[14] A typical three-bedroom apartment costs, on average, 3,461,683.94 Birr, which approximately is $64,035.88, in 2023, in December 2016 prices, according to the data in this study.[15] Spatially, average house prices and rents tend to be higher in the city center compared to the peripheries. As shown in Figure 3.1, this trend was evident in 2023, with Meskel Square demonstrating relatively high house and rental prices. Notably, the difference was more pronounced for rents than for purchase prices. However, it's important to note that the property price gradient across the city is not uniform. Certain prime locations in Addis Ababa, including Lideta, Balders, Gotera, and Gerji, which are not far from the center, command higher prices. This is especially true for condominium homes, which are particularly expensive in these areas compared to other parts of the city, as The Reporter (2022) indicated.

This study estimates the rent gradient for Addis Ababa using the generated data for prices and rents. The rent gradient is estimated using a simple log-linear equation, following the Alonso-Muth condition in Equation 3.7. The most commonly used functional form for the gradients is the simple negative exponential function (McMillen, 2006).

$$\ln p_i = \beta_0 + \beta_1 x_i + \varepsilon_i, \tag{3.12}$$

In this equation, p_i represents the hedonic price or rent of property i in Birr

[14]According to data from (World Salaries, 2024), the average monthly salary in Addis Ababa is approximately $161 in 2024. For a university teacher in Addis Ababa, it is around $231. These figures are significantly lower than the average monthly mortgage payments for a 30-year loan on a one-bedroom apartment in the city (Centre for Affordable Housing Finance, 2023).

[15]The median prices are 3,166,226.91 Birr and $58,570.37. Note that in December 2023 prices, the average price for the three-bedroom apartment is about $271,063.87. In 2021, the average buying price for a high-end residential property, comprising three to four bedrooms, ranges between $2,000 and $3,000 per square meter, according to a real estate consultancy company (Knight Frank-EMC, accessed March 2024, Archived). Correspondingly, the monthly rent for these properties can reach up to $6,000 in the city's prime locations.

per square meter estimated in Equation 3.11, x_i denotes the distance to the CBD in kilometers, and ε_i is the error term.[16] The coefficient of interest is β_1 which represents the slope of the rent gradient. Given the available data, we estimate Equation 3.12 for different years.

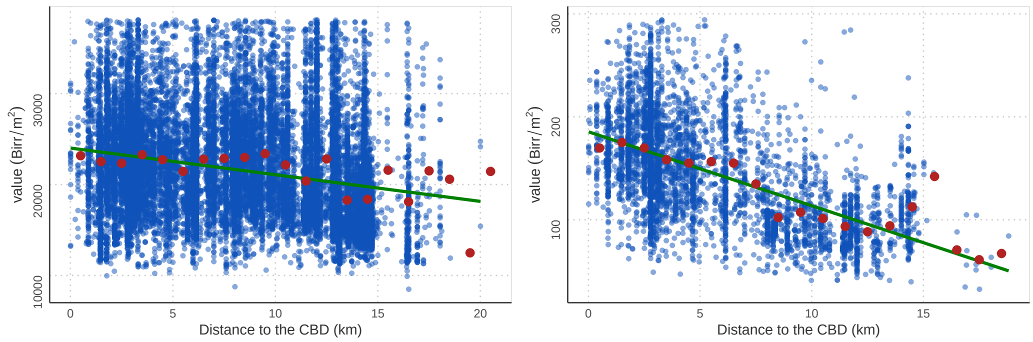
The estimated rent gradients are displayed in Table 3.3. For 2023, the rent gradients are shown graphically in Figure 3.5. The same estimation for split samples by property types is shown in Table 3.B.2 and Figure 3.B.2 in the Appendix.

The estimated rent gradients are consistently negative for both house prices and rents across all years. Results from fixed-effects and pooled OLS estimations in columns (1) and (2) of each panel in Table 3.3 also indicate negative slope estimates. Thus, our estimates are consistent with the predictions of the AMM model, as we recall from the Alonso-Muth condition in Equation 3.7 that the slope of the rent gradient is negative. The magnitudes of the slope coefficients range between -0.028, -0.005 for prices, between -0.080, -0.015 for rents, over the years, excluding the "anomalies" (positive or insignificant coefficient). There are only two instances in 2017 and 2018 and note that the number of observations is small.

The penultimate column in Table 3.3 (i.e., for 2023) shows that house prices decline by 1.51% with each additional kilometer from the CBD. The R^2 value indicates that only about 5.19% of the variation in house prices is explained by distance to the CBD. The magnitudes of our estimates closely match those found by Liotta et al. (2022), who reported an average gradient of -0.014, with an interquartile range of (-0.019, -0.006) across their city sample, for rents (Liotta et al., 2022, sec. 4.1.4). Another interesting finding is that the rent gradient is steeper than the price gradient. This suggests that renters in cities such as Addis Ababa, where traffic congestion is prevalent, commuting is lengthy, and public transportation

[16]The error term ε_i accounts for locational characteristics that we could not observe but capitalize into house prices and rents (See Cheshire and Sheppard (1995); Ahlfeldt (2011)).

is underdeveloped, may be more sensitive to distance to the CBD than home buyers. Given that home buyers often possess cars, they may find longer commutes acceptable for spacious and cheaper houses further away from the CBD.



(a) Price (b) Rent

Figure 3.5: The rent gradient in Addis Ababa in 2023.

Notes: The figure depicts the rent gradient for house prices and rents against the distance to the CBD (i.e., Meskel Square). As expected, both gradients are negatively sloping, steeper for rents, indicating that prices and rents decrease as the distance from the CBD increases, consistent with the prediction of the AMM model. Lighter points represent individual property values, while darker points represent averages within 2 km distance bins. Property values with missing location data are excluded from the plot.

3.5.2 The structural density gradient

As shown in Equation 3.10, the AMM model predicts that structural density is a decreasing function of distance to the CBD, as land is cheaper and buildings are shorter, farther from the CBD. The decline in building heights over distance is also observed in real-world cities. This gradient has not been empirically analyzed as extensively as population densities or land values (McMillen, 2006, sec. 8.5). Consequently, it is interesting to explore whether cities in developing countries exhibit lower structural densities in their peripheries, given their distinct urban forms and development patterns. These cities often display different urban configurations (see Taubenböck et al. (2020)) from their counterparts in developed coun-

Table 3.3: The rent gradient estimates

(a) Price

	Fixed Effects (1)	Pooled (2)	2017 (3)	2018 (4)	2019 (5)	2020 (6)	2021 (7)	2022 (8)	2023 (9)	2024 (10)
dist	-0.0140***	-0.0146***	-0.0067	0.0046	-0.0099***	-0.0133***	-0.0142***	-0.0047***	-0.0151***	-0.0284***
	(0.0025)	(0.0003)	(0.0052)	(0.0038)	(0.0017)	(0.0006)	(0.0008)	(0.0007)	(0.0004)	(0.0008)
Constant		10.04***	10.04***	9.909***	9.976***	9.962***	9.937***	10.02***	10.10***	10.09***
		(0.0025)	(0.0520)	(0.0335)	(0.0160)	(0.0058)	(0.0065)	(0.0054)	(0.0042)	(0.0086)
Standard-Errors	year					IID				
Observations	55,968	55,968	282	475	1,524	7,280	7,658	11,752	21,431	5,566
R^2	0.09549	0.04625	0.00583	0.00312	0.02112	0.06460	0.03799	0.00369	0.05187	0.18367
Within R^2	0.04248									

(b) Rent

	Fixed Effects (1)	Pooled (2)	2017 (3)	2018 (4)	2019 (5)	2020 (6)	2021 (7)	2022 (8)	2023 (9)	2024 (10)
dist	-0.0538***	-0.0576***	-0.0804***	-0.0146***	-0.0441***	-0.0597***	-0.0518***	-0.0572***	-0.0559***	-0.0493***
	(0.0023)	(0.0008)	(0.0067)	(0.0040)	(0.0053)	(0.0027)	(0.0024)	(0.0019)	(0.0012)	(0.0021)
Constant		5.265***	5.322***	5.148***	5.384***	5.320***	5.280***	5.276***	5.229***	4.979***
		(0.0049)	(0.0569)	(0.0232)	(0.0319)	(0.0180)	(0.0130)	(0.0092)	(0.0081)	(0.0168)
Standard-Errors	year					IID				
Observations	14,089	14,089	208	738	537	1,299	2,101	3,816	4,398	992
R^2	0.31100	0.26957	0.40819	0.01757	0.11506	0.27963	0.17731	0.19419	0.33918	0.35446
Within R^2	0.24251									

Notes: The table presents regression estimates for the slope of the rent gradient over time. The dependent variable is the logarithm of the property price, and the independent variable is the distance to the CBD in kilometers. The pooled sample combines the data from all the years under consideration. The fixed-effects estimations include year-fixed effects. The pooled sample combines the data from all the years under consideration. Robust (clustered by year for fixed-effects) standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

tries. In developing countries, informal settlements tend to be more prevalent, transportation infrastructure is underdeveloped or fragmented, and land use regulations are not strictly enforced. Addis Ababa is a prime example of a city in a developing country with such urban characteristics.

Addis Ababa is not known for its high-rise buildings, there are a few buildings that are taller than 100 meters in 2024. Interestingly, these tallest buildings, primarily serving as head offices of banks and other big companies, are clustered in the city center, forming the new CBD of Addis Ababa (Reqiq Insights (2023), accessed March 2024, Archived). Based on WSF 3D data, the average building height in the city (for areas built before 2012), is around 60.80m, and the maximum building height is 75.02m.[17] After 2019, many tall buildings were built in the city. The tallest one, the 209m

[17]The WSF 3D uses WSF-IMP and TDX-DEM. WSF-IMP covers 2017-2019, TDX-DEM covers 2011-2013. TDX-DEM does not have heights for new settlements built after 2012. Thus, the tall buildings in Addis Ababa constructed after 2019 are not included in WSF 3D and that is why the max height is way below the current tallest building in the city.

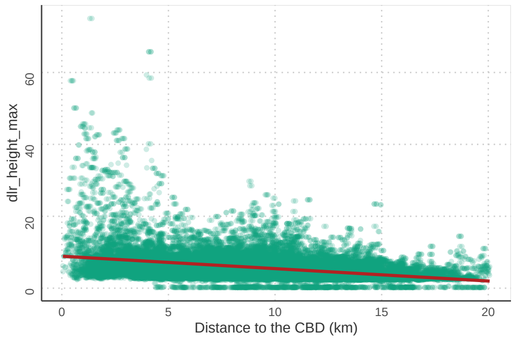
tall Commercial Bank of Ethiopia Head Office, is one of the tallest buildings in East Africa. These tall buildings are all in the city center, close to Meskel Square.

Similar to the rent gradient estimating equation Equation 3.12, the negative structural density gradient in Equation 3.10 is represented as:

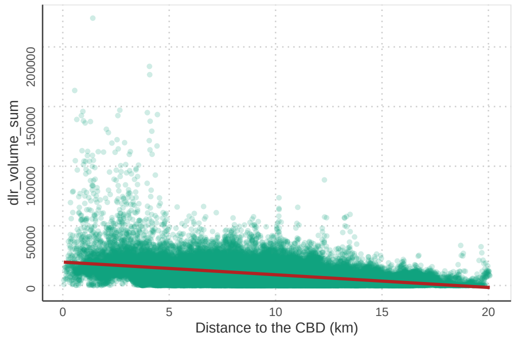
$$\ln k_i = \alpha_0 + \alpha_1 x_i + \epsilon_i \tag{3.13}$$

In this equation, k_i denotes a measure of structural density within a $100m \times 100m$ grid cell, denoted as i. α_1 estimates the the structural density gradient. Equation 3.13 is estimated using WSF 3D and 2019v1 datasets from the DLR, and the Open Buildings dataset from Google (see Section 3.4.4). The capital intensity of buildings is measured by their height. The data includes building volume, floorspace, and counts within grid cells, and we provide gradient estimates for these characteristics as well, which can be proxies for density (de Bellefon et al., 2021). We use the building floorspace as a proxy for the housing consumption gradient defined in Equation 3.8. The results are shown in Table 3.4.

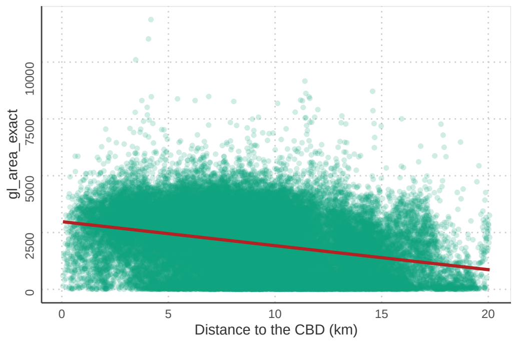
The monocentric model suggests that buildings should be taller in the city center. As shown in Figure 3.6, panel (a), buildings are taller in the center of Addis Ababa. This pattern also applies to building volume and floorspace, with higher volume and wider buildings present in the city center. The estimated gradient for building height is negative and highly statistically significant: -0.059. Our estimates are similar to McMillen (2006)'s floor-area ratio estimates (-0.055, taken from Table 8.1 of the paper). The negative coefficient indicates that building heights, measuring the structural density, tend to decrease as one moves farther away from the CBD. Specifically, buildings located 1 kilometer away from the CBD are approximately 5.9% shorter than buildings in the CBD, holding all other factors constant. The gradient for building volume is also negative, suggesting the presence of voluminous buildings in the urban core.



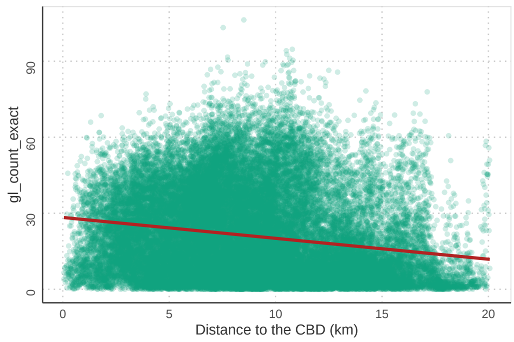
(a) Height (m)



(b) Volume (m^3)



(c) Area (m^2)



(d) Count (n)

Figure 3.6: Building characteristics against distance to the CBD.

Notes: The figure shows the relationship between building characteristics, such as building height, volume, and the number of buildings, against the distance to the CBD. Building characteristics are computed from the Google Open Buildings and DLR datasets. The spatial scale is $100m \times 100m$.

The monocentric city model also implies the presence of wider dwellings farther from the CBD (see Brueckner (1987)), which can be proxied by building floorspace. The structural density may also be proxied by the floor-area ratio, building area divided by lot size (see, for example, McMillen (2006)). In the presence of building height data, it is a better proxy than the floor-area ratio. We argue that building floorspace may account for the level of house consumption even though the model's prediction is about individual dwelling units (see Duranton and Puga, 2015; Brueckner, 1987). The size of buildings (measured by the total building floorspace within a $100m \times 100m$ grid cell) does not increase with distance to the CBD, contradicting the model's prediction (see panel (c) in Figure 3.6). The estimated slope of this gradient equals -0.10, which is about two times steeper than the building height gradient. In other words, building ground area decreases faster than height, on average, as we move away from the center. Note that the building datasets lack type information, so it is unclear whether the housing consumption gradient can be observed for residential buildings only. Understanding the distribution of high-income and low-income residents in the city can also help us understand this pattern. The model (the version that allows for the (income) heterogeneity of households) implies (see Glaeser (2008)), that high-income households tend to occupy larger houses and larger houses are found farther away from the CBD. If in reality larger houses and high-income households are concentrated in the center, the inverted housing gradient may make sense.

Unlike cities in developed countries, where there is strong suburban demand by high-income households, Addis Ababa appears to exhibit a different pattern. Affluent residents tend to concentrate in central areas of the city, such as the central district of Bole and nearby neighborhoods like Old Airport and Sarbet. These central zones predominantly feature larger residential properties, villas, hotels, and embassies (The Africanvestor, 2023). This may explain the observed pattern of building floorspace in Addis Ababa.

Furthermore, urban planning in Addis Ababa prioritizes radical changes that disadvantage the poor, a phenomenon termed the "violence of urbanization" — a war against the poor, not poverty (Pedrazzini et al., 2014). This approach leads to the destruction of landmarks, and public spaces, and the displacement of low-income residents to the outskirts, rather than reducing poverty. In the past five years, the Ethiopian government, led by Abiy Ahmed, has carried out grand urban development projects that have significantly impacted the city's urban fabric. For instance, the LaGare and Beautifying Sheger projects target rich and elite Ethiopians, foreign investors, and the Ethiopian diaspora living in the US and Western Europe, while displacing the poor (Terrefe, 2020).

Currently, in April 2024, the city's central areas, including Piassa, its historic center, are undergoing extensive demolition as part of the so-called Corridor Development Project, resulting in mass evictions of the poor (fanabc, 2024; Addis Standard, 2024). In addition, the city has long-standing border demarcation issues with the neighboring Oromia region, leading to uncertainty in people's purchasing decisions despite cheaper land in the peripheries of the city (see Section 3.A). All these points show that the actual realities of today's cities are more complex than the assumptions made in the model. Thus, the inverted floorspace gradient may be a feature of Addis Ababa, not a measurement or estimation issue.

One may argue that the floorspace within a grid cell can serve as a proxy for structural density, similar to the floor-area ratio concept discussed in McMillen (2006). This is because we measure the building area within a grid cell, and the area of the grid cell can be considered the lot size. In such a case, the floorspace gradient is another confirmation of the structural density gradient. It is also worth noting that the outskirts of Addis Ababa are not as developed as the inner areas of the city. This systematically makes the area size of the grids in the inner city more pronounced. Investigating the negative housing gradient is an interesting topic for future research.

Furthermore, the density of buildings near the CBD is relatively higher, as

Table 3.4: The structural density gradient estimates

	Max	Mean	Max	Mean	Total		*Total*	Count	*Count*
	Height (m)		**Volume (m^3)**		**Area (m^2)**			**Count**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	2.116***	1.806***	10.03***	9.651***	9.998***	8.183***	7.949***	4.007***	3.161***
	(0.0069)	(0.0062)	(0.0141)	(0.0145)	(0.0199)	(0.0176)	(0.0171)	(0.0162)	(0.0160)
dist	-0.0592***	-0.0473***	-0.1350***	-0.1347***	-0.1728***	-0.1297***	-0.0972***	-0.1001***	-0.0745***
	(0.0007)	(0.0006)	(0.0014)	(0.0015)	(0.0020)	(0.0018)	(0.0017)	(0.0017)	(0.0016)
Observations	43,330	43,330	42,231	42,231	42,231	42,233	40,653	35,922	40,653
R^2	0.14215	0.11707	0.17410	0.16642	0.14860	0.11107	0.07115	0.08766	0.04882

Notes: The table presents estimates of the slope of the structural density gradient. The dependent variable is the logarithm of the building characteristics, regressed on the distance to the CBD in kilometers. Italicized variables are constructed from the Google Open Buildings dataset, while the remaining variables are from the DLR datasets. All building characteristics are aggregated at the $100m \times 100m$ grid cell level. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

shown in panel (d) in Figure 3.6, and aligns with the monocentric model, indicating a higher building concentration in the city center. The number of buildings is a good proxy for the population density gradient. The density of buildings is higher in the middle (between 2 to 10 kilometers from the CBD) than in the CBD itself (see panel (d) in Figure 3.6). Based on the author's observation, dense settlements are prevalent outside the central areas, and clusters of public housing projects such as condominiums and real estate developments are found across sections of the city.

In summary, the built-up environment in Addis Ababa is an unexplored topic. In the data, we observe a concentration of high-rise buildings in the city center. However, the floorspace size of buildings does not increase as we move further away from the CBD. The city center features taller, more voluminous, and wider buildings, on the contrary, the peripheries have shorter, less voluminous, and narrower buildings. Surprisingly, the number of buildings does not strictly decrease with distance from the CBD, indicating clusters of dense dwellings at shorter distances from the CBD. Despite the city's unique configuration, a city that is not planned, the findings suggest that the monocentric model predicts the distribution of building characteristics well, except for the dwelling size (building floorspace).

3.6 Conclusion

The monocentric model, a key model in urban economics, has strong theoretical and empirical support, especially in cities in developed countries. However, there are gaps between theory and evidence, largely due to past data limitations. This study examines the model's relevance in Addis Ababa, a rapidly developing country city. It provides new empirical evidence on rent and structural gradients, indicating that house prices, rents, and building heights decrease with distance from the CBD. These findings are consistent with the monocentric city model and studies in developed countries.

Quantitatively, our rent gradient estimates are similar to those of Liotta et al. (2022), who provide average estimates for a global sample of cities including Addis Ababa. However, their Addis Ababa estimates are inconclusive due to data limitations. This paper presents reliable rent gradient estimates for Addis Ababa using panel and cross-sectional settings, from 2017 to 2024, based on more than 72,665 unique property listings. In addition, the results show that the rent gradient is steeper for rents than for house prices, suggesting that rent is more sensitive to distance to the CBD than home purchases. This could be attributed to the city's limited public transportation system, leading to longer commutes and increased rental demand near the CBD.

The study also estimates the structural density gradient by analyzing building data from the DLR and Google building footprint datasets. The results show that building height, volume, and count decrease with distance from the CBD, consistent with the model's predictions. However, the floorspace (building ground area coverage) gradient does not increase with distance. The study emphasizes analyzing the distribution of high-income and low-income residents to understand this gradient.

The findings of this study suggest that the monocentric model is quite capable of explaining the urban structure of Addis Ababa, despite its different urban form and growth patterns compared to cities in developed countries. Furthermore, the study also demonstrates the potential of new data sources leveraging data generation methods such as web scraping and utilization of newly available satellite-based building footprint datasets for urban economics research, especially in developing countries where urban data is scarce. It provides a unique real estate dataset for Addis Ababa, which can be a valuable resource for learning new insights not only from Addis Ababa but also from other cities in developing countries. This study emphasizes the importance of analyzing land prices, population density, and income dynamics in the city. However, due to data limitations, these aspects were beyond the scope of this study. Examining the location of the poor and the rich is particularly interesting in understanding land use in Addis Ababa and its urban structure. Future research could also explore the impacts of transportation infrastructure, land tenure system and use regulations, and other urban factors on the rapidly changing urban dynamics of Addis Ababa.

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Appendix

3.A Background of Addis Ababa

This background provides the context for studying Addis Ababa's urban spatial structure. The city's rapid growth, migrant-driven urbanization, unique land tenure system, dynamic housing market, and social and inequality issues make it an interesting case to test the applicability of urban economics models in a developing country setting.

Addis Ababa, founded in 1886, is Ethiopia's capital and largest city by population size. It is the epicenter of the country's economic, financial, and political activities. The city's population has rapidly grown from 2.74 million in 2006 to 5.5 million in 2023 and is projected to reach 9 million by 2035 (United Nations, Department of Economic and Social Affairs, Population Division, 2018).[18]

Addis Ababa attracts migrants from across Ethiopia due to its concentration of economic opportunities. In 2021, internal migrants constituted 42.2% of the city's total population (CSA (2021), accessed March 2024, Archived). The city's physical size has also rapidly expanded, incorporating nearby suburbs and leading to rising population density. However, the city's official boundaries remain undefined. Addis Ababa's rapid spatial expansion has led to jurisdictional disputes with the surrounding Oromia region. The city's expansion into Oromia land has sparked protests and political tensions.

Land ownership in Addis Ababa is characterized by state ownership, with residents leasing land and owning property built on it.[19] The housing market faces challenges meeting the surging demand, with high construction costs further complicating the situation (The Reporter (2022), accessed

[18]See (CSA (2007), accessed March 2024, Archived)

[19]In Ethiopia, all land is publicly owned as per the 1995 Ethiopian Constitution (Article 40(3)). Individuals cannot own land privately but can lease it from the government, with the right to lease land and own property on leased land guaranteed by the constitution.

March 2024, Archived). Most property transactions, especially rentals, are conducted through informal local brokerages. Online property listings are not yet widespread.

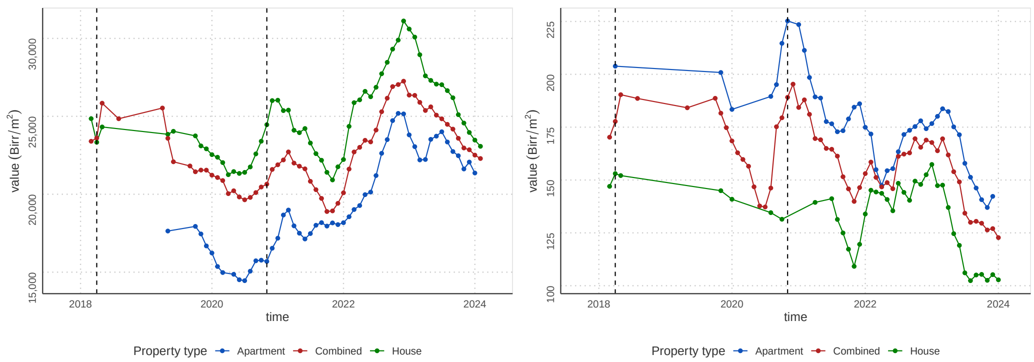
Residential real estate prices in Addis Ababa vary significantly across neighborhoods based on factors like location, amenities, and infrastructure. In 2023, prices ranged from 73,000 to 270,000 Birr per square meter, with affluent central areas like Bole and Kirkos commanding the highest prices. Condominium prices have also risen sharply in recent years (Miles Africa, Residential Report H2, (2023), accessed March 2024, Archived).

Furthermore, Addis Ababa faces significant challenges related to poverty, unemployment, and inequality. In 2022, approximately 24% of the city's population lived below the poverty line, according to estimates by the UNDP (2023). There are stark disparities in living conditions between the city's formal and informal settlements. Many informal settlements lack basic services such as clean water, sanitation, and electricity. The rapid growth of the city has put pressure on infrastructure and social services. Ensuring sufficient housing, healthcare, education, and transportation for the growing population remains an ongoing challenge.

In recent years, Addis Ababa has seen extensive demolitions of informal settlements and older neighborhoods, "to make way for new developments and redevelopment projects". In March 2024, the city administration announced that up to 11,000 people have been relocated from the Piassa neighborhood — the famous historical center of Addis Ababa, with close to 2,000 houses torn down for road expansion and redevelopment (The Reporter (2024), accessed March 2024, Archived). The mayor stated that the residents were provided with condominium units as compensation. Since 2019, many families, numbering in the tens of thousands, have been evicted and relocated, often to the outskirts of the city. The demolitions and evictions have sparked controversy (Amnesty International (2020), accessed March 2024, Archived). Residents complain about insufficient compensation and the disruption of their social networks and livelihoods. Some argue that the process unfairly targets the poor and specific ethnic groups. The government asserts that redevelopment is necessary to upgrade dilapidated areas and improve infrastructure. However, the process has faced criticism for its lack of transparency and community involvement (Kloosterboer, 2019).

The government has taken some measures to address the housing crisis by legalizing informal settlements, introducing public housing schemes like condominiums with long-term payment options, and reforming property tax collection. However, these efforts have not fully met the housing needs of the growing urban population, especially of the low-income residents. More policy reforms and public investments are necessary to improve access to affordable housing. Rental control and tenant protection laws have not been widely implemented. In April 2024, the Ethiopian Parliament passed a sweeping rent control bill that caps annual rent increases, mandates minimum lease terms, and imposes vacancy taxes in an effort to improve housing affordability and stability in Addis Ababa (Addis Fortune (2024), accessed April 2024, Archived).

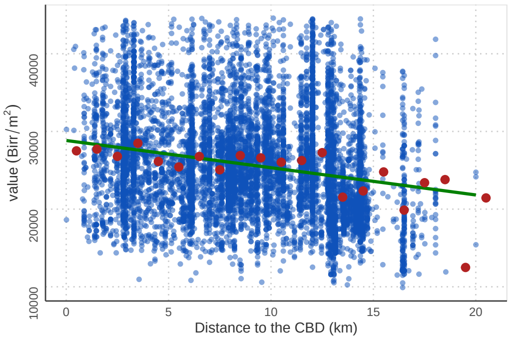
3.B Additional tables and figures



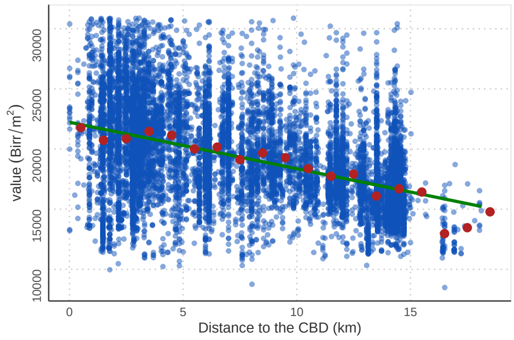
(a) Price (b) Rent

Figure 3.B.1: Average house and rental prices in Addis Ababa, by property types.

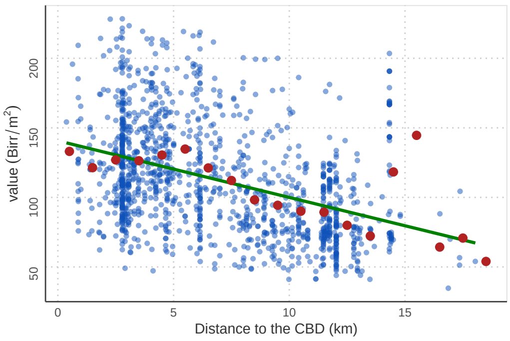
Notes: The figure shows trends in the average house and rental prices in Addis Ababa. The left panel depicts the trends in price, while the right panel shows rent, for houses, apartments, and combined. These values are raw values, unadjusted for property characteristics, in Birr per square meter, adjusted for inflation using Ethiopia's CPI, with December 2016 as the base period. The first dashed line marks the beginning of Abiy Ahmed's time as Prime Minister of Ethiopia (April 2018), and the second dashed line indicates the start of the Tigray conflict (November 2020). Months with fewer than 55 advertisements (a minimum of 5 per subcity monthly), are omitted. The series is smoothed with a 4-month moving average for clarity.



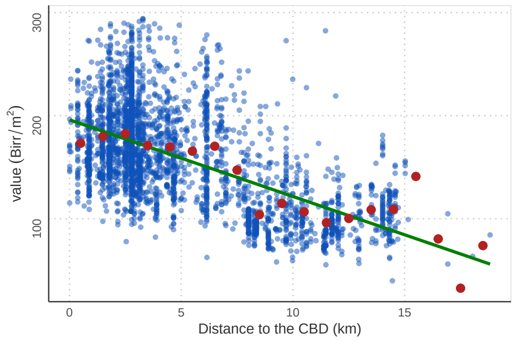
(a) Price (House)



(b) Price (Apartment)



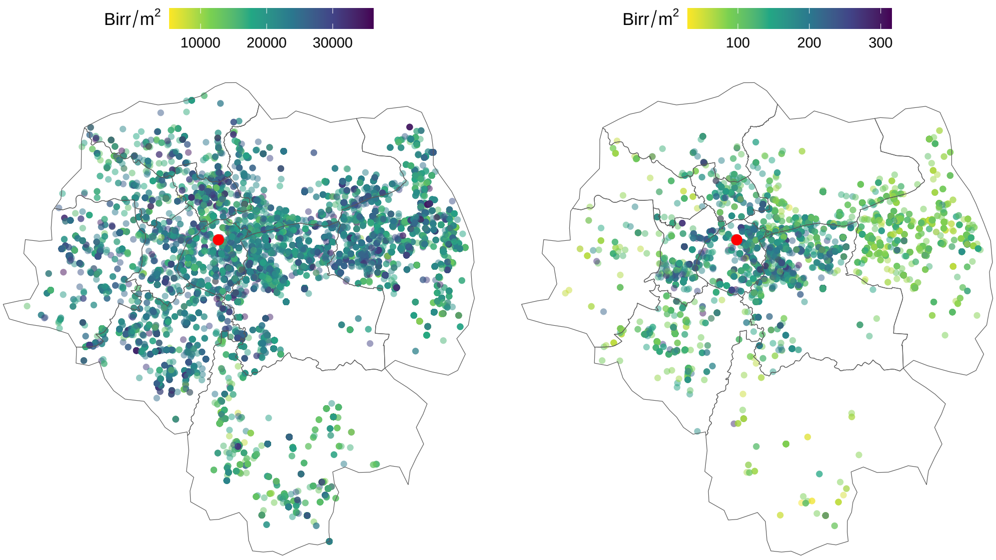
(c) Rent (House)



(d) Rent (Apartment)

Figure 3.B.2: The rent gradient in Addis Ababa in 2023, by property types.

Notes: The figure depicts the rent gradient for house prices and rents against the distance to the CBD (i.e., Meskel Square). Blue dots represent individual property values, while red points represent averages within 2 km distance bins. The green lines are fitted over the blue data points. Property values with missing location data are excluded from the plot.



(a) Price (b) Rent

Figure 3.B.3: The spatial distribution of property prices in Addis Ababa in 2017 - 2024.

Notes: The map illustrates the average house prices and rents per square meter in Birr during 2017 - 2024. Lighter colors indicate lower prices. The red point marks the CBD, Meskel Square. Properties with missing location data are excluded from the map.

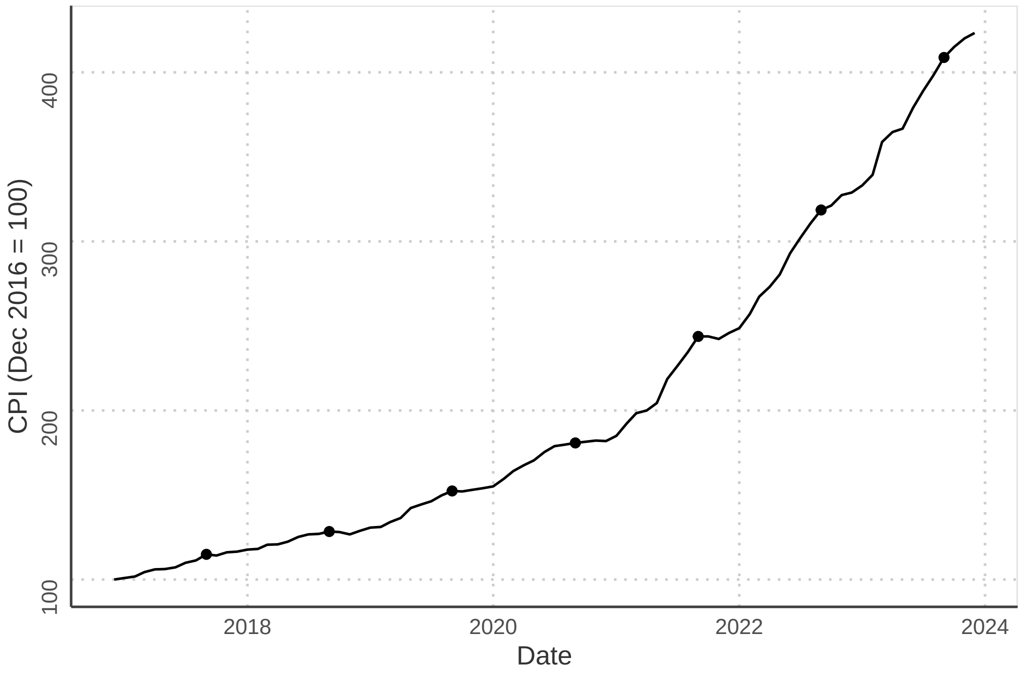
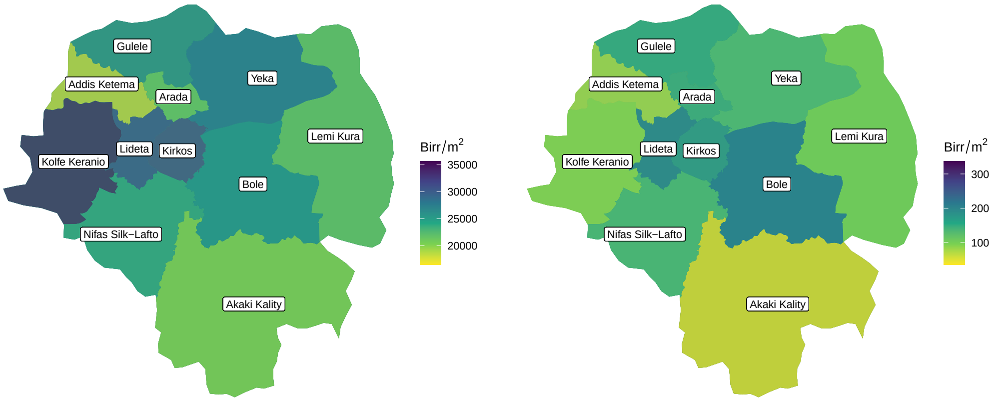


Figure 3.B.4: Consumer Price Index (CPI).

Notes: The figure shows the monthly General CPI in Ethiopia, with the base period December 2016. Source: Ethiopian Statistical Service.



(a) Price (b) Rent

Figure 3.B.5: The spatial distribution of property prices in Addis Ababa by subcity in 2023.

Notes: The map illustrates the (unadjusted for property characteristics) average house prices and rents per square meter in Birr in 2023, based on listings within each subcity. Prices adjusted for inflation using Ethiopia's CPI with December 2016 as the base period.

Table 3.B.1: Property listings by providers

Provider	For Rent			For Sale			**Total**
	Apartment	House	Other	Apartment	House	Other	
Afrotie	370	781	62	5053	8750	1788	**16804**
Beten	24	10	7	229	395	153	**818**
Engocha	211	11	2	967	163	128	**1482**
Ethiopianproperties	2	5	1	4	29	6	**47**
Ethiopiapropertycentre	119	83	6	1495	578	50	**2331**
Jiji	1605	374	-	3145	1654	10	**6788**
Livingethio	204	86	5	115	160	21	**591**
Loozap	6022	3240	425	16570	16909	4771	**47937**
Qefira	31	463	11	180	1620	264	**2569**
Realethio	361	106	102	89	122	52	**832**
Zegebeya	52	68	6	29	186	15	**356**
Total	**9001**	**5227**	**627**	**27876**	**30566**	**7258**	**80555**

Table 3.B.2: The rent gradient estimates by property types

(a) Price (House)

	Fixed Effects (1)	Pooled (2)	2017 (3)	2018 (4)	2019 (5)	2020 (6)	2021 (7)	2022 (8)	2023 (9)	2024 (10)
dist	-0.0197***	-0.0233***	0.0061	-0.0002	-0.0168***	-0.0165***	-0.0229***	-0.0108***	-0.0169***	-0.0389***
	(0.0038)	(0.0004)	(0.0063)	(0.0035)	(0.0020)	(0.0006)	(0.0012)	(0.0011)	(0.0008)	(0.0010)
Constant		10.25***	10.08***	10.02***	10.13***	10.05***	10.23***	10.28***	10.30***	10.24***
		(0.0042)	(0.0609)	(0.0317)	(0.0182)	(0.0064)	(0.0107)	(0.0094)	(0.0074)	(0.0111)
Standard-Errors	year					IID				
Observations	28,324	28,324	170	404	1,055	5,501	3,093	4,787	9,164	4,150
R^2	0.24336	0.09455	0.00556	6.92×10^{-6}	0.06388	0.10593	0.10491	0.01912	0.05191	0.26674
Within R^2	0.07891									

(b) Price (Apartment)

	Fixed Effects (1)	Pooled (2)	2017 (3)	2018 (4)	2019 (5)	2020 (6)	2021 (7)	2022 (8)	2023 (9)	2024 (10)
dist	-0.0198***	-0.0186***	-0.0145***	-0.0071	-0.0021	-0.0104***	-0.0257***	-0.0174***	-0.0213***	-0.0173***
	(0.0015)	(0.0003)	(0.0037)	(0.0096)	(0.0019)	(0.0008)	(0.0007)	(0.0007)	(0.0004)	(0.0010)
Constant		9.934***	9.877***	9.606***	9.687***	9.759***	9.851***	9.948***	10.02***	9.874***
		(0.0024)	(0.0378)	(0.0727)	(0.0173)	(0.0076)	(0.0052)	(0.0046)	(0.0034)	(0.0097)
Standard-Errors	year					IID				
Observations	27,644	27,644	112	71	469	1,779	4,565	6,965	12,267	1,416
R^2	0.24232	0.13490	0.12434	0.00782	0.00275	0.08630	0.21708	0.09068	0.20792	0.16253
Within R^2	0.16006									

(c) Rent (House)

	Fixed Effects (1)	Pooled (2)	2017 (3)	2018 (4)	2019 (5)	2020 (6)	2021 (7)	2022 (8)	2023 (9)	2024 (10)
dist	-0.0420***	-0.0470***	-0.0528***	-0.0196***	-0.0650***	-0.0524***	-0.0436***	-0.0453***	-0.0407***	-0.0284***
	(0.0030)	(0.0014)	(0.0122)	(0.0049)	(0.0077)	(0.0040)	(0.0040)	(0.0031)	(0.0024)	(0.0034)
Constant		5.047***	5.141***	5.082***	5.432***	5.116***	5.024***	5.004***	4.963***	4.703***
		(0.0095)	(0.0884)	(0.0281)	(0.0497)	(0.0305)	(0.0239)	(0.0177)	(0.0187)	(0.0316)
Standard-Errors	year					IID				
Observations	5,156	5,156	108	520	258	537	693	1,248	1,345	447
R^2	0.25991	0.18812	0.15042	0.02929	0.21731	0.23859	0.14888	0.15007	0.17840	0.13395
Within R^2	0.15625									

(d) Rent (Apartment)

	Fixed Effects (1)	Pooled (2)	2017 (3)	2018 (4)	2019 (5)	2020 (6)	2021 (7)	2022 (8)	2023 (9)	2024 (10)
dist	-0.0493***	-0.0536***	-0.1087***	-0.0073	-0.0245***	-0.0546***	-0.0432***	-0.0424***	-0.0543***	-0.0516***
	(0.0035)	(0.0009)	(0.0060)	(0.0048)	(0.0073)	(0.0032)	(0.0027)	(0.0020)	(0.0012)	(0.0025)
Constant		5.335***	5.577***	5.326***	5.366***	5.406***	5.351***	5.326***	5.293***	5.074***
		(0.0051)	(0.0572)	(0.0293)	(0.0410)	(0.0198)	(0.0132)	(0.0089)	(0.0077)	(0.0166)
Standard-Errors	year					IID				
Observations	8,933	8,933	100	218	279	762	1,408	2,568	3,053	545
R^2	0.35412	0.28259	0.77016	0.01039	0.03937	0.27618	0.15630	0.14563	0.39660	0.44495
Within R^2	0.25821									

Notes: The table presents estimates of the slope of the rent gradient over time, for houses and apartments separately. The dependent variable is the logarithm of the property price, and the independent variable is the distance to the CBD in kilometers. The fixed-effects estimations include year-fixed effects. The pooled sample combines the data from all the years under consideration. Robust (clustered by year for fixed-effects) standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3.B.3: Hedonic regression results

	Price (1)	Rent (2)
Floorspace (m^2)	-0.0010***	-0.0030***
	(0.0002)	(0.0003)
Floorspace squared	8.8×10^{-7}***	2.16×10^{-6}***
	(3.36×10^{-7})	(4.25×10^{-7})
Property type House	0.2441***	-0.1748***
	(0.0194)	(0.0201)
Num. Bedrooms	0.0183***	0.0245***
	(0.0050)	(0.0059)
Num. Bathrooms	0.1336***	0.1147***
	(0.0083)	(0.0132)
Num. Images in the ad	0.0171***	0.0067***
	(0.0017)	(0.0016)
Furnishing Semi-furnished	-0.0695***	-0.3554***
	(0.0179)	(0.0346)
Furnishing Unfurnished	-0.1287***	-0.2406***
	(0.0135)	(0.0159)
Condition Underconstruction	-0.1245***	0.1027**
	(0.0160)	(0.0423)
Condition Used	-0.0174	0.0407***
	(0.0108)	(0.0140)
Garden Yes	0.0945***	0.1753***
	(0.0131)	(0.0157)
Parking Yes	-0.0018	0.0455***
	(0.0133)	(0.0140)
Kitchen Yes	0.0155	-0.0759***
	(0.0113)	(0.0114)
Balcony Yes	-0.0423***	-0.0179
	(0.0134)	(0.0119)
Elevator Yes	-0.1354***	0.0481**
	(0.0202)	(0.0192)
Power Yes	0.0711***	0.0577***
	(0.0144)	(0.0160)
Observations	55,973	14,089
R^2	0.29030	0.44041
Within R^2	0.20504	0.23983
Time-Subcity fixed effects	✓	✓

Notes: The dependent variable is the logarithm of the property value in Birr/m^2. The model includes time and subcity fixed effects. It also controls for the usual structural characteristics of the property, condition, furnishing levels, and additional property amenities. Furthermore, the model accounts for the subcity in which the property is located to control for unobserved systematic differences across the subcities of Addis Ababa. The number of images is imputed for the provider Qefira. Clustered (time, subcity) standard errors in parentheses. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 3.B.4: List of online real estate providers

Name	Num of Ads	Remark
EthiopianHome - https://www.ethiopianhome.com/city/addis/_ababa-1/	990	
Ethiopian Properties - https://www.ethiopianproperties.com/property-type/residential/	880	
Betbegara - https://www.betbegara.com/	83	
Qefira - https://web.archive.org/web/20230530142104/https://www.qefira.com/property-rentals-sales/addis-ababa	8121	Shutdown in June 2023
Addis Property Listings - https://addispropertylistings.com/all-properties	76	
Loozap Ethiopia - https://et.loozap.com/category/real-estate-house-apartment-and-land	75358	
Sarrbet - https://sarrbet.com/with-list-layout/	741	
Ethiopia Realty - https://ethiopiarealty.com/search-results/?location/%5B/%5D=addis-ababa	717	
Ermithe Ethiopia - https://ermitheethiopia.com/all-ads/listing-category/property/	645	
LiveEthio - https://livingethio.com/site/property	625	
Shega Home - https://shegahome.com/properties	60	
ZeGebeya.com - https://zegebeya.com/properties/	560	
Zerzir - https://zerzir.com/ads/real-estate/	539	
Real Addis - https://www.realaddis.com/property-search/	513	
Beten - https://betenethiopia.com/	495	
Kemezor - https://et.kemezor.com/products?type=house/&city=addis/%20ababa	434	22 pages
Cari Africa Homes - https://homes.et.cari.africa/	42612	Aggregator: cross-posting platform
HahuZon - https://hahuzon.com/listing-category/property-rentals-sales/	400	
Ethiopia Property Centre - https://ethiopiapropertycentre.com/addis-ababa	3649	
Realtor Ethiopia - https://realtor.com.et/store/	33	
Addis Gojo - https://addisgojo.com	32	
Ethiobetoch - https://www.ethiobetoch.com/propertylisting	315	17 pages
AfroTie - https://play.google.com/store/apps/details?id=com.ewaywednesday.amoge.ewaywednesday/&hl=en/_US/&gl=US	30000	Does not have a website, an Android app.
Verenda - https://www.verenda.et/	285	
Mondinion - https://www.mondinion.com/Real/_Estate/country/Ethiopia/	268	
Yegna Home - https://yegnahome.com/search-result-page?propertyType=Apartment	247	
Expat - https://www.expat.com/en/housing/africa/ethiopia/addis-ababa/	233	
Keys to Addis - https://keystoaddis.com/search-results/?keyword=/&location/%5B/%5D=addis-ababa	219	
Ebuy - https://www.ebuy.et/properties?type=property	216	
Engocha - https://engocha.com/classifieds	2059	
Addis Agents - https://rentinaddisagent.com/listing/	195	
Rent in Addis Agent - https://www.addisagents.com/property-types/residential/	175	
Real Ethio - https://www.realethio.com/search-result-page/?location/%5B/%5D=addis-ababa	1585	
Betoch - https://www.betoch.com/property/	126	
JIji - https://jiji.com.et/real-estate	12272	Part of Jiji Africa
Sheger Home - https://shegerhome.com/	120	Over 23 pages, 6 ads per page.
Ethio Broker - https://www.ethiobroker.com/property/filter?is/_rental=0	105	20 pages: 5 ads per page.
Airbnb Addis Ababa - https://www.airbnb.com/s/Addis/%20Ababa-Ababa-{}-Ethiopia/homes?adults=	1000	For a single adult.

Notes: Status and number of ads as of April 2024. Qefira shut down in June 2023.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the author utilized Grammarly Premium to enhance language and readability. After utilizing this tool, the author reviewed and edited the content as necessary and assumes full responsibility for its accuracy.

Erklärung

gemäß §10 Abs. 6 der Promotionsordnung der Mercator School of Management, Fakultät für Betriebswirtschaftslehre der Universität Duisburg-Essen, vom 11. Juni 2012.

Hiermit versichere ich, dass ich die vorliegende Dissertation selbständig und ohne unerlaubte Hilfe angefertigt und andere als die in der Dissertation angegebenen Hilfsmittel nicht benutzt habe. Alle Stellen, die wörtlich oder sinngemäß aus anderen Schriften entnommen sind, habe ich als solche kenntlich gemacht.

Essen, 16. April 2024

Eyayaw Beze

DOI: 10.17185/duepublico/82247
URN: urn:nbn:de:hbz:465-20240814-140201-1