The Effects of Institutional, Political and Macroeconomic Factors on the German Housing and Land Markets

Dissertation zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaft

eingereicht an der Fakultät für Wirtschaftswissenschaften der Universität Regensburg

vorgelegt von: Stefanie Braun

Berichterstatter: Prof. Gabriel S. Lee, PhD., Prof. Dr. Fabian Kindermann

Tag der Disputation: 19.07.2021

The Effects of Institutional, Political and Macroeconomic Factors on the German Housing and Land Markets

Stefanie Braun

May 12, 2021

The Effects of Institutional, Political and Macroeconomic Factors on the German Housing and Land Markets

A dissertation submitted to the graduate faculty in partial fulfillment of the requirements for the degree of Doktor der Wirtschaftswissenschaft (Dr. rer. pol.).

Adivsors:
Prof. Gabriel Lee, PhD
Prof. Dr. Fabian Kindermann

Wirtschaftswissenschaftliche Fakultät
Universität Regensburg
Regensburg, Germany

Acknowledgments

This thesis could not have been possible without my main adviser, Prof. Gabriel Lee. I am deeply grateful to him for his guidance, input, advice and support both throughout this thesis and my time at the University of Regensburg. His influence is clearly evident throughout this dissertation.

I am also greatly appreciative of the assistance provided by Prof. Fabian Kindermann. As my second supervisor, he also contributed to the improvement of this dissertation. I thank him for his support and advice.

Further, I thank Andreas Kunert, vdpResearch and the BKI for providing data used in this thesis.

I would also like to thank Vanessa Kunzmann and Johanna Starkl for personal support, encouragement and proofreading various parts of this dissertation.

My gratitude and love also goes out to my family, especially my parents and my sister. Their unconditional support, trust and loving encouragement throughout my life led me to be who I am today.

Contents

List of Figures **v**

List of Tables **vii**

1 Introduction **1**

2 Land Price Estimation for German Counties **10**
2.1 Introduction . . . 10
2.2 Literature Review . . . 13
2.3 Methods and Data . . . 15
2.4 Results . . . 23
2.5 Discussion/Conclusion . . . 43
2.6 Appendix . . . 44

3 Agglomeration Spillover Effects in German Land and House Prices at the County-Level **72**
3.1 Introduction . . . 72
3.2 Previous Literature on Spatial Spillovers in House Prices, Agglomeration, and Land Prices . . . 76
3.3 Baseline Model . . . 79
3.4 Empirical Framework and Data . . . 81
3.5 Estimation Results . . . 84
3.6 Concluding Remarks . . . 102
3.7 Appendix . . . 105

4 Effects of Preferential Tax Treatment on German Homeownership **117**
4.1 Introduction . . . 117
4.2 Housing Market Policies . . . 120
4.3 Model . . . 122
4.4 Calibrating a Benchmark Model for Germany . . . 125
4.5 Results . . . 128
4.6 Conclusion . . . 135
4.7 Appendix . . . 137

5 Conclusion **142**

References **147**

List of Figures

1.1 Nominal house price index development by country, 1975-2020q3 2
1.2 Landvalue per sqm. (A) and vdp-Research house price index for single-and double family houses (B) 2014 for German counties 3
1.3 Percentage change in landvalue per sqm. (A) and house price index (B) (2014-2018) for German counties 3
1.4 Percent of household that are owning (with and without mortgage) by country, 2010-2018 4

2.1 Number of observations by county 20
2.2 Components of home value by county in 2014 25
2.3 Change in components of home value by county - 2014-2018 29
2.4 Estimated land values per square meter of lotsize by county in 2014 and 2018 30
2.5 Berlin, Munich and surrounding Counties 33
2.6 Cumulative distribution of land's share of home value across the sample of 379 German counties 34
2.7 Cumulative distribution of land values across the sample of 379 German counties 34
2.8 Estimated land values vs. expert based land values per square meter of lotsize in Hessen 2014 and their percentage deviation from expert based values . . . 36
2.9 Estimated land values vs. expert based land values per square meter of lotsize in Thüringen 2016 and their percentage deviation from expert based values . 37
2.10 Comparison estimated values vs. land values from undeveloped land ready for construction (EUR/sqm.) - 2014 39
2.11 Components of home value by county in 2018 49
2.12 Components of home value by county in 2018 - legend adjusted to 2014 . . . 50
2.13 Relationship of important economic variables and house prices, 2014 60
2.14 Relationship of important economic variables and land prices, 2014 61
2.15 Changes in residential land values and building land values, 2014-2018 62
2.16 Changes in residential land values and building land values, 2014-2018 (Quintiles adjusted to residential land values) 63
2.17 Land values of undeveloped land vs. accessed land values, EUR/sqm. (perc. deviation) - Thüringen 2016 64
2.18 Land values of undeveloped land vs. accessed land values, EUR/sqm. (perc. deviation) - Hessen 2014 65
2.19 Land share's by county, 2014 - different cost functions 66
2.20 Land share's by county, 2014 - different deltas 67
2.21 Land share's by county, 2014 - different thetas 68

2.22 Land share's by county, 2014 - different housing stock measures 69
2.23 Distribution of land's share for construction cost model 3 and 5 70
2.24 Distribution of land's share for different (baseline) depreciation rates 70
2.25 Distribution of the difference value-replacement cost 71

3.1 Development of house prices (2014-2020) and land prices (2014-2018) - Selected German and international cities 72
3.2 Moran scatterplot for land and house prices - First order contiguity matrix . 73
3.3 Housing market decomposition by country - 2000-2020q3 74
3.4 Measuring agglomeration - German counties in 2014 75
3.5 Top 7 agglomerations and surrounding counties 85
3.6 Construction cost by state, 2014-2018 115
3.7 Median income by state, 2014-2018 115
3.8 Population density by state, 2014-2018 116

4.1 Homeownership rates - selected European Countries (Source: Eurostat) . . . 120
4.2 Price-to-income ratios - selected European countries (Sources: OECD, Eurostat) 121
4.3 Rate of return on savings when $\tau_{ir} = 0$, with and without mortgage interest deductibility 124
4.4 German labor income process for each quintile (SOEP v.34) 126
4.5 Rate of return on savings for the average individual at each age 134
4.6 Average consumption bundle over lifetime of average individual 134

List of Tables

2.1 Number of appraiser-assessed land values available over BORIS-D by state . . 17
2.2 Descriptive statistics 19
2.3 Components of home value in 2014 by state 26
2.4 Change in components of home value by state - 2014 through 2018 27
2.5 Percentage change in land value per m^2 lot size - Berlin and surrounding Counties 31
2.6 Percentage change in land value per m^2 lot size - Munich and surrounding Counties 32
2.7 Various cost function estimations 40
2.8 Construction cost estimated - summary statistics 41
2.9 Land share for different cost functions - summary statistics 41
2.10 Depreciation rate - summary statistics 42
2.11 Land share for different deltas - summary statistics 42
2.12 Land share for different thetas - summary statistics 43
2.13 Land share for different housing stock measures - summary statistics 43
2.14 Components of home value in 2018 by state 48
2.15 Data sources 51
2.16 Data sources - continued 51
2.17 Data sources - continued 2 52
2.18 Number of observations by county 53
2.19 Number of observations by county - continued 54
2.20 Number of observations by county - continued 2 55
2.21 Number of observations by county - continued 3 56
2.22 Correlation of house price, land values, unemployment rate and mean income by state 57
2.23 Percentage change in building land value per m^2 - Berlin and surrounding Counties 58
2.24 Percentage change in building land value per m^2 - Munich and surrounding Counties 59

3.1 Descriptive statistics 84
3.2 Sum of counties in Tier 1-3 for each of the Big 7 cities 84
3.3 Moran's I (year=2014) 87
3.4 Baseline estimation results - Germany 88
3.5 Baseline estimation results - Germany (direct and indirect effects) 88

3.6 Spatial Durbin Model - Baseline estimation results for Top 7 cities as well as West and East Germany . . . 92
3.7 Spatial Durbin Model - Baseline estimation results for Top 7 cities as well as West and East Germany (direct and indirect effects) . . . 93
3.8 House price estimation - Germany . . . 94
3.9 House price estimation - Germany (direct and indirect effects) . . . 95
3.10 House price estimation - Germany (including log(Land value per m^2)) . . . 95
3.11 House price estimation - Germany (including log(Land value per m^2); direct and indirect effects) . . . 96
3.12 Spatial Durbin Model - House price estimation results for Top 7 cities as well as West and East Germany . . . 97
3.13 Spatial Durbin Model - House price estimation results for Top 7 cities as well as West and East Germany (direct and indirect effects) . . . 98
3.14 SDM estimation results for different sets of controls variables - Germany . . . 99
3.15 SDM estimation results for different sets of controls variables - Germany (direct and indirect effects) . . . 100
3.16 Estimation results - Germany - Inverse distance matrix . . . 101
3.17 Estimation results - Germany - Inverse distance matrix (direct and indirect effects) . . . 101
3.18 Estimation results - Germany - Vacant vs. residential land values . . . 103
3.19 Estimation results - Germany - Vacant vs. residential land values (direct and indirect effects) . . . 103
3.20 Dependent and explanatory variables . . . 105
3.21 Sources - Figure 1 . . . 106
3.22 German Big 7 cities and surrounding counties (Tier 1-3) . . . 107
3.23 Percentage changes in land value per m^2 - Top 7 agglomerations and surrounding tiers . . . 110
3.24 Percentage changes in house price index - Top 7 agglomerations and surrounding tiers . . . 113
3.25 Non-spatial estimation results, tests . . . 114

4.1 GDP (Source: OECD) . . . 121
4.2 Model parameters for the German economy . . . 125
4.3 Statistics for the three tax codes . . . 130
4.4 Welfare effects Experiment 1 (Germany) . . . 132
4.5 Welfare effects Experiment 2 (Germany) . . . 133
4.6 Household's balance sheet (Gervais, 2002) . . . 138

Chapter 1

Introduction

The housing sector plays a vital role in the economy at both micro and macro levels. First, the housing sector accounts for a substantial fraction of national and households' wealth in Western countries. For example, in most countries of the Euro area housing contributes to around one-half of households' portfolios (Kaas et al., 2019). Second, boom and bust cycles in the housing sector occurred antecedent to many past great recessions, especially before the most recent financial crisis of 2008-2010. Many countries across the globe are still continuously experiencing higher house prices (Figure 1.1). Consequently, understanding the critical drivers for housing market dynamics is crucial as housing markets play an important role in economic prosperity, aggregate economic behavior and financial stability. As housing capital represents both investment and consumption goods, housing is affected by various markets as well as political and institutional factors. The determinants of housing markets are macroeconomic (e.g., interest rates and economic growth), socio-economic (e.g., household incomes and demography), as well as political and institutional factors (e.g., mortgage market regulation, land use regulation, rental market regulation and tax policies). While there has been much effort to understand the effects of macro-economic factors on housing markets, in its report the European Central Bank (2003) points out the need for further studies on the impacts of institutional and political factors on the European housing markets.

Moreover, literature[1] highlights several stylized facts of the German housing market that raise interest in understanding its development and determinants. First, Figure 1.1 shows that over the long run and especially before, during and after the financial crisis of 2008-2010, German housing prices remained constant compared to other Western countries. Second, from 2012 onward, house prices in Germany and other Western countries experienced an ongoing upward trend. A growing strand of literature, for example, Knoll et al. (2017) and Davis and Heathcote (2007), supports the theory that land prices instead of replacement costs are key in understanding the increasing path of housing prices worldwide. While the construction cost trajectory stays relatively flat, a surge in land prices reflects a low price elasticity of housing supply when additional land for construction is scarce (Knoll et al., 2017). Besides land supply being geographically fixed, supply elasticities of land for development can artificially vary across space and over time in consequence of local zoning restrictions (Glaeser and Gyourko, 2003). Ahlfeldt and McMillen (2014) for Chicago, Barr et al. (2018) for Manhattan and Knoll et al. (2017) for the U.S. and 13 mostly European

[1] For example Kofner (2014) and Voigtländer (2014).

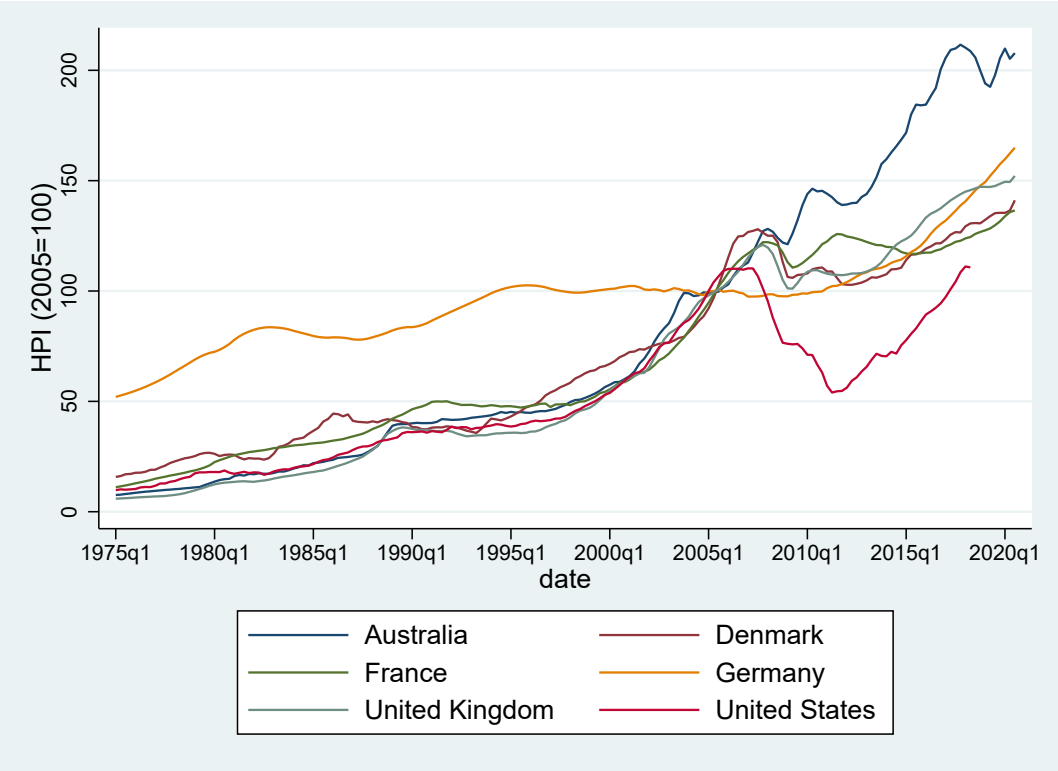


Figure 1.1: Nominal house price index development by country, 1975-2020q3
Note: Federal Reserve Bank of Dallas - International house price data base

countries, study the development of historical and current land values and real estate prices. Particularly over the recent decades, these prices rose more dramatically than income and inflation (Barr et al., 2018), further emphasizing the importance of understanding driving components of housing and land markets. Thus, third, Figure 3.3 shows that the surge in land prices outpaced house price increases not only in Germany but also in other countries such as the U.K. and the U.S. Fourth, house and land prices do not only vary over time but also across counties. From Figure 1.2 one can observe significant spatial clustering patterns in land and house prices across German counties. Moreover, the magnitude of the growth in German house and land prices varies across Germany (See Figure 1.3). Fifth, Germany's homeownership rate ranks at the bottom end in international comparison (See Figure 1.4). Since 2010, the percentage of homeowner's in Germany stagnated at a level of 44 percent. Using the Eurosystem Household Finance and Consumption Survey 2013, Mathä et al. (2017) reveal variations in European homeownership rates between 44 percent (Germany) and 90 percent (Slovakia). Lastly, with mean contributions of housing capital to total net wealth in euro area countries of 30 percent (Cyprus) to 74 percent (Solvakia), Germany ranks with 38 percent second lowest in cross-european comparison in 2013 (Mathä et al., 2017).[2]

The objective of this dissertation is to analyze different aspects of economic, structural and political housing market determinants in the German housing and land markets. To be exact, the emphasis of this dissertation is twofold.

[2]Kaas et al. (2019) show a strong negative correlation between wealth inequality and homeownership rates for several European countries including Germany.

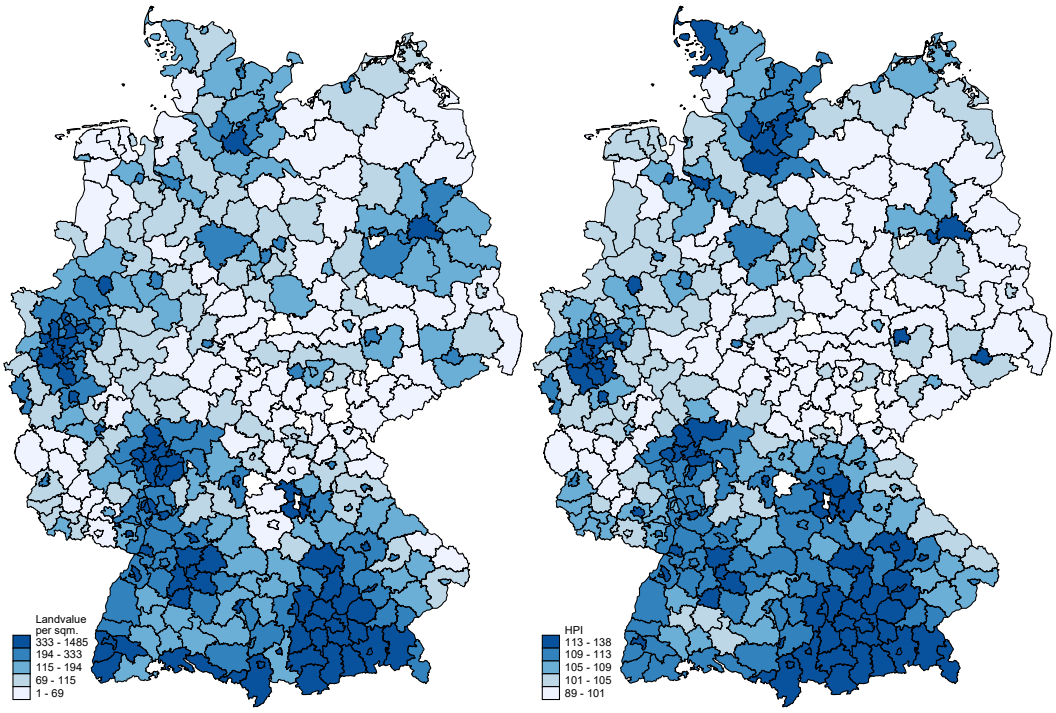


Figure 1.2: Landvalue per sqm. (A) and vdp-Research house price index for single-and double family houses (B) 2014 for German counties

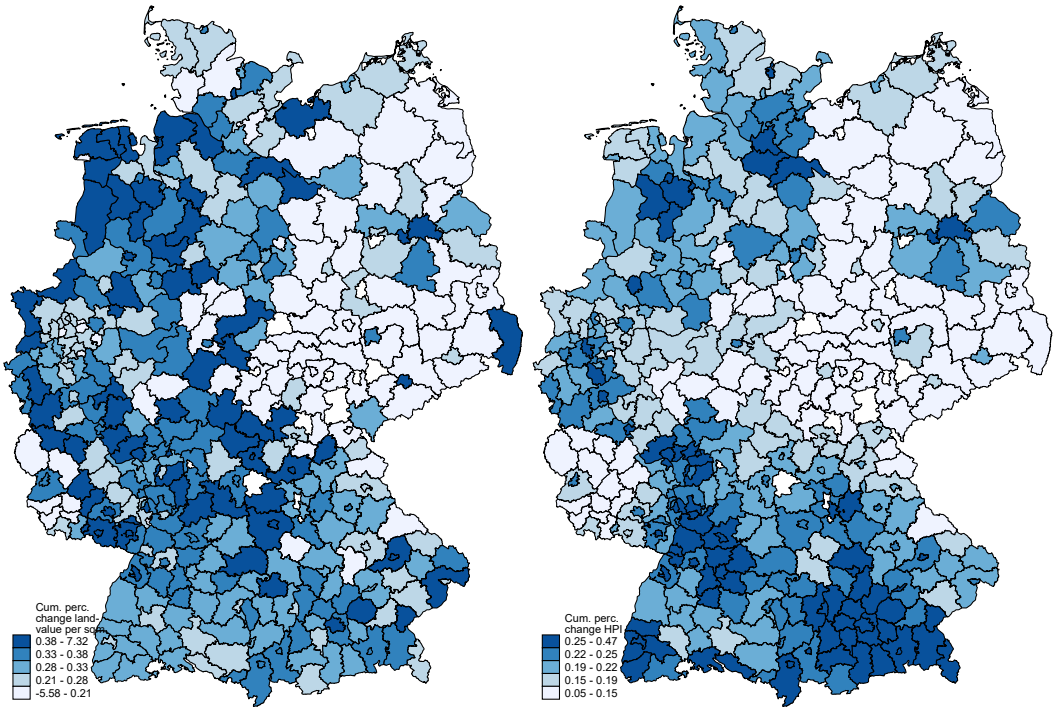


Figure 1.3: Percentage change in landvalue per sqm. (A) and house price index (B) (2014-2018) for German counties

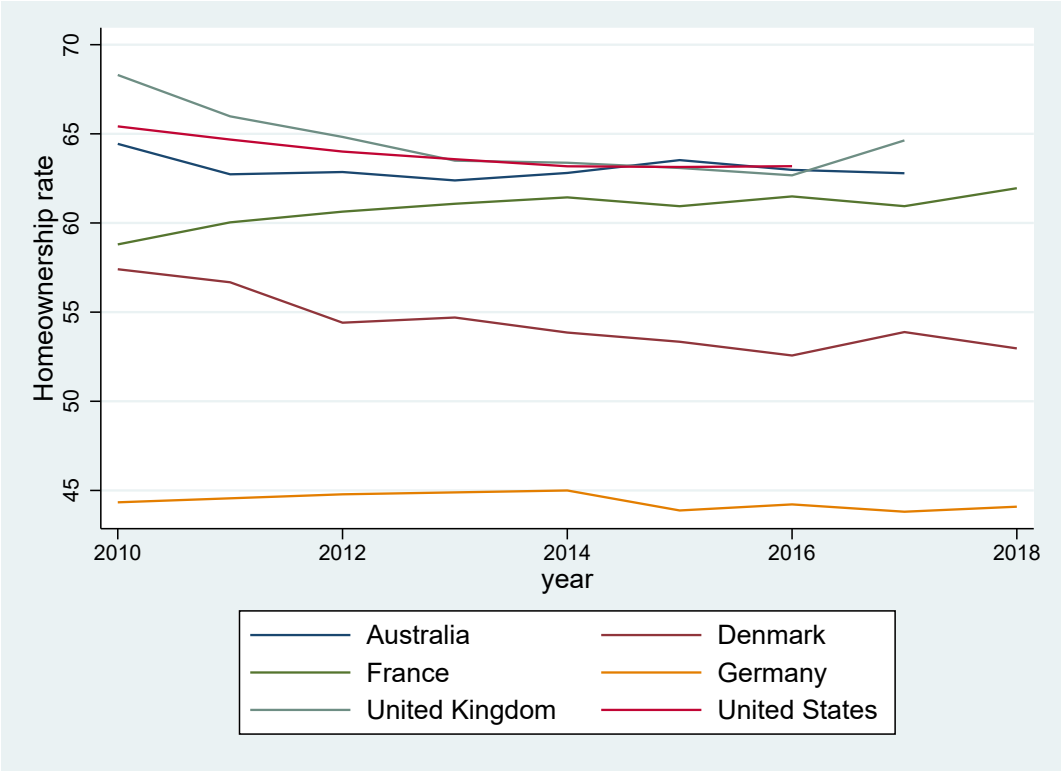


Figure 1.4: Percent of household that are owning (with and without mortgage) by country, 2010-2018
Note: OECD Affordable Housing Database

Chapters 2 and 3 of this dissertation focus on the decomposition of the housing bundle in Germany into its two components - land and structure - and the developments of their values over space and time. In Chapter 2, I build a database for the costs of housing structures and residential land values at the county-level based on the residual method of Davis and Heathcote (2007) and Davis and Palumbo (2008) for 2014 to 2018. Chapter 3 uses the database built in Chapter 2 to analyze the existence of various spatial dependence patterns in German counties' residential land and housing markets. Chapter 4 focuses on Germany's low homeownership rate and evaluates the effects of two housing tax policies on the German homeownership rate, individual life-cycle decisions and welfare.

More specifically, in Chapter 2, I estimate changes in the value and price of (sub-urban) residential land for 379 German counties ("Landkreise") from 2014 to 2018 using a total of 42,674 single- and double-family housing unit observations. The two-step residual method by Davis and Heathcote (2007) and Davis and Palumbo (2008) that decomposes the value of a home into its structure cost and land value is applied to build a database for the cost of housing structures and residential land values at the county-level. I find that the price of residential land has increased significantly more than the structure costs and house prices in most of the German counties. While the average structure and home values increased only by 14 and 20 percent, respectively, average land values increased by 27 percent. This indicates that cycles in the German land prices are more likely to affect the trajectory of house prices in the future. Moreover, I show that the estimated land prices vary significantly to the expert based land price valuations in two of the German Federal States (Hessen and

Thüringen).

In Chapter 3, I estimate spatial effects in German land prices using the county-level residential land prices from Chapter 2 for 378 counties[3] from 2014 to 2018. I use "off-the shelf" spatial models to account for two types of spatial spillovers in land and house prices: First, exogenous interaction effects such as agglomeration and network externalities. Second, endogenous spatial patterns as for example displacement effects. The chapter seeks to answer several questions: First, can cross-county spillovers explain variation in land and house prices for Germany, and the Top 7 German agglomerations? Second, to what extent can clustering patterns in house prices be attributed to spatial variations in land prices? Third, do different land price measurements convey different conclusions? I show that county-level spatial agglomeration effects play a large and significant role in explaining the cross-county variations in land prices. For example, a one percent increase in the median income causes an increase of 3.45 percent in land prices, whereas a one percent increase in the population density accounts for an increase of 5.47 percent in land prices, ceteris paribus. I find that similar empirical patterns also hold for house prices but less so for the seven major German agglomerations. This result suggests, unlike Gyourko et al. (2013), that the Big 7 German cities do not exhibit the characteristics of the so-called Superstar Cities. Moreover, housing supply factors such as the available land to build and the restrictiveness of housing supply are crucial factors in explaining land and house prices. Furthermore, I show that the land price spillover effects are among the dominating factors in the formation of regional house prices. These results, as in Gyourko et al. (2013), suggest that changes in agglomeration variables such as median income (productivity) and population density cannot completely explain disparate local land and house prices. Lastly, running estimations with two different land price measurements for Germany shows that direct and indirect agglomeration spillover effects can explain more variation in residential land prices than vacant land prices.

In Chapter 4, I analyze the effects of mortgage interest deductibility and untaxed imputed rental income on the German homeownership. I use the deterministic general equilibrium life-cycle framework with heterogeneous agents by Gervais (2002), where a minimum down-payment constraint on purchases of housing capital is the critical element of the model framework. Conducting counterfactual experiments, I find that both tax policies would increase Germany's low homeownership rate. However, these tax policies would entail substantial welfare losses for individuals of all income quintiles in the long run. Finally, wealth effects are relatively small and the welfare analysis shows that individuals would prefer to live in an economy without preferential tax treatment of housing.

The dissertation follows and combines several lines of literature.[4] The second chapter follows the literature on decomposing the housing price bundle into both its land and structural component. I apply the residual method by Davis and Heathcote (2007) and Davis and Palumbo (2008) for Germany. Apart from this method, economists brought about various other carefully considered approaches to appraise land values with different strength and weaknesses over the last years that can largely be attributed to the second line of research. Besides different angles on the theory, (limited) data availability often constrains researchers' choice of methodology.

[3] In contrast to Chapter 2, I used the new county Göttingen after the consolidation of the old counties Göttingen and Osterode im Harz after 2016.

[4] A more detailed discussion of literature follows in each of the upcoming chapters.

More recent works extend the two-step residual procedure, that relies on depreciation assumptions for existing structures. By using only new homes to estimate land shares (Davis et al., 2017) and excluding homes with an effective age of more than 10 years as suggested by an option tear down model (Davis et al., 2021) assumptions on the depreciation of structures can be avoided.

The second strand of literature builds upon spatial transaction based approaches that use a structural approach to the production function for housing under zero profit and constant returns to scale assumptions (Epple et al., 2010) or non-parametric estimation (McMillen, 1996). In contrast to the residual method, this approach avoids the need for depreciation assumptions as it treats both the quantity and price of housing services as unobservables. Albouy et al. (2018), Nichols et al. (2013) and Haughwout et al. (2008) apply spatial transaction based approaches using vacant land sales data for the U.S. For 190 CBSAs[5] and 20 thousand Census tracts, Ahlfeldt and McMillen (2020) are able to take a step ahead by matching repeated sales pairs, i.e. including the sale of the vacant plot and the sale of the same parcel after development within four years. Tideman and Plassmann (2018) define the land value as the opportunity cost of leaving a parcel undeveloped. They argue that rather the existing buildings' value should be modeled as the residual not the land value, as positive external shocks increase a parcels' land value but at the same time decrease the value of the now inefficiently small existing building.

Due to different land value estimation approaches, the estimates of land values in these studies vary significantly. Between 1995 and 2005, Davis and Heathcote (2007) show an increase in land values by a factor of 2.5. In comparison, Nichols et al. (2013)' estimates on vacant and teardown land sales and those by Tideman and Plassmann (2018) quadrupled over the same period. Although Davis and Heathcote (2007) and Davis and Palumbo (2008) estimates tend to be lower compared to other recent estimates in the literature, with average land shares of 17 percent, the estimates of the novel parcel-matching method by Ahlfeldt and McMillen (2020) range at the bottom end of land share estimates in recent literature.

While the largest part of these studies estimate land values for the U.S., land value estimations for Germany are rare. Previous works on German land prices are for example Kolbe et al. (2012, 2015, 2019). These studies can be attributed to the spatial transaction based approach using non-parametric estimation as in McMillen (1996). All three focus on land price estimation with transaction data from local surveyor commissions for Germany's capital Berlin using different non-parametric estimation methods. Kolbe et al. (2012, 2015, 2019) generate highly correlated land value estimates to expert-based assessments and show that land price estimation can be harmonized across different German federal states. Their methods, however, require high computational power suggesting that the methods are mostly applicable on a very local level. Thus, the objective of Chapter 2 is to estimate German land prices on county levels using housing data that is publicly available for research purposes.

Chapter 3 that aims to explain spatial variations in land and house prices for German counties, combines three lines of literature: Literature that empirically studies the spatial dependence of house prices, the impact of agglomeration effects on real estate prices as well as the land price estimation literature discussed in Chapter 2.

[5]Metropolitan and Micropolitan Statistical Areas are collectively referred to as Core-Based Statistical Areas (United States Census Bureau, 2016).

One is aware from practice and theory that house prices of spatially adjacent housing units, neighborhoods or more aggregated regions shape the determination of the house price of a given object of interest. Theoretical explanations for spatial dependence and variation of housing markets are manifold. Mechanisms such as displacement effects (Fingleton, 2008); yardstick competition (Brady, 2014); network externalities (Gong et al., 2020) or the ripple effect, that explains spillover effects between neighboring housing markets for example through migration patterns, spatial arbitrage or equity transfer (Meen, 1999; Kuethe and Pede, 2011) are popular in the spatial econometrics literature on determining spatial housing market spillovers. Moreover, various studies that apply hedonic house price analysis and incorporate spatial interaction effects for several (primarily U.S.) urban housing markets[6]. Recent, studies have focused on (dynamic) spillovers patterns across more aggregated housing markets, e.g., between cities, counties or states. Using spatial autoregressive models (SAR) for 353 UK districts in 2001 and from 2000-2007, Fingleton and Le Gallo (2008) and Baltagi et al. (2014) find evidence for endogenous house price spillovers in the U.K. For the U.S., Brady (2011, 2014) find persistent spatial diffusion processes by estimating spatial impulse response functions based on SAR type models for California counties for the period 1995-2002 and across the United States for the period 1975-2011.

Besides endogenous spillover effects, exogenous interactions mechanisms are considered as another cause of cross-county interactions in literature. For example, Gong et al. (2020) explore the existence of exogenous interaction mechanisms such as network effects in a county or city grid using cross-section data for an urban-network in Eastern China. Using different market potential measures, Camagni et al. (2017) and Partridge et al. (2009) show evidence for agglomeration spillover effects in housing markets for 136 large European urban zones and U.S. counties, respectively. The popular density-productivity relationship (**?**) and a positive relationship between population density and real estate prices informally support the existence of agglomeration effects (Glaeser, 2019). Along with this informal evidence for the existence of agglomeration effects among German counties that correlates with high house and land prices (Figure 3.4), from land value estimation studies that use the spatial transaction based approach, one also finds indirect support for the existence of agglomeration effects in land markets. For example, Ahlfeldt and McMillen (2020) report that variation in land shares is likely influenced by demand-side factors that are exogenous to the production function of housing and less by inelasticities in housing supply as commonly believed in literature. Albouy et al. (2018)'s results support agglomeration forces to play a role in the variation of land shares and indirectly show evidence for monocentric cities as they find downward-sloping land price gradients with increasing distance to the city center.

Research that studies spatial interaction of house prices for Germany is quite limited. Using panel data on German land prices from land sales of land ready for construction for 412 counties from 1995-2010, Otto and Schmid (2018) find cross-county house price spillovers estimating dynamic spatial panel data models. They find evidence for the ripple effect that is timely delayed and diminishes with distance to the region a shock occurred. Möller (2009) also use data on building land but focus on West German labor market regions only to analyze the impact of regional labor markets on real estate prices. As suggested by their theoretical model, their results reveal that a wider spread of the wage distribution and

[6]See for example Can (1990, 1992); Dubin (1988, 1992); Basu and Thibodeau (1998).

lower unemployment rates positively influence the price for building land.

Therefore, using data on house prices and the residential land prices from Chapter 2 on German county level, the objective of Chapter 3 is to study spatial spillover patterns across German counties' land and housing markets. Thereby, one of the main emphasis is to explain the impact of agglomeration economies on residential land markets.

The fourth chapter uses the simple framework by Gervais (2002). Gervais (2002) was one of the first to study preferential tax treatment of housing in a general equilibrium life cycle framework. On the one hand, among others, Chambers et al. (2009), Floetotto et al. (2016) and Sommer and Sullivan (2018) followed this strand of literature by for example introducing income risk, pension systems and endogenizing prices. On the other hand, Poterba and Sinai (2011), Rosen (1979a), Rosen (1985) and Albouy and Hanson (2014), among others, use the partial equilibrium user cost approach to study the impact of mortgage interest deductibility and other tax subsidies to homeowners on income tax liabilities and the user cost of owner-occupied housing. For Germany, Kaas et al. (2021) analyses the impacts of different policy changes on the homeownership rate in Germany in a life-cycle model with uninsurable income risk, endogenous homeownership and social housing. While not considering imputed rental income, Kaas et al. (2021) focuses on the reduction of the social housing sector and real estate transfer tax (RETT). Fatica and Prammer (2018) also evaluate preferential tax treatment of housing in Germany and the Euro Area, however, by applying the user cost approach in a reduced form.

This dissertation contributes to housing literature in the following manner.

Chapter 2 builds a database for the cost of housing structures and (sub-urban) residential land values for 379 German counties from 2014 to 2018 based on the two-step residual method by Davis and Heathcote (2007) and Davis and Palumbo (2008). Despite some short-comings of this approach[7], I combine data from several sources that facilitate the estimation of land values on county level in Germany. The main contribution is the constructed database as availability of data on county-level residential land prices is limited for Germany[8]. Moreover, I study the development of the housing bundles' components across German counties from 2014-2018 and compare the estimates for residential land values per m^2 of lotsize to available measurements of land prices in German counties. Lastly, Section 2 contributes to the literature on the decomposition of a house into land value and construction cost by a sensitivity analysis of the two-step residual method towards the choice of several critical parameters in the model.

Chapter 3 is one of a few studies that analyzes spatial dependence of land prices[9] and to the best of my knowledge the first that focuses on spatial interaction effects in land values and house prices between German counties. I estimate endogenous spatial interaction effects of house and land prices. I also analyze exogenous spillover effects (agglomeration effects) on land prices between German counties. Furthermore, I also show the importance of understanding that these spillovers in house prices are driven by land prices as the key component of growth in house prices. In addition, I take a closer look at differences in the magnitude of land price and agglomeration spillover effects between counties within the Top 7 German agglomerations. Finally, Chapter 3 analyses differences in the strength of spatial

[7]Strength and Weaknesses are discussed in Chapter 2.
[8]Availability on German residential land prices is discussed in Chapter 2.
[9]The land value per m^2 of lotsize concept of Chapter 2 is used here.

spillover patterns for different land price measurements: (sub-urban) residential land and vacant building land.

Chapter 4 contributes to literature that studies the impact of preferential tax treatment of owner-occupied housing on German homeownership. In contrast to Kaas et al. (2021), I use a simple framework by Gervais (2002) and focus on the impact of two tax policies - mortgage interest deduction and taxation of imputed rents - on German homeownership. This set up allows me to focus on the relationship between tenure choice and tax code as the main channel responsible for distortion in individual decisions. I calibrate the model for the German economy. Further, I conduct two counterfactual experiments to study the effects of mortgage interest deduction and a tax of imputed rents on the German homeownership rate. Lastly, I discuss my results in light of recent advances in literature and compare the results for Germany to those found by Gervais (2002) for the U.S.

This dissertation comprises 5 chapters. The upcoming Chapter 2 builds a database for residential land values in German counties. Chapter 3 uses the estimated land values from Chapter 2 to detect spatial dependencies in German counties' land and housing markets. Chapter 4 conducts counterfactual experiments in a heterogeneous agent, deterministic life-cycle model to evaluate the impact of tax policies on homeownership. Chapter 5 concludes.

Chapter 2

Land Price Estimation for German Counties

2.1 Introduction

Given the recent macroeconomic experience of most developed countries, few students of the economy would argue that the housing sector is a critical component for financial stability, aggregate economic behavior, and household net wealth. One of the key lessons from the Great Financial Crisis of 2008 is that sustained imbalances in housing valuation can jeopardize the financial sector's soundness due to banks' central role as mortgage lenders and the use of real estate as collateral.[1] Moreover, on a micro-level, the European Central Bank (2018) reports that post-2008 EU area house price run-ups suggest a worsening of housing affordability for new buyers. Consequently, understanding the housing price variation is paramount in assessing the housing and financial sectors' risks. Recent studies on land prices such as Ahlfeldt and McMillen (2020), Albouy et al. (2018) and Davis et al. (2021), with different objectives in mind, have shown for the U.S. that most of the variations in house prices are due to the underlying land values and shares. Knoll et al. (2017) also document that rising land values and shares mainly drive house price increases for many developed economies since World War II.[2] In this chapter, I also argue that the movements in land - and structure values are crucial for understanding the development of German housing markets and policy measures that accompany these movements.

Bonnet et al. (2021) show that the housing component of national private wealth explains the spectacular rise of wealth relative to national income in several countries: the historical increase in housing wealth is in significant part due to the increase in land share. The OECD data on Germany also confirms the observation by Bonnet et al. (2021). The recent development of households' housing wealth (including both structures and land) and housing prices for Germany from 1999 to 2017[3] shows three salient features. First, housing accounts for 62 percent of national wealth in Germany at the end of 2017. Second, housing prices have been sharply increasing in the last ten years. Lastly, the fraction of land in total wealth has been increasing over the last six years, but the fraction of dwellings' value in total wealth

[1] For example, Koetter and Poghosyan (2010) show that deviation of house prices from their fundamental value contributes to bank distress using the data on regional real estate prices and individual banks in Germany from 1995 to 2004.

[2] On a city level, Barr et al. (2018), for example, also show that vacant land values have dramatically increased for Manhattan, New York City in the period between 1950 to 2014.

[3] From the OECD national accounts data set, I construct the total national wealth as the sum of fixed non-financial assets and land, and the net financial wealth. For the housing wealth, I use the total values of dwellings and land.

has been steadily decreasing. These stylized facts suggest that housing value changes may significantly affect the German macroeconomy and could be due to the movements in the land - and structure values.

Consequently, this chapter estimates changes in the value and price of residential land for 379 German counties ("Landkreise")[4] from 2014 to 2018 by combining data from several sources that are publicly available for academic researchers. The absence of reliable data on actual residential land transaction prices in the past makes it necessary to estimate land prices using other data sources.[5] In doing so, I build a database for the cost of housing structures and residential land values at the county-level. The framework of the approach in this chapter is that of Davis and Heathcote (2007), who decompose the value of a home into the value of the structure and land value on the aggregate level for the U.S., and Davis and Palumbo (2008), who estimate the land prices for 46 large U.S. metropolitan areas. To account for capital depreciation, previous works on German land prices such as Kolbe et al. (2012, 2015, 2019) use land value assessment methods employing transaction data from local surveyor commissions. Kolbe et al. (2012, 2015, 2019), who focus only on the city of Berlin, generate land value estimates that are highly correlated with expert-based assessments and show that, using semi - and non-parametric methods, land price estimation can be harmonized across different German federal states. Their methods, however, require high computational power and some financial costs suggesting that the methods are mostly applicable on a very local level. However, I estimate German land prices on county level using housing data that is publicly available for research purposes.[6]

There are three main reasons to estimate German residential land prices at the county-level using Davis and Palumbo (2008) framework to build up the dataset. First, there are no publicly available county-level transaction residential land prices in all Federal German States. The Federal Statistics Office provides only the publicly available vacant land prices on a national level from 2010. Second, seven out of sixteen federal states provide land prices at the county-level but at costs.[7] Lastly, unlike many other countries that use statistical standard mass land appraisal systems for their use in property taxation and real estate development projects[8], Germany still uses independent appraisal methods for each of the federal states. Despite being based on detailed guidelines, these existing land price valuations rely heavily on surveyors' knowledge and expertise.[9] And given Germany's federal state structure, there is no assurance that each state's valuation meets the national standard quality. Thus, the motivation to estimate the German land prices on the county level is to provide a systematic method and to build-up a harmonized land price valuation database

[4]Official administrative boundaries as of 2014.

[5]I emphasize here that I am not using transaction data on vacant land in constructing the land prices and shares.

[6]I provide a detailed data description in Appendix 6.1 and 6.3.

[7]For example, the state of Rheinland-Pfalz requires 120 Euros per year. The land price dataset is provided by each state's Independent Surveyor Commission (Gutachterausschuss für Grundstückswerte, GAA). Moreover, the data accessibility for those states that provide data free of charge is limited and time-consuming.

[8]At least 15 countries have implemented statistical mass appraisal systems for property taxation. Among these are Australia, Canada, Egypt, Mauritius, New Zealand, South Africa, and the United States. Examples from Europe include Denmark, Finland, Latvia, Lithuania, Russia, Sweden, Northern Ireland in the United Kingdom, and the Netherlands (Almy, 2014).

[9]Two critiques on the expert valuation method are: First, the method is not uniformly conformed at the national level. A second critique is that the valuation occurs irregularly: the valuations are decided annually or biennially either on December 31 of the previous year or January 1 of the current year. (See Paragraph 196, BauGB).

that can address and help some of the German housing markets' measurement issues. For example, besides surveyors' land valuation, the existing large-scale land value measurements in Germany from the Statstische Ämter des Bundes und der Länder (2021) only refer to undeveloped land.[10] Hence, these measurements are not comparable for all single-/double family housing units throughout Germany. Subsequently, the land price estimates could further provide an alternate view for real estate market participants in evaluating their projects' economic feasibility and help policymakers address some of the housing taxation laws. In particular, Bonnet et al. (2021) using a Ramsey taxation model show that the first best optimal taxation is achieved with a property tax on land without resorting to tax on capital. Consequently, having systematic land price estimates could help to improve the current German property tax reform that requires a frequent, systematic, and cost-effective land price valuation methodology.[11]

One of the main results from both Davis and Heathcote (2007) and Davis and Palumbo (2008) is that the prices of both components of the housing bundle evolve quite differently. Consequently, they shed light on the importance of distinguishing between the values of construction costs and residential land when analyzing home prices. Without the decomposition of housing prices, Davis and Palumbo (2008) argue that regression results from housing market-related variables on the fundamentals in determining housing prices can lead to misguiding conclusions. Furthermore, both Davis and Heathcote (2007) and Davis and Palumbo (2008) show that land prices appear to be three times more volatile at business cycle frequencies than the value of the structural component. Moreover, the average share of a home's value attributed to residential land increased significantly between 1984 and 2004. While the inflation-adjusted land price increased by more than 400 percent, the price of housing structures appreciated by only 33 percent. Consequently, to estimate and identify land prices in a systematic method is crucial in understanding housing prices.

As with Davis and Palumbo (2008), I also show that despite the short time series, the price of residential land has become relatively more expensive in the majority of German counties. The counties around urban centers such as Munich, Stuttgart, Berlin, Hamburg, Dresden, and the Ruhr area cities experienced the highest land price increases. However, in general, an upward shift in home values, land values, and residential land share occurred in almost every state. The most significant differences in the changes in land prices are between the new and old Federal States of Germany. Although the differences in the average land's share of home value increased between East ("new") and West ("old"), the absolute differences in home values, the value of residential land, and replacement costs did not decrease. Specifically, the cumulative change in land values from 2014 to 2018 varies between 4 and 56 percent. On average, the home values increased by 23 and 13 percent for West and East German counties, respectively. In contrast, the land values increased by 31 and 17 percent for West and East Germany and structure values increased by only 15 and 11 percent for West and East. The findings imply that cycles in the German land values are likely to

[10] These statistics are available at the regional statistics website from the German Federation and countries' Statistical Offices

[11] The calculation of the property tax is based on decades-old property values. For West German counties, they are based on land values from 1964 and for East German counties on the year 1935. As land values have developed quite differently since these years, the new regulation deadline is set on December 31, 2019, to eliminate unequal tax treatment. If a new regulation is introduced by the end of 2019, then the old rules can still be applied until 2024. Starting in 2025, the new legal regulation must then be used (Federal Ministry of Finance, 2019a).

influence house prices more in the future than they did in the past. Lastly, I also show that the land prices vary significantly to the expert-based land price valuation in two German state governments (Hessen and Thüringen). The results are also robust to various sensitivity analyses. In particular, the robustness checks on the land share estimates using different cost functions, the structure intensities of new housing, and housing stock growth measures all show almost no variations in the land shares. However, the effect of depreciation rates for structure on land shares is significant as I account for capital depreciation for various structure ages in the sample: an increase in the depreciation rate from 2 to 4 percent results in a rise of 45.4 to 62.3 percent in the land shares.

The next section briefly overviews the literature. I then outline the methodology in Section 2.3 as well as the detailed description of Davis and Heathcote (2007) and Davis and Palumbo (2008) version for Germany. The empirical results and discussions are in Section 2.4. Section 2.5 concludes, followed by the Appendix in Section 2.6.

2.2 Literature Review

The literature on the estimation of land prices can broadly be attributed to two strands of literature. First, the residual method, for example, by Davis and Heathcote (2007) and Davis and Palumbo (2008) measures the price of land as the difference between housing value and the replacement cost of the structure. The second line of research follows spatial transaction based approaches that use a structural approach to the production function for housing as in Epple et al. (2010) or non-parametric land price estimation as in McMillen (1996). Eurostat (2013, 2017a) promotes another approach in estimating residential and commercial land prices: A hedonic regression, as in Diewert et al. (2015), to separate house value into its land and structure components. However, to my knowledge, Eurostat (2013, 2017a) has not followed up on its plan to estimate land prices at the level of property transactions in the EU economies since its publications. The delays and difficulties in the Eurostat implementation could be because land and structure values tend to be correlated across properties, which hinders the proper identification in the approach.

Davis and Heathcote (2007) and Davis and Palumbo (2008) decompose the value of a home into the value of the structure and land value, both on the aggregate level for the U.S. as well as for 46 large U.S. metropolitan areas. The two-step procedure calculates estimates of replacement costs of residential structures in a given base year and builds an aggregate structure share for a given regional unit in that year. In the second step, the benchmark estimates for the structure share and replacement costs are extrapolated, and the growth in land prices over the time series is derived. They show the importance of distinguishing between construction costs and residential land values rather than using exclusively home prices in addressing macroeconomic and housing market implications.

Recent work by Davis et al. (2017) extends the two-step residual method by focusing on new homes using proprietary data on zip-code level for the Washington DC metro area. By doing so, Davis et al. (2017) avoid estimating the depreciation of structure costs, and hence reducing the amount of estimation error. Davis et al. (2021) exclude homes with an effective age of more than ten years, given the predictions of a calibrated option model of teardowns, to ensure that market values are represented by estimated replacement cost. Davis et al.

(2021) also account for the size of a lot when estimating land values to standardize land values to a per-acre basis. They then apply spatial interpolation methods to estimate land prices, also for housing units without appraisal reports.

Unlike the residual method, the housing production function approach by Epple et al. (2010) decomposes housing into land and structure value using constant returns to scale and zero profit assumptions. One can then recover the price of land and the value of housing per unit of land, whereby the approach treats the quantity and price of housing services as unobservable variables. Consequently, the approach avoids the housing structure depreciation issues that surround the residual approach. Ahlfeldt and McMillen (2020), for example, expand the housing production empirical approach to estimate land shares and the elasticity of substitution between housing unit and land prices.[12] Using CoreLogit data that matches vacant and developed land values at the parcel-level in the U.S., Ahlfeldt and McMillen (2020) find, among other results, that higher land shares correlate with higher land prices in core-based statistical areas. This result is also confirmed by other spatial transaction-based approaches such as Albouy et al. (2018), Nichols et al. (2013) and Haughwout et al. (2008), who use observed market price data on transactions of vacant or almost vacant land (for the U.S., mainly from the CoStar Group Inc.). Albouy et al. (2018), for example, estimate land prices for either only one, several, or close to the universe of metropolitan areas in the U.S. Key assumption in these methods is that the closer land is to the city center, the more valuable it is. As in Ahlfeldt and McMillen (2020), Albouy et al. (2018) also find that land prices in the United States tend to be more volatile than structure prices, which likely arises from the fact that the supply of structures is much more elastic than the supply of land (e.g., Gyourko and Saiz, 2006). These findings supports the so-called land leverage hypothesis, which implies that home prices are more volatile in areas with a relatively large share of land value in housing value (e.g., Bostic et al., 2007).[13]

Another line of spatial transaction based approach is using non-parametric estimation as in McMillen (1996), who estimates Chicago area land values using locally weighted regression. Kolbe et al. (2012, 2015, 2019) focus on German land prices, specifically on the city of Berlin, using non-parametric methods for estimating spatial variation in land values. While all three present different non-parametric land value assessment methods, they all use transaction data from local surveyor commissions from Berlin. Kolbe et al. (2012) estimate land values by first separating the house value into structure and location components. Once the estimated residuals from the first stage is recovered, they then use adaptive weight smoothing approach to estimate the land value surface. One of the main implications of Kolbe et al. (2012) approach is that the developed land values are being estimated. Kolbe et al. (2015), on the other hand, directly use adaptive weight smoothing approach to estimate non-developed land value surface. And Kolbe et al. (2019) use a more general kernel regression to estimate the land value surface using data from transactions of undeveloped lots and data from transactions of developed lots (i.e. single-family houses and condominiums).

[12] Combes et al. (2019) also use the housing production approach to estimate the elasticity of urban costs (housing share) with respect to city population for France.

[13] A few other recent studies that construct and estimate land value indices are: Tideman and Plassmann (2018), who develop a model that decomposes the value of a property into the value of the land and the value of any building in relation to buildings actual size to floor to area ratio (FAR); Gedal and Ellen (2018) construct urban land prices from vacant land sales and "teardown" sales for New York City between 2003 and 2009; Barr et al. (2018) construct a land values index for Manhattan from 150 to 2014 using vacant land sales.

Kolbe et al. (2019) also compare kernel regression results to adaptive weight smoothing in Kolbe et al. (2015) and the two stage non-parametric methods in Kolbe et al. (2012). All three Kolbe et al. (2012, 2015, 2019) show that each method could generate highly correlated estimates with expert-based assessments.

2.3 Methods and Data

I follow Davis and Heathcote (2007) and Davis and Palumbo (2008) in constructing a German land price index at a county level.[14] However, before I outline the residual method below, I want to be upfront about the approach's two apparent shortcomings. First, I do not extensively use a transaction data set of newly built house prices to avoid depreciation of replacement costs when estimating the share of land in home value (e.g., Davis et al., 2017). Moreover, I do not use a simple real options approach as in Davis et al. (2021) to address the residual method's restrictive assumption that houses are constructed with a putty-putty technology. Unlike the residual approach, a real options model that uses prices for new houses could lead to more reasonable land price results representing only the currently available land to be developed. However, to account for the older aged structures in the sample, I use age-specific depreciation rates to estimate the replacement cost of the structure on the land (see Section 2.3.3). In doing so, I address the issue that the residual method is only accurate when houses are relatively young. Second, I also do not use observed market price data on transactions of vacant or almost vacant land as in the spatial transaction-based approaches as in Nichols et al. (2013), Haughwout et al. (2008), and Albouy et al. (2018). I understand these aforementioned shortcomings of the approach. However, given the (lack of) data availability in Germany, I find that the residual approach is the most appropriate method in estimating German residential land prices. I elaborate below the data availability in Germany for vacant land sales, newly built house prices, and appraiser-assessed land values.

2.3.1 Vacant Land Sales, Newly Built House Prices, and Appraiser-assessed Land Values in Germany

Nichols et al. (2013), Haughwout et al. (2008), and Albouy et al. (2018) use the CoStar Group data on near vacant or vacant land sales for the U.S. land price estimation. There is no such comparable data for Germany. Consequently, the spatial transaction-based approaches to estimate land prices are not appropriate for Germany. However, the German regional statistics office records undeveloped land purchased within the municipality building area if its area is larger than 100 square meters.[15] However, these undeveloped land plots are more likely situated on municipalities' outskirts than in the center. I thus think these plots do not represent a good sample to estimate land prices for counties. The regional statistics

[14]The estimation runs on the county level. Estimations on other geographical classifications such as economic regions are not permissible as the balanced matching data for construction costs - and house price indices are not available at the economic region level.

[15]Not included land is 1) land that the owner acquired as a matter of exchange, donation or inheritance 2) developed land such as rented residential, commercial, and factory plots of land. 3) plots of land on which building is prohibited and therefore do not belong to the building area of a municipality 4) Land used for agriculture and forestry, insofar as according to § 33 and § 69 of the German Valuation Act. (BewG) for their sale following the land register traffic law (GrdStVG) and the corresponding implementation regulations, approval is required (Statistisches Bundesamt (Destatis), 2012)

office also keeps a record of land ready sales for construction plots, which are earmarked for development by the municipality. These vacant building land plots are 100 m^2 or more in size and are not differentiable between commercial, residential, and factory construction purposes. Since these plot of land ready for construction are for all-purpose, I am again constrained to the residual approach in estimating the residential land prices.

Another estimation method in the literature is that of the real options approach. However, the real options approach would require to use prices for new houses. Given that the analysis is on the German county level, the sample size for newly built houses is too small for estimation. For example, the raw initial total ImmobilienScout24 dataset consists of 292,583 observations that are classified as new single - and double-family houses between 2014 and 2018.[16] After sorting out the missing data/information on these 292,583 observations, only 492 listings of new single - and double-family houses over 379 German counties are left.

The most commonly used land prices in Germany are from the state-level appraisers. However, despite national valuation norms, local appraisers still have some valuation margins, and the past land values are not always available or costly for the public to access. In 2019, several German federal states created an interactive internet-based database named BORIS-D to promote the transparency and accessibility of the appraiser-assessed land valuation data.[17] The databank's purpose is for the general public to easily assess current and past appraiser-assessed land values for each German federal state. To my knowledge, as of 2020, only 12 out of 16 Federal States list current appraiser-assessed land values on the BORIS-D platform.[18] Table 2.1 summarizes the number of the latest available assessed land values from the BORIS-D website, including areas for residential, commercial, and farming purposes. Not only the website does not provide historical assessed land values, but the interactive mode is also time-consuming in collecting the data: one has to check on each assessed plot of land on the interactive map separately to see further information. Moreover, to obtain some of the historical land prices, one would have to contact each federal state's land valuation association separately and incur high costs in obtaining those data.[19]

2.3.2 Residual Two-Step Approach

I first outline the residual method below. I then describe and present in detail how I merge different data sources to compute annual time series estimates for the average value of land in German counties and county-free cities.

I start with the nominal market value of residential land at date t:

$$p_t^l l_t = p_t^h h_t - p_t^s s_t. \tag{2.1}$$

I denote p_t^l, p_t^h and p_t^s as the quality-adjusted prices per unit of land, houses and structures; and l_t,h_t and s_t represent the quality-adjusted quantities. Hence, $p_t^h h_t$ is the market value of the housing stock and $p_t^s s_t$ the replacement cost of stock of residential structures and

[16] Due to the lead-lag estimation structure, I am constrained to the sample years from 2014 to 2018.

[17] BORIS-D stands for "Bodenrichtwertinformationssystem für Deutschland" (BORIS-D, 2020)

[18] No values are available for Hessen, Baden-Württemberg, Saarland, and Niedersachsen (as of August 26, 2020). However, one could, obtain at costs some of the available land price data by contacting the responsible person for each state.

[19] Most of the states provide real estate market reports that include average county-level BRW (appraiser assessed land value). However, these reports are also costly for seven out of sixteen federal states.

State	Number of appraiser-assessed land values
Bavaria	155
Baden-Württemberg	0
Saarland	0
Rheinland-Pfalz	78676
Hessen	0
Thüringen	18396
Sachsen	101072
Nordrhein-Westfalen	57635
Brandenburg	6251
Berlin	1133
Niedersachsen	0
Bremen	417
Hamburg	249249
Sachsen-Anhalt	602
Mecklenburg-Vorpommern	10447
Schleswig-Holstein	8086

Source: BORIS-D (2020)

Table 2.1: Number of appraiser-assessed land values available over BORIS-D by state

'land' refers to everything that increases home value by more than the replacement cost.

Assuming that houses in a set observed over two successive periods do not change (i.e., structures and land are constant), I can express the growth rate in house prices using the decomposition from Equation (2.1) as

$$\frac{p^h_{t+1}h_t}{p^h_t h_t} = \frac{p^s_{t+1}s_t + p^l_{t+1}l_t}{p^h_t h_t} = \frac{p^s_t s_t(p^s_{t+1}/p^s_t) + p^l_t l_t(p^l_{t+1}/p^l_t)}{p^h_t h_t} = w^s_t \frac{p^s_{t+1}}{p^s_t} + w^l_t \frac{p^l_{t+1}}{p^l_t}, \qquad (2.2)$$

where $w^s_t = \frac{p^s_t s_t}{p^h_t h_t}$ and $w^l_t = \frac{p^l_t l_t}{p^h_t h_t}$ are the shares of home value that are accounted for by replacement cost of structures and market value of land in period t, respectively. As these shares sum to one, I can rearrange Equation (2.2) to express the percentage changes of (constant-quality) land prices for a certain county j in period t as follows:

$$g^{lp}_{jt+1} = \frac{1}{w^l_{jt}}[g^{hp}_{jt+1} - (1 - w^l_{jt})g^{cc}_{jt+1}]. \qquad (2.3)$$

where, g^{lp}_{jt+1} is the value-weighted average growth rate of residential land containing the existing stock of homes in a county j between period t and $t+1$. It is important to note that the index is simply the growth rate of all attributes' price (including location and amenities) that make the homes in a county more expensive than the replacement costs of their structures. It is, however, not a "euro-per-square-meter" concept. To estimate changes in residential land prices for German counties, I apply a two-step procedure similar to Davis and Palumbo (2008) to obtain time series for w^l_{jt} and w^s_{jt}. The next section describes in detail the procedure and data for Germany. However, in short, the first step involves estimating structures share at a benchmark date using real estate data for Germany. In the second step, given these estimated structure shares at a benchmark date, growth in construction cost and house prices, I apply the following dynamic equation to construct a

time series of structure shares:

$$w_{jt}^{s} = w_{jt-1}^{s} \left(\frac{g_{jt}^{cc}}{g_{jt}^{hp}} \right) \left(\frac{h_{jt-1}}{h_{jt}} \right) + \theta_{jt} \frac{\Delta h_{jt}}{h_{jt}} \tag{2.4}$$

where $g_{jt}^{cc} = \frac{p_{jt+1}^{s}}{p_{jt}^{s}}$ is the growth rates in construction cost, $g_{jt}^{hp} = \frac{p_{jt+1}^{h}}{p_{jt}^{h}}$ is the growth rate of house prices, $\frac{h_{jt-1}}{h_{jt}}$ is a proxy for the growth rate of real housing stock, and θ_{jt} is a value for the structure intensity of nominal net new housing.

Some of the implications of Equation (2.4) are worthwhile noting. First, when there is no growth in the housing stock ($h_t = h_{t-1}$), then the structures share in period t equals the structures share of period $t-1$ adjusted for growth in construction cost relative to house prices. Second, for growing cities ($h_t > h_{t-1}$), the growth in construction cost relative to house prices is relatively less important in determining structures share of the next period. Instead, the structure's share of new housing plays a larger role.

2.3.3 Benchmark Estimates for the Replacement Cost of Residential Structures - First Step: German Case

This section describes the approach in computing the annual time series estimates for the average land values in German counties and county-free cities. As described in the previous section, for each county, I use a two-step estimation process following Davis and Palumbo (2008). The goal of this first step, for each county, is to generate a benchmark estimate of the replacement cost of single-/double-family, owner-occupied residential structures and a corresponding share of home values that are represented by the value of residential structures.[20] I focus on single-/double-family homes for two reasons. First, a major fraction of German residential buildings are single- and double family houses. In 2019, the 83 percent of total stock for German residential buildings were designated as single- and double-family houses, whereby the rest of 17 percent were residential buildings that have 3 or more dwelling units. But in terms of the number of dwelling units, the 46 percent of dwellings were in single- and double-family houses and 53 percent were allocated in residential buildings with more than 3 units or other residential establishments.[21] Consequently, since I focus only on single - and double-family houses and that these residential houses tend to be located in the outskirts of CBDs, the estimated land values could be understood as suburban residential land values. Second, the residual method literature commonly focuses on single- and double-family houses (e.g., Davis and Heathcote, 2007; Davis and Palumbo, 2008). I combine three different data sources to recover the county-level structure -,$w_t^s = \frac{p_t^s s_t}{p_t^h h_t}$, and land shares ,$w_t^l = 1 - w_t^s$. I use the vdpResearch GmbH county level house price indexes for single- and double-family houses for the years 2007-2018[22] to approximate the total housing value. Since there is no dataset for the single-/double-family houses residential structure costs at the county level, I first estimate a construction function to proxy the representative single- and double-family houses' residential structure cost. I use 150 observations on

[20] More detailed description of methods and variables that I use is in Appendix 2.6.1

[21] German Federal Statistical Office (2020a)

[22] The time series from 2007 onward are based on evaluations of property databases compiled by the vdpResearch.

	mean	sd	min	max
Average number of observations per county	112.5	106.4	11	1007
Average year built of observations per county	1973.4	11.1	1925.4	1999.6
Average housing size of observations per county	172.4	20.5	117.3	299.9
Average number of floors of observations per county	2.07	0.25	1.35	2.84
Average fraction of observations with basement per county	0.69	0.17	0.19	1
Average quality of observations per county	2.4	0.2	1.77	2.90
Observations	379			

Table 2.2: Descriptive statistics

construction costs for single- and double-family houses from 2016 (BKI, 2016)[23] to estimate the cost function.[24] To build the structure cost database at the county-level, I input the microdata for key housing characteristics from the ImmobilienScout24 website platform into the estimated cost function.

I use the following estimated cost-function as the benchmark that captures the essential variations in costs per square meter across different types as of 2016:

$$\begin{aligned}\log(\text{str_cost_new}) = 7.9 + \underset{(0.07)}{0.1} \cdot I(\text{basement}= 1) - \underset{(0.912)}{0.00005} \cdot \text{living space} \\ - \underset{(0.062)}{0.167} \cdot I(\text{floors} \geq 2) - \underset{(0.000)}{0.433} \cdot I(\text{quality}= 1) - \underset{(0.000)}{0.203} \cdot I(\text{quality} = 2) \quad (2.5)\end{aligned}$$

where, the numbers in brackets represent p-values, basement denotes an indicator whether the housing unit has a basement, living size measures the living space, floors indicates the number of floors, and quality records the quality of a building's facilities. In Equation (2.5), $I(\cdot)$ is an indicator function.[25]

To build the county-level structural cost database, I use a total of 42,647 observations from the ImmobilienScout24 that meet all of the selection criteria. I impute the aforementioned housing characteristics into the cost function as if each observation (house) is brand new as of the year the ad was removed from the ImmobilienScout24 website. Table 2.2 shows summary statistics: the mean number of observations for each county is 112.5, with a minimum sample of 11 and a maximum sample of 1007. I drop 22 of 402 counties that have less than 10 observations per county.[26] Figure 2.1 shows the observed German counties and Tables 2.18-2.21 in Appendix 2.6.4 list the raw number of observations by county. Table 2.2 further shows that the mean year built of observations per county is 1973.4. The average year built of observations per county vary between 1925.4 and 1999.6.

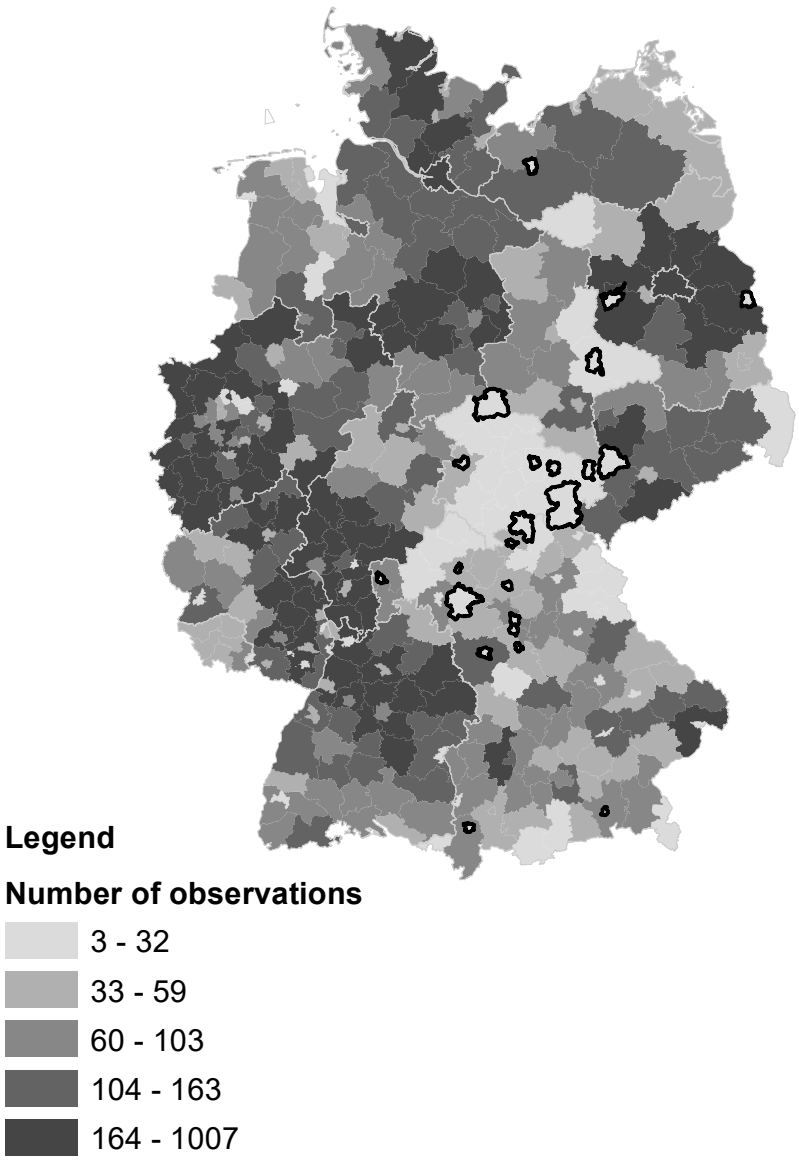
Comparing the age distribution of houses in the sample to the age distribution of Germany's housing stock (Göbel, 2020), the sample appears quite representative for Germany.

[23] BKI stands for Baukosteninformationszentrum Deutscher Architektenkammern: the German Chambers of Architects GmbH.

[24] I could have used the NHK 2010 (Normalherstellungskosten with the base year 2010) instead of the BKI data on construction costs. But the BKI data set was a preferred outlet given the choice of construction cost variables for the estimation.

[25] More details on the cost function estimation are in Appendix 2.6.1. I also estimate different cost functions for the robustness analysis in Section 4.3.1 Table 4.

[26] Estimating cost function with less than 10 observations is statistically insignificant. Consequently, I do not include these counties. Furthermore, I drop the county Altenburger Land as from a closer look at the observations, it looks like 7 of the 11 observations refer to the same object. All dropped counties are indicated by a black outline in Figure 2.1.



Note: The black outlined counties are removed from the sample as there are less than 10 observations or most of the observations are identical.

Figure 2.1: Number of observations by county

Around 16 percent of houses in the sample were built before 1950.[27] More than half are older than 20 but younger than 50 years. Nevertheless, considering each counties' sample (Tables 2.18-2.21 in Appendix 2.6.4) that I use in the benchmark computation the sample might not be representative on county-level. Especially, in the East German counties, the county samples are on average older which coincides with an on average older stock in East German states (Göbel, 2020). This is also the case for the county samples in terms of other relevant variables. From the literature such as Davis et al. (2021), I know that the residual method only estimates accurate land values for young houses. For older houses, after age 20, the residual method undervalues the land component as the value of tearing down the house increases. To account for the variations in aged structures, I use a simple correction in form of age-specific depreciation rates. To this end, to calculate the replacement structure cost that accounts for the depreciation rate, I use the following equation for $s_{i,t}$:

$$s_{i,t} = \begin{cases} str_cost_new_{i,t} \cdot \left(\frac{1}{1+\delta}\right)^{age_{i,t}} & \text{if } age_{i,t} \leq 20 \\ str_cost_new_{i,t} \cdot \left(\frac{1}{1+\delta}\right)^{age_{i,t}} \cdot \left(\frac{1}{1+0.01}\right)^{age_{i,t}-20} & \text{if } 20 < age_{i,t} \leq 50 \\ str_cost_new_{i,t} \cdot \left(\frac{1}{1+\delta}\right)^{age_{i,t}} \cdot \left(\frac{1}{1+0.01}\right)^{30} \cdot \left(\frac{1}{1+0.05}\right)^{age_{i,t}-50} & \text{if } age_{i,t} > 50 \end{cases} \tag{2.6}$$

where, $str_cost_new_{i,t}$ denote the new building cost for structure of housing unit i in period t (using Equation (2.5)). The variable $age_{i,t}$ is the age (in years) of the structure of housing unit i in period t. δ is the annual (baseline) depreciation rate, which I set to 0.025.[28]. In addition, to account for the increasing value of the tear down option for older houses, I depreciate houses aged 21-50 years with an additional 1 percent per year. For example, a house of age 25 would be depreciated by a factor of $0.975^{25} \cdot 0.99^{5}$. Very old houses, after age 50, are depreciated with additional 5 percent per year. For example, a house of age 55 would be depreciated by a factor of $0.975^{55} \cdot 0.99^{30} \cdot 0.95^{5}$.

To conclude the first-step in constructing the county-level structure share, w^s_{jt}, for the year 2012 as a benchmark, I calculate w^s_{jt} in period $t = 2012$ as:

$$w^s_{j,2012} = \sum_i \frac{s_{ij,2012}}{value_{ij,2012}}, j = 1, 2, ..379 \tag{2.7}$$

where I normalize and calculate $s_{ij,2012}$ by

$$s_{ij,2012} = s_{ij,year} * \frac{RF_{2012,j} * CCI_{2012} * CPI_{2012}}{RF_{year,j} * CCI_{year} * CPI_{year}} \tag{2.8}$$

and $value_{ij,2012}$ by

$$value_{ij,2012} = value_{ij,year} * \frac{HPI_{2012,j} * CPI_{2012}}{HPI_{year,j} * CPI_{year}}. \tag{2.9}$$

The index i indicates a housing unit and j refers to a specific county. $year$ refers to the end-of-advertisement year, that I assume to be the year of transaction. RF denotes the

[27] Close to 30 percent of houses aged 50 years and older are indicated as "requires renovation", around 30 percent as "well-kept", only less than 10 percent were at some point in time fully renovated.

[28] I follow the linear depreciation schedule for tax return, where the starting point for calculating depreciation on buildings is the acquisition or construction cost of the building. The proportionate land costs are not included in the basis of assessment. See, Steuertipps (2021)

regional construction cost factors[29] and CCI the Germany-wide construction cost index. CPI refers to the consumer price index and HPI is the house price index on county-level from vdpResearch. *value* denotes the posted listing price of the advertisement of the housing unit. The summation in both the numerator and denominator in Equation (2.7) is over all housing units/households in a particular county. According to the assumption that a home's value is the sum of the replacement cost of the physical structure and the market value of the land, it follows a benchmark land share for a given county of $w_t^l = 1 - w_t^s$.

2.3.4 Extrapolating the Benchmark Estimates for Structures Share and Replacement Cost - Second Step: German Case

To estimate a continuous annual time-series of structure shares, I extrapolate forward the benchmark structures share derived above: This is the second step of the two-step procedure. Recall that the total value of housing in a particular county at date t is defined as:

$$p_t^h h_t = p_t^l l_t + p_t^s s_t, \tag{2.10}$$

where the market value of land is denoted as $p_t^l l_t$ and the overall replacement cost in that county in a given period as $p_t^s s_t$. Furthermore, as in Davis and Palumbo (2008), I also define the total nominal value of structures in a particular county at period $t+1$ as the sum of the total nominal value in the previous period t, revalued for changes in construction costs ($\frac{p_{t+1}^s}{p_t^s}$) and the nominal net new structures ($p_{t+1}^s \Delta s_{t+1}$), i.e. new structures less depreciation:

$$p_{t+1}^s s_{t+1} = p_t^s s_t \left(\frac{p_{t+1}^s}{p_t^s} \right) + p_{t+1}^s \Delta s_{t+1} \tag{2.11}$$

Moreover, I assume that the nominal value of net new structures in a particular county is equal to some proportion (θ_t) of the nominal value of net new housing in a particular county ($p_{t+1}^h \Delta h_{t+1}$):

$$p_{t+1}^s \Delta s_{t+1} = \theta_t p_{t+1}^h \Delta h_{t+1} \tag{2.12}$$

Inserting (2.12) in (2.11) and dividing by the nominal value of housing at $t+1$, $p_{t+1}^h h_{t+1}$, I have the share of structure as

$$\frac{p_{t+1}^s s_{t+1}}{p_{t+1}^h h_{t+1}} = \frac{p_t^s s_t}{p_t^h h_t} \frac{\frac{p_{t+1}^s}{p_t^s}}{\frac{p_{t+1}^h}{p_t^h}} \left(\frac{h_t}{h_{t+1}} \right) + \theta_t \frac{\Delta h_{t+1}}{h_{t+1}}, \tag{2.13}$$

where the identity $p_{t+1}^h h_{t+1} = p_t^h h_t \frac{p_{t+1}^h}{p_t^h} \frac{h_{t+1}}{h_t}$ is used. When I let the total structures share of aggregate house value in a county in period t be defined as $w_t^s = \frac{p_t^s s_t}{p_t^h h_t}$ and inserting into equation (2.3), I obtain Equation (2.4) or

$$w_{t+1}^s = w_t^s \left(\frac{\frac{p_{t+1}^s}{p_t^s}}{\frac{p_{t+1}^h}{p_t^h}} \right) \left(\frac{h_t}{h_{t+1}} \right) + \theta_t \frac{\Delta h_{t+1}}{h_{t+1}}. \tag{2.14}$$

[29] I use BKI construction cost regional factors for German counties from 2012 to 2019. After 2011, the method of calculating the regional construction cost factors was updated. Hence, according to experts from the surveyor commissions, it would not be consistent to use a longer time series.

Given structures share in period t, w_t^s, the growth rates in construction cost and house prices, $\frac{p_{t+1}^s}{p_t^s}$ and $\frac{p_{t+1}^h}{p_t^h}$, a value for the structure intensity of nominal net new housing, θ_t, and a proxy for the growth rate of real housing stock, $\frac{h_t}{h_{t+1}}$, I can now calculate the structures share in period $t+1$, w_{t+1}^s using Equation (2.14).

To implement this dynamic equation, I use the benchmark structures share for each county in 2012 derived in the previous section. For the county's construction cost growth, I multiply county-specific time-series of regional construction cost factors from the BKI with the Germany wide construction cost index for new residential buildings from the German Federal Statistical Office. Both indices are annual time-series.[30] For growth in house prices, I use constant-quality county-specific house prices for single-/double family houses from vdpResearch, based on a property transaction database carried out by vdpResearch.

I approximate the growth in the real housing stock ($\frac{h_{t+1}}{h_t}$) by the growth in the number of households of a county. I assume that both growth rates are proportional. The number of households by county in each period is computed by dividing the population in a particular county by the average household size of Germany in that period.[31] I use population data by county and the number of households of a certain size in Germany from the Federal Statistical Office. The latter is used to construct the average household size in Germany in a given period. Both datasets are reported at an annual frequency.

Lastly, I assume that the fraction of new home value accounted for by new structures , θ_t, is the ratio of estimated cost of residential building completions and the sum of estimated cost of residential building completions and purchase values of land ready for construction in a given year and federal state.[32] Hence, the parameter, θ, allows for varying land intensity of new housing by year and federal state.

2.4 Results

2.4.1 Baseline-Results

Figure 2.2 shows the components of home value by county in 2014. I construct price indices for residential land and estimate average values for the stock of single-/double-family owner-occupied housing. I also estimate their structure and land components by estimating the land's share of home value. I present a detailed description in Table 2.3 below by state, differentiating between the new Federal States[33] and the old Federal States of Germany. I then describe the basic differences among the German states and counties and highlight some trends over time.

[30] I use the "Baupreisindex" series of the German Federal Statistical Office, which is a constant quality-index and should include builder's margins. I could alternatively use the "Baukostenindex" which excludes changes in productivity and builder's margins. In doing so, those changes, however, would be attributed to the value of land instead (Statistisches Bundesamt (Destatis), 2020).

[31] There is no continuous data on average household size by county. Although I am aware that household size varies across counties, I use this assumption as the estimation method only requires percentage changes in the county's average household size to be correct.

[32] The data on estimated cost of building completions of residential buildings is from the German Federal Statistical Office. Whereas the data on purchase values of land ready for construction is taken from the German Regional Statistics database a joint statistics portal of the Federal and State governments.

[33] Also known as "East Germany" and before 1990, part of the German Democratic Republic (GDR).

Components of Home Value in 2014

Table 2.3 shows the home, land and structure values in 1000s € as well as the land's share of home value, and the land value per square meter for German federal states, divided into East and West. On average, homes are more expensive in the West compared to East German states in 2014. The city-states of Hamburg and Berlin, followed by the southern German states of Bavaria and Baden-Württemberg, have the by far highest home values in 2014. This pattern also becomes evident in Figure 2.2.[34] Home values and land values are significantly higher in the south of Germany (especially in Bavaria around Munich and in Baden-Württemberg around Stuttgart). However, the large agglomerations of urban centers in the Ruhr area (Nordrhein-Westfalen) and Hamburg also show high home and land values.

Although there are significant differences in the value of residential land, the states and corresponding counties differ relatively less in terms of the average replacement cost of structures. Two features that highlight the difference between the West and East German states are that the land's share is significantly higher in the West than East (54 versus 41 percent). Second, Table 2.3 also shows that the land value is significantly higher than the structure value in the West (202 versus 141), whereas, in the East, the structure value is higher than the value of land (123 versus 92). At the end of 2014, residential land accounted for between 35 and 51 percent in states of former East Germany and between 44 and 74 percent of home value in Western German states, where Hamburg has the highest share of land in home value, 74 percent.

Changes in Home Value: 2014 - 2018

In Table 2.4[35] and Figure 2.3, I present cumulative changes in the components of home value and land's share of home value between 2014-2018 in real terms, i.e., converted to 2015 Euros using the Consumer Price Index from the German federal statistical office, by state and county, respectively. On average, the changes, in the land value for both West and East Germany are significantly higher than the changes in the home values: 31 versus 23 percent in the West, and 17 versus 13 percent for the East. On the other hand, the structure value increased only marginally, 15 and 11 percent, for the West and East, respectively. The cumulative change in land values varies between 4 and 56 percent. However, replacement costs only vary between 10 and 26 percent. I emphasize that this chapters' goal is to estimate land prices, and hence, I am silent about the reasons for the land price changes in this chapter. But, for example, an increase in Berlin's land values is worth noting and needs a brief explanation. A recent work by Möbert (2020) indicates that, among other factors, Berlin's population growth contributes to a significant increase in demand for housing and land. Berlin has experienced both inward migration (at an average of 40,000 new inhabitants annually) and non-German migration (at an average increase of 8.3 percent of foreign nationals in Berlin annually) since 2011. One other factor that could contribute to Berlin's land value increase in the last few years is the inflow of foreign investments. According to Schaer (2018), up to 68 percent of Berlin's apartments were sold to foreigners in 2015.

[34] In the maps throughout this chapter, I classify the counties into quintiles if not otherwise stated. Moreover, the shape file on German states and counties used to construct the maps in this chapter is from Bundesamt für Kartographie und Geodäsie, Frankfurt am Main (GeoBasis-DE / BKG) (2019).

[35] The average values stated in the abstract are the average over the 16 federal states.

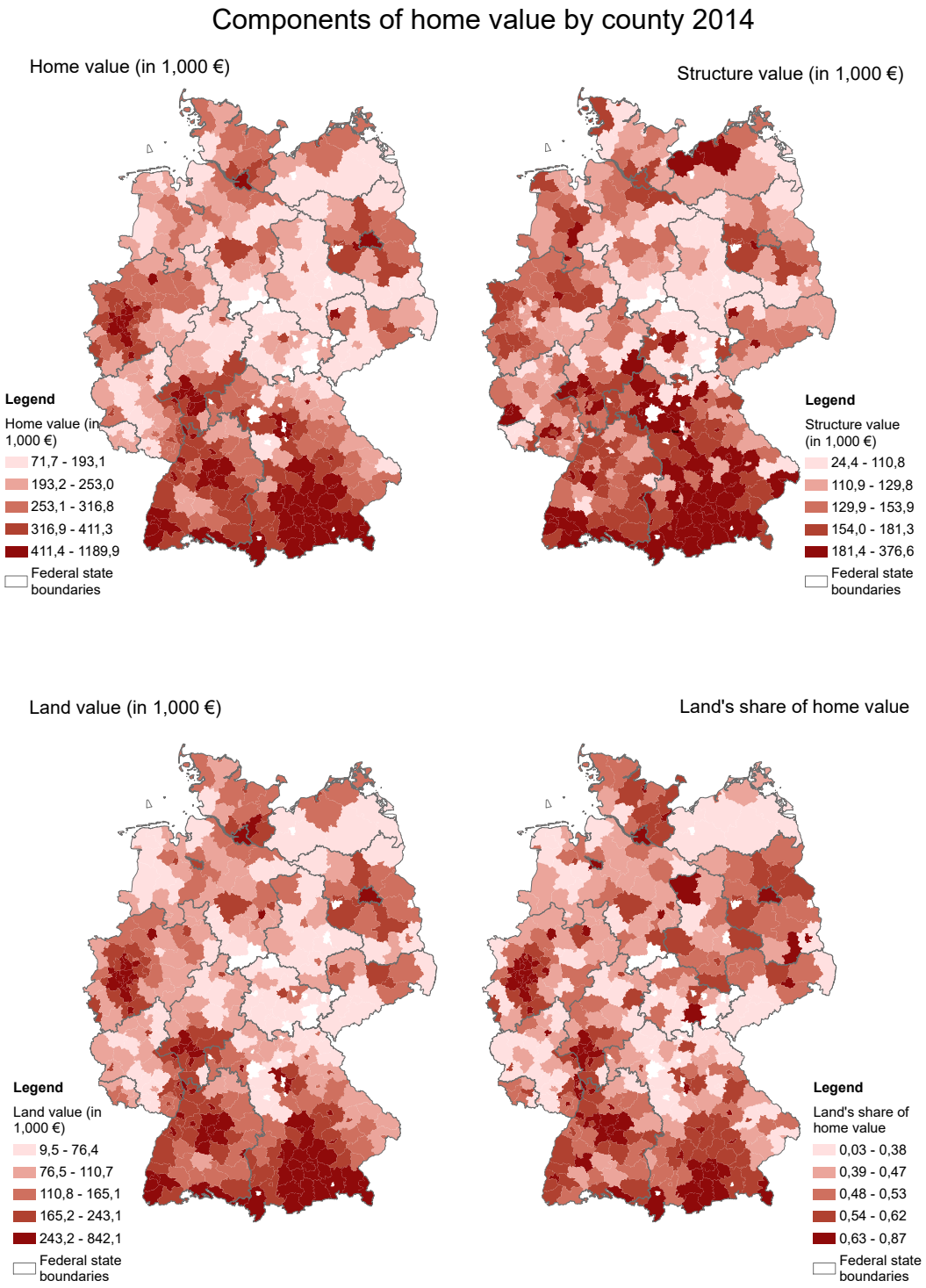


Figure 2.2: Components of home value by county in 2014

Region/State	Home value (1000s Euros)	Land value (1000s Euros)	Land value per per square meter	Structure value (1000s Euros)	Land's share of home value (pct)
West	342	202	277	141	54%
Schleswig-Holstein	278	149	176	129	52%
Hamburg	600	443	575	157	74%
Niedersachsen	227	102	120	125	44%
Bremen	242	120	162	122	48%
Nordrhein-Westfalen	335	198	264	137	56%
Hessen	357	201	311	156	51%
Rheinland-Pfalz	262	130	205	131	45%
Baden-Württemberg	406	247	374	158	58%
Bayern	425	235	322	190	49%
Saarland	200	96	124	105	48%
Berlin	434	298	411	136	69%
East	215	92	104	123	41%
Brandenburg	248	128	141	120	51%
Mecklenburg-Vorpommern	239	89	96	150	36%
Sachsen	239	96	107	143	35%
Sachsen-Anhalt	175	89	101	86	50%
Thüringen	173	59	76	114	36%

Table 2.3: Components of home value in 2014 by state

Region/State	Home value (1000s Euros)	Land value (1000s Euros)	Structure value (1000s Euros)	Land's share of home value (pct)
West	23%	31%	15%	7%
Schleswig-Holstein	21%	27%	17%	6%
Hamburg	26%	29%	18%	2%
Niedersachsen	20%	34%	10%	15%
Bremen	19%	29%	14%	7%
Nordrhein-Westfalen	20%	27%	12%	7%
Hessen	21%	31%	12%	8%
Rheinland-Pfalz	19%	30%	12%	9%
Baden-Württemberg	24%	30%	17%	6%
Bayern	23%	32%	17%	8%
Saarland	14%	17%	13%	6%
Berlin	47%	56%	26%	8%
East	13%	17%	11%	1%
Brandenburg	18%	21%	14%	4%
Mecklenburg-Vorpommern	15%	23%	11%	2%
Sachsen	14%	26%	12%	3%
Sachsen-Anhalt	10%	10%	10%	1%
Thüringen	9%	4%	10%	-4%

Table 2.4: Change in components of home value by state - 2014 through 2018

Figure 2.3 also shows that cumulative changes tend to vary quite significantly between East and West German counties. Moreover, one of the most notable features in Figure 2.3 is that the home values for urban centers such as Hamburg, Berlin, and Munich increased quite substantially more than the surrounding counties. The result reinforces the monocentric Bid-Rent theory, i.e. that the home and land values (rents) are inversely related to the distance away from the central business district (CBD).

The results in Table 2.4 also indicate that the land component is the main driver for the housing price increase between 2014 and 2018 in Germany.[36] Most regions experienced a significant increase in home value and the share of the market value of residential land in home value. At the same time, the change in the replacement cost of structures was comparatively small.

The results further show that land value correlates over time with macroeconomic variables, such as house prices, mean income, and the state-level unemployment rate. These correlations informally indicate that areas with higher land values are associated with a higher economic development increase. For example, Hamburg and Berlin, two city states with the most significant increase in land value, have a correlation of 0.98 between the mean income and land value. However, the correlation between the mean income and land value is relatively low (0.29) for a former East German state, such as Thüringen (See Table 2.22 in Appendix for detailed correlations). Moreover, Figures 2.13 and 2.14 in the Appendix show the relationships of important macroeconomic variables on house and land prices for counties in 2014. In line with the correlations on state level, these Figures show positive relationships of GDP per capita, population density and median income on both house and land prices as well as a negative relationship with unemployment.[37]

Figure 2.4 maps land values per square meter of lot size for German counties in 2014 and 2018.[38] As expected, the most considerable changes in the estimated land values per square meter of lot size are highest in counties in and around large agglomerations areas such as Munich, Stuttgart, Colon, Frankfurt, Berlin, and Hamburg.

Although the residential land values in and around the metropolitan cities in Germany have risen from 2014 to 2018, the percentage changes in values differ from economic centers as the period progresses. For example, Figure 2.5 shows the two biggest cities, Berlin and Munich, as three-tier surroundings. And for these three-tier areas, Tables 2.5 and 2.6 show the percentage changes in land values from 2014 to 2018 for Berlin and Munich, respectively. For Munich, there seems to be a slight "rural" migration as the average percentage changes in prices for tiers two and three are more prominent than tier one (Munich) area in 2018. Berlin and its surrounding areas show the opposite result: An "urban" migration effect. This is shown, as Berlin lies in the middle of "East" Germany and that the general results indicate that the land prices for most of "East" Germany have not increased as much as Berlin.

[36] The estimation results for the components of home value for 2018 is in Appendix 2.6.2.

[37] See Chapter 3, that uses the estimated land value data, for a detailed empirical analysis on the effects of macroeconomic and real estate variables on the land values at the German county-level.

[38] The cut of levels between classes for the year 2018 are adjusted to 2014.

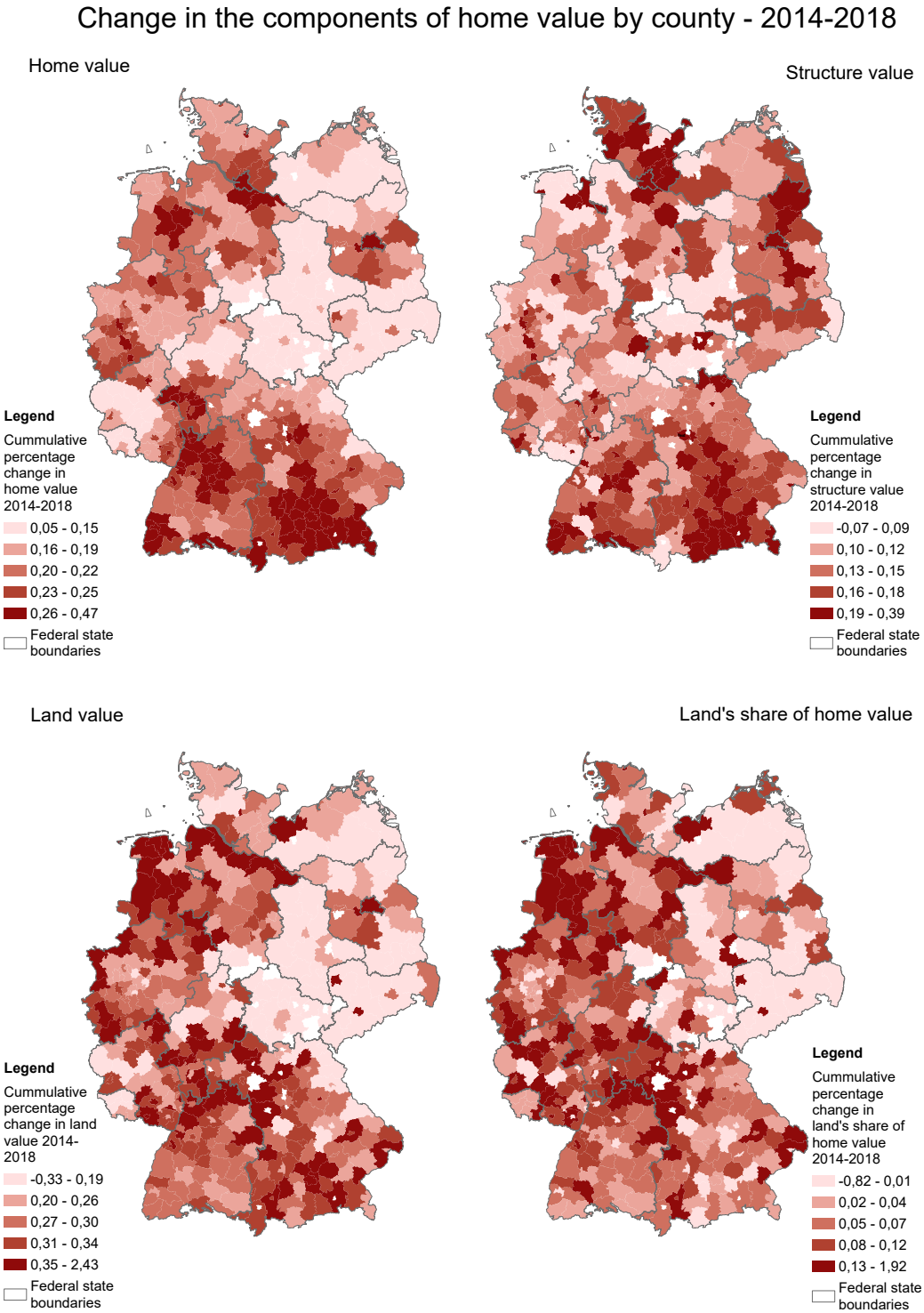


Figure 2.3: Change in components of home value by county - 2014-2018

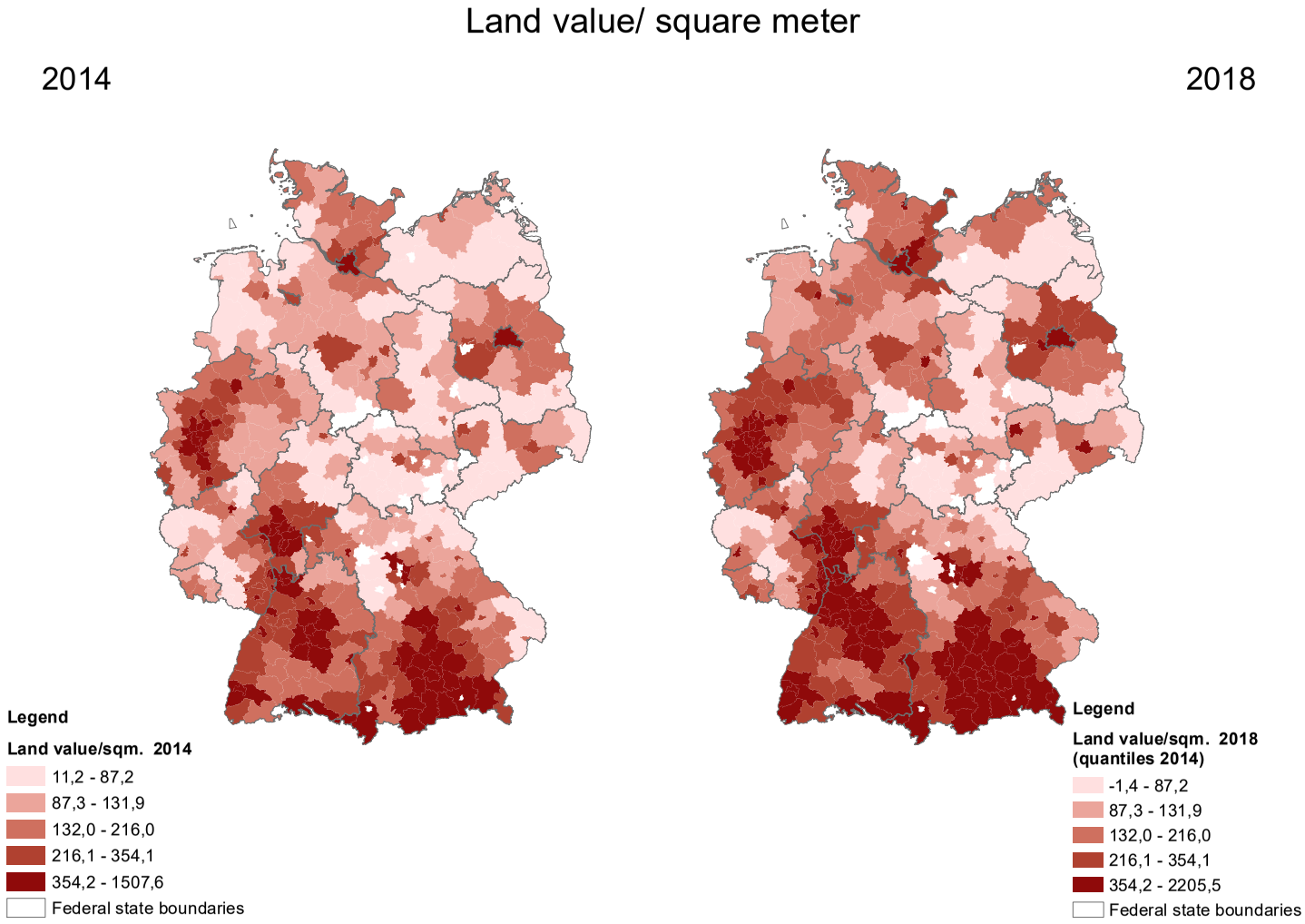


Figure 2.4: Estimated land values per square meter of lotsize by county in 2014 and 2018

County	2015	2016	2017	2018
Tier 1				
SK Berlin	0.04	0.20	0.20	0.12
Tier 2				
SK Potsdam	0.05	0.13	0.14	0.14
LK Barnim	-0.01	0.02	0.07	0.11
LK Dahme-Spreewald	0.04	0.03	0.05	0.07
LK Havelland	0.01	0.06	0.07	0.16
LK Märkisch-Oderland	0.02	0.09	0.09	0.10
LK Oberhavel	0.02	0.05	0.05	0.09
LK Oder-Spree	0.00	-0.01	0.15	0.11
LK Potsdam-Mittelmark	0.02	0.04	0.11	0.10
LK Teltow-Fläming	0.02	0.03	0.13	0.14
Average Tier 2	0.02	0.05	0.10	0.11
Tier 3				
LK Uckermark	0.00	0.01	0.03	0.05
LK Ostprignitz-Ruppin	0.05	0.05	0.04	0.03
SK Cottbus	0.01	0.06	0.06	0.01
LK Elbe-Elster	0.02	-0.05	0.09	0.00
LK Oberspreewald-Lausitz	0.00	0.00	0.05	0.10
LK Prignitz	0.01	0.08	0.08	0.07
LK Spree-Neiße	0.11	0.08	-0.09	0.00
LK Anhalt-Bitterfeld	0.05	0.05	0.08	0.03
LK Jerichower Land	-0.04	0.07	0.04	-0.01
LK Stendal	0.01	0.01	0.00	0.02
LK Wittenberg	0.01	0.04	0.01	-0.01
Average Tier 3	0.02	0.04	0.04	0.03

Table 2.5: Percentage change in land value per m^2 lot size - Berlin and surrounding Counties

County	2015	2016	2017	2018
Tier 1				
SK München	0.11	0.12	0.13	0.05
LK München	0.07	0.12	0.08	0.08
Average Tier 1	0.09	0.12	0.11	0.07
Tier 2				
LK Bad Tölz-Wolfratshausen	0.07	0.08	0.08	0.10
LK Dachau	0.08	0.09	0.12	0.06
LK Ebersberg	0.05	0.11	0.05	0.10
LK Erding	0.13	0.12	0.05	0.10
LK Freising	0.04	0.12	0.10	0.10
LK Fürstenfeldbruck	0.05	0.08	0.09	0.07
LK Miesbach	0.08	0.09	0.07	0.08
LK Landsberg am Lech	0.05	0.10	0.13	0.06
LK Starnberg	0.05	0.05	0.08	0.07
Average Tier 2	0.07	0.09	0.09	0.08
Tier 3				
LK Weilheim-Schongau	0.06	0.07	0.06	0.12
LK Mühldorf a.Inn	0.03	0.06	0.05	0.10
LK Neuburg-Schrobenhausen	0.07	0.09	0.07	0.08
LK Pfaffenhofen a.d.Ilm	0.03	0.06	0.11	0.10
LK Rosenheim	0.06	0.08	0.08	0.12
SK Landshut	0.03	0.08	0.11	0.08
LK Kelheim	0.02	0.09	0.05	0.03
LK Landshut	0.03	0.11	0.09	0.07
LK Aichach-Friedberg	0.03	0.09	0.13	0.08
Average Tier 3	0.04	0.08	0.08	0.09

Table 2.6: Percentage change in land value per m^2 lot size - Munich and surrounding Counties

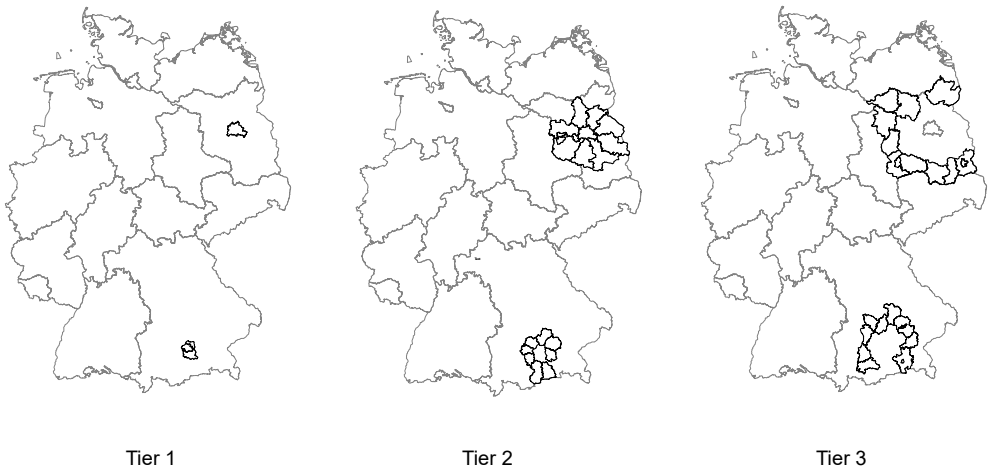


Figure 2.5: Berlin, Munich and surrounding Counties

Changes in the Distribution of Home Value and Residential Land Values; 2014-2018

Figure 2.6 presents the cumulative distribution function of land's share of home value across the 379 German counties and county-free cities in the sample as of 2014 and 2018. Figure 2.6 shows a relatively even rightward shift of around 4 percent for the second to the ninth percentile of the distribution. The lowest and highest 5 percent of the distribution changed, if at all, only very slightly. This change suggests that only the counties in the middle of the distribution experienced an overall rightward shift in the land's share of home value. The range from lowest (around 1 percent) to highest (around 85 percent) land's share of home value stays quite the same between the years. Consistent patterns are shown for the cumulative distribution function of the value of residential land, which is displayed in Figure 2.7 across the 379 German counties in the sample as of 2014 and 2018. But also, one can see from Figure 2.7 that also the upper end of the distribution experienced a rightward shift.

2.4.2 Comparison of Land Value Estimates

Appraiser accessed land values

Figures 2.8 and 2.9 show this chapters' - and the expert-based - land value estimates for counties in Hessen and Thüringen.[39] I choose the states of Hessen (West) and Thüringen (East) for the comparison because these states provide the most available dataset and are representative for West and East Germany, respectively.

[39]I use the 2016 data for Thüringen instead of 2014 (as for Hessen) as the expert-based data was only available for 4 counties in 2014. Furthermore, several counties in Thüringen are missing as these counties only have less than 10 observations.

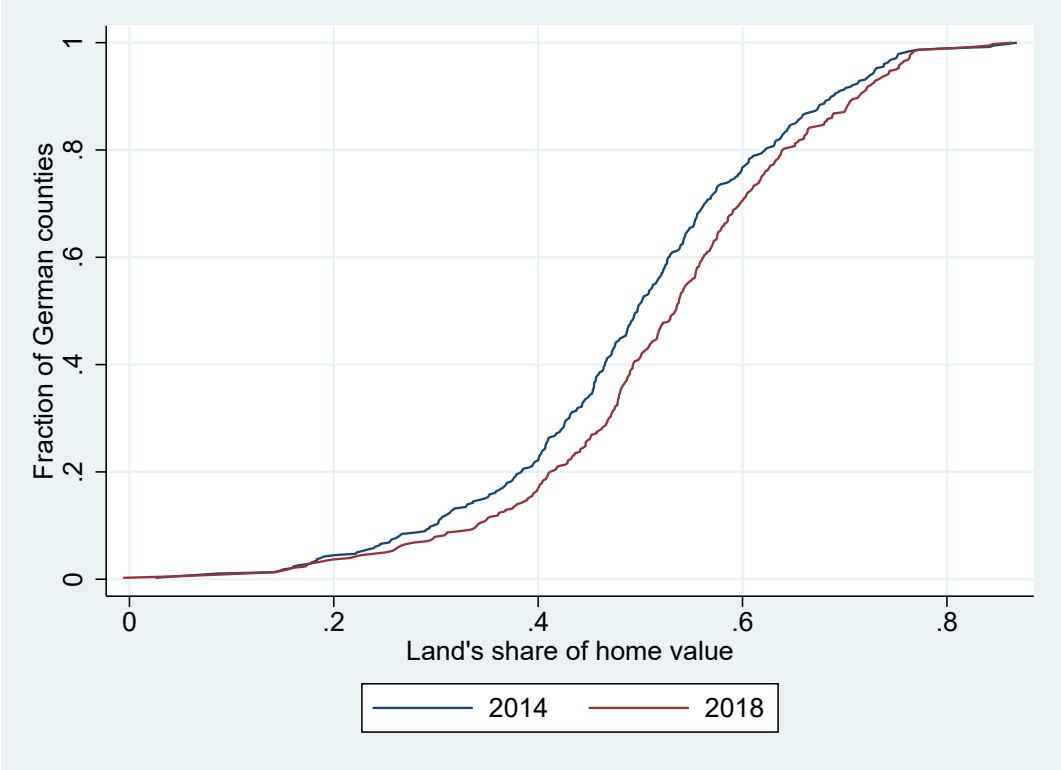


Figure 2.6: Cumulative distribution of land's share of home value across the sample of 379 German counties

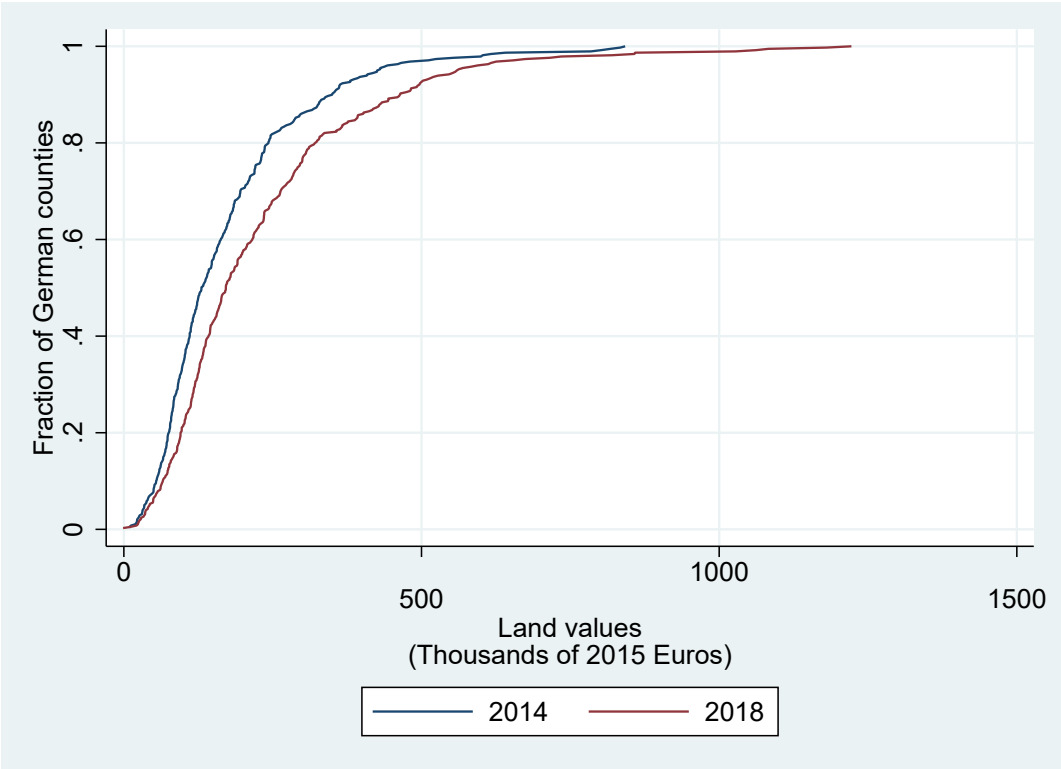


Figure 2.7: Cumulative distribution of land values across the sample of 379 German counties

For Hessen, while expert-based values suggest lower land values in the county-free city of Kassel and higher values in the county of Kassel, the estimates suggest that land values are higher in the city and lower in the county around the city of Kassel. Moreover, the estimates suggest that Wiesbaden's land values are inversely related to the distance from Frankfurt. In general, especially in counties with larger cities my estimates are significantly higher. For the counties Wiesbaden and Frankfurt, this chapters' estimates are 48 and 42 percent higher compared to the expert-based land values, respectively. Figures 2.8 and 2.9 also show the percentage deviations of the estimates from the expert based values by county. The highest deviations are given for the county-free city Kassel, with my estimates being 226 percent and Darmstadt-Dieburg, with my estimates being 65 percent lower.

Despite the missing data for Thüringen, my estimates suggest higher land values in Erfurt (Thüringen's largest city) and surrounding counties. In contrast, expert-based land values are higher in the north and lower in the south of Thüringen: Like in Hessen, land prices appear to increase with the proximity to urban centers (Figure 2.9). Compared to Hessen, for Thüringen, deviations from experts' valuation are, on average, higher than my estimates.[40]

These differences are not trivial and could have large consequences in the land price valuation and housing prices. The differences between the two estimation methods could be attributed to two primary sources. First, the method relies on the proxy estimations of the construction and structural cost functions. Second, the experts' valuation method mainly relies on each county's land valuation law. The land valuation based on a separate guideline highlights the need for a consistent and systematic land valuation method again.

Land values for undeveloped land (ready for construction)

The second available land value option in Germany is the statistics on land sales, which records any undeveloped land, acquired by purchase within the building area of a municipality if its area is larger than 100 square meters. Within these statistics, I focus on sales of land ready for construction. Land ready for construction includes land plots, which are earmarked for development by the municipality. The legal requirements for the development are fulfilled and are allowed for immediate construction. The land plots of 100 square meters or more are recorded. Moreover, the data does not differentiate between commercial, residential and factory plots of land as well as only includes undeveloped plots of land and excludes land plots with less than 100 square meters. One could use this as an additional land value measurement for undeveloped land rather than my estimate for single-family houses. I think this is important because undeveloped plots of land are more likely on the outskirts of municipalities, towns and cities rather than in the center. Hence, possibly both measures are important. Figure 2.10 shows my estimates and the values for undeveloped land ready for construction in 2014. Moreover, Figure 2.10 shows the percentage deviations from the estimates of land values to the values of undeveloped land ready for construction in 2014. One can observe three things: First, the relative patterns of both land value measurements tend to be similar. Second, the estimates tend to be on average 78.8 percent higher than the values for undeveloped land. Lastly, from Figure 2.10 one can see that the largest

[40] One reason for this might also be that my estimates for Thüringen are based on a relatively small number of observations, as I only have around 11 observations for a lot of the remaining counties. (Table 2.21)

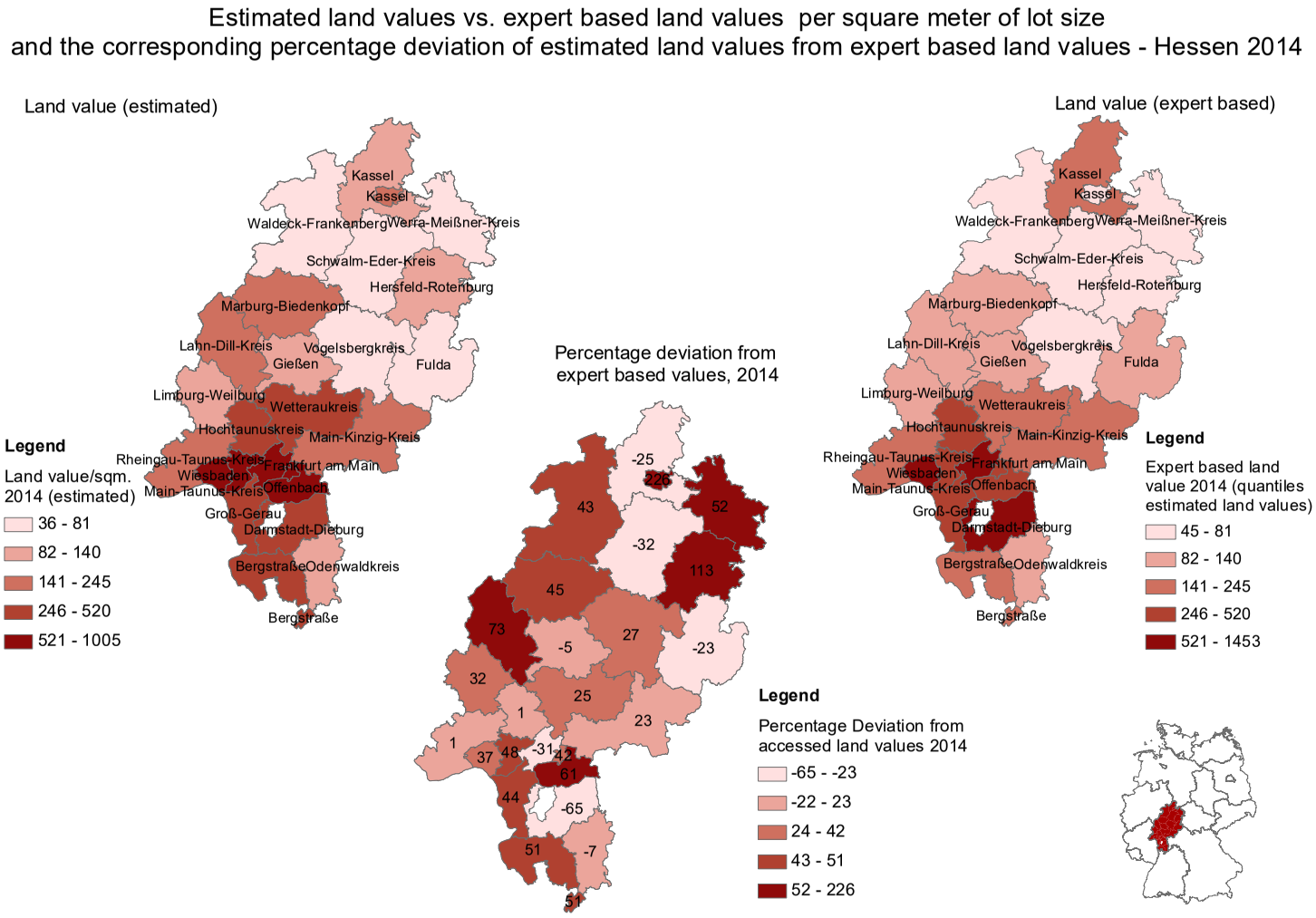


Figure 2.8: Estimated land values vs. expert based land values per square meter of lotsize in Hessen 2014 and their percentage deviation from expert based values

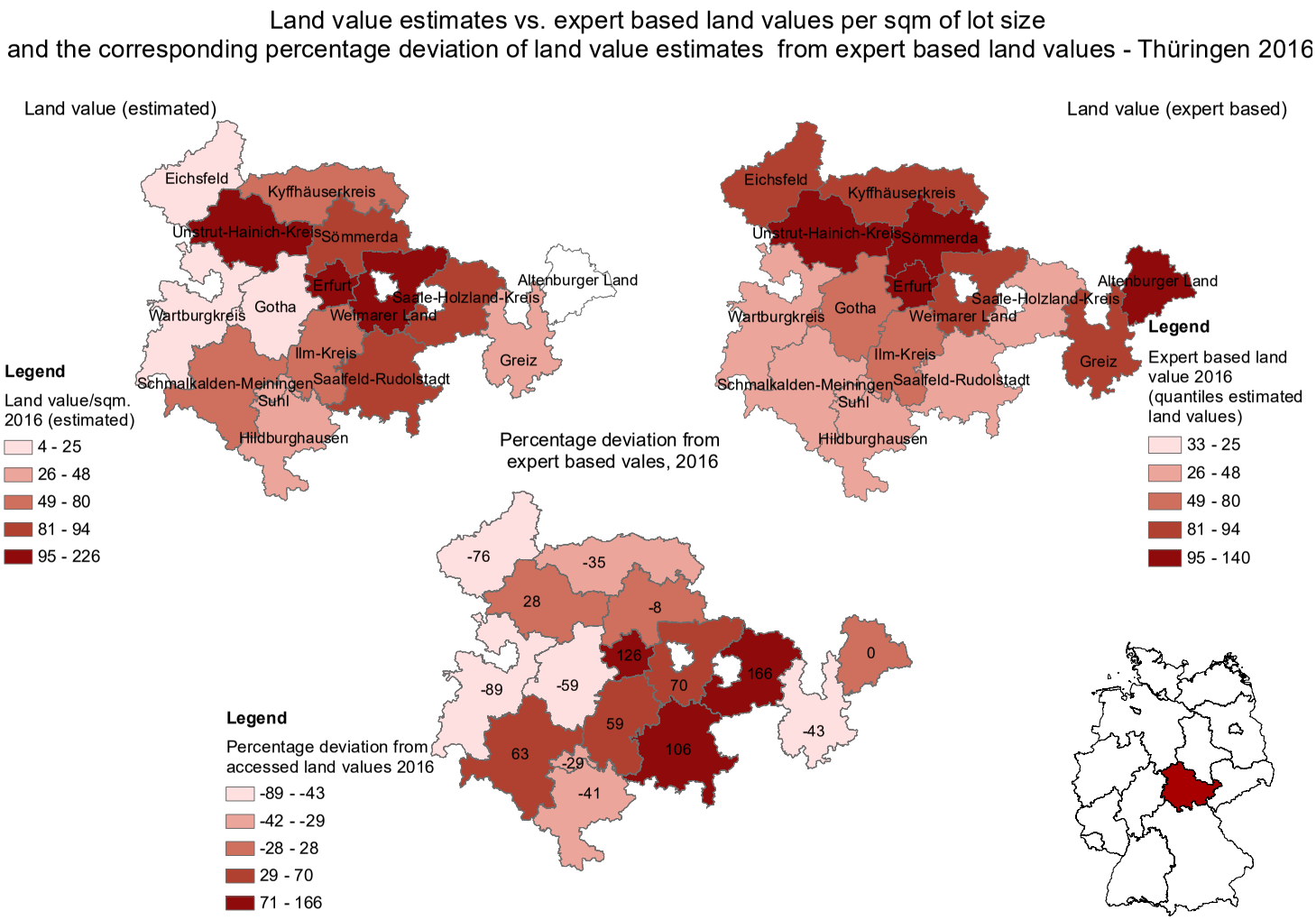


Figure 2.9: Estimated land values vs. expert based land values per square meter of lotsize in Thüringen 2016 and their percentage deviation from expert based values

deviations between the two measurements are for the new Federal States and some of the larger agglomerations.

For the 379 German counties in the dataset as well as Munich and Berlin including their surrounding tiers, I also compare the percentage changes in the residential land values and the vacant land values of land ready for construction from 2014 to 2018. Figures 2.15 and 2.16 in the Appendix show the percentages changes on county level.[41] Tables 2.24 and 2.23 in the Appendix show annual percentage changes for Munich, Berlin and their surrounding counties. The two main observations from these illustrations are: First, while vacant land values show larger increases in former East Germany, Bavaria and the Rhein-Ruhr area, this chapters' residential land values show the largest changes throughout West Germany, and especially around the largest German cities, including Berlin and Hamburg. Secind, the slight "rural" migration effect for Munich and the "urban" migration effect for Berlin discussed in Section 2.4.1 are also observable within the building land data. However, as annual changes from 2014 to 2018 for Munich and Berlin plus their neighboring tiers are relatively constant in the residential land values but vary quite significantly from year to year in the building land dataset, this pattern is less clear in the vacant land sales data.

Furthermore, I compare the values for undeveloped land with the appraiser accessed values. Figures 2.17 and 2.18 show the percentage deviations of values for land ready for construction from expert's evaluations. I show that deviations vary between -77 and 101 for Hessen in 2014, and -82 and 94 for Thüringen in 2016.[42]

[41] Due to missing data in the dataset for building land, only 304 counties remain in the maps on the right.
[42] Please refer to Figures 2.17 and 2.18 in the Appendix for detailed changes at the county-level.

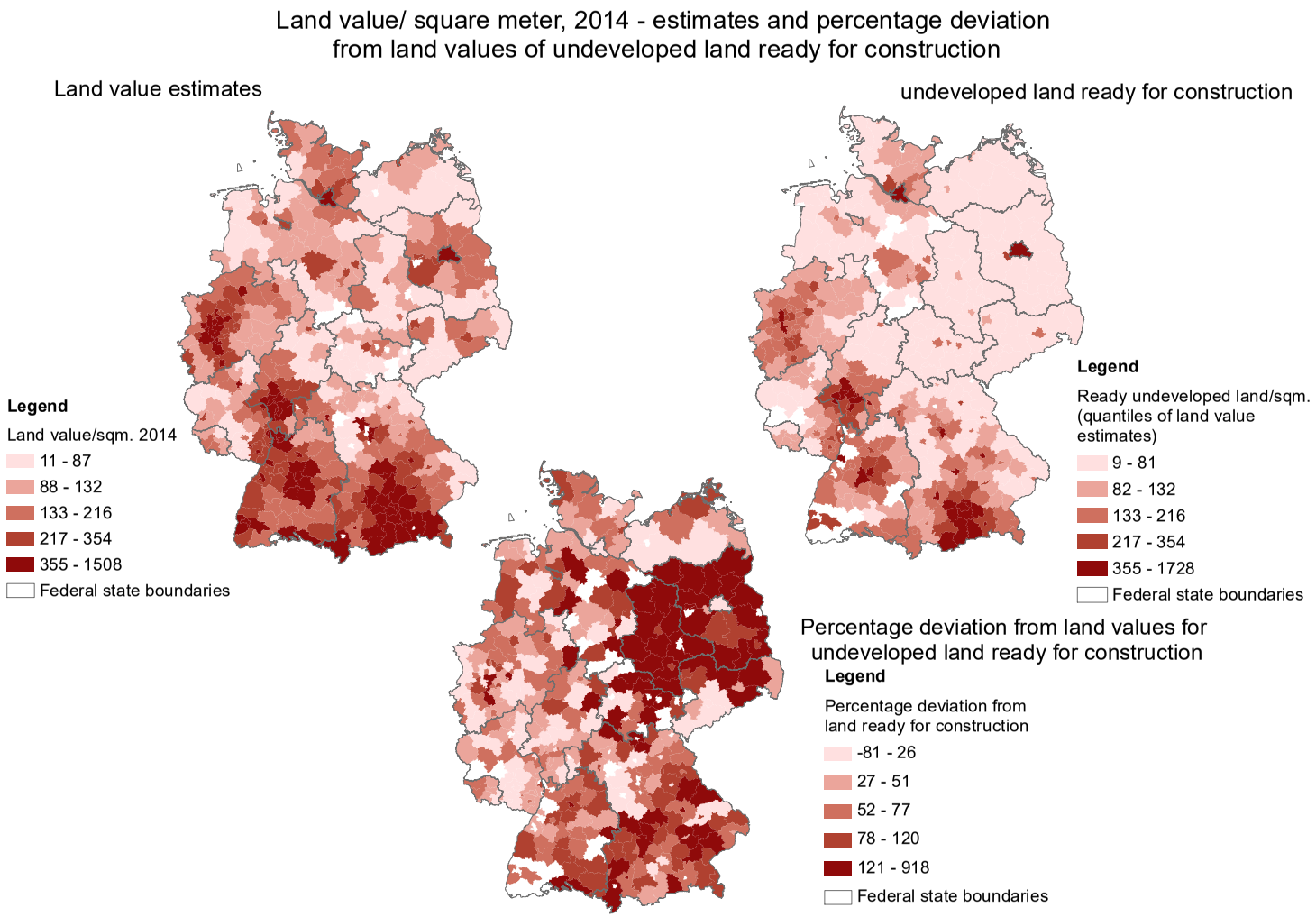


Figure 2.10: Comparison estimated values vs. land values from undeveloped land ready for construction (EUR/sqm.) - 2014

	(1)	(2)	(3)	(4)	(5)	(6)
living space	1.1	1.1	-0.157	-0.222	-0.00005	-0.00008
	(0.173)	(0.160)	(0.839)	(0.779)	(0.912)	(0.861)
floors	-185.8*			-114.0		-0.05
	(0.094)			(0.273)		(0.434)
basement	414.0**	294.4***	269.8***	322.7**	0.1*	0.1
	(0.013)	(0.006)	(0.006)	(0.036)	(0.070)	(0.163)
I(floors≥2)		-477.9***	-397.0**		-0.2*	
		(0.005)	(0.012)		(0.062)	
quality1			-854.0***	-850.3***	-0.4***	-0.4***
			(0.000)	(0.000)	(0.000)	(0.000)
quality2			-427.5***	-446.6***	-0.2***	-0.2***
			(0.000)	(0.000)	(0.000)	(0.000)
_cons	2202.1***	2231.9***	2698.5***	2617.8***	7.9***	7.8***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	150	150	150	150	150	150
Adjusted R2	0.05	0.08	0.23	0.21	0.16	0.15
AIC	2344.4	2339.3	2314.4	2319.6	71.2	74.2
BIC	2356.5	2351.3	2332.4	2337.7	89.2	92.2

p-values in parentheses
the dependent variable in columns (1)-(4) is construction cost,
in columns (5)-(6) log of construction cost
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 2.7: Various cost function estimations

2.4.3 Sensitivity Analysis of Residual Method

As the baseline land share estimates from the residual method rely heavily on various strict assumptions, in the following section, I undertake robustness checks for the land share estimates on the following dimensions: cost function, depreciation rate for structure (δ), the structure intensity of new housing (θ) , and different housing stock growth measures.[43]

Cost function

I estimate six different cost functions, including the benchmark cost function estimation in equation (2.5), to compare the associated land shares for each cost function. I use the AIC, BIC, and adjusted R^2 criteria to select the benchmark cost function. Table 2.7 shows the estimation results for four construction cost functions in level (models 1 to 4) and two semi-log form functions (models 5 to 6). I choose model 5 in Table 2.7 as the benchmark since both the AIC and BIC values are the by far lowest and the adjusted R^2 is the lower than the other semi-log specifications.

Given the results in Table 2.7, I use models 3 to 6 (two in level and two in semi-log)

[43]For expositional purpose, I provide, in the Appendix, Figures 2.19-2.22 that accompany the Tables in this section. In each of the Figures, legends are adjusted to the baseline specification in the Figure.

	mean	sd	min	max
Model 3	397.3	157.1	82.0	1,496.4
Model 4	409.8	160.2	86.4	1,587.7
Model 5	382.4	152.6	82.3	1,450.7
Model 6	393.5	156.1	85.1	1,542.2
N	42647			

*units are in $1,000€

** N is the amount of Immoscout24 listings data used in the estimation

Table 2.8: Construction cost estimated - summary statistics

	mean	sd	min	max
Land share (Model 3)	49.0%	15.4%	-3.5%	86.4%
Land share (Model 4)	47.8%	15.6%	-3.3%	86.4%
Land share (Model 5)	50.7%	14.9%	-0.6%	86.8%
Land share (Model 6)	49.6%	15.0%	-0.6%	86.8%
N	1895			

* is the number of county-year observations

Table 2.9: Land share for different cost functions - summary statistics

to analyze land share estimates' robustness using model 5 as the benchmark.[44] Table 2.8 reports the estimated construction cost's summary statistics as if the houses were brand new for the 42,647 ImmobilienScout24 data observations. Table 2.9 shows the summary statistics of the calculated land shares for the years 2014-2018 for 379 German counties. The land shares range between 47.8 and 50.7 percent, where the baseline model (5) has the highest land share (50.7%), suggesting that the land value estimation results are slightly on the over-valued side. At the county level, Figure 2.19 shows the land shares for the four cost functions in 2014. Both the Tables and Figure suggest that the estimation results are relatively similar to different cost function specifications. Figure 2.23 in the Appendix shows the land's share distribution for 2 different cost functions. Note that the estimates are negative for a very small proportion of county-year observations. However, such results can appear based on the method used to calculate the replacement costs. Davis and Palumbo (2008) also find that land share estimates for a few cities of close to zero and sets them equal to 0.05.

Depreciation rate: δ

To calculate the replacement structure cost, I use age-specific depreciation factors for the current structure as explained in Equation 2.6. I depreciate structures using $\delta_1 = 0.025$ as the baseline and I also calculate the replacement cost of structures with $\delta_2 = 0.02$, $\delta_3 = 0.03$, and $\delta_4 = 0.04$ in obtaining the land share estimates.

Tables 2.10 and 2.11 report the summary statistics of the structural values and land

[44] I do not include garage in the estimated cost function but rather add €10,000, the average cost of a standard size garage in case the housing unit has a garage. Davis and Palumbo (2008); Davis and Heathcote (2007)

	mean	sd	min	max
Value-replacement cost (delta=0.025)	223.4	246.4	-754.9	4,481.8
Value-replacement cost (delta=0.02)	215.5	244.5	-767.8	4,453.4
Value-replacement cost (delta=0.03)	248.6	248.4	-742.2	4,506.8
Value-replacement cost (delta=0.04)	272.8	251.9	-717.3	4,579.1
N	42647			

*units are in $1,000€$

** N is the amount of Immoscout24 listings data used in the estimation

Table 2.10: Depreciation rate - summary statistics

	mean	sd	min	max
Land share (delta=0.025)	50.7%	14.9%	-0.6%	86.9%
Land share (delta=0.02)	45.4%	16.3%	-12.6%	85.4%
Land share (delta=0.03)	55.1%	13.7%	7.8%	88.0%
Land share (delta=0.04)	62.3%	11.9%	13.7%	91.8%
N	1895			

* is the number of county-year observations

Table 2.11: Land share for different deltas - summary statistics

shares for various depreciation rates. As one would expect, both Tables 2.10 and 2.11 show that the estimates of land share increase with higher depreciation rates: a higher depreciation rate lowers the construction cost estimate (Tables 2.10) and hence increases the land shares. The depreciation effect on land shares is one of the residual method's shortcomings and would speak towards using only new houses. As I have noted in the previous section, due to a lack of data availability, I could not avoid using Germany's depreciation rate. The estimated land shares vary quite significantly by choice of δ: the average shares range from 45.4 to 62.3 percent with the benchmark at 50.7 percent.[45] Figure 2.20 shows the land shares variations in 2014 by county for the different depreciation rates considered. Tables 2.10 and 2.11 report that minimum values are negative for land's share of home value and the difference of value and replacement cost, which results from the cost function estimation. However, Figure 2.24 and 2.25 in the Appendix show that less than 1 percent of the county-year observations' land shares is negative. Moreover, the estimated replacement cost of less than 1 percent of the 42,647 observations are larger than the home value on ImmobilienScout24.

θ, parameter on structure intensity of nominal net new housing

As baseline measure for θ, I use the ratio of the estimated cost of residential building completions and the sum of the estimated cost of residential building completions and the purchase values of land ready for construction by state and year. For the θ sensitivity analysis, I estimate land shares by varying θ only over the years (2014 - 2018) and not by states. The results in Table 2.12 for the two different sets of θ's (State and Germany) show that the land shares are not sensitive to changes in θ values over the years for both the state

[45] If I do not account for the age-specific depreciation (i.e. use a uniform depreciation rate of 0.025) then the land shares vary between 35 and 58 percent.

and national level. Figure 2.21 also delivers a relatively identical conclusion.

	mean	sd	min	max
Land share (theta_state)	50.7%	14.9%	-0.6%	86.8%
Land share (theta_germany)	50.7%	14.9%	-0.7%	87.1%
N	1895			

* is the number of county-year observations

Table 2.12: Land share for different thetas - summary statistics

Housing stock growth

The last sensitivity analysis that I perform is on the different measures of housing stock growth. The baseline approach uses the growth in the number of households as a proxy for the growth in housing stock. I use two alternate measures in estimating the land shares: the growth of the residential buildings consists of single-family dwellings and the growth of total residential dwelling stocks. Table 2.13 shows the land shares for the three different housing stock growth measures.

As with the cost functions and θ's sensitivity analysis results, the results on land shares also appear to be not very sensitive to different housing stock measures. Figure 2.22 that plots land shares in 2014 by county for different housing stock measures also delivers a similar conclusion.

	mean	sd	min	max
Land share hstock(household growth)	50.7%	14.9%	-0.6%	86.8%
Land share hstock(single-family dwellings)	50.9%	15.1%	0.06%	88.4%
Land share hstock(total dwellings)	50.9%	15.1%	-0.06%	88.4%
N	1895			

* is the number of county-year observations

Table 2.13: Land share for different housing stock measures - summary statistics

2.5 Discussion/Conclusion

I estimate land prices and construct a new database for residential land values across 379 of 402 German counties and county-free cities over time. Using a total of 42,647 observations from 2014 to 2018, I show that residential land price has become relatively more expensive in the majority of German counties. As the urban theory predicts, the highest home and land price increases are in counties around urban centers Munich, Stuttgart, Berlin, Hamburg, Dresden, and the cities in the Ruhr area. In general, almost all the counties show an upward shift in home -, land values, and residential land share in home values. The most significant differences are and seem to remain between the new and old Federal States of Germany. The Eastern states are in par with the West (excluding Berlin) in terms of cumulative percentage changes in the value of the housing bundle's component. However, there is a significant difference in the average land's share of home value increase between East and West.

The results show that a more significant share of land in home value could lead to faster home price appreciation in the future. Consequently, one of the implications of the results is that real land prices drive the movements in home prices and the cycles in the value of land are likely to influence the evolution of house prices more in the future than they did in the past. This implication would affect urban areas with a larger inelasticity of supply in housing. Moreover, this result could lead to more significant swings in house prices due to changes in demand.

In this chapter, I provide a justification for some of the shortcomings of the residual method. However, this line of research could surely benefit in the future by using the simple option model as in Davis et al. (2021). The real options approach would allow me to address the assumption that the value of a home is equal to the sum of the replacement cost of its structure and the value of the land. I could also use a more extensive transaction dataset, if and when the dataset is publicly available. I could then entirely avoid depreciation of replacement costs by using only new homes to estimate the share of land in home value (e.g. Davis et al., 2017).

2.6 Appendix

2.6.1 Details on the Benchmark Estimates for the Replacement Cost of Residential structures: German Case

This section, provides further detailed description of the approach and data merging in computing the annual time series estimates for the average value of land in German counties and county-free cities.

In the first step, I use the house price listings from the internet platform ImmobilienScout24[46] with the RWI - Leibniz Institute for Economic Research as well as the 2016 average construction cost data per square meter of single- and double-family houses. I use the following set of variables from the dataset that characterizes "house": *built* (the year of construction), *basement* (whether the housing unit has a basement), *garage* (the availability of parking lots)[47], *hgsize* (the living size of the dwelling in square meters), *lotsize* (the lot size corresponding to the dwelling in square meters), *floors*(counts the number of floors), *rooms* (counts the number of rooms), *value* (denotes the posted selling price of the advertisement of the housing unit), and *quality* (records the quality of a building's facilities). I categorize the reported qualities into "simple", "normal" and "high", where the latter is combined of the two highest categories in the variable *facilities*.

I use all the listed single-/double-family houses for sale using the variables "house_category" and "real estate type". I, however, exclude semi-attached single-family buildings ("Doppelhaushälften") from the dataset as I cannot identify whether construction costs refer the one or both parts of the duplex ("Doppelhaus").[48] I also exclude all the observations that are listed as "unfinished buildings", i.e., I exclude objects that are still under construction but are listed and the observations that refer to as "holiday homes".

[46] See Boelmann and Schaffner (2019) for data documentation.

[47] Unfortunately, no variable explicitly states the kind of parking lot. However, I think it is reasonable to assume that a substantial fraction of single-/double-family dwellings in Germany is equipped with a garage.

[48] Effenberger (2015) reports that semi-attached single-family buildings ("Doppelhaushälften") make up around 33.5 percent of the stock of single family homes in Germany in 2012. But given the construction cost issue, I exclude these stocks.

I use the variable *dupid_gen* generated by the RWI that classifies object identifiers used more than once to eliminate duplicates. I remove those observations with a duplicate ID of 1, indicating that they are identical in essential variables and were posted several times around the same date. Also, I drop objects with duplicate identifier 2, i.e., close to identical objects as above; however, I keep objects that differ in essential variables and those with object identifiers used only once.

I also eliminate possible scam postings and very luxury objects by dropping extreme outliers and unrealistic values. First, I remove houses with more than 600 or less than 50 square meters living size, more than 15 rooms, and more than 2500 square meters of lot size that are possible for agricultural use. Second, I drop observations with values of less than 10,000 or more than 5,000,000 Euros.[49]

For the cost function estimation, I use the BKI (2016) that publishes how much it would cost per square meter of living space to build a new single-/double-family home on average in Germany in 2016, given several characteristics of the structure. The characteristics published by the BKI include total square meters of living space, the number of stories[50], the veneer/siding, the quality of the building's facilities, the energy-efficiency standard, and whether it has a basement or not. I draw the analysis upon square-foot building costs of single-/double-family homes in the BKI data. Using the sample houses from the BKI database, I have 150 observations for estimating the cost function.[51]

To obtain the total construction cost for each housing unit reported in the sample, I multiply the construction cost per square meter using the cost function by the reported unit size in square meters and add 10,000 for units having a garage.[52] As this current measure of total construction cost is the German average for the year 2016q1[53], I multiply the cost by the following ratio to normalize the construction cost to reflect for the "end of advertisement"-year and a given county.

$$\frac{\text{BKI RF of the county * CCI, "end of advertisement"-year}}{\text{German average of BKI RF* CCI, 2016}} \tag{2.15}$$

An example should help to clarify these calculations. Suppose I wish to calculate the cost of a new single-family home to be built in the county-free city Frankfurt am Main (FFM) in 2014. Further suppose this home is of medium quality, has 150 square meters of living space on two floors, a garage and a basement. According to Equation (2.5), the log(cost-per-square-meter) at the German average in 2016 would be

$$7.8793 + 0.1003 - 0.0000485 * 150 - 0.1668 - 0.2027 = 7.6. \tag{2.16}$$

[49] I follow the restrictions set by the ImmobilienScout24-House-Price-Index.

[50] As there is a picture attached to each housing unit, I can infer this information.

[51] The variables are defined as varying in home size (from about 90 - 350 square meters of living space), quality (low, normal/average, high), veneer/siding (wood, brick, man-made siding), basement (yes and no), and two-height dimensions (more or less than two stories).

[52] I base the number 10,000€ from the website that reports the standard sizes for single-/double-garages (https://www.garagen-welt.de/blog/garagengroesse-garagenbreite.html). I then multiply the standard size of a single- and double-garage in m^3 with average building costs for a middle-sized single-floor garage in €/m^3. See the following document that outlines the garage costs. https://docplayer.org/51789280-Richtwerte-fuer-die-ermittlung-der-verschiedenen-baukosten-als-grundlage-der-festsetzung-von-baugenehmigungsgebuehren.html.

[53] Inclusive of 16 percent value-added tax.

Thus, the cost-per-square-meter at the German average in 2016 is

$$e^{7.6} = 2,003.85€. \tag{2.17}$$

The total construction cost including the cost of the garage, would be

$$2,003.85 * 150 + 10,000 = 310,577.5€. \tag{2.18}$$

Converting the total construction cost to the cost for the county-free city FFM in 2014, requires applying the 2014 regional construction cost factor of FFM according to (2.15),

$$310,577.5€ * \frac{1.082 * 98.5}{0.979 * 102.1} = 331,150.22€, \tag{2.19}$$

where 98.5 is the CCI for Germany in 2014, 1.082 is the BKI regional factor for FFM, 102.1 is the CCI for Germany in 2016 and 0.979 the German average of regional factors in 2016.

After the cost adjustment by Equation (2.15), I depreciate the structure cost based on its age to better estimate the actual replacement cost of the structure, i.e., if the land had no value. Following Davis and Palumbo (2008), one could take depreciation as the expense that it would cost to renovate the existing structure to "like-new" standards. Consequently, the replacement cost of the structure after accounting for depreciation is[54]

$$s_{i,t} = \begin{cases} str_cost_new_{i,t} \cdot \left(\frac{1}{1+\delta}\right)^{age_{i,t}} & \text{if } age_{i,t} \leq 20 \\ str_cost_new_{i,t} \cdot \left(\frac{1}{1+\delta}\right)^{age_{i,t}} \cdot \left(\frac{1}{1+0.01}\right)^{age_{i,t}-20} & \text{if } 20 < age_{i,t} \leq 50 \\ str_cost_new_{i,t} \cdot \left(\frac{1}{1+\delta}\right)^{age_{i,t}} \cdot \left(\frac{1}{1+0.01}\right)^{30} \cdot \left(\frac{1}{1+0.05}\right)^{age_{i,t}-50} & \text{if } age_{i,t} > 50 \end{cases}$$

2.6.2 Components of Home Value in 2018

In this section, I provide the analysis for 2018 that is compatible to Section 2.4.1 where I compare the results for 2014 and 2018. Table 2.14 and Figure 2.11 display values of the components of the housing bundle in 1,000s € as well as the land's share of home value in percent and the land value per square meter of lot size for German federal states and counties, respectively. Comparing Figure 2.2 and Figure 2.11 one can see that differences between counties stayed almost the same. However, Figure 2.12[55] and Table 2.14 indicate that especially home and land values became more expensive compared to 2014. Especially the counties around the prosperous urban centers in the Southern states of Germany and Nordrhein-Westfalen became more expensive in terms of home values and land values, but also values around the city-states Berlin and Hamburg (Figure 2.11). The most affordable home values and land values remain to be in Germany's central part and in some regions in the East of Germany. Average home values vary between 191,000€ in Thüringen (located quite in the middle of Germany (Figure 2.1)) and 771,000€ in Hamburg. With average home values of around 550,000€ Berlin, Bavaria and Baden-Württemberg follow the leader in terms of expensive home values. The same picture results for land's share of home values. The average lot was worth between 35 percent of a home's value in Thüringen and 74 and 76

[54] For details, please refer to Section 2.3.3

[55] In Figure 2.12 I adjusted the cut-off values in the legend to the corresponding values of 2014.

percent in Berlin and Hamburg. While the counties in the new Federal States of Germany do not lag in terms of cumulative changes in home value and residential land value, the cross-regional differences remain.

Region/State	Home value (1000s Euros)	Land value (1000s Euros)	Land value per per square meter	Structure value (1000s Euros)	Land's share of home value (pct)
West	438	275	378	163	57%
Schleswig-Holstein	344	192	227	152	55%
Hamburg	771	584	758	187	76%
Niedersachsen	278	140	165	139	50%
Bremen	294	156	211	138	51%
Nordrhein-Westfalen	410	256	341	154	59%
Hessen	449	275	426	174	55%
Rheinland-Pfalz	320	172	271	147	49%
Baden-Württemberg	514	328	496	186	61%
Bayern	539	314	432	225	52%
Saarland	231	112	146	119	49%
Berlin	672	497	688	174	74%
East	249	111	126	138	42%
Brandenburg	302	163	181	139	52%
Mecklenburg-Vorpommern	280	113	124	166	38%
Sachsen	277	116	129	161	36%
Sachsen-Anhalt	195	99	113	96	51%
Thüringen	191	64	82	127	35%

Table 2.14: Components of home value in 2018 by state

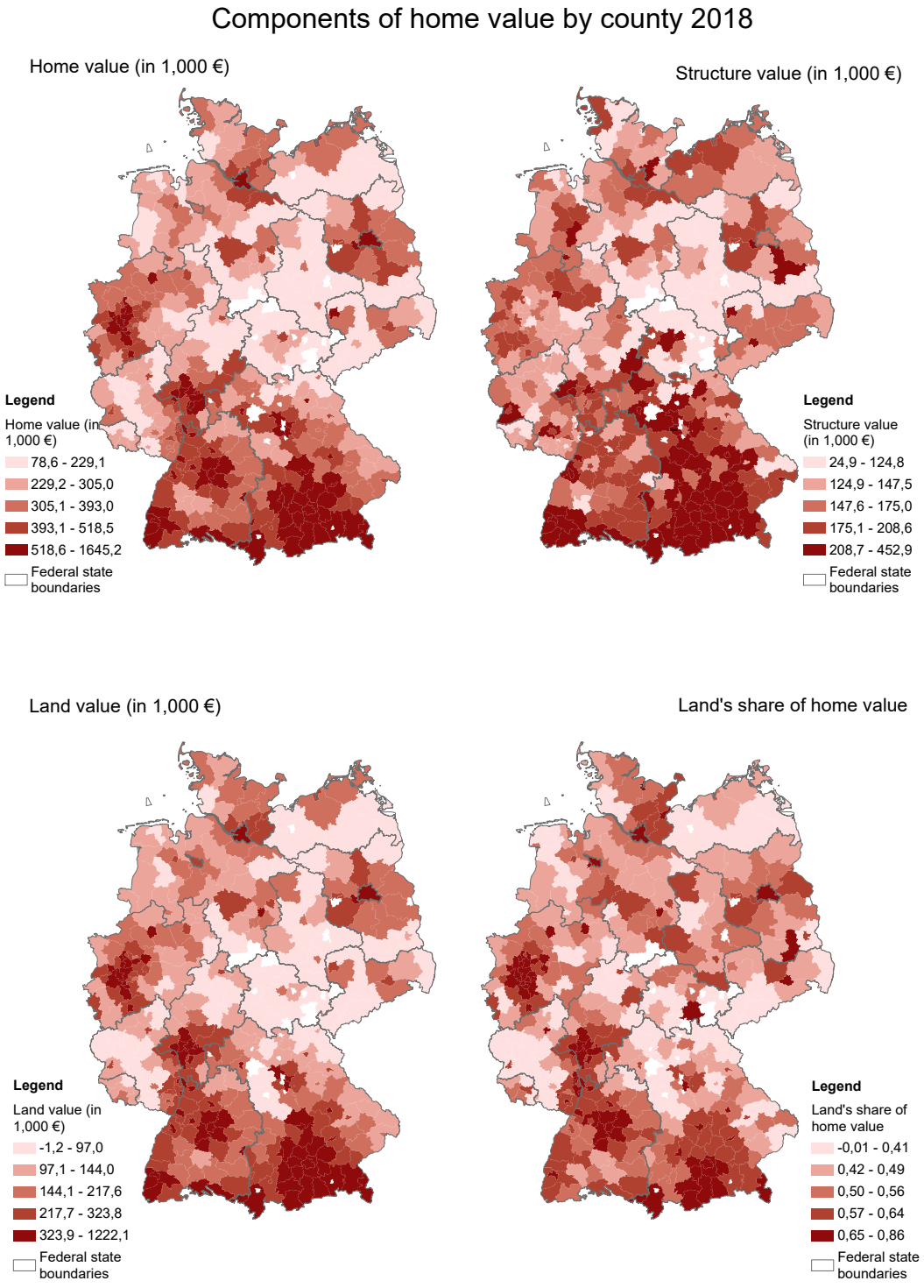


Figure 2.11: Components of home value by county in 2018

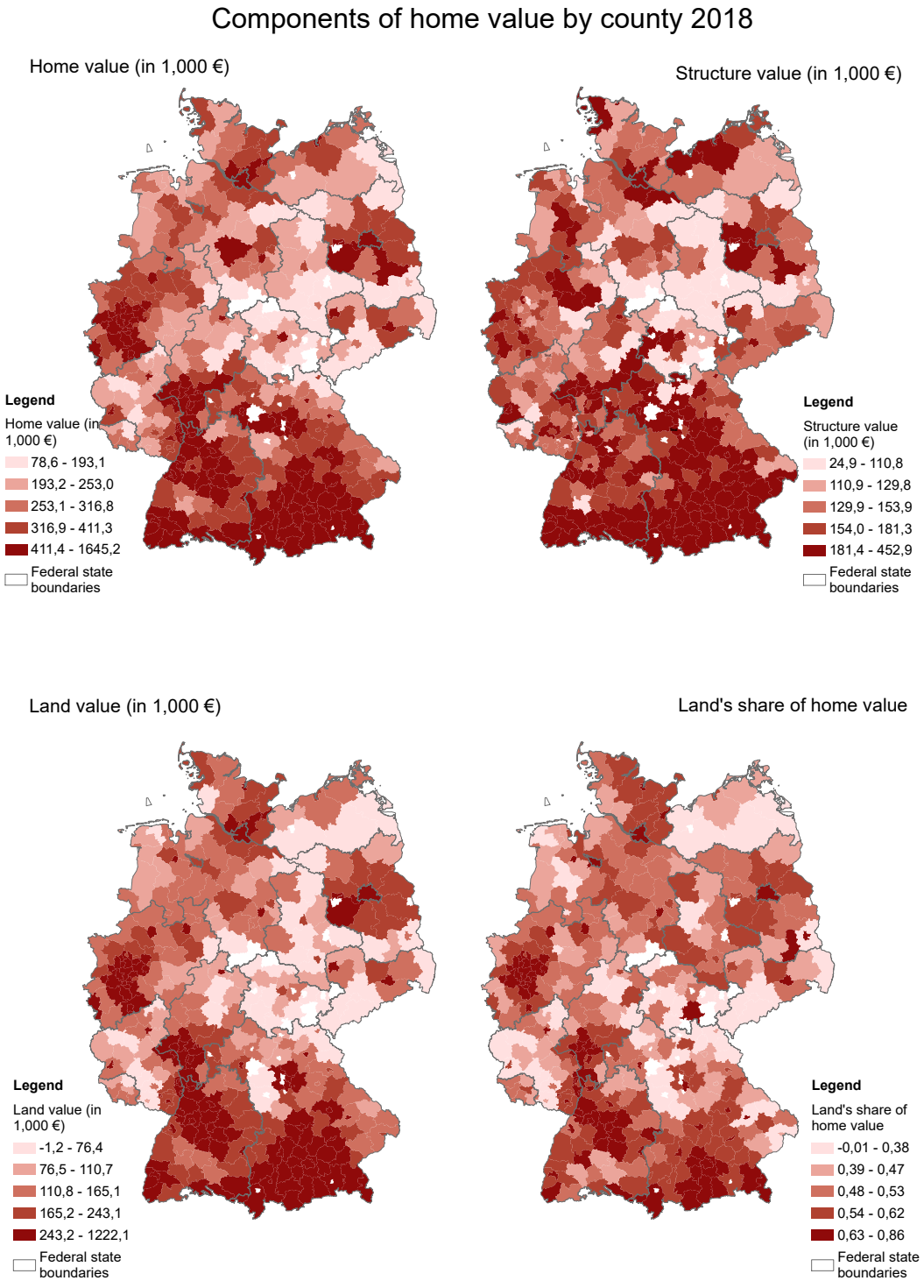


Figure 2.12: Components of home value by county in 2018 - legend adjusted to 2014

2.6.3 Data

The following section lists the data sources used for the several steps in the estimation procedure.

Cost function estimation

Data: Observed structure cost from BKI (2016) that publishes how much it would cost per square meter of living space to build a new single-/double-family home on average in Germany in 2016, given several characteristics of the structure for standard building types.

Construction cost calculation ("like brand new 2016") for Immoscout Data observations

Data: House price listings from the internet platform ImmobilienScout24 provided by the RWI - Leibniz Institute for Economic Research.

From construction cost ("like new 2016") to replacement costs in the year of the listing

The data sources used in this step are listed in Table 3.4.2.

Data	Frequency	Aggregation Level	Source
ImmobilienScout24 listings data	-	-	RWI - Leibniz Institute for Economic Research
Construction Cost Index (CCI)	annual	Germany	Federal Statistical Office
Regional construction cost factore (RF)	annual	County	BKI
Depreciation Rate	fixed	Germany	Steuertipps (2021) (See footnote 28)

Table 2.15: Data sources

County Benchmark Structure Shares - 2012

The data sources used to estimate the county benchmark structure shares in 2012 are listed in Table 2.16.

Data	Frequency	Aggregation Level	Source
House Price Index (HPI)	annual	County	vdpResearch
Consumer Price Index (CPI)	annual	Germany	Federal Statistical Office

Table 2.16: Data sources - continued

Extrapolating Benchmark Structure Shares

The data sources used for the step on extrapolating benchmark estimates are listed in Table 2.17.

Data	Frequency	Aggregation Level	Source
Population	annual	County	Federal Statistical Office
Average Household Size	annual	Germany	Federal Statistical Office
Housing Stock	annual	Germany	Federal Statistical Office
Estimated cost of building completions of residential buildings	annual	State	Federal Statistical Office
Purchase values of land ready for construction	annual	State	Regional database Germany

Table 2.17: Data sources - continued 2

2.6.4 Tables

Region	State	County	obs.	State	County	obs.	State	County	obs.
West	Schleswig-	SK Flensburg	37		LK Osterholz	76		LK Wesel	334
	Holstein	SK Kiel	49		LK Rotenburg (Wümme)	104		SK Bonn	88
		SK Lübeck	47		LK Soltau-Fallingbostel	121		SK Köln	163
		SK Neumünster	34		LK Stade	109		SK Leverkusen	50
		LK Dithmarschen	152		LK Uelzen	116		SK Städteregion Aachen	227
		LK Herzogtum Lauenburg	121		LK Verden	63		LK Düren	191
		LK Nordfriesland	86		SK Delmenhorst	45		LK Rhein-Erft-Kreis	256
		LK Ostholstein	116		SK Emden	14		LK Euskirchen	247
		LK Pinneberg	214		SK Oldenburg	81		LK Heinsberg	259
		LK Plön	100		SK Osnabrück	68		LK Oberbergischer Kreis	296
		LK Rendsburg-Eckernförde	358		SK Wilhelmshaven	17		LK Rheinisch-Bergischer Kreis	236
		LK Schleswig-Flensburg	257		LK Ammerland	74		LK Rhein-Sieg-Kreis	581
		LK Segeberg	217		LK Aurich	94		SK Bottrop	29
		LK Steinburg	107		LK Cloppenburg	63		SK Gelsenkirchen	20
		LK Stormarn	128		LK Emsland	87		SK Münster	59
	Hamburg	SK Hamburg	223		LK Friesland	50		LK Borken	205
	Niedersachsen	SK Braunschweig	99		LK Grafschaft Bentheim	51		LK Coesfeld	155
		SK Salzgitter	111		LK Leer	64		LK Recklinghausen	233
		SK Wolfsburg	158		LK Oldenburg	59		LK Steinfurt	229
		LK Gifhorn	457		LK Osnabrück	153		LK Warendorf	101
		LK Göttingen	85		LK Vechta	27		SK Bielefeld	113
		LK Goslar	109		LK Wesermarsch	26		LK Gütersloh	78
		LK Helmstedt	178		LK Wittmund	46		LK Herford	152
		LK Northeim	88	Bremen	SK Bremen	141		LK Höxter	103
		LK Osterode am Harz	101		SK Bremerhaven	18		LK Lippe	385
		LK Peine	163	Nordrhein-	SK Düsseldorf	91		LK Minden-Lübbecke	253
	Westfalen	LK Wolfenbüttel	183		SK Duisburg	98		LK Paderborn	136
		LK Region Hannover	917		SK Essen	85		SK Bochum	32
		LK Diepholz	72		SK Krefeld	71		SK Dortmund	124
		LK Hameln-Pyrmont	204		SK Mönchengladbach	104		SK Hagen	55
		LK Hildesheim	214		SK Mülheim an der Ruhr	59		SK Hamm	31
		LK Holzminden	65		SK Oberhausen	41		SK Herne	11
		LK Nienburg (Weser)	64		SK Remscheid	55		LK Ennepe-Ruhr-Kreis	153
		LK Schaumburg	172		SK Solingen	60		LK Hochsauerlandkreis	123
		LK Celle	214		SK Wuppertal	115		LK Märkischer Kreis	235
		LK Cuxhaven	118		LK Kleve	256		LK Olpe	54
		LK Harburg	161		LK Mettmann	186		LK Siegen-Wittgenstein	203
		LK Lüchow-Dannenberg	126		LK Rhein-Kreis Neuss	314		LK Soest	139
		LK Lüneburg	134		LK Viersen	280		LK Unna	224

Table 2.18: Number of observations by county

State	County	obs.	State	County	obs.	State	County	obs.
Hessen	SK Darmstadt	33		LK Vulkaneifel	40		SK Mannheim	50
	SK Frankfurt am Main	112		LK Trier-Saarburg	132		LK Neckar-Odenwald-Kreis	130
	SK Offenbach am Main	24		SK Frankenthal (Pfalz)	22		LK Rhein-Neckar-Kreis	299
	SK Wiesbaden	97		SK Kaiserslautern	78		SK Pforzheim	70
	LK Bergstraße	248		SK Landau in der Pfalz	31		LK Calw	158
	LK Darmstadt-Dieburg	231		SK Ludwigshafen am Rhein	48		LK Enzkreis	253
	LK Groß-Gerau	189		SK Mainz	60		LK Freudenstadt	95
	LK Hochtaunuskreis	357		SK Neustadt an der Weinstraße	41		SK Freiburg im Breisgau	13
	LK Main-Kinzig-Kreis	366		SK Pirmasens	36		LK Breisgau-Hochschwarzwald	83
	LK Main-Taunus-Kreis	165		SK Speyer	25		LK Emmendingen	38
	LK Odenwaldkreis	164		SK Worms	45		LK Ortenaukreis	135
	LK Offenbach	228		SK Zweibrücken	24		LK Rottweil	130
	LK Rheingau-Taunus-Kreis	252		LK Alzey-Worms	213		LK Schwarzwald-Baar-Kreis	61
	LK Wetteraukreis	391		LK Bad Dürkheim	228		LK Tuttlingen	91
	LK Gießen	215		LK Donnersbergkreis	185		LK Konstanz	73
	LK Lahn-Dill-Kreis	274		LK Germersheim	124		LK Lörrach	68
	LK Limburg-Weilburg	292		LK Kaiserslautern	232		LK Waldshut	126
	LK Marburg-Biedenkopf	100		LK Kusel	88		LK Reutlingen	177
	LK Vogelsbergkreis	132		LK Südliche Weinstraße	168		LK Tübingen	112
	SK Kassel	36		LK Rhein-Pfalz-Kreis	153		LK Zollernalbkreis	139
	LK Fulda	57		LK Mainz-Bingen	289		SK Ulm	28
	LK Hersfeld-Rotenburg	108		LK Südwestpfalz	141		LK Alb-Donau-Kreis	148
	LK Kassel	104	Baden-Württemberg	SK Stuttgart	89		LK Biberach	137
	LK Schwalm-Eder-Kreis	49		LK Böblingen	178		LK Bodenseekreis	59
	LK Waldeck-Frankenberg	49		LK Esslingen	220		LK Ravensburg	87
	LK Werra-Meißner-Kreis	80		LK Göppingen	158		LK Sigmaringen	69
Rheinland-Pfalz	SK Koblenz	42		LK Ludwigsburg	212	Bayern	SK Ingolstadt	100
	LK Ahrweiler	140		LK Rems-Murr-Kreis	252		SK München	81
	LK Altenkirchen	145		SK Heilbronn	50		SK Rosenheim	4
	LK Bad Kreuznach	294		LK Heilbronn	302		LK Altötting	60
	LK Birkenfeld	54		LK Hohenlohekreis	123		LK Berchtesgadener Land	20
	LK Cochem-Zell	37		LK Schwäbisch Hall	219		LK Bad Tölz-Wolfratshausen	21
	LK Mayen-Koblenz	275		LK Main-Tauber-Kreis	54		LK Dachau	51
	LK Neuwied	229		LK Heidenheim	141		LK Ebersberg	52
	LK Rhein-Hunsrück-Kreis	160		LK Ostalbkreis	285		LK Eichstätt	119
	LK Rhein-Lahn-Kreis	152		SK Baden-Baden	44		LK Erding	37
	LK Westerwaldkreis	335		SK Karlsruhe	36		LK Freising	53
	SK Trier	24		LK Karlsruhe	266		LK Fürstenfeldbruck	79
	LK Bernkastel-Wittlich	67		LK Rastatt	137		LK Garmisch-Partenkirchen	32
	LK Eifelkreis Bitburg-Prüm	83		SK Heidelberg	23		LK Landsberg am Lech	64

Table 2.19: Number of observations by county - continued

State	County	obs.	State	County	obs.	Region	State	County	obs.
	LK Miesbach	36		LK Kronach	27			LK Donau-Ries	50
	LK Mühldorf a.Inn	52		LK Kulmbach	38			LK Oberallgäu	83
	LK München	106		LK Lichtenfels	11		Saarland	LK Regionalverband Saarbrücken	52
	LK Neuburg-Schrobenhausen	84		LK Wunsiedel i.Fichtelgebirge	16			LK Merzig-Wadern	51
	LK Pfaffenhofen a.d.Ilm	86		SK Ansbach	3			LK Neunkirchen	59
	LK Rosenheim	94		SK Erlangen	8			LK Saarlouis	39
	LK Starnberg	70		SK Fürth	5			LK Saarpfalz-Kreis	82
	LK Traunstein	72		SK Nürnberg	77			LK St. Wendel	36
	LK Weilheim-Schongau	47		SK Schwabach	9		Berlin	SK Berlin	1007
	SK Landshut	29		LK Ansbach	106	East	Brandenburg	SK Brandenburg an der Havel	8
	SK Passau	26		LK Erlangen-Höchstadt	65			SK Cottbus	34
	SK Straubing	13		LK Fürth	41			SK Frankfurt (Oder)	7
	LK Deggendorf	147		LK Nürnberger Land	71			SK Potsdam	45
	LK Freyung-Grafenau	115		LK Neustadt/Aisch-B.Windsh.	53			LK Barnim	265
	LK Kelheim	69		LK Roth	49			LK Dahme-Spreewald	276
	LK Landshut	105		LK Weißenburg-Gunzenhausen	32			LK Elbe-Elster	60
	LK Passau	189		SK Aschaffenburg	9			LK Havelland	185
	LK Regen	34		SK Schweinfurt	3			LK Märkisch-Oderland	250
	LK Rottal-Inn	55		SK Würzburg	11			LK Oberhavel	240
	LK Straubing-Bogen	59		LK Aschaffenburg	67			LK Oberspreewald-Lausitz	64
	LK Dingolfing-Landau	107		LK Bad Kissingen	28			LK Oder-Spree	168
	SK Amberg	17		LK Rhön-Grabfeld	15			LK Ostprignitz-Ruppin	39
	SK Regensburg	30		LK Haßberge	35			LK Potsdam-Mittelmark	246
	SK Weiden i.d.OPf.	13		LK Kitzingen	8			LK Prignitz	16
	LK Amberg-Sulzbach	60		LK Miltenberg	66			LK Spree-Neiße	51
	LK Cham	55		LK Main-Spessart	27			LK Teltow-Fläming	125
	LK Neumarkt i.d.OPf.	57		LK Schweinfurt	46			LK Uckermark	33
	LK Neustadt a.d.Waldnaab	31		LK Würzburg	69		Mecklenburg-Vorpommern	SK Rostock	41
	LK Regensburg	96		SK Augsburg	111			SK Schwerin	9
	LK Schwandorf	131		SK Kaufbeuren	37			LK Mecklenburgische Seenplatte	115
	LK Tirschenreuth	19		SK Kempten (Allgäu)	8			LK Rostock	136
	SK Bamberg	4		SK Memmingen	21			LK Vorpommern-Rügen	49
	SK Bayreuth	16		LK Aichach-Friedberg	98			LK Nordwestmecklenburg	73
	SK Coburg	8		LK Augsburg	199			LK Vorpommern-Greifswald	42
	SK Hof	19		LK Dillingen a.d.Donau	68			LK Ludwigslust-Pachim	123
	LK Bamberg	43		LK Günzburg	62		Sachsen	SK Chemnitz	44
	LK Bayreuth	64		LK Neu-Ulm	80			LK Erzgebirgskreis	209
	LK Coburg	34		LK Lindau (Bodensee)	28			LK Mittelsachsen	118
	LK Forchheim	35		LK Ostallgäu	55			LK Vogtlandkreis	118
	LK Hof	43		LK Unterallgäu	67			LK Zwickau	127

Table 2.20: Number of observations by county - continued 2

State	County	obs.	State	County	obs.	State	County	obs.
	SK Dresden	125		LK Harz	76		LK Wartburgkreis	38
	LK Bautzen	106		LK Jerichower Land	30		LK Unstrut-Hainich-Kreis	13
	LK Görlitz	29		LK Mansfeld-Südharz	57		LK Kyffhäuserkreis	13
	LK Meißen	144		LK Saalekreis	135		LK Schmalkalden-Meiningen	32
	LK Sächsische Schweiz-Osterzgebirge	132		LK Salzlandkreis	78		LK Gotha	30
	SK Leipzig	111		LK Stendal	84		LK Sömmerda	26
	LK Leipzig	177		LK Wittenberg	21		LK Hildburghausen	24
	LK Nordsachsen	83	Thüringen	SK Erfurt	22		LK Ilm-Kreis	28
Sachsen-Anhalt	SK Dessau-Roßlau	4		SK Gera	8		LK Weimarer Land	23
	SK Halle (Saale)	43		SK Jena	7		LK Sonneberg	9
	SK Magdeburg	45		SK Suhl	16		LK Saalfeld-Rudolstadt	22
	LK Altmarkkreis Salzwedel	34		SK Weimar	7		LK Saale-Holzland-Kreis	14
	LK Anhalt-Bitterfeld	31		SK Eisenach	4		LK Saale-Orla-Kreis	5
	LK Börde	99		LK Eichsfeld	13		LK Greiz	27
	LK Burgenlandkreis	56		LK Nordhausen	9		LK Altenburger Land	11

Table 2.21: Number of observations by county - continued 3

Schleswig-Holstein			Hessen			Brandenburg		
	HPI	land value per sqm		HPI	land value per sqm		HPI	land value per sqm
land value per sqm	0.59		land value per sqm	0.8		land value per sqm	0.84	
mean income	0.52	0.59	mean income	0.73	0.83	mean income	0.75	0.58
unemployment rate	-0.31	-0.03	unemployment rate	0.07	0.32	unemployment rate	-0.65	-0.62
Hamburg			**Rheinland-Pfalz**			**Mecklenburg-Vorpommern**		
	HPI	land value per sqm		HPI	land value per sqm		HPI	land value per sqm
land value per sqm	0.99		land value per sqm	0.67		land value per sqm	0.7	
mean income	0.99	0.98	mean income	0.46	0.58	mean income	0.75	0.63
unemployment rate	-0.99	-0.98	unemployment rate	0.05	0.18	unemployment rate	-0.3	-0.09
Niedersachsen			**Baden-Württemberg**			**Sachsen**		
	HPI	land value per sqm		HPI	land value per sqm		HPI	land value per sqm
land value per sqm	0.65		land value per sqm	0.55		land value per sqm	0.72	
mean income	0.29	0.5	mean income	0.53	0.63	mean income	0.93	0.69
unemployment rate	-0.24	-0.03	unemployment rate	-0.02	0.4	unemployment rate	-0.26	-0.03
Bremen			**Bayern**			**Sachsen-Anhalt**		
	HPI	land value per sqm		HPI	land value per sqm		HPI	land value per sqm
land value per sqm	0.86		land value per sqm	0.69		land value per sqm	0.75	
mean income	0.94	0.96	mean income	0.58	0.61	mean income	0.88	0.62
unemployment rate	-0.82	-0.97	unemployment rate	-0.25	0	unemployment rate	-0.25	-0.1
Nordrhein-Westfalen			**Saarland**			**Thüringen**		
	HPI	land value per sqm		HPI	land value per sqm		HPI	land value per sqm
land value per sqm	0.69		land value per sqm	0.57		land value per sqm	0.49	
mean income	0.62	0.71	mean income	0.68	0.63	mean income	0.69	0.29
unemployment rate	-0.03	0.33	unemployment rate	0.16	0.66	unemployment rate	-0.35	0.28
			Berlin					
				HPI	land value per sqm			
			land value per sqm	0.99				
			mean income	0.99	0.98			
			unemployment rate	-0.99	-0.99			

Table 2.22: Correlation of house price, land values, unemployment rate and mean income by state

County	2015	2016	2017	2018
Tier 1				
SK Berlin	0.35	-0.12	0.98	0.30
Tier 2				
SK Potsdam	0.06	0.09	0.02	0.91
LK Barnim	0.22	0.03	0.18	0.25
LK Dahme-Spreewald	0.14	0.16	0.04	0.20
LK Havelland	0.16	0.08	0.42	0.27
LK Märkisch-Oderland	0.08	0.13	0.30	0.18
LK Oberhavel	0.21	0.08	0.24	0.09
LK Oder-Spree	0.29	-0.02	-0.02	0.13
LK Potsdam-Mittelmark	-0.12	0.33	0.26	0.06
LK Teltow-Fläming	0.16	0.07	0.30	0.06
Average Tier 2	0.13	0.11	0.19	0.24
Tier 3				
LK Uckermark	-0.20	0.52	-0.26	0.27
LK Ostprignitz-Ruppin	0.40	-0.41	0.27	-0.17
SK Cottbus	-0.04	0.32	0.27	-0.35
LK Elbe-Elster	0.09	0.36	-0.21	0.49
LK Oberspreewald-Lausitz	0.19	-0.05	-0.13	0.34
LK Prignitz	0.03	0.25	0.00	0.08
LK Spree-Neiße	-0.12	0.29	0.06	-0.24
LK Anhalt-Bitterfeld	0.81	-0.02	-0.03	-0.25
LK Jerichower Land	0.16	0.06	0.05	0.06
LK Stendal	0.10	0.10	-0.15	-0.01
LK Wittenberg	0.00	-0.16	0.23	0.27
Average Tier 3	0.13	0.11	0.01	0.04

Table 2.23: Percentage change in building land value per m^2 - Berlin and surrounding Counties

County	2015	2016	2017	2018
Tier 1				
SK München	0.14	0.07	0.30	-0.04
LK München	-0.14	0.73	0.02	0.21
Average Tier 1	0.00	0.40	0.16	0.09
Tier 2				
LK Bad Tölz-Wolfratshausen	-0.29	0.54	0.49	-0.07
LK Dachau	0.42	0.54	0.37	-0.19
LK Ebersberg	0.08	-0.09	0.48	-0.20
LK Erding	-0.07	0.68	0.20	-0.31
LK Freising	0.15	0.30	0.24	-0.11
LK Fürstenfeldbruck	0.33	0.28	0.05	0.32
LK Miesbach	-0.24	0.74	0.52	0.02
LK Landsberg am Lech	0.08	0.23	0.14	-0.14
LK Starnberg	0.13	0.03	0.21	-0.09
Average Tier 2	0.07	0.36	0.30	-0.09
Tier 3				
LK Weilheim-Schongau	-0.18	0.00	0.49	0.22
LK Mühldorf a.Inn	-0.10	0.07	0.28	0.07
LK Neuburg-Schrobenhausen	0.19	0.00	0.28	0.25
LK Pfaffenhofen a.d.Ilm	0.20	0.13	0.19	0.05
LK Rosenheim	0.09	0.14	0.18	0.07
SK Landshut	-0.03	0.74	0.00	0.08
LK Kelheim	-0.02	0.16	0.01	0.13
LK Landshut	0.24	0.10	-0.05	0.08
LK Aichach-Friedberg	0.26	0.02	0.20	0.05
Average Tier 3	0.07	0.15	0.17	0.11

Table 2.24: Percentage change in building land value per m^2 - Munich and surrounding Counties

2.6.5 Figures

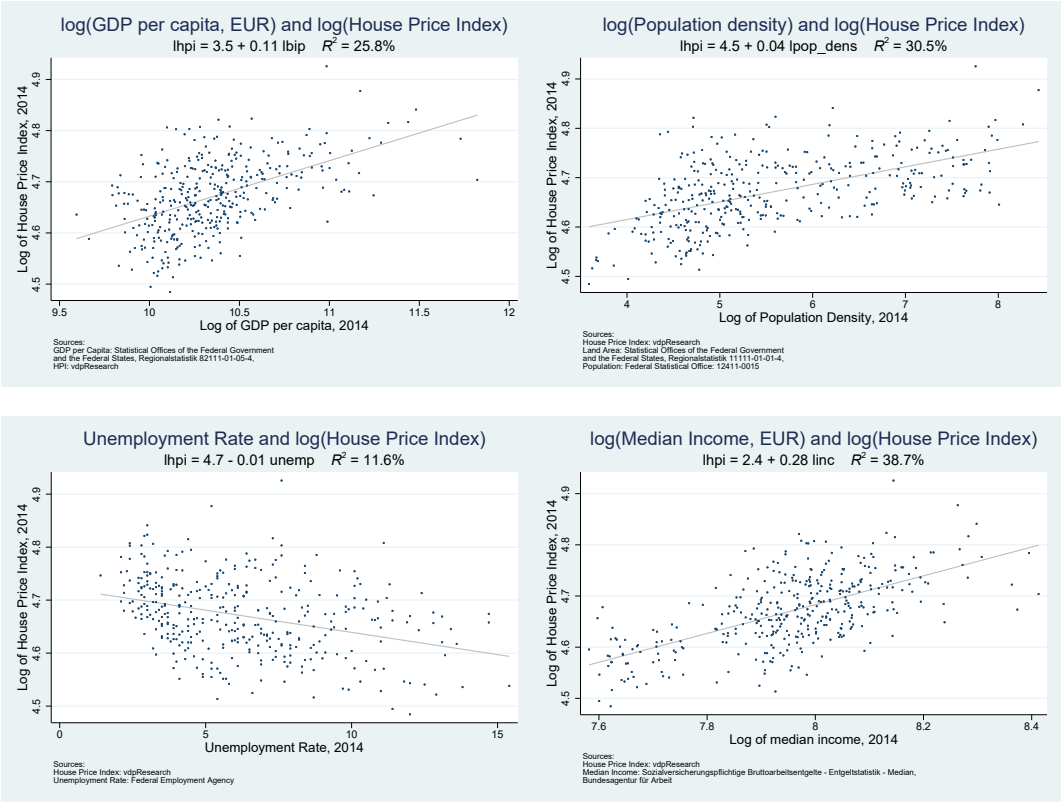


Figure 2.13: Relationship of important economic variables and house prices, 2014

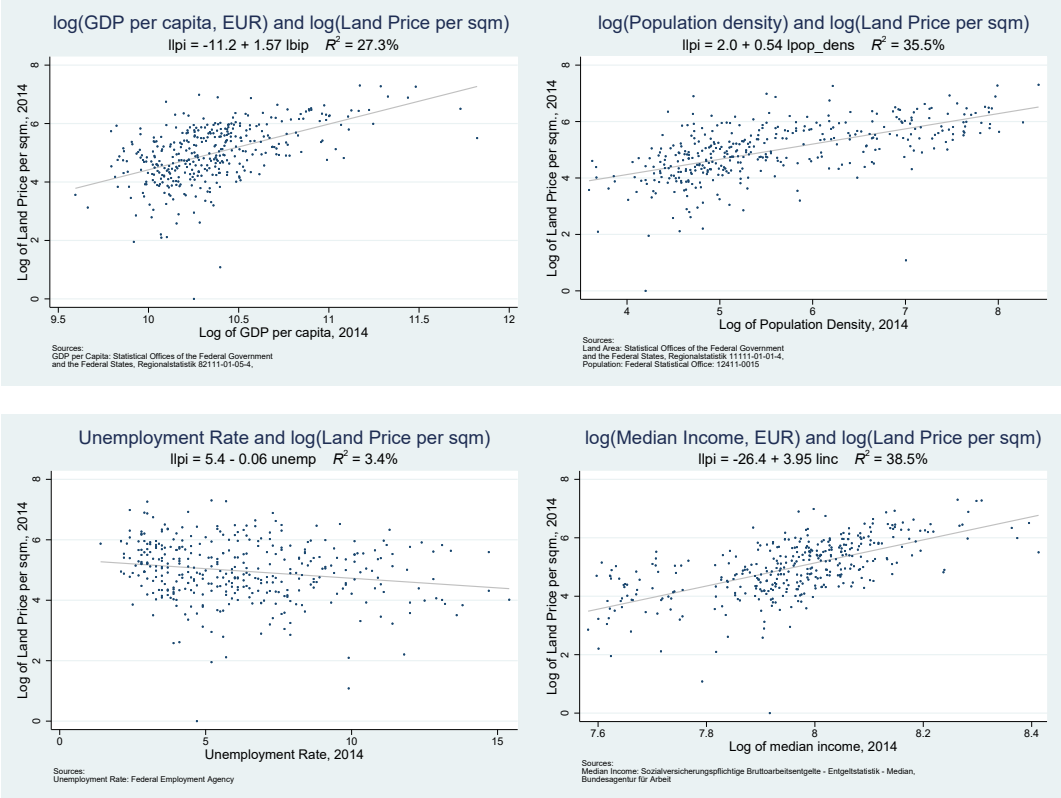


Figure 2.14: Relationship of important economic variables and land prices, 2014

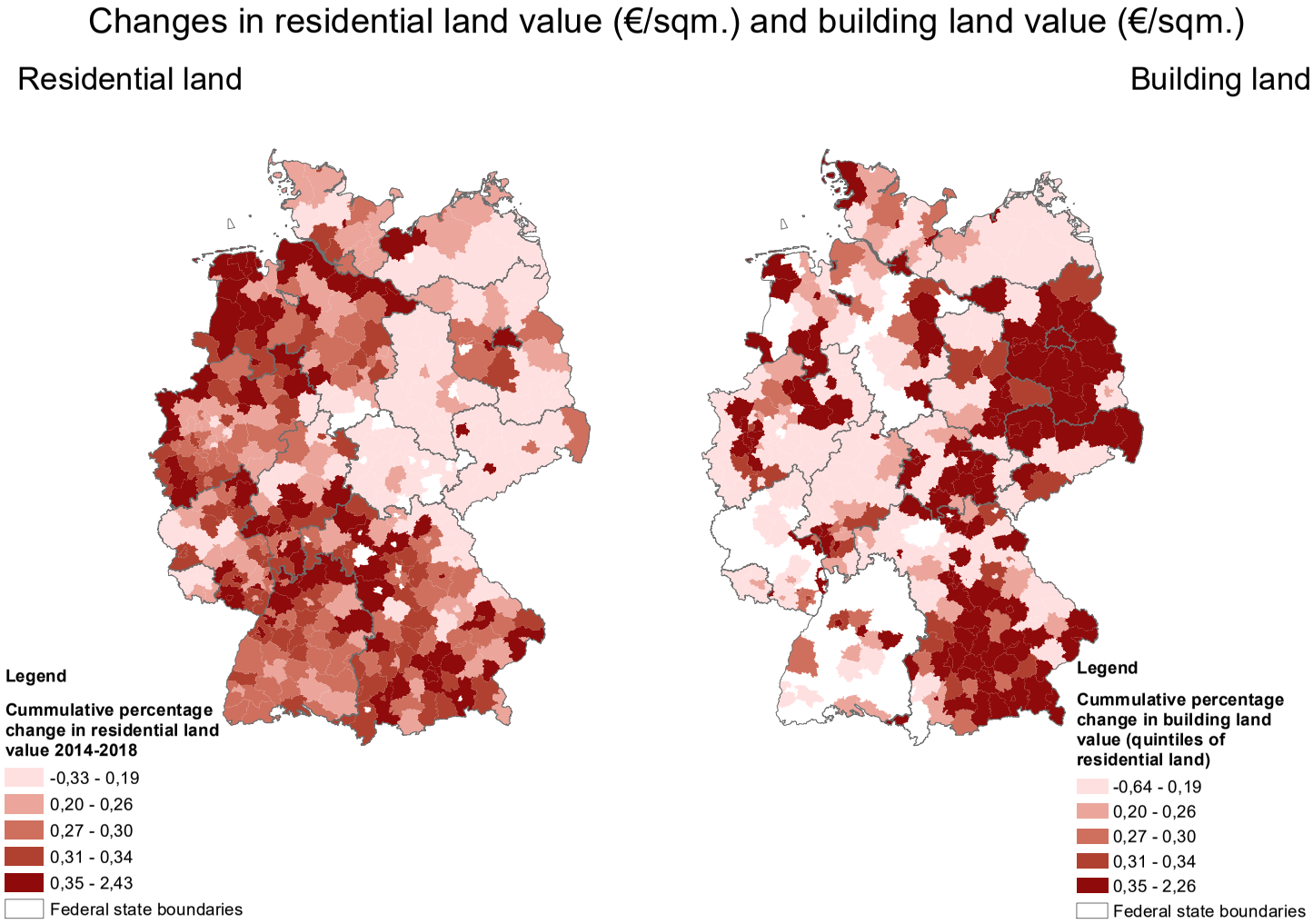


Figure 2.15: Changes in residential land values and building land values, 2014-2018

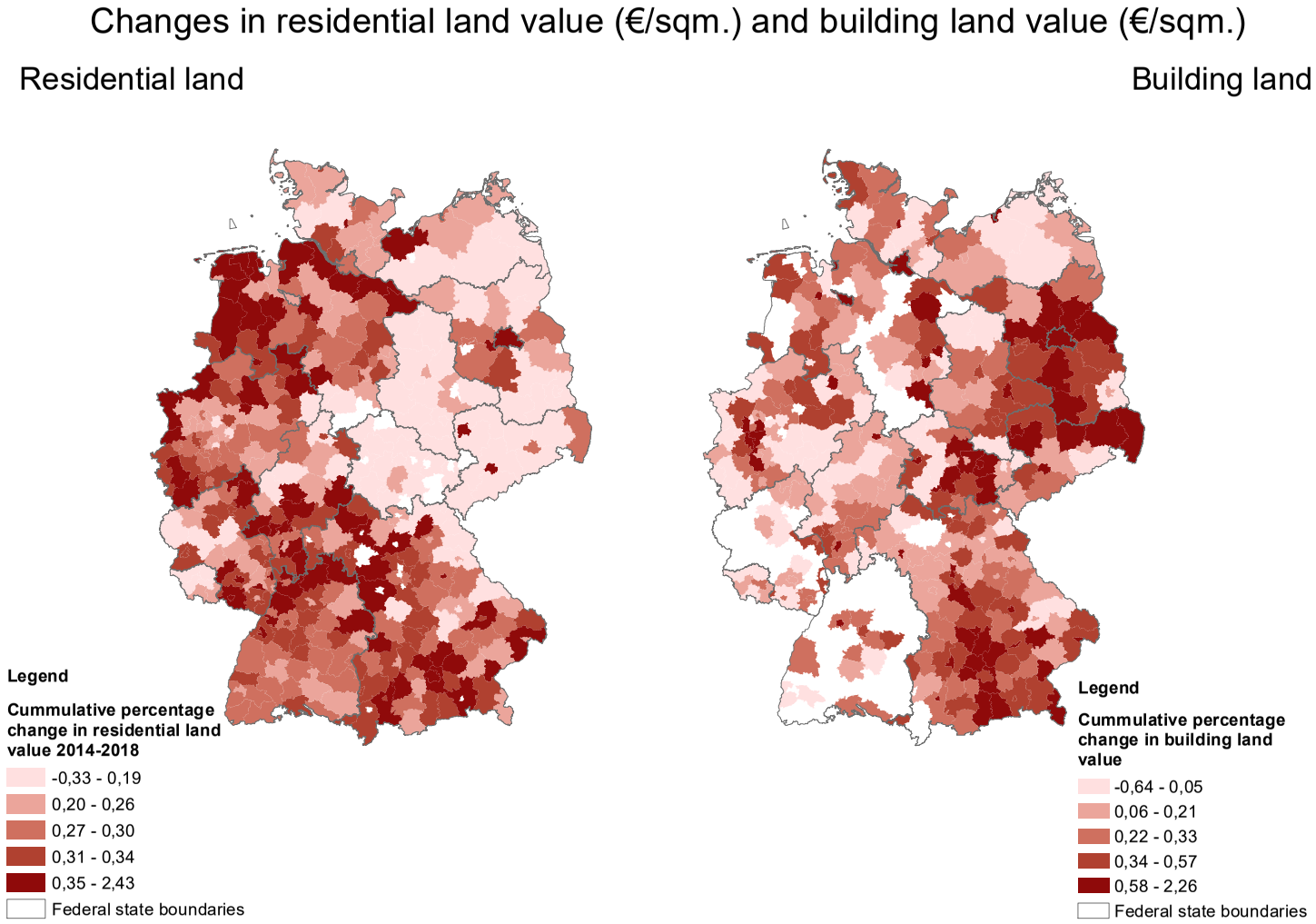


Figure 2.16: Changes in residential land values and building land values, 2014-2018 (Quintiles adjusted to residential land values)

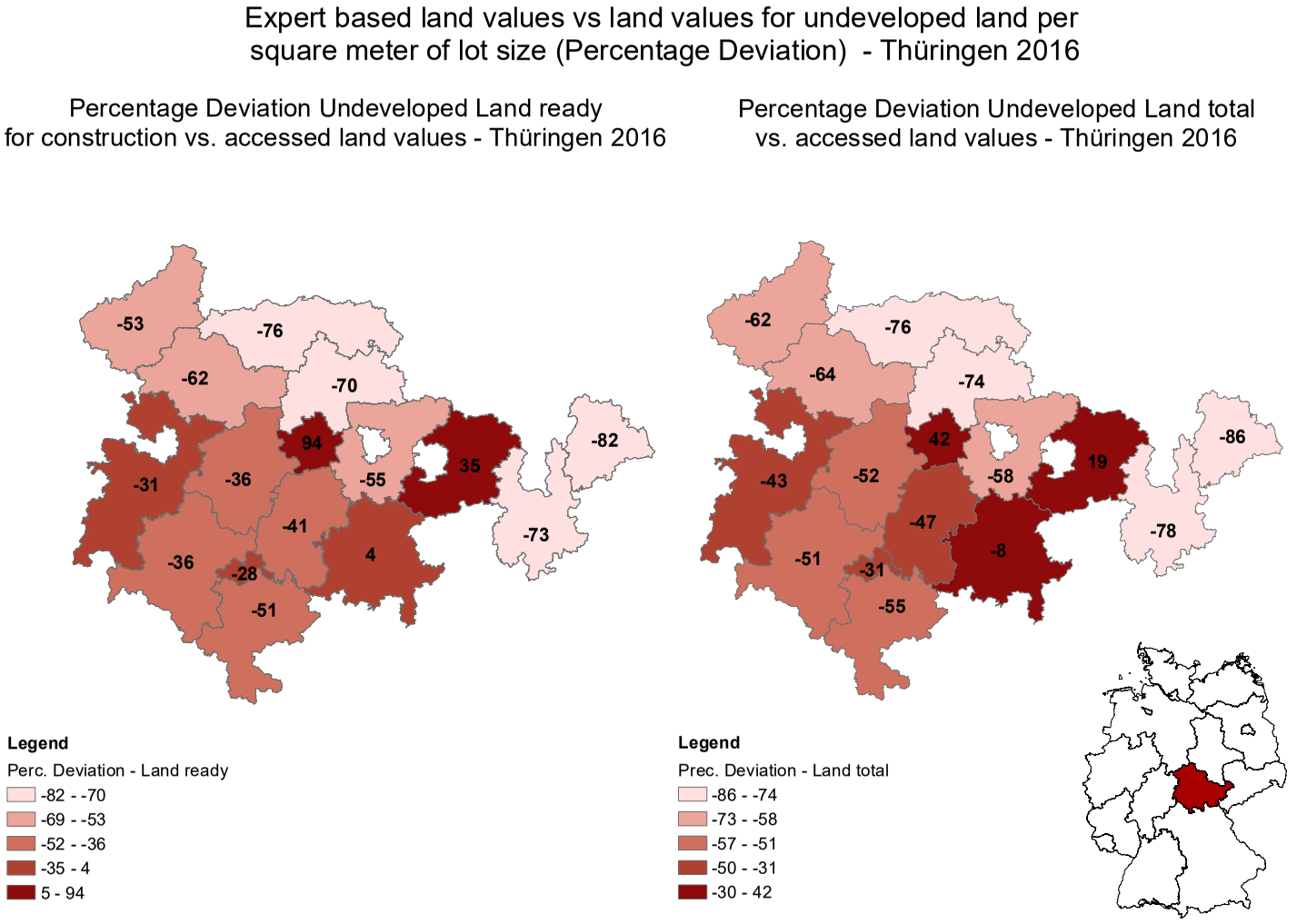


Figure 2.17: Land values of undeveloped land vs. accessed land values, EUR/sqm. (perc. deviation) - Thüringen 2016

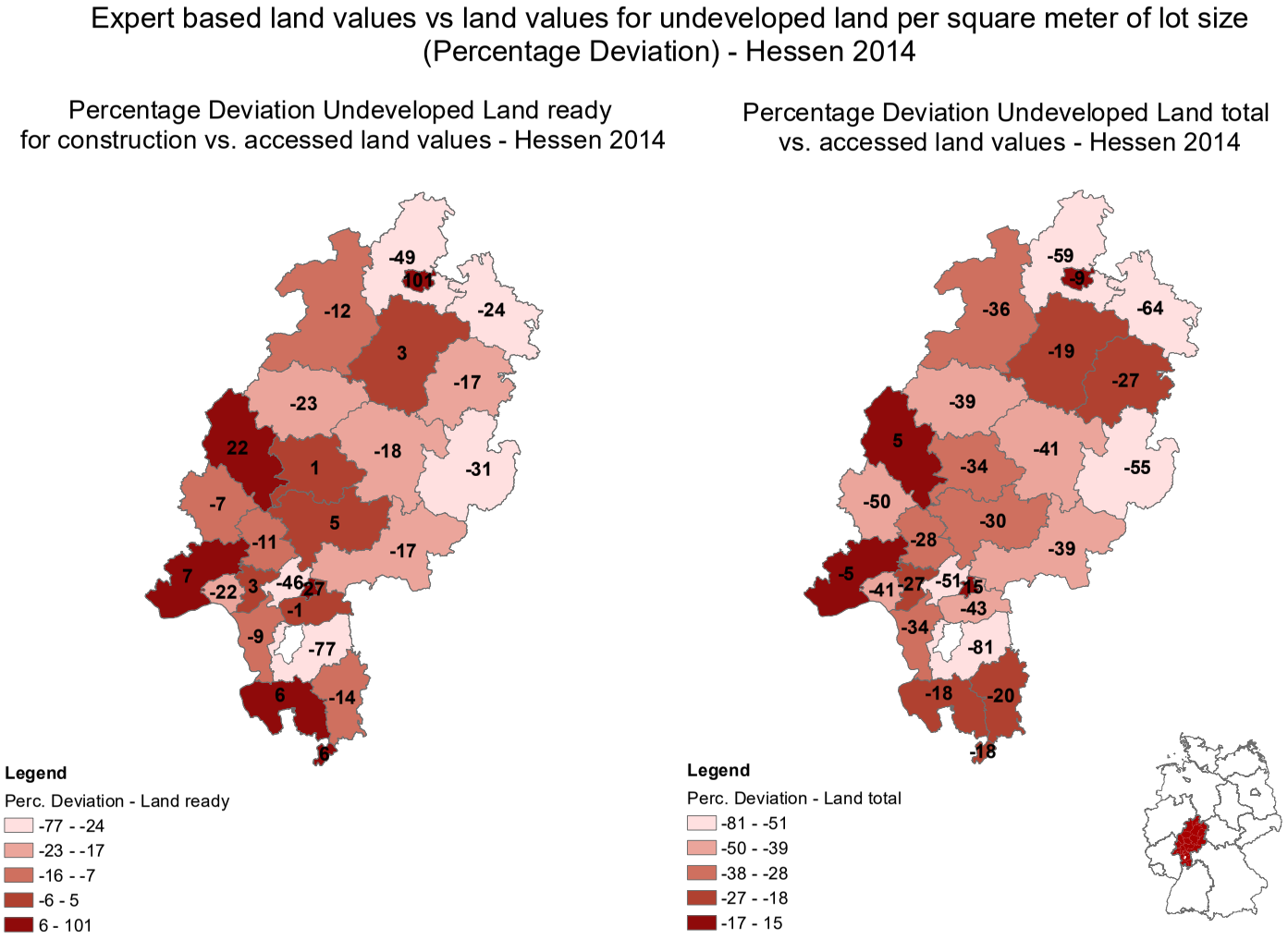


Figure 2.18: Land values of undeveloped land vs. accessed land values, EUR/sqm. (perc. deviation) - Hessen 2014

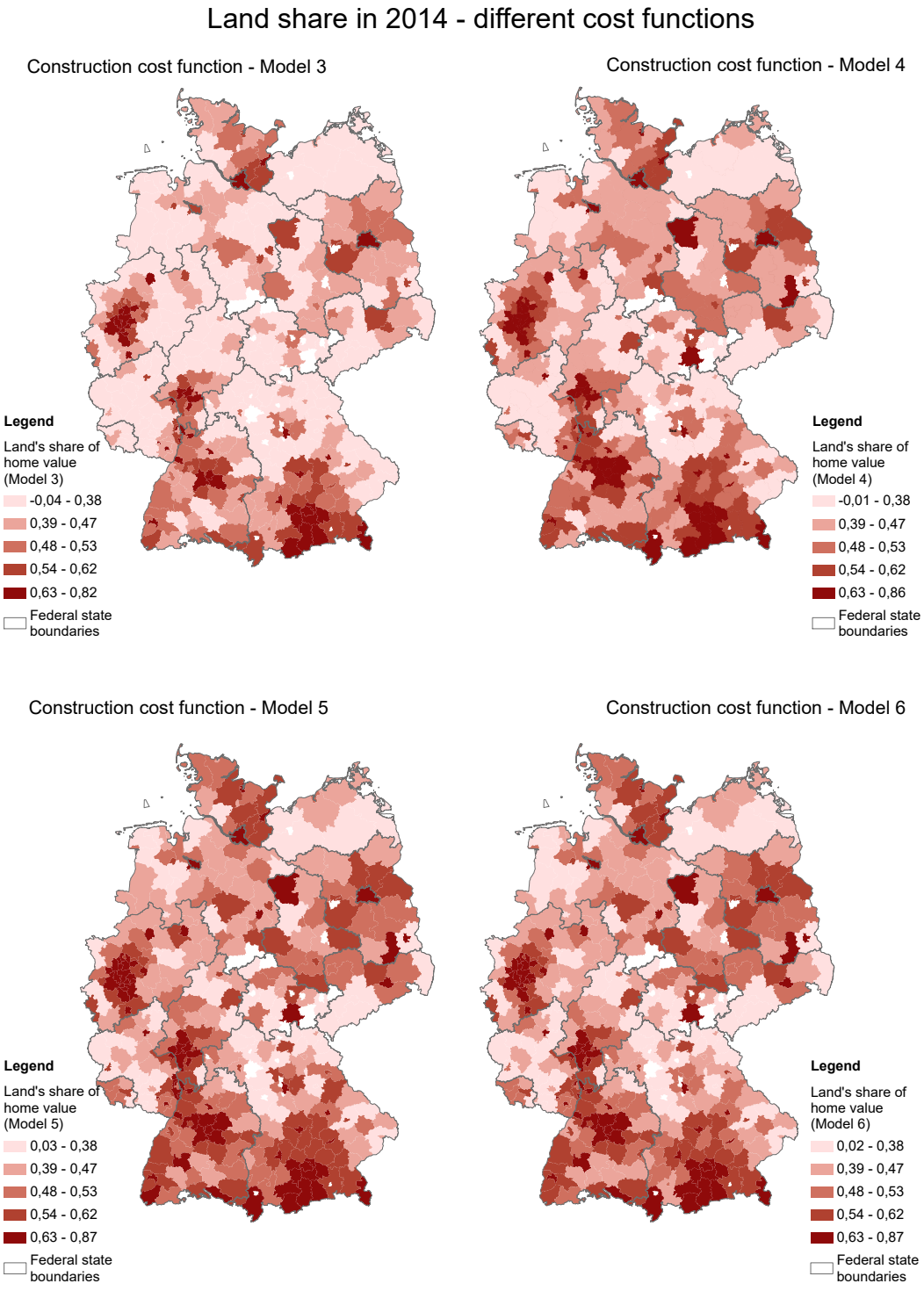


Figure 2.19: Land share's by county, 2014 - different cost functions

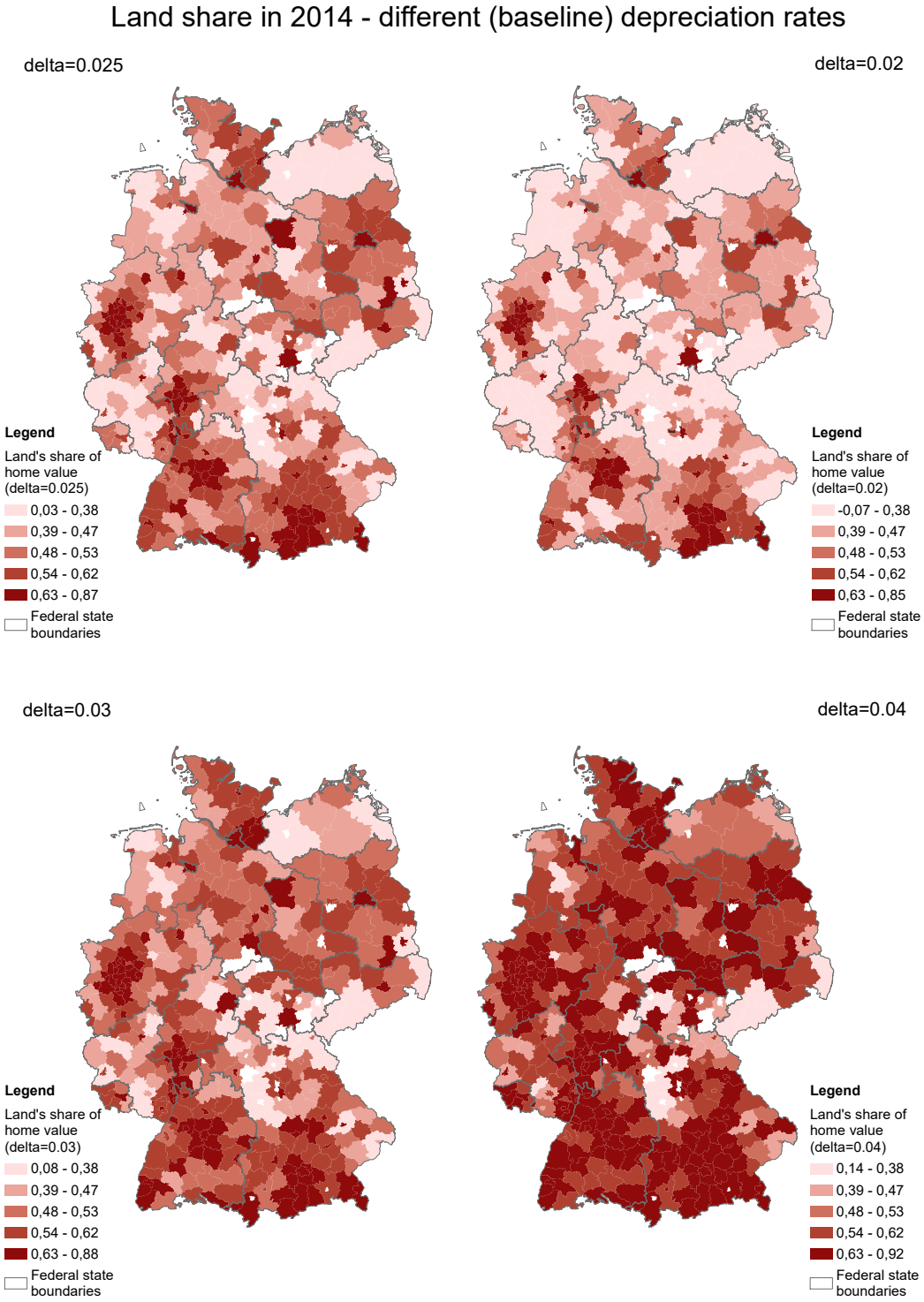


Figure 2.20: Land share's by county, 2014 - different deltas

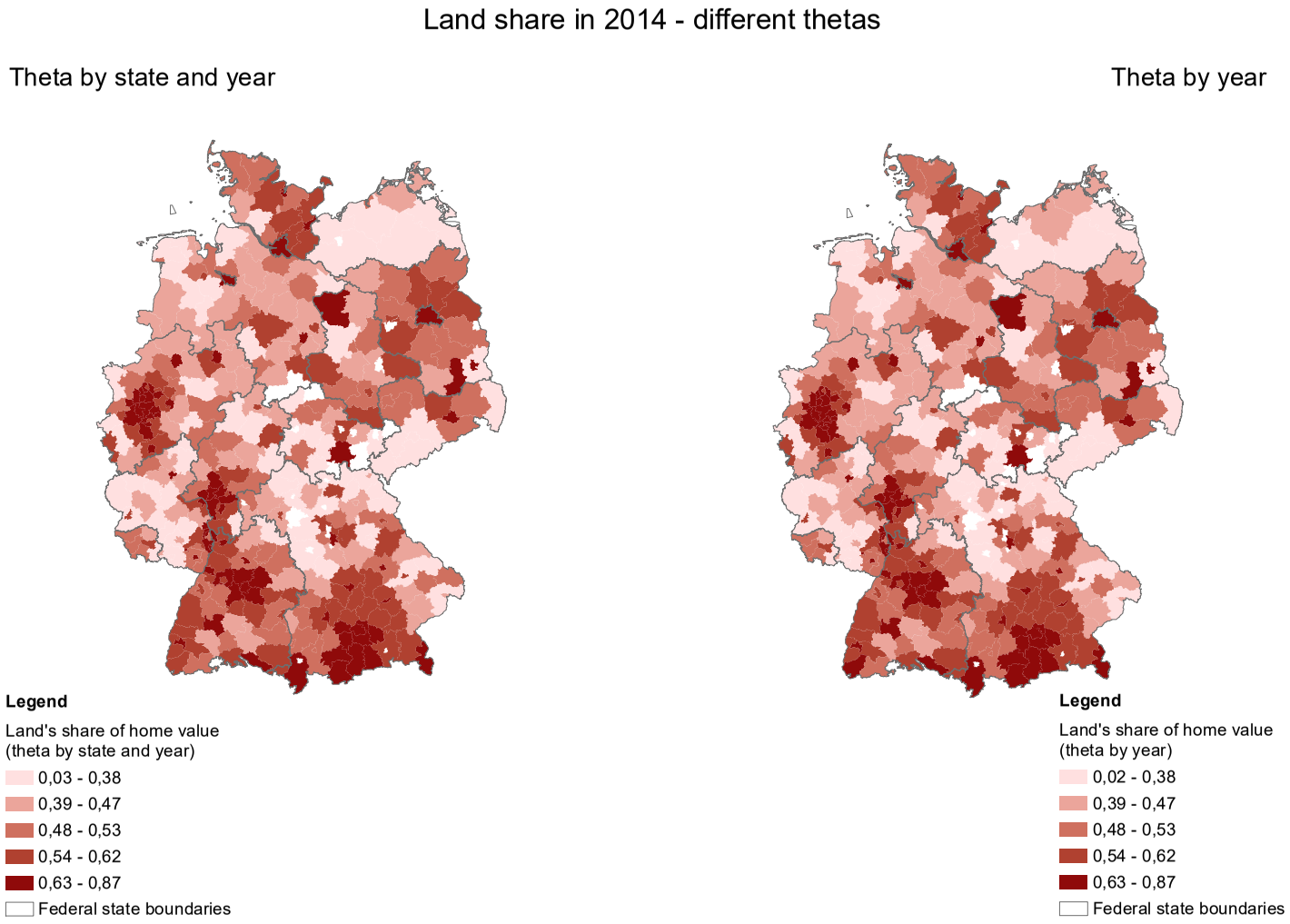


Figure 2.21: Land share's by county, 2014 - different thetas

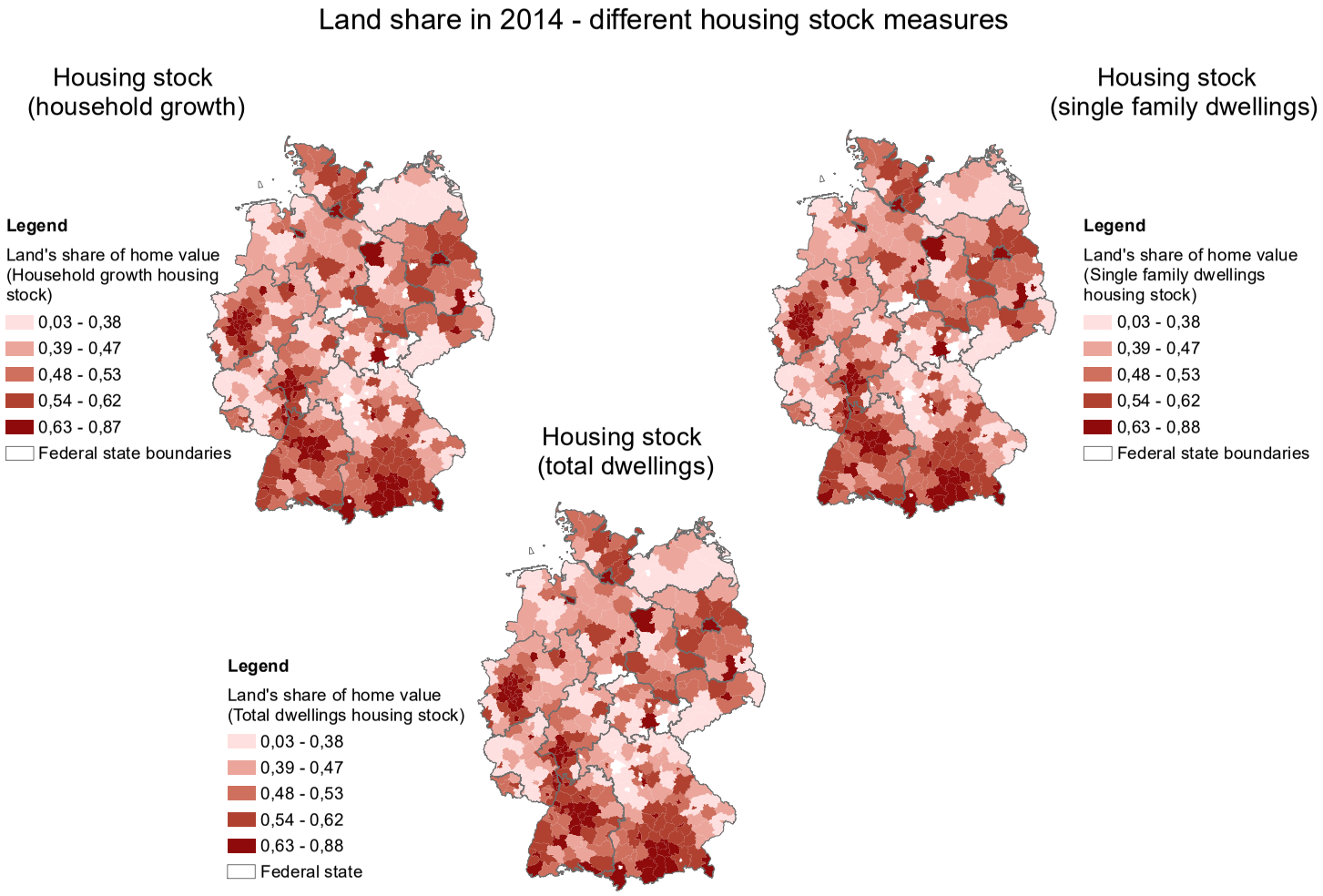


Figure 2.22: Land share's by county, 2014 - different housing stock measures



Figure 2.23: Distribution of land's share for construction cost model 3 and 5
Note: Distribution over 1,895 county-year observations

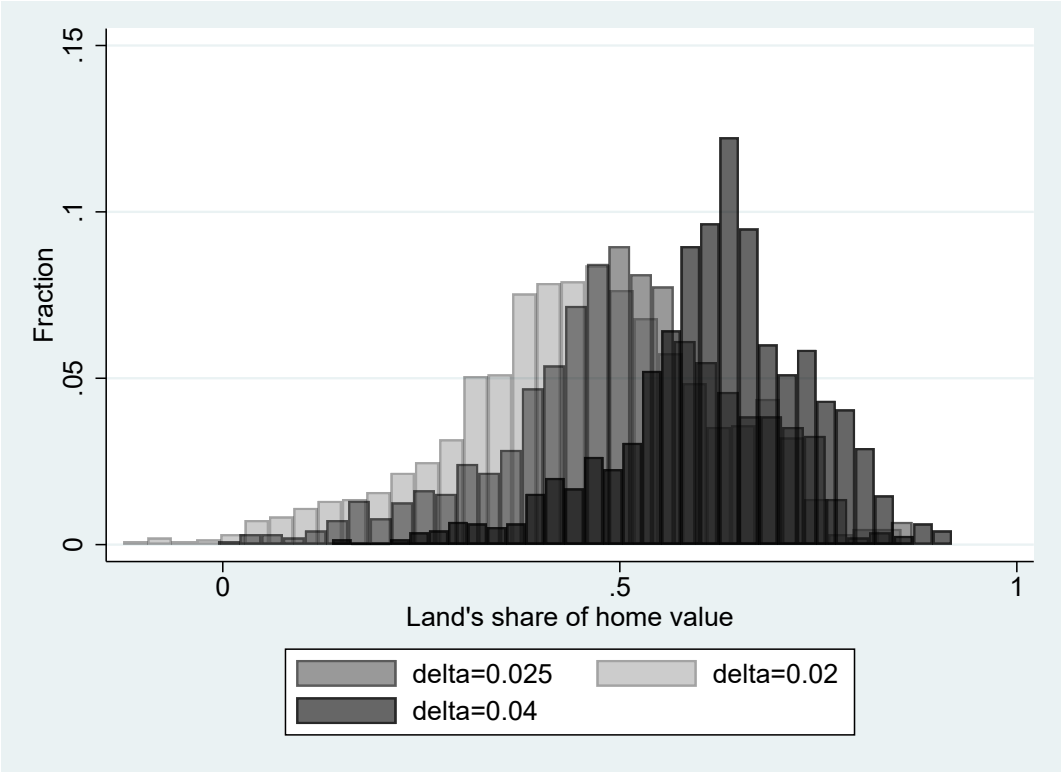


Figure 2.24: Distribution of land's share for different (baseline) depreciation rates
Note: Distribution over 1,895 county-year observations

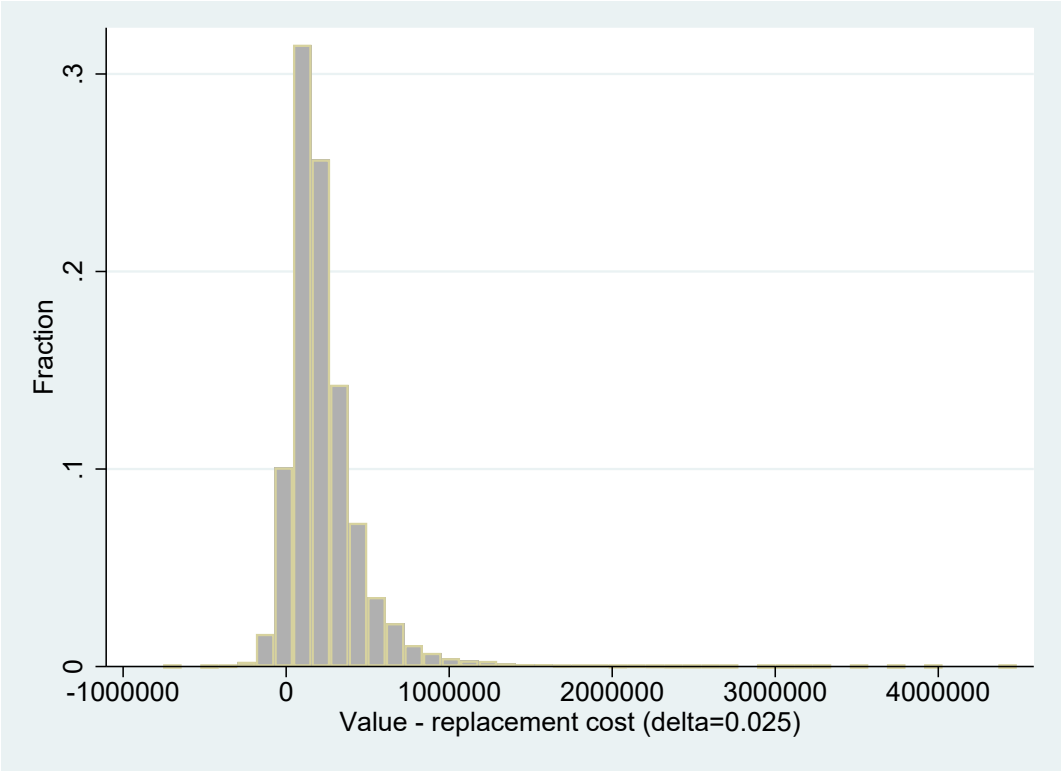


Figure 2.25: Distribution of the difference value-replacement cost
Note: Distribution over 42,647 observations

Chapter 3

Agglomeration Spillover Effects in German Land and House Prices at the County-Level

3.1 Introduction

Figure 3.1 shows robust growth in house and land prices for the seven biggest German cities[1] that outpaced both New York and London since 2014.

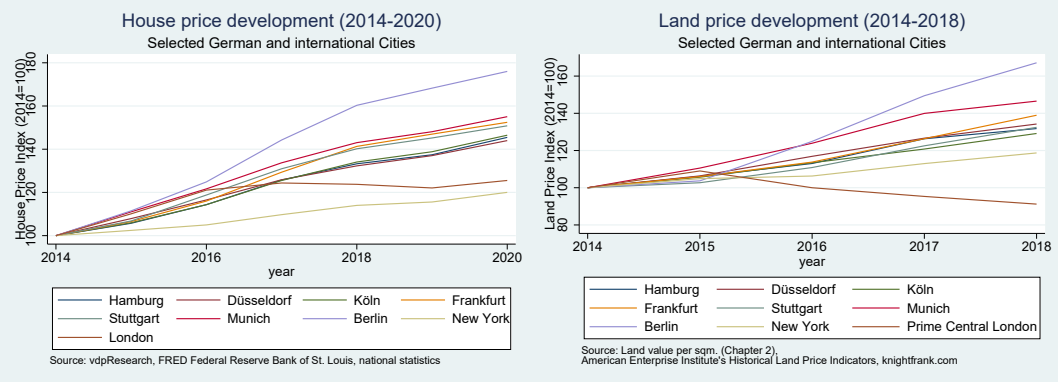


Figure 3.1: Development of house prices (2014-2020) and land prices (2014-2018) - Selected German and international cities

Surrounding areas for these seven cities have also experienced a similar growth pattern in house and land prices from 2014 to 2018.[2] The average real house price appreciation for these German cities' first contiguous surrounding areas ranges between 11 percent and 34 percent. For the same surroundings, the land prices appreciated between 12 percent to 31 percent, whereby both the house and land prices for Munich had the highest and Leipzig had the lowest growth.[3] Figure 3.2, which plots the Moran scatterplots that measure spatial correlation for house and land prices in 2014, shows clear positive spatial correlations for 378 German counties including these cities and their surrounding areas: the first order contiguity

[1] I use the Big 8 cities that are also chosen by Gröbel et al. (2020) as the biggest residential markets. But, given their spatial proximity, I combine Cologne and Düsseldorf to represent the biggest German agglomeration. Consequently, I either speek of Top 7 cities or agglomerations in the following chapter.

[2] German house prices have been appreciating at a much faster rate than both New York and London since 2010. However, the analysis starts from 2014 as I use the German land price dataset from Chapter 2 at the county level that begins from 2014 to 2018.

[3] Tables 3.23 and 3.24 in the Appendix show house and land price development for the first three tiers of the seven cities from 2014 to 2018.

spatial correlations for house and land prices are 0.66 and 0.58, respectively.

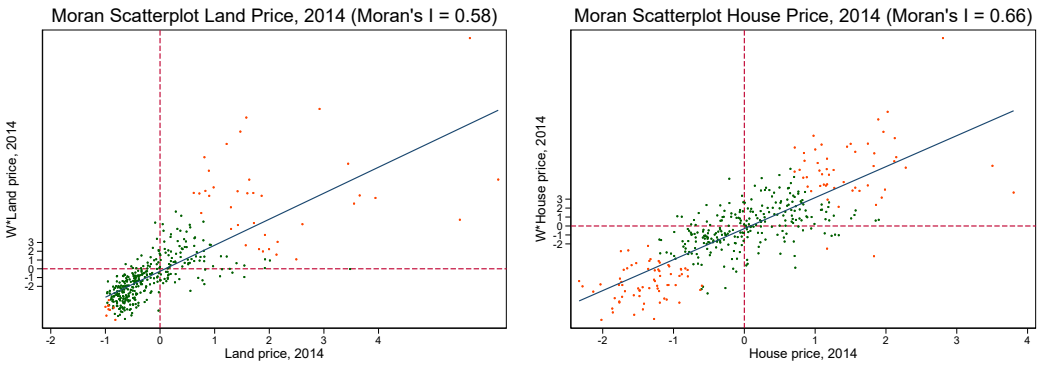


Figure 3.2: Moran scatterplot for land and house prices - First order contiguity matrix

These apparent regional house price spatial spillover effects are well documented for various geographical regions.[4] The main take-away message from the spatial correlation literature is clear: the spatial spillover effects matter in understanding real estate markets. Yet, the economic causes for these spillovers in house prices are less understood as most of the studies focus on the mechanisms of the spatial and temporal lags on housing prices.

The objective of this chapter is to analyze the impact of agglomeration effects on spatial price variations for German real estate markets in 378 administrative counties and cities from 2014 to 2018.[5] While most spatial correlation literature focuses on the spatial interaction effects in house prices, the focus of this chapter is on the spatial spillovers in land prices affected by the clustering of production and workers, also known as agglomeration economies. Consequently, one of the distinguishing characteristics of this chapters' framework is the role played by land prices. I focus on land prices as recent studies on the U.S. land prices such as Ahlfeldt and McMillen (2020), Albouy et al. (2018), Davis et al. (2021), and Chapter 2 of this thesis, on German land prices, with different objectives in mind, have shown that most of the variations in house prices are due to the underlying land values and shares. For the international evidence, Knoll et al. (2017) also document that rising land values and shares mainly drive house price increases for many developed economies since World War II. For example, Figure 3.3 that plots the quarterly time series for housing, imputed land, and construction cost indexes for Germany, the U.K., and the U.S., from 2000 to 2020:q3 also informally shows the importance of land price development for housing markets.

[4]For example, among others, Otto and Schmid (2018) and Möller (2009) for Germany, Gong et al. (2020) and Guo and Qu (2019) for China, Fingleton (2008) and Baltagi et al. (2014) for the U.K., and Brady (2014) and Cohen et al. (2016), Pijnenburg (2017) for the U.S.

[5]The official number of administrative counties in Germany is 401 as of 2019. Given the territorial boundaries from 2016, I use 378 counties due to the lack of data for the rest.

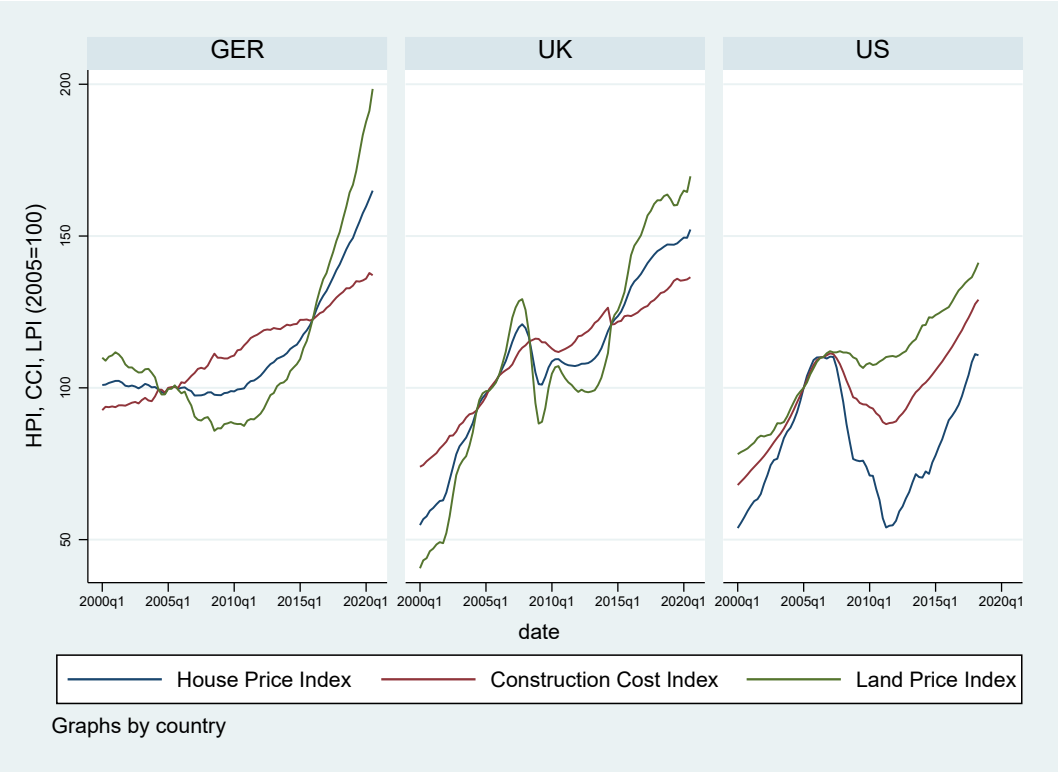


Figure 3.3: Housing market decomposition by country - 2000-2020q3
Note: The sources are listed in Table 3.21. The imputed land value is calculated according to Knoll et al. (2017) with $\alpha = 0.5$.

I use the German residential land price dataset from Chapter 2 for two reasons. First, Figure 3.3 shows that although German housing prices have been sharply increasing since 2010, the residential land share in total wealth has increased but the structure share in total wealth has been steadily decreasing. Moreover, it shows that residential land prices have increased significantly more than the structure costs and house prices in most of the German counties from 2014 to 2018. Consequently, the findings from Chapter 2 imply that cycles in the German land values are more likely to affect house prices in the future. Second, Chapter 2, that constructs the German residential land prices at a county level, provides the first and only publicly available dataset. Previously available land price datasets are from the Federal Statistical Office, which only provides the vacant land prices on a national level from 2010 and from the Statistical Offices of the Federal and State Governments, which provide the vacant land prices on a county level from 1995.[6]

The other main focus is the impact of spatial agglomeration effects on real estate markets. Well established empirical evidence that supports the existence of agglomeration economies are the positive relationships between population density and productivity (wages) as well as between population density and real estate prices. Figure 3.4 shows positive relationships between the log of population density versus the log of GDP per capita (0.59), the log of median income (0.60), the log of house price index (0.55), and the log of land price per square meter (0.60) for German counties in 2014.

[6]Appraiser assessed land values are available from regional Independent Surveyor Commissions at costs. However, these Surveyor Commissions use independent appraisal methods. Despite being based on detailed guidelines, these existing land price valuations rely on surveyors' knowledge and expertise. For more details on German land price measurements see Chapter 2.

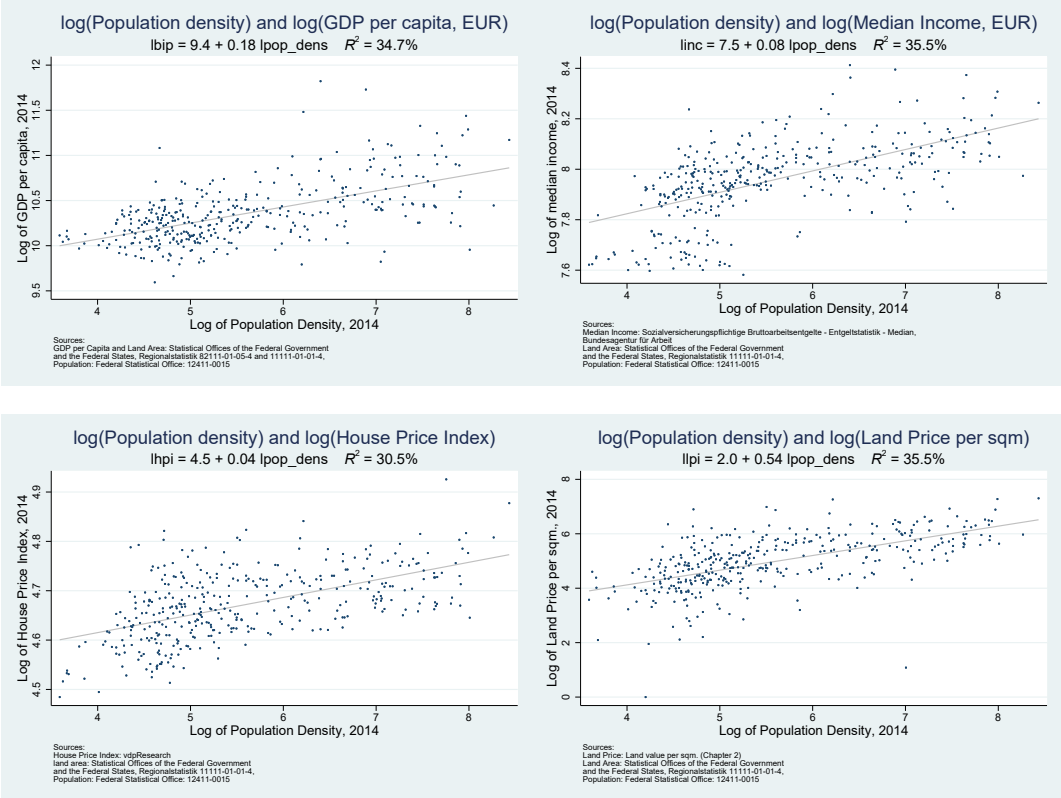


Figure 3.4: Measuring agglomeration - German counties in 2014

These positive relationships informally indicate the well-documented density-productivity relationship in the United States by Ciccone and Hall (1996) and in Europe by Ciccone (2002). Consequently, the spatial equilibrium framework by Rosen (1979b) and Roback (1982) suggests that these positive correlations between density and real estate prices can either mean that dense places have become more pleasant over time or that dense places have become more productive. The literature on land value estimation also lend an indirect support for the existence of agglomeration effects in house and land markets. For example, Ahlfeldt and McMillen (2020) report that variation in land shares is likely influenced by demand-side factors that are exogenous to the production function of housing and less by inelasticities in housing supply. Albouy et al. (2018) further provide indirect evidence of agglomeration effects on land prices by showing that monocentric cities have spatially varying negative land price gradients with increasing distance to the city center.

This chapter estimates spatial land price and agglomeration spillovers using a standard spatial econometrics framework that accounts for the effects of localization and network externalities as well as spatial spillovers in house and land prices. I first estimate panel data with fixed effects as a benchmark. Then, the analysis is extended using a spatial framework that accounts for spatial lags of dependent (house and land prices) and agglomeration variables, the so-called Spatial Durbin Model (SDM). I also estimate the Spatial Lag of X Model (SLX) and the Spatial Autoregressive Model (SAR) that account for either only exogenous spillovers or endogenous spillovers, respectively. More specifically, I address the following questions: First, can cross-county agglomeration spillovers explain variation in land and house prices for Germany, including the seven largest German cities and their surrounding

counties?[7] Second, to what extent can clustering patterns in house prices be attributed to spatial variations in land prices? Lastly, how do spillover effects on house price variations differ between the residential land prices and the land prices on vacant land, which are provided from the Statistical Offices of the Federal Government and the German States?

One of the main results is that there are large and significant local and spatial agglomeration effects on land and house prices. For example, if there is an one percent increase in the median income the land price changes by 2.6 percent, ceteris paribus. A corresponding one percent increase in median income of the neighboring counties raises land prices by 0.85 percent in the county of interest. A one percent change in the population density of the county itself and its neighboring counties has a similar effect on land prices, with land price increases of 3.48 percent and 1.99 percent, respectively. I find that comparable empirical patterns also hold for house prices, but less so for the seven major German cities. This result suggests, unlike Gyourko et al. (2013), that the Big 7 German cities do not exhibit the characteristics of the so-called Superstar Cities. Although the direct median income and population density effects are significant for all seven cities, the indirect (spatial) effects for the variables are significant for only four out of seven cities.

Moreover, housing supply factors such as the available land to build and a proxy for the restrictiveness of housing supply also significantly affect land and house prices on county and city levels. Furthermore, I show that the land price spillover effects are among the dominating factors in the formation of regional house prices. These results, as in Gyourko et al. (2013), suggest that disparate local land and house prices can be driven by other housing variables and cannot be explained entirely by the agglomeration effects such as median income (productivity) and population density levels in those areas. Lastly, estimation on two different land price measurements for Germany shows that direct and indirect agglomeration spillover effects can explain more variation in residential land values than in vacant land prices from the Statistical Offices of the Federal Government and the German States.

The rest of this chapter is organized as follows. In Section 3.2, I overview the literature on spatial effects in housing prices. Section 3.3 outlines a simple baseline framework on network spillovers in housing and land prices across counties for the empirical analysis. Section 3.4 presents the empirical model specifications and outlines the data sources. In Section 3.5, I present the empirical findings that include various robustness analysis. Section 3.6 concludes, followed by the Appendix.

3.2 Previous Literature on Spatial Spillovers in House Prices, Agglomeration, and Land Prices

This chapter combines three strands of literature: Literature on spatial spillovers in house prices, agglomeration effects on real estate prices, and land prices. This section, thus, provides a literature review on the significance of spatial correlation in regional housing markets, the agglomeration effects on real estate markets, and the upward trend in land prices.

The literature on spatial interaction in real estate markets is clear in the importance of

[7] Figure 3.5 shows those seven cities (Tier 1) as well as their surrounding counties that I assigned into Tier 2 and 3. The upper right map highlights the new German Federal States (Former "East Germany" and before 1990, part of the German Democratic Republic (GDR).).

spatial correlation in determining property values. These so-called spatial spillover effects in house prices are widely studied in the literature using spatial econometric methods for different countries and different geographic aggregation levels.

Prior to 2007, spatial econometrics mostly focused on models that contained one type of spatial spillover effect. These models that contain either an endogenous interaction effect (i.e., a spatially lagged dependent variable) or correlated effects (i.e., spatially autocorrelated error terms were introduced in the seminal work by Anselin (1988)). After 2007, the literature includes model estimation with several types of interaction effects. Kelejian and Prucha (1998); Kelejian et al. (2004) and Kelejian and Prucha (1999) developed estimation techniques for models that contain both spatially lagged dependent variables and autocorrelated error terms. Whereas, LeSage and Pace (2009) introduced the Spatial Durbin Model (SDM) that incorporates both endogenous as well as exogenous interaction effects, where a exogenous interaction effect supposes that the house price of a region depends on other regions' explanatory variables (Elhorst, 2010).

Many studies use hedonic house price analysis that incorporates spatial interaction effects to investigate mechanisms for spillovers between prices of neighboring houses. On the least aggregated (MSA) level, Can (1990, 1992) shows that for Columbus, Ohio, USA, accounting for different spatial effects using spatial econometric models is superior to simple hedonic pricing models. Dubin (1988) examines spatial autocorrelation in hedonic house price residuals using a Maximum Likelihood procedure for data on 221 property transactions of homes in Baltimore sold in 1978. She extends her earlier work in Dubin (1992) by presenting an alternative approach to model spatial autocorrelation in hedonic house price residuals. Based on structural characteristics of properties and the average of hedonic residuals of nearby properties, she predicts market values for homes by Kriging. Other studies that examine spatial autocorrelation in house prices within Metropolitan areas using similar methodologies to Can (1990, 1992) and Dubin (1988, 1992) are for example Basu and Thibodeau (1998) that use transaction data of home sales in Dallas 1991:4-1993:1 and Clapp and Tirtiroglu (1994) that use data for the Hartford area, 1982-1988. Helbich et al. (2014) and Pijnenburg (2017) emphasize the importance of comparing different estimation techniques (parametric, non-parametric, and non-linear spatial effects) to account for the presence of spatial heterogeneity in hedonic house prices in Austria and the U.S.

Spatial interactions of house prices, however, do not only occur within urban housing markets. They also appear between aggregated housing markets, such as between different counties, cities, or states. Many studies used spatial autoregressive models that include endogenous interaction effects to investigate house price interaction effects. Fingleton (2008) motivates this type of interaction by displacement effects in supply and demand. Fingleton (2008) finds evidence for endogenous house price spillovers among 353 districts in the U.K. estimating a spatial autoregressive model (SAR) model in 2001. Also for the U.K., Baltagi et al. (2014) support this finding even after using random nested error terms with panel data from 2000-2007 for the 353 districts. Gong et al. (2020) also show endogenous cross-region spillover effects for the Chinese housing markets. Another mechanism that a SAR model empirically estimates is yardstick competition, which assumes that participants of the demand and supply side of a housing market take actions of neighboring housing markets into account when forming their buying and selling strategies (Brady, 2014; Gong et al., 2020).

For the U.S., Brady (2014, 2011) find persistent spatial diffusion processes by estimating spatial impulse response functions based on a SAR model for California counties for the period, 1995-2002 and across the U.S. States for the period, 1975-2011. Similarly, using a spatial-temporal model Holly et al. (2010) examine to what extent movements in house prices can be explained by fundamentals for the States of the U.S. For regions in the U.K., Holly et al. (2011) analyze spatial and temporal diffusion processes of shocks in a dominant region (London) in a spatial-temporal setting.

For Germany, Otto and Schmid (2018) find evidence for the existence of cross-county house price spillovers estimating dynamic spatial panel data models for their dataset on German real estate prices in 412 counties. The found ripple effect is timely delayed and diminishes with distance to the region a shock occurred. Möller (2009) also finds similar spatial effects for vacant land ready for development when analyzing the relationship between the regional German labor market and the market for building land.

Endogenous spillover effects are not the only cause of cross-county interactions considered in the literature. Cross-county spillovers can also emerge due to exogenous interaction mechanisms such as network effects in a county or city grid. The presence of agglomeration effects between counties, was first implemented by Krugman (1991) in the new economic geography theory (NEG). The existence of this type of spatial spillover effects is, for example, supported by Gong et al. (2020) who applies the spatial lag of X model (SLX) using cross-sectional housing market data on an urban network in eastern China. They also find common shocks to cause cross-city dependence of housing prices, estimating the Spatial Durbin Error Model (SDEM). Some other studies that show evidence for network spillover effects in housing markets use different market potential measures. For 136 European large urban zones, Camagni et al. (2017) find a significant impact of static and dynamic agglomeration economies on house prices. For U.S. counties, Partridge et al. (2009) analyze the impact of hierarchical geographic proximity and market potential on median earnings and housing costs. They find especially housing costs to be higher with closer proximity to higher-tier urban cores.

While most of this literature focuses on spatial interaction effects in house prices, this chapters' goal is to analyze spatial spillovers in land prices. The literature on land prices shows the upward trend in land prices and large land shares in housing wealth for many developed economies. Most of these studies equate house prices to the cost of putting up the structure plus the value of land, where the latter is often seen as pricing any geographical and regulatory barriers to housing supply, as well as amenities accessible at a given location (Glaeser et al., 2006; Davis and Heathcote, 2007; Davis and Palumbo, 2008). Studies such as Davis and Heathcote (2007), Davis and Palumbo (2008), and Davis et al. (2017), Davis et al. (2021) have shown, for the U.S., that most of the variations in house prices are due to the underlying land value. In Chapter 2 of this thesis, I argue that movements in the land - and structure values are crucial for understanding the development of German housing markets and policy measures that accompany these movements. Studies that estimate land values and shares via spatial transaction based approaches such as Albouy et al. (2018) and Ahlfeldt and McMillen (2020) support the presence of network externalities in land values. For example, Albouy et al. (2018)'s land value estimates indirectly support the monocentric city theory as they increase with decreasing distance to the center of an agglomeration.

Ahlfeldt and McMillen (2020) argue that the factors to the demand side that are exogenous to the housing production function such as higher income and larger preferences for certain amenities are positively correlated with high land values.

3.3 Baseline Model

The main empirical interest lies in the spatial interaction patterns of land prices both of endogenous and exogenous nature and the clustering patterns in house prices that can be contributed to spatial variations in land prices. Rather than simply presenting spatial lag models for the empirical analysis, I present a simple reduced form of the spatial housing market which captures variables that affect both supply and demand functions.

As in Fingleton and Le Gallo (2008), consider an economy with n counties. In this economy, the determination process of house price within a region i may not assume to be only a function of demand and supply factors of that region but also of regions within commuting distance from county i. Consequently, I assume that demand for real estate (q_i) reacts to changes in income (w_i) of both region i and surrounding regions to reflect the travel-to-work patterns that require to cross county borders. Moreover, I assume that demand for real estate depends on natural attributes of a county (E_i) such as green coverage as well as two types of externalities: 1) local externalities formed by agglomeration economies (l_i) and 2) network externalities from cross-county connections (Wl_i, where W is a spatial weighting matrix). A prime example for agglomeration economies is that higher population density counties can increase the likelihood of enjoyable social contacts and meet like-minded peers, especially attracting young single people. Also, so-called higher-order amenities, such as opera, expensive restaurants that require substantial scales of economies to be sustained, can mostly be found in higher population density places. I also include the size of land (Combes et al., 2010) and median income (Ciccone and Hall, 1996; Combes and Gobillon, 2015) to measure the agglomeration effect.

One can further link the local externality to its agglomeration level in economic activities. Mechanisms that support this connection are, for example, a shared and larger labor pool that improves firm-worker matching and knowledge spillovers through shared information during face-to-face meetings (Glaeser et al., 2001; Gong et al., 2020; O'sullivan, 2007). Switching from the single county to a network of counties,[8] the previously mentioned connection can cause the same benefits resulting from agglomeration economies within such a network. For example, higher-order amenities can be used by people from less dense populated nearby counties in order for them to complement their shopping and entertainment facilities. But these amenities also need to be demanded by those people in order to support and maintain the higher population density counties' functionality and local externalities (Gong et al., 2020; Meijers et al., 2016; Meijers and Burger, 2017).[9] Finally, while demand in region i is assumed to negatively depend on the region's house price p_i, this reduced demand spills over to neighboring regions (displaced demand effect: $\sum_{i \neq j}^{n} W_{ij} p_j$). Consequently, the

[8] I focus on network connections between counties located in geographical proximity to each other. As mentioned in Camagni et al. (2017), network externalities can, however, also emerge between regions located far from each other but linked through a horizontal, non-hierarchical network given a similar size.

[9] The productivity of counties with smaller urban cores can be increased given the so-called "borrowed size" effect, when located next to counties with major urban cores, by borrowing their technological externalities. Moreover, proximity to larger consumer and supplier markets increases productivity by saving transportation costs and often correlates with higher wage levels (Gong et al., 2020).

demand function for housing is[10]

$$\begin{aligned} q_i &= a_0 + a_1 w_i + \overline{a} \sum_{i \neq j}^{n} W_{ij} w_j + a_2 E_i + a_3 l_i + \widehat{a} \sum W_{ij} l_i \\ &\quad - a_4 p_i + \widetilde{a} \sum_{i \neq j}^{n} W_{ij} p_j + \omega_i, \end{aligned} \tag{3.1}$$

where W_{ij} spatially links counties with each other. ω_i is the error term that contains other unmodelled demand factors.

The corresponding supply function for housing takes the following form

$$q_i = b_0 + b_1 p_i + b_2 H_i - b \sum_{i \neq j}^{n} W_{ij} p_j + \eta_i, \tag{3.2}$$

where η_i is the unobserved supply error term. The supply of housing is assumed to increase in the price level of housing in region i. High real estate prices attract real estate developers and it may be more likely that homeowners are offering their properties for sale. However, this also means that high property prices in neighboring counties "steal" away supply of housing from region i (displaced supply effect: $\sum_{i \neq j}^{n} W_{ij} p_j$). As in Gong et al. (2020), supply is assumed to depend on the restrictiveness of housing supply, H_i.

Rewriting the supply function by solving for p_i, I have

$$p_i = \frac{1}{b_1} q_i - \frac{b_0}{b_1} - \frac{b_2}{b_1} H_i + \frac{1}{b_1} b \sum_{i \neq j}^{n} W_{ij} p_j - \frac{\eta_i}{b_1}. \tag{3.3}$$

Substituting for q_i yields

$$\begin{aligned} p_i = c_1 \Bigg[a_0 + a_1 w_i + \overline{a} \sum_{i \neq j}^{n} W_{ij} w_j + a_2 E_i + a_3 l_i + \widehat{a} \sum_{i \neq j}^{n} W_{ij} l_i - a_4 p_i + \widetilde{a} \sum_{i \neq j}^{n} W_{ij} p_j + \omega_i \Bigg] \\ - c_0 - c_2 H_i + c_3 \sum_{i \neq j}^{n} W_{ij} p_j - \nu_i. \end{aligned} \tag{3.4}$$

Simplifying the equation further gives the empirical form that includes spatial effects as

$$\begin{aligned} p_i = d_0 + d_1 w_i + \overline{d} \sum_{i \neq j} W_{ij} w_j + d_2 E_i + d_3 l_i + \widehat{d} \sum_{i \neq j} W_{ij} l_i + \\ + d_4 H_i + \widetilde{d} \sum_{i \neq j} W_{ij} p_j + u_i, \end{aligned} \tag{3.5}$$

where $u_i = c_1 \omega_i + \nu_i$.

Since the focus is on land prices, I modify Equation (3.5) by including construction costs. As Davis and Heathcote (2007) and Davis and Palumbo (2008), Glaeser et al. (2006) argue

[10] In the empirical analysis, I also include unemployment, housing stock, and open accommodation as control variables.

that the determination of house price is more complex in a sense, that the costs of new construction consist of the cost of putting up the structure in addition to any geographical or regulatory barriers to housing supply. While the former can be assumed to be supplied highly elastically, the latter can cause housing supply to be highly inelastic depending on locations. Following the residual approach in Chapter 2[11], I decompose house value into a physical cost of construction and the land value. Therefore, from the housing supply perspective, the price of housing will be determined by the cost of new construction, defined above as the sum of construction cost and land value, in places where demand is sufficiently large to justify new construction. Incorporating this decomposition into Equation (3.5), the land value is defined as:

$$\begin{aligned} lp_i = d_0 + d_1 w_i + \bar{d} \sum_{j \neq i} W_{ij} w_j + d_2 E_i + d_3 l_i + \\ \hat{d} \sum_{j \neq i} W_{ij} l_j + d_4 H_i + \tilde{d} \sum_{j \neq i} W_{ij} p_j + \lambda cc_i + u_i \end{aligned} \tag{3.6}$$

where lp_i is the land value per m^2 in county i, cc_i is a county-specific construction cost factor and λ measures the effect of county-specific construction cost on land value. In the next section I outline the empirical methodology.

3.4 Empirical Framework and Data

I am interested in two types of spatial spillover effects in land and house prices: First, exogenous interaction effects within the explanatory variables. Second, endogenous interaction effects within the dependent variable.

There are different types of spatial regression model specifications that include spatial lags of the dependent variable. But Anselin (1988); LeSage and Pace (2009) argue that one specification, the spatial Durbin model (SDM), stands out as superior in a vast number of applied situations. The SDM is shown in Equation (3.7). It includes a spatial lag of the dependent variable ($ln(P)$) as well as agglomeration variables in (l):

$$ln(P) = \rho M ln(P) + \alpha_0 \mathbf{1} + X\beta + Wl\theta + \epsilon, \epsilon \sim N\left(0, \sigma^2\right) \tag{3.7}$$

where, $\mathbf{P}_{n\times 1}$ is the vector of land values or house prices, $\mathbf{X}_{n\times r}$ incorporates the county-specific characteristics and agglomeration economies and $\mathbf{Wl}_{n\times r}$ represents the network externalities. In the empirical analysis, I use the same weight matrix for $\mathbf{M}_{n\times n}$ and $\mathbf{W}_{n\times n}$ (Anselin, 1988; LeSage and Pace, 2009). **W (M)** is the spatial weight matrix that defines how counties are spatially connected. This matrix allows for local externalities **l** to spillover between spatially linked counties and hence spillover effects can be modeled as **Wl**.

Apart from estimating the model in Equation (3.7), I also estimate three other models. I first start with a panel fixed effects model ($\rho = \theta_{1\times r} = 0$), and then add two other spatial lagged models, namely the Spatial Autoregressive Model (SAR: $\theta = 0$) and the Spatial Lag of X Model (SLX: $\rho = 0$).

The latter is seen as more appropriate for applied studies and superior to SAR-type spec-

[11] The two-step residual approach has been used in Davis and Heathcote (2007); Davis and Palumbo (2008) and Chapter 2

ifications as it does not suffer from identification problems (Halleck Vega and Elhorst, 2015; Gibbons and Overman, 2012; Gong et al., 2020). Also, next to the SDM, this model provides a flexible way to model exogenous interaction effects among the explanatory variables.

However, for economic reasons I use the SDM as the main model of interest as the likelihood of displacement effects in land and house prices causing cross-county spillovers being present in the process of house price determination is pretty high. For example, high house prices in one region cause demand for housing to decrease. However, this demand is likely to be displaced to regions nearby. Another mechanism that can explain this type of spillover effect is "yardstick competition". For example, house sellers and buyers might take into account price signals from house price transactions in a neighboring county, spatially linking house prices with each other (Brady, 2014; Gong et al., 2020).

Note that a significant estimate of ρ could either be attributed to pure spatial spillover effects in house prices or reflect information picked up from omitted variables such as network externalities (Corrado and Fingleton, 2012; Gibbons and Overman, 2012; Gong et al., 2020). However, one can statistically justify estimating Equation (3.7) by evaluating the role of network externalities when testing the SDM model against the SAR model with the restriction $\theta = 0$.[12]

3.4.1 Direct vs. Indirect Effects

In spatial econometrics, due to the presence of the spatial weights matrix, the interpretation of point estimates as spatial spillover effects is misleading in some models (Elhorst, 2010; LeSage and Pace, 2009). To circumvent delusive conclusions from hypothesis tests based on point estimates, LeSage and Pace (2009) present the partial derivative approach for finding the impact of a change in variables for different model specification as being more valid. Given this approach, the direct effect represents the effect of a change in a county-specific variable on that counties' land value. I am however, interested in cross-county spillovers. By definition this refers to the indirect effect, the impact of a change in a county-specific variable on land values of other counties (Gong et al., 2020; LeSage and Pace, 2009; Elhorst, 2010).

I briefly outline the direct and indirect effects below, but the interested reader may refer to LeSage and Pace (2009) and Elhorst (2010) for more details. Equation (3.7) can be written as

$$ln(P) = (I - \rho M)^{-1} (X\beta + Wl\theta + R), \tag{3.8}$$

where R includes intercept and the error terms. The marginal effect of agglomeration on the land or house prices can be clearly seen by taking the derivatives of $ln(P)$ with respect to the rth l :

$$\frac{\partial ln(P)}{\partial l}_{n\times r} = (I - \rho M)^{-1} (1_{n\times 1}\beta_{1\times r} + W_{n\times n}1_{n\times 1}\theta_{1\times r}).$$

For the SDM, the diagonal elements of $(I - \rho M)^{-1} (1_{n\times 1}\beta_{1\times r} + W_{n\times n}1_{n\times 1}\theta_{1\times r})$ represent direct effect and the off-diagonal elements are the indirect effects. For the SLX, $\beta_{1\times r}$ and $\theta_{1\times r}$ are the direct and indirect effects, respectively. Lastly, for the SAR, the diagonal

[12]For more details on the spatial econometric models outlined in this section the reader may refer for example to Anselin (1988) and LeSage and Pace (2009).

elements of $(I - \rho M)^{-1}(1_{n\times 1}\beta_{1\times r})$ represent direct effect and the off-diagonal elements are the indirect effects.

3.4.2 Data

I use the annual (2014-2018) land value per square meter of lot size estimates for German counties and county-free cities from Chapter 2 as a measure for residential land price. Since one of the main focuses of this chapter rests on land prices, the data from Chapter 2 is briefly summarized here. It estimates changes in the value and price of residential land for the 379 German counties ("Landkreise") from 2014 to 2018 by combining data from several publicly available sources for academic researchers. In doing so, a database for the cost of housing structures and residential land values at the county-level is built. The framework of the approach used is that of Davis and Heathcote (2007), who decompose house value into the value of the structure and land value on the aggregate level for the U.S. Some of the results from Chapter 2 lend support to this chapters' spatial analysis. For example, it shows that residential land price has become relatively more expensive in the majority of German counties. Moreover, the counties around urban centers such as Munich, Stuttgart, Berlin, Hamburg, Dresden, and the Ruhr area cities experienced the highest land price increases. However, I also note that, in general, an upward shift in home values, land values, and residential land share occurred in almost every state.

I use annual house price indexes for single- and double-family houses from vdpResearch at the county and independent city level available for the years 2007-2018 based on transaction data. I control for several county-level characteristics in different model specifications (Table 3.14). First, I use the following variables to measure the agglomeration economies of each county that are known to generate local and network externalities: the counties' land area in km^2, its median income, and population density (Gong et al., 2020). The latter is calculated by dividing county's population by its land area in km^2 in a given year. That is, population density is equal to 100 in a county with 100 individuals per km^2.[13] Second, I include county-specific natural and economic characteristics in different model specifications. As an indicator for the environmental amenities of a city, I include the green residential area that is used for recreational purposes divided by a county's land area in km^2 (green coverage). I measure amenities of a county in terms of history and culture with the number of available accommodation facilities in that county (e.g., hotels, etc.). Moreover, I include the housing stock of single and double family housing as a measure of housing supply and the arable land per km^2 of land area to measure for the restrictiveness of housing supply (Gyourko et al., 2013; Gong et al., 2020). Finally, I use the construction cost, income, and unemployment rate as measures for a counties' economic situation as control variables. The data and sources are described in detail in the Appendix in Table 3.20. Descriptive statistics are provided in Table 3.1.

[13] As land values(/house prices) and population are usually determined simultaneously, population density could cause endogeneity. To circumvent this problem, I use one-year lagged population density.

[15] Median of gross financial wages of full-time workers with compulsory social insurance.

[16] Construction permits of new residential buildings and apartments in residential buildings, annual sum.

	Mean	Std.Dev.	Min	Max
House price index	117.5	14.33	88.64	189.5
Land value per m^2 (Chapter 2)	252.2	255.3	0.987	2184.2
Land value per m^2 (Vacant land ready for construction)	175.3	231.3	8.960	2737.8
Population density (person per km^2)	516.0	702.0	35.78	4736.1
Median income[14]	3012.5	455.1	1961.8	4896.9
Unemployment rate	5.605	2.629	1.300	15.40
Housing starts[15]	310.1	255.2	10	2708
Open accomodation facilities	131.3	152.0	5	1398
Green coverage (percent of 'green' recreation area within residential areas)	0.0150	0.0207	0	0.121
Land area (km^2)	931.5	722.4	40.02	5495.6
Total housing stock	48924.3	32291.1	6977	326882
Housing stock (Single family houses)	32650.8	20562.1	4235	169251
Housing stock (Double family houses)	8081.0	5250.1	762	30681
Construction cost index	101.3	10.74	65.20	160.3

Table 3.1: Descriptive statistics

City	no. of counties
Berlin	21
Munich	19
Hamburg	19
Cologne/ Düsseldorf	28
Frankfurt am main	22
Leipzig	18
Stuttgart	15

Table 3.2: Sum of counties in Tier 1-3 for each of the Big 7 cities

3.5 Estimation Results

I focus on the first-order contiguity matrix[16] estimation results for land values as spatial baseline results. I estimate the models outlined in Section 3.4 for the total of 378 counties, 314 counties in the old Federal States, 64 counties in the new Federal States, and the Big 7 German cities, including their surrounding counties. For expositional purpose, I present Figure 3.5 that shows the counties assigned to each Tier and Table 3.2 that presents the number of total counties within Tiers 1-3.[17]

As I use an annual panel data set for German counties from 2014-2018 I need to consider both time and cross effects in the estimation methods. However, I only account for county fixed effects in the estimations for two reasons.[18] First, I observe slight heterogeneity over

[16]To construct spatial weight matrices and maps in this chapter, the shape files with coordinates on German states and counties from Bundesamt für Kartographie und Geodäsie, Frankfurt am Main (GeoBasis-DE / BKG) (2019) are used.

[17]The states highlighted in red in the map in the upper right corner of Figure 3.5 denote former East Germany. For a detailed representation of the counties assigned in each tier for the 7 agglomerations, refer to Table 3.22 in the Appendix, where counties highlighted in red are missing in the dataset of Chapter 2 and are therefore not included in the estimation.

[18]Omitting time fixed effects could lead to a significant upward bias in the spatial lag's coefficient (Lee and Yu, 2010b; Halleck Vega and Elhorst, 2015).

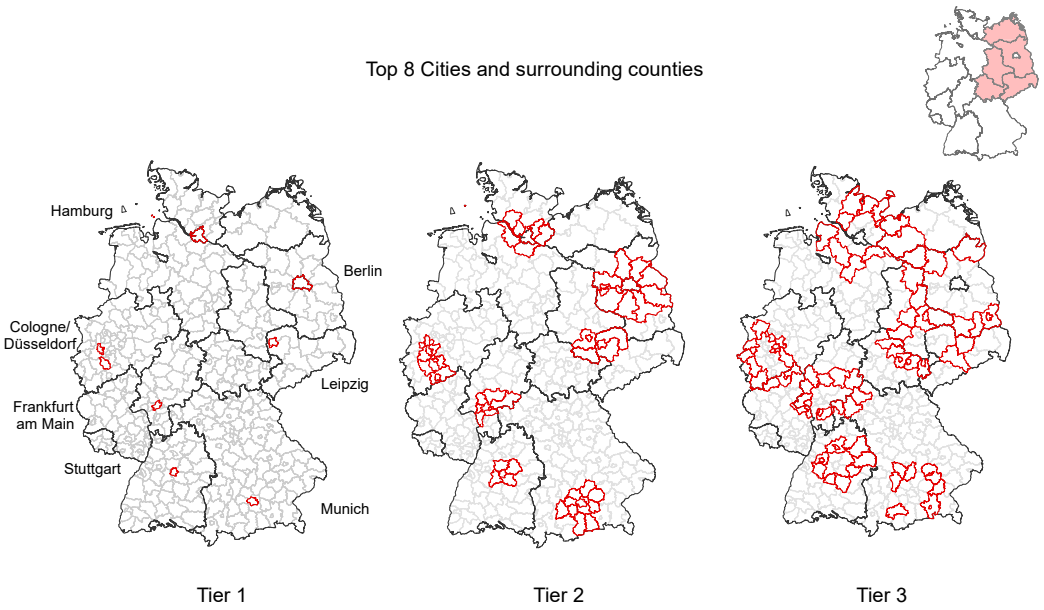


Figure 3.5: Top 7 agglomerations and surrounding counties

time due to the short time period. Figures 3.6 to 3.8 [19] in the Appendix show only little variation in the time-varying explanatory variables by the state over time. Second, including a set of time dummies in column (2) in Table 3.25, I find time dummies to be insignificant at all common significant levels except for the year 2018. The results from the $F-Test$ on joint significance of the time variables also do not reject the null that they together are not different from zero ($p-value = 0.27$). Moreover, comparing random and fixed effects estimation results with the Hausman test, I also reject the use of random effects ($p-value = 0.00$). To circumvent various serial autocorrelation issues for short panels, I use the transformation approach maximum likelihood (ML) estimation with county fixed effects as in Lee and Yu (2010a).[20]

3.5.1 Spatial correlation of land and housing prices

Table 3.3 shows global Moran's I statistics that measure the spatial correlations for house and land prices in 2014. The first correlations use the first-order contiguity and inverse distance weight matrix. Other spatial correlations use three binary weight matrices that assign a weight of one if two counties are located within a certain distance and 0 otherwise. The distance bands for the correlations I use are 0-60km, 60-120km, and 120-180km to reflect the distances between Tier levels. Columns (1) and (2) show a significant positive auto-correlation both in house and land prices, that diminishes with increasing distance of neighboring counties. These spatial correlations lend informal for endogenous interaction of

[19] The data and sources are described in detail in the Appendix in Table 3.20.

[20] Lee and Yu (2010a) introduce the bias correction procedures for Spatial Error Model (SEM), SDM, SAR and SDEM models to correct for biased parameter estimates in models with spatial fixed effects (and time fixed effects).

house and land prices.

Other explanatory variables also display similar spatial correlation patterns. Table 3.3 also provides the global spatial cross-correlation coefficient by Chen (2015), R_c. If exogenous spillover effects in land and housing markets exist, one would expect spatial cross-correlation between housing and land markets with agglomeration variables. I find significantly positive cross-correlations between a county's land and house prices and neighboring counties' median income and population density. However, especially, the cross-correlation with population density quickly vanishes with distance. The land area is negatively cross-correlated with both house and land prices. These spatial correlation patterns also show informal evidence for exogenous spillover effects.

3.5.2 Non-spatial estimation results

Baseline results for Germany are displayed in Tables 3.4 and 3.5. Tables 3.6 and 3.7 compare the Spatial Durbin Model results for West and former East Germany and the Big 7 Agglomerations.

I first estimate a non-spatial model as a benchmark. Column (1) of Table 3.4 reports the estimation results for the non-spatial model accounting for fixed effects. In column (1), all coefficients are statistically significant on the 1 or 10% significance level and have the expected sign. Except for the coefficient on green coverage, I would expect the opposite sign as green coverage proxies local amenities. However, green coverage could also indicate a restriction on available land to build. A city with a higher median income and higher population density is likely to have higher land values, ceteris paribus. Besides income and population density, the variable land area per km^2 that is also supposed to measure agglomeration economies has a statistically significant effect on land prices. If population density increases by one percent, land value per m^2 increases land values by 4.3 percent, ceteris paribus. An increase in land area per km^2 by one percent drives up land values by 3.08 percent. If arable land per capita increases by one percent, the land price per m^2 decreases by 0.61 percent. In other words, a less restrictive housing supply is associated with lower land values. Lastly, the independent variables in the model specification (FE) explain around 52 percent of the cross-county land price variation.

3.5.3 Spatial estimation results

Despite the SDM model being the main model of interest, the first part of this section is divided by the type of spillover effects: First, agglomeration effects are discussed in light of the SLX model, followed by endogenous spillover effects in SDM and SAR models. The subsequent parts focus on the difference in direct and indirect interactions, diagnostics, estimations for the Top 7 agglomerations and house price index as an alternate dependent variable.

Exogenous spillover effects: SLX model

For the SLX model, the choice of the spatial weights matrix is important as it determines the structure of spatial spillovers across counties. Although LeSage and Pace (2014) suggest that spatial estimation results are not as sensitive to the choice of spatial weights as commonly

	Moran's I	Moran's I	R_c with Income		R_c with Population Density		R_c with Land area (km^2)	
	HPI	Land value	HPI	Land value	HPI	Land value	HPI	Land value
First order contiguity	0.66***	0.58***	0.48***	0.46***	0.29***	0.34***	-0.21***	-0.22***
	(20.87)	(18.35)	(15.14)	(14.59)	(8.92)	(10.70)	(6.45)	(6.69)
Inverse Distance	0.15***	0.14***	0.12***	0.14***	0.04***	0.07***	-0.05***	-0.06***
	(24.29)	(22.77)	(20.13)	(22.00)	(7.58)	(12.04))	(7.13)	(8.82)
Distance 0-60 km	0.46***	0.49***	0.34***	0.40***	0.20***	0.32***	-0.16***	-0.21***
	(23.32)	(24.81)	(17.17)	(19.93)	(10.29)	(15.89)	(7.61)	(10.19)
Distance 60-120 km	0.25***	0.18***	0.22***	0.23***	-0.01	0.02**	-0.04***	-0.04***
	(19.94)	(14.72)	(17.56)	(18.08)	(0.53)	(2.05)	(3.25)	(2.88)
Distance 120-180 km	0.18***	0.08***	0.18***	0.15***	0.01	-0.005	-0.05***	-0.02*
	(17.33)	(8.16)	(16.70)	(14.21)	(1.03)	(0.17)	(4.08)	(1.95)

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.3: Moran's I (year=2014)

	(1) FE	(2) SLX	(3) SAR	(4) SDM
main				
log(median income)	3.08***	2.52***	2.58***	2.56***
	(23.42)	(11.63)	(16.72)	(10.76)
log(Lag Population density (person per km^2))	4.30***	3.34***	3.70***	3.38***
	(15.74)	(8.98)	(12.30)	(8.28)
green coverage	-6.98*	-7.26***	-7.11***	-7.18***
	(-7.04)	(-7.42)	(-6.64)	(-6.68)
log(construction cost index)	-1.09***	-1.17***	-1.19***	-1.20***
	(-10.78)	(-11.65)	(-10.91)	(-10.90)
log(arable land (sqkm) per capita)	-0.61***	-0.63***	-0.58***	-0.59***
	(-3.49)	(-3.68)	(-3.09)	(-3.12)
log(land area (km^2))	3.90***	2.34	2.94*	2.51
	(2.68)	(1.60)	(1.86)	(1.57)
F				
log(median income)		0.10**		0.01
		(2.63)		(0.26)
log(Lag Population density (person per km^2))		0.37***		0.15
		(4.19)		(1.47)
log(Land value per m^2))			0.05***	0.04***
			(9.99)	(7.21)
N	1890.00	1890.00	1890.00	1890.00
R2	0.516	0.529	0.522	0.524
Log-Likelihood	1654.2	1679.8	1680.1	1682.3

t statistics in parentheses
dependent variable: log(landvalue per m^2)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4: Baseline estimation results - Germany

	(2) SLX	(3) SAR	(4) SDM
direct			
log(median income)	2.52***	2.62***	2.60***
	(11.63)	(17.11)	(11.10)
log(Lag Population density (person per km^2))	3.34***	3.75***	3.48***
	(8.98)	(12.44)	(9.04)
indirect			
log(median income)	0.10***	0.95***	0.85***
	(2.63)	(7.48)	(3.56)
log(Lag Population density (person per km^2))	0.37***	1.35***	1.99***
	(4.19)	(6.70)	(3.43)
Observations	1890	1890	1890

t statistics in parentheses
dependent variable: log(landvalue per m^2)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5: Baseline estimation results - Germany (direct and indirect effects)

believed in literature, I capture the nature of spatial interaction with two spatial weight matrices. First, I estimate the spatial models outlined in Section 3.4 using a first-order binary contiguity matrix as the network externalities are highest among neighboring counties.[21] Second, to allow for network externalities between counties further apart, the models are re-estimated using an inverse distance matrix (See Section 3.5.4). Inverse distance matrices depict spatial interaction by weights that diminish with distance.

I find empirical support for the presence of network externalities for the model in column (2). The coefficients on the spatial lag of a counties' population density and median income are positive and significant. For example, an increase in the population density in a neighboring county of one percent increases land values per m^2 in the county of interest by 0.37 percent, ceteris paribus. The direct effects of median income and population density are smaller compared to the fixed effects specification (1). For income, the coefficient falls by 0.56, and the coefficient on population density falls by 0.96. The other explanatory variables, if at all, change only slightly and are all still highly significant in model (2) compared to the non-spatial model specification. The effect of a county's scale is lower in column (2) compared to column (1) and statistically insignificant.

Although I present statistical support for network spillover effects in land values, the spatial dependence may also be caused by pure spatial spillovers in land values. For this reason, I compare the SLX results with the SAR and SDM models below.

Endogenous spillover effects: SAR and SDM models

If spatial dependence is still present after accounting for network externalities, it can be attributed to pure land value spillovers or common shocks. Consequently, if pure land value spillovers cause the remaining spatial dependence, then the SDM would be a more valid specification.

Column 4 and 5 in Tables 3.4 and 3.5 show the QMLE estimates of the SAR and the SDM models for the first order contiguity matrix. The significant estimated coefficient (0.05 and 0.04 for the SAR and SDM, respectively) on WY_t in both columns (3) and (4) support pure land value spillovers.

Except for land area, the coefficients in the SAR model (3) and SDM model (4) remain highly significant and increase either slightly or stay almost the same compared to column (2). When including exogenous spillover effects into the model in column (4), the coefficient estimate of the spatial lags for median income and population density becomes insignificant. However, as discussed in Section 3.4.1, this interpretation may be misleading in the Spatial Durbin Model as there might be some network effects, which are more discussed in the following section. Compared to column (2), the SAR model slightly decreases explanatory power but comparing models (4) and (3), I find the SDM to be slightly superior. Moreover, the Likelihood Ratio (LR) tests, where the SDM is defined as the unrestrictive model, clearly reject the null-hypothesis that both the SLX and SAR are significantly preferred to the SDM.[22]

[21] Table 3.3 shows both higher auto-correlations and cross-correlations coefficients for the global Moran's I statistics using a first-order contiguity matrix compared to an inverse distance matrix.

[22] For example, the likelihood ratio test of $LR = 2ln\left(\frac{unrestrictive}{restrictive}\right)$ for SLX vs. SDM gives $LR = 2\,(1682.3 - 1679.8) = 5$ with the critical $\chi^2_{0.95,8} = 2.73$

Network effects

As discussed in Section 3.4.1, spatial regressors' point estimates in spatial models (2)-(4) do not exactly show the direct and indirect spillover effects. I use the partial derivative approach to calculate direct and indirect spatial effects (See Table 3.5). It shows both evidence for a direct and indirect effect of population density and median income on a counties' land value. For example, a one percent increase in median income and population density in neighboring counties increases land values in the SLX model in a given county by 0.10 and 0.37 percent, respectively, ceteris paribus. On the other hand, the total (direct plus indirect) effects of a one percent increase in median income and population density in neighboring counties increase land values in a given county for median income and population density on land prices are 2.62 percent and 3.71 percent, respectively.

Overall, the direct effects of population density and median income stay relatively robust across non-spatial and spatial models. In contrast, spillover effects vary between model specifications. Taking a closer look at Table 3.5, the cross-county spillover effects for median income and population density are higher in the SAR and SDM models compared to model (2). The increase in the spillover effects of median income and population density from the SLX to SAR model suggests that besides network externalities, pure interaction mechanisms also play a role in land value determination.

Taken the results of all models together, I conclude that cross-county dependencies in land values are driven not only by network spillovers but also by pure land value spillovers. However, the magnitude and form of the underlying spatial interaction vary between the three types of spillovers.

Diagnostics

For consistency, the QMLE estimation by Lee and Yu (2010a) assumes residuals to be independent and identically distributed with Normal zero mean and finite $(4 + \zeta)$ th moment, where $\zeta > 0$. Hence, this section tests for the residual assumptions in the baseline specification.

To check for normality of the error terms, I use Pearson's Chi-squared goodness-of-fit test. The test cannot reject the null of normality of the error terms for all three spatial models (SLX, SAR, SDM) at the 5% significance level. The spatial autocorrelation among the residuals is measured by Moran's I statistics for each of the years 2014-2018. I conduct this statistics to check whether the models capture the spatial correlation structure of the data. The Moran's I for the first order contiguity matrix does not significantly differ from zero at a 5% significance level for all years in the three spatial models. This result indicates that the models entirely capture the spatial correlation structure. To check for autocorrelation among the residuals, I conduct a Durbin-Watson test for each of the three models. Again, the test cannot reject the null that there is no autocorrelation in each case for a 5% significance level. Finally, the Breusch-Pagan test and the White test are used to check for homoscedasticity. Both tests do not reject the null of constant variance. Hence, there is no evidence for heteroskedasticity in the spatial models' residuals.

Given the conducted residual diagnostics, I conclude that the assumptions for consistency mentioned above are fulfilled and that the models capture the spatial correlation structure

within the data quite well.

City comparison and West-East disparities

This section discusses the Spatial Durbin Model's estimation results for 314 counties in the old Federal States, 64 counties in the new Federal States, and the Big 7 German cities, including their surrounding counties. I find three main results from Tables 3.6 and 3.7. First, I do not find significant spillover effects in land values (W*log(land value per m^2)), except for East German counties and Cologne/Düsseldorf as well as a negative spillover effect for Hamburg. Second, Table 3.7 shows that there are significant direct effects of median income and population density in all regions except for population density in Hamburg. These direct agglomeration effects are stronger in the old Federal States than the new federal states, at least for median income. The Top 7 agglomerations' results further support this result. The estimated coefficients on median income are higher (and positive) for agglomerations in former West Germany. No clear pattern is observed for population density for the Top 7 cities. Third, Table 3.7 also shows that there is some empirical support for network externalities and spatial spillovers in land values. While for West German counties, I find spillover effects in median income, I find a significant negative coefficient on the spatial lag of population density for East German counties. The positive income spillover effect is also present in 3 of 5 West German agglomerations considered and Leipzig. While there is evidence for negative spillover effects of population density for all East German counties. This effect is significantly positive for Berlin on the 10 percent significance level. This result is economically sensible as Berlin is the largest agglomeration in the former East German area.[23] The negative externality of a high population density county on neighboring counties' land prices may be explained by a lack of large agglomerations in former East German counties. A lower spatial correlation between land values and population density compared to median income is also reflected in Table 3.3.

Alternate Dependent Variable: log(HPI)

One of the main research questions is to analyze whether land values, besides construction costs, are the driving component in house prices.[24] To address this question, the models from Section 3.4 are re-estimated with log(HPI) as the dependent variable (Tables 3.8 and 3.9) and including log(land value per m^2) as an explanatory variable (Tables 3.10 and 3.11). The estimation results support land values to be a major determinant in housing prices. The coefficients of interest in Tables 3.8 and 3.9 are much smaller compared to those in Tables 3.4 and 3.5. Additionally, controlling for log(land value per m^2) the coefficients further decrease in Tables 3.10 and 3.11 and the coefficient of log(land value per m^2) is positive and statistically significant on the 1 percent significance level in models (1)-(4). Controlling for the log(land value per m^2) in the estimation on house prices, the coefficient on green-coverage now has the expected positive sign and is either statistically significant on a 1 or 5% significance level in the spatial models (2)-(4).[25]

[23] Berlin as the German capital is denoted as West German, although some parts of Berlin were located in East Germany before 1990.

[24] Davis and Heathcote (2007); Davis and Palumbo (2008) and Chapter 2

[25] While the log(construction cost index) coefficient in the land price estimation was negative by construction, it now is strongly statistically significant and positive. See Section 3.5.4 for more discussion.

	West	East	Berlin	Munich	Hamburg	Cologne /Düsseldorf	Frankfurt	Leipzig	Stuttgart
log(Median income)	3.46***	2.79***	1.78***	2.21***	2.02***	3.29***	2.93***	1.65***	3.19***
	(18.21)	(3.96)	(5.24)	(8.72)	(3.62)	(10.21)	(7.96)	(6.03)	(11.66)
log(Lag Population density (person per km^2))	2.01***	5.10***	3.31***	2.78***	1.33	1.08	2.74**	2.16***	0.35
	(6.17)	(3.95)	(4.98)	(5.12)	(0.88)	(1.51)	(3.97)	(3.44)	(1.13)
Green coverage	-1.25	-11.33***	5.55	2.17	2.48	-1.33	-33.59***	-1.85	-13.83
	(-1.06)	(-4.16)	(0.69)	(0.68)	(0.31)	(-0.69)	(-2.83)	(-1.54)	(-1.21)
log(Construction cost index)	-1.09***	-3.06***	-1.04***	-0.46***	-1.41***	-0.30*	-0.66***	-1.61***	-0.51***
	(-13.28)	(-6.49)	(-5.18)	(-3.93)	(-6.50)	(-1.91)	(-2.96)	(-8.31)	(-3.49)
log(arable land (sqkm) per capita)	-0.50***	-1.50**	-0.15	-0.38**	-1.50***	-0.05	-1.69*	-0.40	-1.45
	(-3.30)	(-2.38)	(-0.19)	(-2.37)	(-3.18)	(-0.18)	(-1.81)	(-0.57)	(-0.61)
log(Land area (km^2))	1.91*	15.32	20.42	-98.30**	6.48	8.40	38.62	-10.41	2.47
	(1.74)	(0.87)	(1.10)	(-2.11)	(0.86)	(0.67)	(1.02)	(-0.99)	(0.73)
F									
log(Mean income)	0.15***	0.04	-0.01	0.02	0.83***	-0.23**	0.18	0.07	0.02
	(3.30)	(0.30)	(-0.15)	(0.26)	(3.96)	(-2.51)	(1.27)	(1.23)	(0.88)
log(Population density (person per km^2))	0.05	-1.42**	0.54*	-0.03	-0.05	0.10	-0.06	0.08	-0.01
	(0.61)	(-2.44)	(1.83)	(-0.17)	(-0.12)	(0.45)	(-0.29)	(0.28)	(-0.10)
log(Land value per m^2)	0.01	0.03*	0.02	0.04	-0.08**	0.08***	0.002	0.04	0.04
	(0.76)	(1.95)	(0.65)	(1.47)	(-2.34)	(4.25)	(0.08)	(1.24)	(1.02)
N	1570.00	320.00	105.00	95.00	95.00	140.00	110.00	90.00	75.00
R2	0.754	0.280	0.811	0.974	0.845	0.912	0.914	0.707	0.972
Log-Likelihood	2035.7	115.8	187.8	243.1	153.5	290.7	207.4	169.1	191.5

t statistics in parentheses
dependent variable: log(landvalue per m^2)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6: Spatial Durbin Model - Baseline estimation results for Top 7 cities as well as West and East Germany

	West	East	Berlin	Munich	Hamburg	Cologne/Dusseldorf	Frankfurt	Leipzig	Stuttgart
direct									
log(Median income)	3.45***	2.83***	1.81***	2.22***	1.80***	3.30***	2.94***	1.67***	3.22***
	(17.71)	(4.16)	(5.51)	(8.85)	(2.92)	(10.47)	(7.89)	(6.06)	(12.27)
log(Lag Population density (person per km^2))	2.02***	4.97**	3.40***	2.81***	1.33	1.20*	2.72***	2.20***	0.35*
	(6.27)	(3.81)	(5.26)	(5.25)	(0.81)	(1.66)	(3.91)	(3.38)	(1.14)
indirect									
log(Median income)	0.88***	0.69	0.10	0.64	2.28***	0.44	0.83*	0.64**	0.68**
	(4.62)	(1.15)	(0.25)	(1.56)	(3.08)	(0.86)	(1.67)	(2.13)	(2.18)
log(Lag Population density (person per km^2))	0.33	-6.63**	2.81*	0.48	-0.54	1.44	-0.20	0.83	0.03
	(0.78)	(-2.18)	(1.93)	(0.68)	(-0.32)	(1.13)	(-0.23)	(0.49)	(0.05)
Observations	1570	320	105	95	95	140	110	90	75

t statistics in parentheses
dependent variable: log(landvalue per m^2)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: Spatial Durbin Model - Baseline estimation results for Top 7 cities as well as West and East Germany (direct and indirect effects)

	(1) FE	(2) SLX	(3) SAR	(4) SDM
main				
log(median income)	1.14***	1.06***	0.79***	1.11***
	(41.74)	(25.13)	(24.62)	(27.03)
log(Lag Population density (person per km^2))	2.40***	1.72***	1.98***	1.66***
	(42.47)	(23.80)	(34.11)	(23.62)
green coverage	0.002	-0.12	-0.16	-0.14
	(0.01)	(-0.63)	(-0.81)	(-0.77)
log(construction cost index)	0.27***	0.23***	0.21***	0.20***
	(12.87)	(12.05)	(10.16)	(10.48)
log(arable land (sqkm) per capita)	-0.15***	-0.16***	-0.16***	-0.14***
	(-4.26)	(-4.74)	(-4.63)	(-4.38)
log(land area (km^2))	1.77***	0.87***	1.20***	1.20***
	(5.88)	(3.08)	(4.09)	(4.33)
F				
log(median income)		0.01		-0.12***
		(0.79)		(-13.10)
log(Lag Population density (person per km^2))		0.25***		-0.04*
		(14.57)		(-1.91)
log(House price index)			0.05***	0.09***
			(20.68)	(19.92)
N	1890.00	1890.00	1890.00	1890.00
R2	0.916	0.928	0.926	0.930
Log-Likelihood	4631.7	4779.7	4866.03	4961.8

t statistics in parentheses
dependent variable: log(house price index)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8: House price estimation - Germany

I complement this analysis by the Spatial Durbin Model estimation results for 314 counties in the old Federal States, 64 counties in the new federal states, and the Big 7 German cities including their surrounding counties (Tables 3.12 and 3.13). As for the total German sample, the coefficients are smaller than those with land value as a dependent variable. Compared to former East Germany, land prices have a higher impact on house prices in the old Federal States on the county of interest itself but not on neighboring counties. I only find positive statistically significant indirect spillover effects of land value on house prices for Berlin, Leipzig, and all new Federal States' counties. A county's land value has a statistically positive effect on the county's house price in all Top 7 agglomerations, ceteris paribus. However, controlling for land prices in this house price estimation, I only find occasional evidence for agglomeration spillover effects. I even find a negative agglomeration spillover effect of median income on house prices when controlling for log(land value per m^2) both among former East and West German counties. For population density, network effects are only significant for the old federal states, Berlin and Frankfurt on the 1% and for Leipzig on the 10% significance level. The next section discusses the robustness of the results using different explanatory variables and the inverse distance matrix.

	(2) SLX	(3) SAR	(4) SDM
direct			
log(median income)	1.06***	0.80***	1.10***
	(25.13)	(26.00)	(27.36)
log(Lag Population density (person per km^2))	1.72***	2.01***	1.73***
	(23.80)	(34.15)	(24.96)
indirect			
log(median income)	0.01	0.28***	-0.25***
	(0.79)	(17.85)	(-4.12)
log(Lag Population density (person per km^2))	0.25***	0.71***	1.21***
	(14.57)	(15.23)	(8.42)
Observations	1890	1890	1890

t statistics in parentheses
dependent variable: log(house price index)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9: House price estimation - Germany (direct and indirect effects)

	(1) FE	(2) SLX	(3) SAR	(4) SDM
main				
log(Land value per m^2)	0.10***	0.08***	0.08***	0.07***
	(24.03)	(21.01)	(18.82)	(18.09)
log(median income)	0.87***	0.86***	0.60***	0.92***
	(30.57)	(22.69)	(19.68)	(23.53)
log(Lag Population density (person per km^2))	1.97***	1.45***	1.70***	1.43***
	(37.44)	(22.71)	(31.27)	(21.76)
green coverage	0.70***	0.51***	0.42**	0.40**
	(3.86)	(3.03)	(2.33)	(2.35)
log(construction cost index)	0.38***	0.32***	0.30***	0.29***
	(20.06)	(18.37)	(15.91)	(16.04)
log(arable land (sqkm) per capita)	-0.09***	-0.09***	-0.11***	-0.10***
	(-2.93)	(-3.20)	(-3.53)	(-3.24)
log(land area (km^2))	1.38***	0.73***	0.98***	0.98***
	(5.22)	(2.97)	(3.70)	(3.87)
F				
log(Land value per m^2)		0.01***		0.002
		(9.36)		(1.35)
log(median income)		-0.03***		-0.11***
		(-4.07)		(-12.62)
log(Lag Population density (person per km^2))		0.15***		-0.03
		(9.47)		(-1.42)
log(House price index)			0.04***	0.08***
			(18.80)	(15.26)
N	1890.00	1890.00	1890.00	1890.00
R2	0.936	0.946	0.943	0.948
Log-Likelihood	4884.5	5054.8	5063.3	5155.9

t statistics in parentheses
dependent variable: log(house price index)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.10: House price estimation - Germany (including log(Land value per m^2))

	(2) SLX	(3) SAR	(4) SDM
direct			
log(Land value per m^2)	0.08***	0.08***	0.08***
	(21.01)	(19.65)	(19.18)
log(median income)	0.86***	0.60***	0.89***
	(22.69)	(20.48)	(24.01)
log(Lag Population density (person per km^2))	1.45***	1.72***	1.46***
	(22.71)	(31.74)	(23.36)
indirect			
log(Land value per m^2)	0.01***	0.02***	0.07***
	(9.36)	(12.96)	(5.51)
log(median income)	-0.03***	0.17***	-0.40***
	(-4.07)	(15.24)	(-7.03)
log(Lag Population density (person per km^2))	0.15***	0.48***	0.71***
	(9.47)	(13.95)	(5.69)
Observations	1890	1890	1890

t statistics in parentheses
dependent variable: log(house price index)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.11: House price estimation - Germany (including log(Land value per m^2); direct and indirect effects)

3.5.4 Robustness Analysis

In this section, I focus on land values as the dependent variable and evaluate the robustness of the results in terms of two factors: different sets of explanatory variables and the inverse distance matrix as spatial weighting pattern. Moreover, I also discuss the results in light of different land value measurements for Germany. The results estimated using the land values estimated in Chapter 2 are compared with estimations using the land prices on vacant land sales of land ready for construction.

Control variables

I re-estimate the models (1)-(4) using different sets of explanatory variables. Tables 3.14 and 3.15 present the results for the SDM model, with the baseline specification in column (1).

In column (2), I remove the log(land area km^2). Column (3) repeats column (1) and includes the spatial lag of log(land area km^2). Column (4) additionally controls for the log(number of accommodation facilities in a county), the log(housing stock of single-/double family houses)) and unemployment rates.

I find most of the estimated coefficients of the baseline model (1) to be robust throughout the 4 specifications. But, the controls for tourism, housing stock and unemployment in a county have no significant impact on the dependent variable. Thus, they are excluded from the benchmark model. Moreover, Table 3.15 shows no evidence for network effects of the size of a county on land values. Due to this fact and given that explanatory power does not increase significantly from columns 1 and 2, I also exclude the spatial lag of land area.

	West	East	Berlin	Munich	Hamburg	Cologne /Düsseldorf	Frankfurt	Leipzig	Stuttgart
log(Land value per m^2)	0.12***	0.02***	0.48***	0.53***	0.29***	0.30***	0.25***	0.20***	0.32***
	(18.64)	(4.82)	(21.91)	(21.52)	(12.63)	(11.02)	(9.85)	(9.07)	(6.15)
log(Median income)	0.97***	0.87***	-0.26***	0.07	0.08	0.45***	0.49***	0.40***	0.88***
	(20.85)	(15.19)	(-3.39)	(0.95)	(0.65)	(3.66)	(4.19)	(6.26)	(4.36)
log(Lag Population density (person per km^2))	1.33***	1.57***	-0.27*	0.49***	0.57*	1.26***	1.23***	0.58***	0.40***
	(18.40)	(14.95)	(-1.84)	(3.54)	(1.85)	(6.31)	(6.86)	(4.47)	(3.13)
Green coverage	0.23	0.26	1.01	1.97***	-1.61	-1.52***	-14.51***	-0.12	14.24***
	(0.93)	(1.17)	(0.65)	(2.86)	(-1.06)	(-2.68)	(-4.77)	(-0.51)	(2.99)
log(Construction cost index)	0.31***	0.12***	0.71***	0.31***	0.45***	0.37***	0.26***	0.34***	0.29***
	(16.11)	(3.02)	(16.00)	(11.40)	(8.56)	(8.11)	(4.68)	(6.60)	(4.40)
log(arable land (sqkm) per capita)	-0.15***	-0.01	0.0004	-0.24***	-0.13	-0.21**	-0.33	-0.28**	0.83
	(-4.55)	(-0.12)	(0.003)	(-6.48)	(-1.19)	(-2.36)	(-1.46)	(-2.09)	(0.85)
log(Land area (km^2))	1.03***	0.16	7.57**	34.99***	-4.10***	-1.45	20.52**	-2.50	-0.83
	(4.27)	(0.17)	(2.12)	(3.36)	(-2.80)	(-0.41)	(2.25)	(-1.22)	(-0.6)
F									
log(Land value per m^2)	-0.005*	0.004*	0.02*	0.01	0.02*	-0.04***	-0.08***	0.01	-0.04*
	(-1.84)	(1.92)	(1.73)	(0.31)	(1.80)	(-3.00)	(-5.45)	(1.10)	(-1.71)
log(Median income)	-0.09***	-0.09***	-0.01	0.02	0.11*	-0.01	0.05	-0.02	-0.02
	(-6.51)	(-5.18)	(-0.43)	(0.64)	(1.69)	(-0.37)	(1.04)	(-0.89)	(-0.27)
log(Lag Population density (person per km^2))	-0.05**	-0.10*	0.19***	-0.08	0.05	-0.07	0.09	0.11	-0.07
	(-2.37)	(-1.86)	(3.40)	(-1.53)	(0.48)	(-1.05)	(1.30)	(1.36)	(-1.35)
log(House price index)	0.07***	0.08***	-0.01	0.02	-0.04	0.09***	0.11***	0.03	0.09***
	(11.37)	(5.33)	(-0.26)	(0.79)	(-1.28)	(5.03)	(6.81)	(1.04)	(3.39)
N	1570.00	320.00	105.00	95.00	95.00	140.00	110.00	90.00	75.00
R2	0.960	0.923	0.988	0.998	0.985	0.986	0.985	0.972	0.992
Log-Likelihood	4402.2	924.1	362.6	390.3	311.5	470.2	360.7	319.1	257.8

t statistics in parentheses
dependent variable: log(house price index)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.12: Spatial Durbin Model - House price estimation results for Top 7 cities as well as West and East Germany

	West	East	Berlin	Munich	Hamburg	Cologne /Düsseldorf	Frankfurt	Leipzig	Stuttgart
direct									
log(Land value per m^2)	0.12***	0.03***	0.48***	0.53***	0.29***	0.29***	0.21***	0.21***	0.32***
	(18.14)	(5.38)	(21.46)	(21.65)	(12.57)	(10.82)	(6.77)	(8.95)	(5.59)
log(Median income)	0.96***	0.86***	-0.26***	0.07	0.06	0.47***	0.58***	0.39***	0.91***
	(20.55)	(15.66)	(-3.36)	(0.95)	(0.46)	(3.81)	(4.38)	(5.92)	(4.24)
log(Lag Population density (person per km^2))	1.35***	1.59***	-0.27*	0.48***	0.57*	1.28***	1.42***	0.59***	0.38***
	(19.22)	(15.36)	(-1.79)	(3.67)	(1.81)	(6.47)	(7.52)	(4.52)	(2.91)
indirect									
log(Land value per m^2)	0.03	0.04***	0.08**	0.06	0.05	-0.13	-0.51***	0.07*	-0.11
	(1.32)	(2.75)	(2.39)	(1.19)	(1.07)	(-1.14)	(-2.67)	(1.74)	(-0.60)
log(Median income)	-0.23**	-0.13**	-0.04	0.09	0.40*	0.21	1.15**	-0.06	0.44
	(-2.46)	(-2.28)	(-0.39)	(0.67)	(1.74)	(0.67)	(2.19)	(-0.69)	(0.73)
log(Lag Population density (person per km^2))	0.30**	0.15	0.79***	-0.32	0.09	0.35	2.54***	0.55*	-0.22
	(2.24)	(0.50)	(3.40)	(-1.40)	(0.25)	(0.63)	(3.26)	(1.73)	(-0.63)
Observations	1570	320	105	95	95	140	110	90	75

t statistics in parentheses
dependent variable: log(house price index)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.13: Spatial Durbin Model - House price estimation results for Top 7 cities as well as West and East Germany (direct and indirect effects)

	(1)	(2)	(3)	(4)
log(median income)	2.56***	2.59***	2.55***	2.54***
	(10.76)	(10.94)	(10.74)	(9.33)
log(Lag Population density (person per km^2))	3.38***	3.27***	3.43***	3.39***
	(8.28)	(8.12)	(8.39)	(8.18)
green coverage	-7.18***	-7.22***	-7.28***	-7.14***
	(-6.68)	(-6.72)	(-6.78)	(-6.63)
log(construction cost index)	-1.20***	-1.20***	-1.21***	-1.20***
	(-10.90)	(-10.88)	(-10.95)	(-10.89)
log(arable land (sqkm) per capita)	-0.59***	-0.55***	-0.60***	-0.58***
	(-3.12)	(-2.96)	(-3.18)	(-3.05)
log(land area (km^2))	2.51		2.69*	2.54
	(1.57)		(1.67)	(1.58)
log(open accomodation facilities)				-0.03
				(-0.56)
log (housing stock (single/double family houses))				0.09
				(0.66)
unemployment rate				-0.0001
				(-0.01)
F				
log(median income)	0.01	0.01	0.02	0.01
	(0.26)	(0.33)	(0.51)	(0.23)
log(Lag Population density (person per km^2))	0.15	0.18*	0.16	0.14
	(1.47)	(1.91)	(1.57)	(1.35)
log(Land value per m^2)	0.04***	0.04***	0.04***	0.04***
	(7.21)	(6.63)	(6.81)	(7.20)
log(land area (km^2))			-0.90*	
			(-1.65)	
N	1890.00	1890.00	1890.00	1890.00
R2	0.524	0.525	0.526	0.524
Log-Likelihood	1682.3	1680.8	1684.0	1682.8

t statistics in parentheses
dependent variable: log(landvalue per m^2)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.14: SDM estimation results for different sets of controls variables - Germany

	(1)	(2)	(3)	(4)
direct				
log(median income)	2.60***	2.64***	2.58***	2.56***
	(11.31)	(11.63)	(11.53)	(9.62)
log(Lag Population density (person per km^2))	3.45***	3.34***	3.51***	3.46***
	(8.58)	(8.56)	(8.43)	(8.50)
log(land area (km^2))			2.49	
			(1.54)	
indirect				
log(median income)	0.84***	0.78***	0.87***	0.83***
	(3.52)	(3.39)	(3.74)	(352)
log(Lag Population density (person per km^2))	2.04***	2.20***	2.01***	1.96***
	(3.60)	(3.88)	(3.45)	(3.18)
log(land area (km^2))			-5.18	
			(-1.48)	
Observations	1890	1890	1890	1890

t statistics in parentheses
dependent variable: log(landvalue per m^2)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.15: SDM estimation results for different sets of controls variables - Germany (direct and indirect effects)

Inverse distance matrix

As outlined in Section 3.5.3, I further re-estimate models (FE)-(SDM) using an inverse distance matrix to measure spatial dependence between counties and also account for spatial dependence between counties that are geographically further apart. The weight between two counties i and j is calculated as

$$w_{ij} = 1/d_{ij} \tag{3.9}$$

and diminishes with distance d. Results are presented in Tables 3.16 and 3.17.

Overall, the results are more or less robust to the specification of the spatial weight matrix with the first-order contiguity. The estimated coefficients for the explanatory variables do not change dramatically in terms of significance and size. Except for log(median income) coefficients are significantly smaller but still significant at the one percent significance level compared to the baseline specification. However, given that spatial dependence is now also allowed between counties of higher neighbor-order, the spatial interaction effects increase in size (See Table 3.17). The fact that the indirect spillover effects of median income and population density increase substantially from the SLX to SAR model suggests that besides network externalities, pure interaction mechanisms also play an important role in land value determination. However, with the inverse distance weight matrix specification, there is no evidence for agglomeration spillovers between counties regarding population density. I even find a negative effect that is significant on the 10% significance level. This result is not surprising as it coincides with the Moran's I cross-correlation measure for population density and land values in Table 3.3 that drastically decreases with distance.

	(1) FE	(2) SLX	(3) SAR	(4) SDM
main				
log(median income)	3.08***	0.73***	1.46***	1.01***
	(23.42)	(3.59)	(9.76)	(4.43)
log(Lag Population density (person per km^2))	4.30***	3.20***	2.65***	3.09***
	(15.74)	(10.07)	(8.56)	(8.80)
green coverage	-6.98***	-8.01***	-7.82***	-8.12***
	(-7.04)	(-8.49)	(-7.51)	(-7.79)
log(construction cost index)	-1.09***	-1.37***	-1.31***	-1.35***
	(-10.78)	(-13.98)	(-12.30)	(-12.46)
log(arable land (sqkm) per capita)	-0.61**	-0.43***	-0.41**	-0.41**
	(-3.49)	(-2.59)	(-2.21)	(-2.25)
log(land area (km^2))	3.90***	3.39**	2.69*	3.29**
	(2.68)	(2.43)	(1.75)	(2.14)
inv				
log(median income)		3.75***		1.55***
		(12.53)		(3.73)
log(Lag Population density (person per km^2))		-1.54*		-2.80***
		(-1.89)		(-2.91)
log(Land value per m^2)			0.82***	0.68***
			(25.55)	(8.43)
N	1890.00	1890.00	1890.00	1890.00
R2	0.516	0.565	0.446	0.551
Log-Likelihood	1654.2	1775.0	1738.4	1748.2

t statistics in parentheses
dependent variable: log(landvalue per m^2)
spatial weight matrix: inverse distance
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.16: Estimation results - Germany - Inverse distance matrix

	(1) SLX	(2) SAR	(3) SDM
direct			
log(median income)	0.75***	1.47***	1.03***
	(3.59)	(9.74)	(4.60)
log(Lag Population density (person per km^2))	3.20***	2.71***	3.09***
	(10.07)	(8.84)	(8.73)
indirect			
log(median income)	3.75***	6.34***	7.00***
	(12.53)	(4.67)	(3.27)
log(Lag Population density (person per km^2))	-1.54*	11.61***	-2.23
	(-1.89)	(4.86)	(-0.76)
Observations	1890	1890	1890

t statistics in parentheses
dependent variable: log(landvalue per m^2)
spatial weight matrix: inverse distance
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.17: Estimation results - Germany - Inverse distance matrix (direct and indirect effects)

Vacant land prices (ready for construction)

In the land price estimation literature, there are several popular approaches to measuring land prices. Based on the underlying data and methods to estimate land prices, one can argue that each of the resulting land price indices represents different purposes. In this section, using the SDM, I compare the spatial analysis for the land values from Chapter 2, the house price index from vdpResearch, and the land values based on vacant land sales of land ready for construction from the Statistical Offices of the Federal Government and the German States.[26] Results for the SDM are displayed in Tables 3.18 and 3.19.

The main methodological difference between the residential and vacant land prices is the following. While Chapter 2 estimates the price of residential land with a two-step residual approach using listings data from the ImmobilienScout24 website on single-/double-family housing, the vacant land price statistic calculates a per m^2 price of the transaction prices of vacant land sales ready for construction (Statistisches Bundesamt, 2012).

One can see two noteable results from Tables 3.18 and 3.19. First, direct and indirect spillover effects are larger and more statistically significant for residential land prices compared to vacant land price estimation results (Table 3.19). For example, in the results on the SDM model, if median income increases by one percent, the land price changes by 2.88 percent or 1.06 percent, respectively, ceteris paribus. I do not find indirect spatial effects for median income in all specifications in the smaller sample. However, the spatial spillover effects for population density are also much more significant using the residential land prices estimates and even insignificant in the SDM model for the price of vacant land. If population density in a county increases by 1 percent. In that case, land prices in neighboring counties increase by 2.24 percent, ceteris paribus, for the SDM using residential land prices. At the same time, there is no significant indirect effect on vacant land prices. From my perspective, this result is because the residential land prices denote everything except for the structure's replacement cost to the land component in the housing bundle. Hence, the residential land prices more likely reflect the presence of agglomeration economies/amenities. On the other hand, I argue that vacant land transactions are more likely to occur in new development areas that often are located on the outskirts of towns and cities. Second, by construction, the construction cost index should significantly negatively impact the residential land prices resulting from the residual approach. However, as expected, the construction costs have a significant positive effect on the vacant land prices and house prices.

3.6 Concluding Remarks

In this chapter, I analyze spatial spillover patterns in German land and house prices. I estimate the SLX, SAR, and SDM model for the total of 378 counties, 314 counties in the old Federal States, 64 counties in the new Federal States, and the Big 7 German cities including their surrounding counties using a panel data set for 378 German counties from 2014-2018. Besides local housing market determinants, I find evidence for the importance of both exogenous and endogenous spatial interaction patterns between housing and land markets.

[26] As there is no vacant land sales data for some county-year observations, the sample size reduces to 1520 from 1890. To maintain a balanced panel, I have to remove observations of 74 counties that have one or more missing county-year observations.

	log(landvalue per m^2) (residential land) SDM	log(landvalue per m^2) (vacant land sales) SDM	log(house price index) SDM
main			
log(median income)	2.87***	1.08***	1.19***
	(11.53)	(2.72)	(27.68)
log(Lag Population density (person per km^2))	3.45***	2.10***	1.63***
	(7.95)	(3.05)	(21.90)
green coverage	-7.39***	-0.80	-0.18
	(-6.57)	(-0.45)	(-0.93)
log(construction cost index)	-1.11***	0.59***	0.21***
	(-8.93)	(2.98)	(10.00)
log(arable land (sqkm) per capita)	-0.64***	-1.01***	-0.17***
	(-2.95)	(-2.93)	(-4.43)
log(land area (km^2))	2.81*	0.62	1.42***
	(1.77)	(0.25)	(5.18)
F			
log(median income)	-0.11**	-0.12	-0.15***
	(-2.32)	(-1.64)	(-14.86)
log(Lag Population density (person per km^2))	0.16	0.07	-0.04
	(1.40)	(0.44)	(-1.55)
log(dependent variable)	0.06***	0.04***	0.10***
	(8.15)	(5.83)	(19.01)
N	1520.00	1520.00	1520.00
R2	0.51	0.23	0.93
Log-Likelihood	1374.5	675.2	4020.5

t statistics in parentheses
spatial weight matrix: first order contiguity
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.18: Estimation results - Germany - Vacant vs. residential land values

	log(landvalue per m^2) (residential land) SDM	log(landvalue per m^2) (vacant land sales) SDM	log(house price index) SDM
direct			
log(median income)	2.88***	1.06***	1.16***
	(11.96)	(2.61)	(27.59)
log(Lag Population density (person per km^2))	3.58***	2.16***	1.71***
	(8.54)	(3.22)	(24.12)
indirect			
log(median income)	0.36	-0.43	-0.34***
	(1.53)	(0.95)	(-5.98)
log(Lag Population density (person per km^2))	2.24***	0.95	1.21***
	(3.81)	(1.05)	(8.37)
Observations	1520	1520	1520

t statistics in parentheses
spatial weight matrix: first order contiguity
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.19: Estimation results - Germany - Vacant vs. residential land values (direct and indirect effects)

The results are summarized as follows. First, I find that cross-county spillovers can explain variation in land values for Germany. While these spillovers are relatively weak in a smaller dataset on a more local level for new and old Federal States and 7 Big German cities and their surrounding counties, I find agglomeration effects to be more substantial in the West than East German counties, at least for median income. This result is also similar for the Top 7 German agglomerations but to a lesser degree. Consequently, I show, unlike Gyourko et al. (2013), that the Big 7 German cities do not exhibit the characteristics of the so-called Superstar Cities. Second, while still significant, I show that the spatial effects are smaller when using house prices as the dependent variable. Third, when including the land price in house price estimation, the spillover effects in house prices further decrease. Moreover, the significantly positive coefficient on land value per m^2 both for direct and indirect spatial effects supports the theory that clustering patterns in house prices can be attributed to spatial variations in land prices. Lastly, I explore these patterns in two different land price measurements for Germany. The direct and indirect spillover effects can explain more variation in residential land values than in vacant land prices of land ready for construction from the Statistical Offices of the Federal Government and the German States.

These results suggest that changes in agglomeration variables such as median income (productivity) and population density cannot completely explain disparate local land and house prices. Consequently, the results support the theory that house and land prices, indeed are a local phenomenon and that land prices are a major determinant for the development of house prices. The fact that I find spillover effects in land prices raises the question whether more rural counties may be better off in investing in public goods and services to increase attractiveness and strengthen local externality (spillover) effects.

Focusing more on the urban-peripheral inequalities would be an interesting extension for future research. Moreover, one could pay more attention to the impact of climate conditions and other environmental and natural amenities on land prices. For example, do German's value the spatial proximity to the mountainside or the sea? A longer time series would also be a great extension to focus more on the spatio-temporal dimension.

3.7 Appendix

3.7.1 Tables

Dependent Variable	Availability	Source	Regional Level
House Price Index	2012-2018	vdpResearch	County
Land value per m^2	2014-2018	Chapter 2	County
Land value m^2 (vacant land sales)	1995-2019	Statistical Offices of the Federal Government and the German States (Statistic 61511-01-03-4)	County
Control Variable			
Land area km^2	2008-2019	Statistical Offices of the Federal Government and the German States (Statistic 11111-01-01-4)	County
Income	2014-2019	Federal Employment Agency	County
Population	1995-2019	Federal Statistical Office (Statistic 12411-0015)	County
Unemployment Rate	2008-2018	Federal Employment Agency	County
Construction Cost Index	1958-2020	Federal Statistical Office (Statistic 61261-0001)	National
Regional Construction Cost Factors	2012-2019	BKI	County
Amount of accomodation facilities	1995-2019	Statistical Offices of the Federal Government and the German States (Statistic 45412-01-02-4)	County
Green coverage	1995-2019	Statistical Offices of the Federal Government and the German States (Statistic 33111-01-02-4 and 33111-01-01-4)	County
Housing Stock measures	1995-2019	Statistical Offices of the Federal Government and the German States (Statistic 31231-02-01-4)	County

Table 3.20: Dependent and explanatory variables

House price index data	
GER,FRA,UK,DNK,AUT	Internatioal House Price Database - Federal Reserve Bank of Dallas
US	Davis and Heathcote (2007)
Construction cost index data	
GER	Destatis statistic 61261-0014: Construction cost indices for residential buildings: Germany, quarters, type of construction costs
FRA	Institut national de la statistique et des études économiques Identifier 000008630: Cost-of-Construction Index (CCI)
DNK	Statistics Denmark BYG42: Construction cost index for residential buildings
UK	1975-2012: BCIS Series Numbers 7504/7505 "Output price index for All Work (New Construction and Repair& Maintenance)" 2013-2020: Office for National Statistics "All construction output prices"
AUT	Australian Bureau of Statistics. 2020. Australian National Accounts 5206005: National Income, Expenditure and Product. Table 5. Expenditure on Gross Domestic Product (GDP), Implicit price deflators
US	Davis and Heathcote (2007)

Table 3.21: Sources - Figure 1

City/Tier	County	City/Tier	County	City/Tier	County	City/Tier	County	City/Tier	County	County
Berlin			LK Freising		LK Cuxhaven		SK Oberhausen		LK Halle(Saale)	LK Heilbronn
Tier 1			LK Fürstenfeldbruck		LK Lüneburg		LK Wesel		LK Saalekreis	SK Heilbronn
	SK Berlin		LK Miesbach		LK Rotenburg (Wümme)	Frankfurt am Main			LK Burgenlandkreis	LK Enzkreis
Tier 2			LK Landberg am Lech		LK Heidekreis	Tier 1			LK Nordsachsen	SK Pforzheim
	SK Potsdam		LK Starnberg	Cologne/Düsseldorf			SK Frankfurt am Main	Tier 3		LK Calw
	LK Barnim	Tier 3		Tier 1		Tier 2			LK Mandfeld-Südharz	LK Tübingen
	LK Dahme-Spreewald		LK Weilheim-Schongau		SK Köln		LK Offenbach		LK Salzlandkreis	LK Reutlingen
	LK Havelland		LK Mühldorf am Inn		SK Düsseldorf		LK Groß-Gerau		SK Dessau-Roßlau	
	LK Märkisch-Oderland		LK Neuburg-Schrobenhausen	Tier 2			SK Offenbach am Main		LK Anhalt-Bitterfeld	
	LK Oberhavel		LK Pfaffenhofen a.d. Ilm		LK Mettmann		LK Main-Minzig-Kreis		LK Wittenberg	
	LK Oder-Spree		LK Rosenheim		LK Rhein-Kreis Neuss		LK Wetteraukreis		LK Elbe-Elster	
	LK Potsdam-Mittelmark		LK Landshut		SK Bonn		LK Hochtaunuskreis		LK Meißen	
	LK Teltow-Fläming		SK Landshut		SK Leverkusen		LK Main-Taunus-Kreis		Mittelsachsen	
Tier 3			LK Aichach-Friedberg		LK Rhein-Erft-Kreis	Tier 3			LK Altenburger Land	
	LK Uckermark	Hamburg			LK Rheinisch-Bergischer Kreis		SK Aschaffenburg		SK Gera	
	LK Ostprignitz-Ruppin	Tier 1			LK Rhein-Sieg-Kreis		LK Aschaffenburg		LK Greiz	
	SK Cottbus		SK Hamburg		SK Krefeld		SK Mainz		LK Saale-Holzland-Kreis	
	LK Elbe-Elster	Tier 2			SK Mülheim an der Ruhr		LK Mainz-Bingen		SK Jena	
	LK Ostspreewald-Lausitz		LK Herzogtum Lauenburg		SK Duisburg		SK Darmstadt		LK Weimarer Land	
	LK Prignitz		LK Pinneberg	Tier 3			SK Wiesbaden		SK Weimar	
	LK Spree-Neiße		LK Segeberg		LK Ahrweiler		LK Darmstadt-Dieburg		LK Sömmerda	
	LK Anhalt-Bitterfeld		LK Stormarn		LK Altenkirchen (Westerwald)		LK Rheingau-Taunus-Kreis		LK Kyffhäuserkreis	
	LK Jerichower Land		LK Harburg		LK Neuwied		LK Gießen	Stuttgart		
	LK Stendal		LK Stade		SK Essen		LK Lahn-Dill-Kreis	Tier 1		
	LK Wittenberg	Tier 3			SK Mönchengladbach		LK Limburg-Weilburg		SK Stuttgart	
Munich			LK Schwerin		SK Remscheid		LK Vogelbergkreis	Tier 2		
Tier 1			LK Nordwestmecklenburg		SK Solingen		LK Fulda		LK Böblingen	
	SK München		LK Ludwigslust-Parchim		SK Wuppertal		LK Main-Spessart		LK Esslingen	
Tier 2			SK Lübeck		LK Viersen		LK Bad Kissingen		LK Ludwigsburg	
	LK München		SK Neumünster		LK Düren	Leipzig			LK Rems-Murr-Kreis	
	LK Bad Tölz-Wolfratshausen		LK Ostholstein		LK Einkirchen	Tier 1		Tier 3		
	LK Dachau		LK Plön		LK Heinsberg		SK Leipzig		LK Göppingen	
	LK Ebersberg		LK Rendsburg-Eckernförde		LK Oberbergischer Kreis	Tier 2			LK Ostalbkreis	
	LK Erding		LK Steinburg		LK Ennepe-Ruhr-Kreis		LK Leipzig		LK Schwäbisch Hall	

Table 3.22: German Big 7 cities and surrounding counties (Tier 1-3)

City	Tier	Kreis	Landvalue/sqm			
			2015	2016	2017	2018
Berlin	1	SK Berlin	0.04	0.21	0.21	0.12
		Average Tier 2	0.02	0.05	0.10	0.12
Berlin	2	SK Potsdam	0.05	0.14	0.14	0.15
Berlin	2	LK Barnim	-0.01	0.02	0.07	0.11
Berlin	2	LK Dahme-Spreewald	0.04	0.03	0.05	0.07
Berlin	2	LK Havelland	0.01	0.06	0.08	0.16
Berlin	2	LK Märkisch-Oderland	0.02	0.09	0.09	0.10
Berlin	2	LK Oberhavel	0.02	0.05	0.05	0.10
Berlin	2	LK Oder-Spree	0.00	-0.02	0.16	0.11
Berlin	2	LK Potsdam-Mittelmark	0.02	0.04	0.11	0.10
Berlin	2	LK Teltow-Fläming	0.03	0.03	0.15	0.15
		Average Tier 3	0.02	0.03	0.04	0.02
Berlin	3	LK Uckermark	0.00	0.00	0.02	0.04
Berlin	3	LK Ostprignitz-Ruppin	0.06	0.05	0.05	0.02
Berlin	3	SK Cottbus	0.00	0.07	0.07	-0.01
Berlin	3	LK Elbe-Elster	0.05	-0.13	0.15	-0.02
Berlin	3	LK Ostspreewald-Lausitz	-0.02	-0.03	0.05	0.13
Berlin	3	LK Prignitz	0.01	0.11	0.10	0.08
Berlin	3	LK Spree-Neiße	0.14	0.10	-0.12	-0.02
Berlin	3	LK Anhalt-Bitterfeld	0.06	0.06	0.09	0.03
Berlin	3	LK Jerichower Land	-0.05	0.08	0.05	-0.02
Berlin	3	LK Stendal	0.01	0.01	-0.01	0.01
Berlin	3	LK Wittenberg	0.00	0.05	0.00	-0.04
Munich	1	SK München	0.11	0.12	0.13	0.05
		Average Tier 2	0.07	0.10	0.09	0.08
Munich	2	LK München	0.07	0.12	0.08	0.08
Munich	2	LK Bad Tölz-Wolfratshausen	0.07	0.08	0.08	0.10
Munich	2	LK Dachau	0.08	0.09	0.12	0.06
Munich	2	LK Ebersberg	0.05	0.11	0.05	0.10
Munich	2	LK Erding	0.13	0.12	0.05	0.11
Munich	2	LK Freising	0.04	0.13	0.10	0.10
Munich	2	LK Fürstenfeldbruck	0.05	0.08	0.09	0.07
Munich	2	LK Miesbach	0.08	0.09	0.07	0.08
Munich	2	LK Landberg am Lech	0.05	0.10	0.13	0.06
Munich	2	LK Starnberg	0.05	0.05	0.08	0.07
		Average Tier 3	0.04	0.08	0.09	0.09
Munich	3	LK Weilheim-Schongau	0.06	0.07	0.06	0.12
Munich	3	LK Mühldorf am Inn	0.03	0.06	0.06	0.10
Munich	3	LK Neuburg-Schrobenhausen	0.08	0.10	0.07	0.08
Munich	3	LK Pfaffenhofen a.d. Ilm	0.03	0.06	0.11	0.10
Munich	3	LK Rosenheim	0.06	0.08	0.08	0.12
Munich	3	LK Landshut	0.03	0.11	0.09	0.07
Munich	3	SK Landshut	0.03	0.08	0.12	0.08
Munich	3	LK Aichach-Friedberg	0.03	0.09	0.13	0.08
Hamburg	1	SK Hamburg	0.06	0.07	0.12	0.04
		Average Tier 2	0.04	0.09	0.06	0.12
Hamburg	2	LK Herzogtum Lauenburg	0.04	0.05	0.00	0.16
Hamburg	2	LK Pinneberg	0.06	0.04	0.10	0.15
Hamburg	2	LK Segeberg	0.03	0.11	0.04	0.08
Hamburg	2	LK Stormarn	0.02	0.05	0.04	0.09
Hamburg	2	LK Harburg	0.01	0.11	0.12	0.14
Hamburg	2	LK Stade	0.08	0.15	0.08	0.10
		Average Tier 3	0.04	0.05	0.06	0.08
Hamburg	3	LK Nordwestmecklenburg	-0.04	0.17	0.20	0.32

Hamburg	3	LK Ludwigslust-Parchim	0.07	-0.03	-0.01	-0.07
Hamburg	3	SK Lübeck	0.06	0.05	0.07	0.08
Hamburg	3	SK Neumünster	0.05	0.14	0.11	0.21
Hamburg	3	LK Ostholstein	0.08	0.05	0.03	0.06
Hamburg	3	LK Plön	0.08	0.12	0.03	0.10
Hamburg	3	LK Rendsburg-Eckernförde	0.03	0.04	0.05	0.04
Hamburg	3	LK Steinburg	0.00	0.16	0.00	0.20
Hamburg	3	LK Cuxhaven	0.15	0.19	0.18	0.01
Hamburg	3	LK Lüneburg	0.08	0.12	0.20	0.13
Hamburg	3	LK Rotenburg (Wümme)	0.02	0.10	0.05	0.06
Hamburg	3	LK Heidekreis	-0.02	0.08	0.12	0.07
Düsseldorf/Köln	1	SK Köln	0.06	0.07	0.06	0.07
Düsseldorf/Köln	1	SK Düsseldorf	0.07	0.10	0.09	0.06
		Average Tier 2	0.04	0.09	0.07	0.08
Düsseldorf/Köln	2	LK Mettmann	0.03	0.09	0.09	0.07
Düsseldorf/Köln	2	LK Rhein-Kreis Neuss	0.01	0.12	0.08	0.10
Düsseldorf/Köln	2	SK Bonn	0.04	0.10	0.06	0.07
Düsseldorf/Köln	2	SK Leverkusen	0.04	0.09	0.07	0.08
Düsseldorf/Köln	2	LK Rhein-Erft-Kreis	0.09	0.10	0.06	0.08
Düsseldorf/Köln	2	LK Rheinisch-Bergischer Kreis	0.07	0.08	0.06	0.08
Düsseldorf/Köln	2	LK Rhein-Sieg-Kreis	0.03	0.11	0.11	0.09
Düsseldorf/Köln	2	SK Krefeld	0.02	0.11	0.01	0.11
Düsseldorf/Köln	2	SK Mülheim an der Ruhr	0.02	0.05	0.05	0.09
Düsseldorf/Köln	2	SK Duisburg	0.04	0.06	0.10	0.01
		Average Tier 3	0.03	0.09	0.09	0.09
Düsseldorf/Köln	3	LK Ahrweiler	-0.01	0.12	0.11	0.04
Düsseldorf/Köln	3	LK Altenkirchen (Westerwald)	0.01	0.10	0.15	0.22
Düsseldorf/Köln	3	LK Neuwied	0.11	0.02	0.17	0.05
Düsseldorf/Köln	3	SK Essen	0.01	0.09	0.09	0.05
Düsseldorf/Köln	3	SK Mönchengladbach	0.04	0.13	0.02	0.11
Düsseldorf/Köln	3	SK Remscheid	0.04	0.02	0.06	0.07
Düsseldorf/Köln	3	SK Solingen	0.04	0.06	0.05	0.08
Düsseldorf/Köln	3	SK Wuppertal	0.00	0.06	0.08	0.10
Düsseldorf/Köln	3	LK Viersen	-0.01	0.15	0.11	0.14
Düsseldorf/Köln	3	LK Düren	0.04	0.17	0.06	0.12
Düsseldorf/Köln	3	LK Einkirchen	0.05	0.10	0.10	0.14
Düsseldorf/Köln	3	LK Heinsberg	0.11	0.07	0.12	0.06
Düsseldorf/Köln	3	LK Oberbergischer Kreis	0.07	0.11	0.04	0.11
Düsseldorf/Köln	3	LK Ennepe-Ruhr-Kreis	0.00	0.06	0.08	0.09
Düsseldorf/Köln	3	SK Oberhausen	0.00	0.08	0.12	0.08
Düsseldorf/Köln	3	LK Wesel	0.02	0.06	0.08	0.06
Frankfurt am Main	1	SK Frankfurt am Main	0.06	0.07	0.11	0.10
		Average Tier 2	0.07	0.10	0.08	0.10
Frankfurt am Main	2	LK Offenbach	0.03	0.09	0.10	0.09
Frankfurt am Main	2	LK Groß-Gerau	0.06	0.08	0.08	0.10
Frankfurt am Main	2	SK Offenbach am Main	0.11	0.10	0.06	0.14
Frankfurt am Main	2	LK Main-Minzig-Kreis	0.09	0.09	0.05	0.12
Frankfurt am Main	2	LK Wetteraukreis	0.10	0.10	0.08	0.10
Frankfurt am Main	2	LK Hochtaunuskreis	0.06	0.11	0.09	0.08
Frankfurt am Main	2	LK Main-Taunus-Kreis	0.07	0.10	0.10	0.08
		Average Tier 3	0.05	0.12	0.08	0.10
Frankfurt am Main	3	LK Aschaffenburg	0.07	0.06	0.05	0.14
Frankfurt am Main	3	SK Mainz	0.04	0.07	0.10	0.09
Frankfurt am Main	3	LK Mainz-Bingen	0.04	0.10	0.03	0.11
Frankfurt am Main	3	SK Darmstadt	0.02	0.08	0.07	0.08
Frankfurt am Main	3	SK Wiesbaden	0.10	0.11	0.10	0.11
Frankfurt am Main	3	LK Darmstadt-Dieburg	0.07	0.11	0.06	0.15
Frankfurt am Main	3	LK Rheingau-Taunus-Kreis	0.12	0.15	0.13	0.06
Frankfurt am Main	3	LK Gießen	0.08	0.17	0.08	0.09
Frankfurt am Main	3	LK Lahn-Dill-Kreis	0.03	0.12	0.06	-0.01
Frankfurt am Main	3	LK Limburg-Weilburg	-0.02	0.13	0.10	0.07
Frankfurt am Main	3	LK Vogelbergkreis	0.06	0.13	0.01	0.16

Frankfurt am Main	3	LK Fulda	0.06	0.19	-0.03	0.24
Frankfurt am Main	3	LK Main-Spessart	0.03	0.05	0.11	0.08
Frankfurt am Main	3	LK Bad Kissingen	0.07	0.15	0.28	-0.05
Leipzig	1	SK Leipzig	0.01	0.06	0.13	0.16
		Average Tier 2	-0.03	0.00	0.09	0.05
Leipzig	2	LK Leipzig	0.00	-0.03	0.14	0.06
Leipzig	2	LK Halle(Saale)	-0.02	0.04	0.12	0.05
Leipzig	2	LK Saalekreis	-0.09	0.06	0.06	-0.06
Leipzig	2	LK Burgenlandkreis	0.05	0.04	0.06	0.03
Leipzig	2	LK Nordsachsen	-0.07	-0.09	0.09	0.16
		Average Tier 3	0.05	-0.04	0.04	0.02
Leipzig	3	LK Mandfeld-Südharz	0.09	-0.04	0.08	0.02
Leipzig	3	LK Salzlandkreis	-0.03	0.05	-0.07	0.11
Leipzig	3	LK Anhalt-Bitterfeld	0.06	0.06	0.09	0.03
Leipzig	3	LK Wittenberg	0.00	0.05	0.00	-0.04
Leipzig	3	LK Elbe-Elster	0.05	-0.13	0.15	-0.02
Leipzig	3	LK Meißen	0.00	-0.02	0.07	0.05
Leipzig	3	Mittelsachsen	0.24	-0.21	0.04	0.10
Leipzig	3	LK Greiz	0.15	-0.18	-0.07	-0.03
Leipzig	3	LK Saale-Holzland-Kreis	-0.03	-0.02	0.05	-0.01
Leipzig	3	LK Weimarer Land	-0.01	0.00	0.01	0.09
Leipzig	3	LK Sömmerda	0.01	-0.04	0.07	0.06
Leipzig	3	LK Kyffhäuserkreis	0.07	0.04	0.10	-0.11
Stuttgart	1	SK Stuttgart	0.03	0.08	0.11	0.08
		Average Tier 2	0.05	0.07	0.09	0.11
Stuttgart	2	LK Böblingen	0.07	0.06	0.12	0.09
Stuttgart	2	LK Esslingen	0.04	0.07	0.08	0.11
Stuttgart	2	LK Ludwigsburg	0.06	0.08	0.07	0.12
Stuttgart	2	LK Rems-Murr-Kreis	0.02	0.08	0.09	0.12
		Average Tier 3	0.06	0.08	0.09	0.10
Stuttgart	3	LK Göppingen	0.07	0.13	0.03	0.10
Stuttgart	3	LK Ostalbkreis	0.07	0.05	0.20	0.10
Stuttgart	3	LK Schwäbisch Hall	0.04	0.08	0.09	0.08
Stuttgart	3	LK Heilbronn	0.06	0.08	0.08	0.14
Stuttgart	3	SK Heilbronn	0.04	0.06	0.07	0.09
Stuttgart	3	LK Enzkreis	0.04	0.04	0.09	0.11
Stuttgart	3	SK Pforzheim	0.04	0.11	0.12	0.08
Stuttgart	3	LK Calw	0.08	0.08	0.09	0.11
Stuttgart	3	LK Tübingen	0.07	0.08	0.05	0.15
Stuttgart	3	LK Reutlingen	0.06	0.09	0.10	0.06

Table 3.23: Percentage changes in land value per m^2 - Top 7 agglomerations and surrounding tiers

City	Tier	Kreis	HPI			
			2015	2016	2017	2018
Berlin	1	SK Berlin	0.04	0.17	0.14	0.12
		Average Tier 2	0.03	0.04	0.07	0.08
Berlin	2	SK Potsdam	0.06	0.07	0.11	0.11
Berlin	2	LK Barnim	0.01	0.03	0.05	0.09
Berlin	2	LK Dahme-Spreewald	0.03	0.04	0.05	0.08
Berlin	2	LK Havelland	0.03	0.04	0.06	0.08
Berlin	2	LK Märkisch-Oderland	0.04	0.05	0.07	0.08
Berlin	2	LK Oberhavel	0.03	0.04	0.05	0.08
Berlin	2	LK Oder-Spree	0.02	0.03	0.06	0.07
Berlin	2	LK Potsdam-Mittelmark	0.03	0.04	0.07	0.08
Berlin	2	LK Teltow-Fläming	0.03	0.04	0.07	0.08
		Average Tier 3	0.01	0.02	0.03	0.04
Berlin	3	LK Uckermark	0.02	0.03	0.04	0.05
Berlin	3	LK Ostprignitz-Ruppin	0.02	0.03	0.04	0.05
Berlin	3	SK Cottbus	0.02	0.03	0.04	0.05
Berlin	3	LK Elbe-Elster	0.00	0.01	0.04	0.02
Berlin	3	LK Ostspreewald-Lausitz	0.02	0.02	0.04	0.07
Berlin	3	LK Prignitz	0.02	0.03	0.04	0.05
Berlin	3	LK Spree-Neiße	0.01	0.02	0.02	0.05
Berlin	3	LK Anhalt-Bitterfeld	0.01	0.02	0.02	0.02
Berlin	3	LK Jerichower Land	0.01	0.02	0.02	0.01
Berlin	3	LK Stendal	0.01	0.01	0.02	0.02
Berlin	3	LK Wittenberg	0.01	0.01	0.03	0.02
Munich	1	SK München	0.08	0.10	0.10	0.06
		Average Tier 2	0.06	0.08	0.07	0.08
Munich	2	LK München	0.07	0.09	0.07	0.08
Munich	2	LK Bad Tölz-Wolfratshausen	0.05	0.08	0.08	0.08
Munich	2	LK Dachau	0.05	0.08	0.08	0.07
Munich	2	LK Ebersberg	0.06	0.08	0.06	0.09
Munich	2	LK Erding	0.07	0.08	0.06	0.08
Munich	2	LK Freising	0.05	0.07	0.08	0.09
Munich	2	LK Fürstenfeldbruck	0.05	0.08	0.07	0.07
Munich	2	LK Miesbach	0.06	0.08	0.07	0.08
Munich	2	LK Landberg am Lech	0.05	0.07	0.07	0.07
Munich	2	LK Starnberg	0.04	0.06	0.09	0.07
		Average Tier 3	0.05	0.07	0.07	0.08
Munich	3	LK Weilheim-Schongau	0.05	0.07	0.06	0.08
Munich	3	LK Mühldorf am Inn	0.05	0.06	0.05	0.08
Munich	3	LK Neuburg-Schrobenhausen	0.05	0.06	0.06	0.07
Munich	3	LK Pfaffenhofen a.d. Ilm	0.04	0.06	0.08	0.07
Munich	3	LK Rosenheim	0.05	0.07	0.07	0.08
Munich	3	LK Landshut	0.04	0.06	0.07	0.07
Munich	3	SK Landshut	0.05	0.07	0.07	0.09
Munich	3	LK Aichach-Friedberg	0.04	0.06	0.07	0.07
Hamburg	1	SK Hamburg	0.05	0.06	0.09	0.05
		Average Tier 2	0.04	0.06	0.06	0.08
Hamburg	2	LK Herzogtum Lauenburg	0.04	0.05	0.05	0.09
Hamburg	2	LK Pinneberg	0.04	0.06	0.06	0.09
Hamburg	2	LK Segeberg	0.03	0.06	0.06	0.08
Hamburg	2	LK Stormarn	0.04	0.06	0.06	0.08
Hamburg	2	LK Harburg	0.04	0.07	0.08	0.08
Hamburg	2	LK Stade	0.04	0.06	0.05	0.07
		Average Tier 3	0.01	0.01	0.01	0.01
Hamburg	3	LK Nordwestmecklenburg	0.02	0.03	0.06	0.04

Hamburg	3	LK Ludwigslust-Parchim	0.02	0.02	0.04	0.03
Hamburg	3	SK Lübeck	0.03	0.05	0.07	0.08
Hamburg	3	SK Neumünster	0.03	0.05	0.07	0.06
Hamburg	3	LK Ostholstein	0.03	0.05	0.04	0.07
Hamburg	3	LK Plön	0.03	0.06	0.05	0.05
Hamburg	3	LK Rendsburg-Eckernförde	0.03	0.05	0.05	0.05
Hamburg	3	LK Steinburg	0.03	0.04	0.05	0.07
Hamburg	3	LK Cuxhaven	0.04	0.05	0.07	0.05
Hamburg	3	LK Lüneburg	0.06	0.07	0.07	0.09
Hamburg	3	LK Rotenburg (Wümme)	0.03	0.04	0.06	0.05
Hamburg	3	LK Heidekreis	0.03	0.03	0.05	0.04
Düsseldorf/Köln	1	SK Köln	0.05	0.07	0.07	0.06
Düsseldorf/Köln	1	SK Düsseldorf	0.06	0.09	0.09	0.06
		Average Tier 2	0.04	0.06	0.06	0.06
Düsseldorf/Köln	2	LK Mettmann	0.04	0.07	0.07	0.07
Düsseldorf/Köln	2	LK Rhein-Kreis Neuss	0.04	0.06	0.06	0.07
Düsseldorf/Köln	2	SK Bonn	0.05	0.07	0.07	0.07
Düsseldorf/Köln	2	SK Leverkusen	0.03	0.06	0.07	0.05
Düsseldorf/Köln	2	LK Rhein-Erft-Kreis	0.04	0.06	0.05	0.06
Düsseldorf/Köln	2	LK Rheinisch-Bergischer Kreis	0.04	0.05	0.06	0.08
Düsseldorf/Köln	2	LK Rhein-Sieg-Kreis	0.04	0.06	0.07	0.07
Düsseldorf/Köln	2	SK Krefeld	0.04	0.06	0.03	0.07
Düsseldorf/Köln	2	SK Mülheim an der Ruhr	0.03	0.05	0.05	0.06
Düsseldorf/Köln	2	SK Duisburg	0.02	0.04	0.07	0.04
		Average Tier 3	0.03	0.05	0.05	0.06
Düsseldorf/Köln	3	LK Ahrweiler	0.03	0.05	0.04	0.07
Düsseldorf/Köln	3	LK Altenkirchen (Westerwald)	0.03	0.06	0.05	0.05
Düsseldorf/Köln	3	LK Neuwied	0.02	0.04	0.06	0.05
Düsseldorf/Köln	3	SK Essen	0.03	0.05	0.08	0.06
Düsseldorf/Köln	3	SK Mönchengladbach	0.04	0.06	0.06	0.07
Düsseldorf/Köln	3	SK Remscheid	0.02	0.04	0.04	0.04
Düsseldorf/Köln	3	SK Solingen	0.03	0.05	0.05	0.06
Düsseldorf/Köln	3	SK Wuppertal	0.02	0.04	0.06	0.08
Düsseldorf/Köln	3	LK Viersen	0.04	0.06	0.05	0.07
Düsseldorf/Köln	3	LK Düren	0.04	0.05	0.05	0.06
Düsseldorf/Köln	3	LK Einkirchen	0.04	0.06	0.06	0.07
Düsseldorf/Köln	3	LK Heinsberg	0.02	0.04	0.06	0.06
Düsseldorf/Köln	3	LK Oberbergischer Kreis	0.03	0.05	0.05	0.06
Düsseldorf/Köln	3	LK Ennepe-Ruhr-Kreis	0.02	0.03	0.06	0.06
Düsseldorf/Köln	3	SK Oberhausen	0.02	0.04	0.07	0.06
Düsseldorf/Köln	3	LK Wesel	0.03	0.05	0.04	0.05
Frankfurt am Main	1	SK Frankfurt am Main	0.05	0.06	0.10	0.09
		Average Tier 2	0.05	0.07	0.07	0.07
Frankfurt am Main	2	LK Offenbach	0.04	0.06	0.07	0.07
Frankfurt am Main	2	LK Groß-Gerau	0.04	0.06	0.07	0.07
Frankfurt am Main	2	SK Offenbach am Main	0.05	0.07	0.07	0.09
Frankfurt am Main	2	LK Main-Minzig-Kreis	0.05	0.06	0.05	0.07
Frankfurt am Main	2	LK Wetteraukreis	0.04	0.06	0.07	0.07
Frankfurt am Main	2	LK Hochtaunuskreis	0.05	0.07	0.06	0.06
Frankfurt am Main	2	LK Main-Taunus-Kreis	0.06	0.08	0.08	0.07
		Average Tier 3	0.04	0.05	0.05	0.06
Frankfurt am Main	3	LK Aschaffenburg	0.04	0.06	0.03	0.08
Frankfurt am Main	3	SK Mainz	0.04	0.07	0.08	0.09
Frankfurt am Main	3	LK Mainz-Bingen	0.04	0.06	0.04	0.07
Frankfurt am Main	3	SK Darmstadt	0.03	0.05	0.08	0.07
Frankfurt am Main	3	SK Wiesbaden	0.05	0.08	0.07	0.09
Frankfurt am Main	3	LK Darmstadt-Dieburg	0.05	0.06	0.06	0.09
Frankfurt am Main	3	LK Rheingau-Taunus-Kreis	0.05	0.07	0.06	0.07
Frankfurt am Main	3	LK Gießen	0.04	0.06	0.06	0.06
Frankfurt am Main	3	LK Lahn-Dill-Kreis	0.02	0.04	0.05	0.04
Frankfurt am Main	3	LK Limburg-Weilburg	0.03	0.04	0.06	0.04
Frankfurt am Main	3	LK Vogelbergkreis	0.02	0.03	0.04	0.04

Frankfurt am Main	3	LK Fulda	0.03	0.04	0.03	0.07
Frankfurt am Main	3	LK Main-Spessart	0.03	0.04	0.04	0.06
Frankfurt am Main	3	LK Bad Kissingen	0.04	0.05	0.05	0.04
Leipzig	1	SK Leipzig	0.02	0.04	0.08	0.08
		Average Tier 2	0.01	0.02	0.04	0.05
Leipzig	2	LK Leipzig	0.02	0.03	0.06	0.05
Leipzig	2	LK Halle(Saale)	0.02	0.03	0.06	0.05
Leipzig	2	LK Saalekreis	0.00	0.01	0.02	0.04
Leipzig	2	LK Burgenlandkreis	0.02	0.01	0.04	0.02
Leipzig	2	LK Nordsachsen	0.01	0.01	0.03	0.08
		Average Tier 3	0.02	0.02	0.03	0.03
Leipzig	3	LK Mandfeld-Südharz	0.02	0.02	0.02	0.03
Leipzig	3	LK Salzlandkreis	0.01	0.02	0.02	0.03
Leipzig	3	LK Anhalt-Bitterfeld	0.01	0.02	0.02	0.02
Leipzig	3	LK Wittenberg	0.01	0.01	0.03	0.02
Leipzig	3	LK Elbe-Elster	0.00	0.01	0.04	0.02
Leipzig	3	LK Meißen	0.02	0.01	0.04	0.05
Leipzig	3	Mittelsachsen	0.02	0.02	0.03	0.03
Leipzig	3	LK Greiz	0.01	0.01	0.00	0.03
Leipzig	3	LK Saale-Holzland-Kreis	0.02	0.03	0.01	0.03
Leipzig	3	LK Weimarer Land	0.02	0.03	0.03	0.06
Leipzig	3	LK Sömmerda	0.01	0.02	0.03	0.03
Leipzig	3	LK Kyffhäuserkreis	0.02	0.01	0.02	0.02
Stuttgart	1	SK Stuttgart	0.05	0.07	0.11	0.08
		Average Tier 2	0.05	0.07	0.08	0.08
Stuttgart	2	LK Böblingen	0.05	0.06	0.10	0.08
Stuttgart	2	LK Esslingen	0.05	0.07	0.07	0.08
Stuttgart	2	LK Ludwigsburg	0.05	0.07	0.06	0.09
Stuttgart	2	LK Rems-Murr-Kreis	0.05	0.06	0.07	0.08
		Average Tier 3	0.04	0.06	0.06	0.08
Stuttgart	3	LK Göppingen	0.05	0.06	0.05	0.07
Stuttgart	3	LK Ostalbkreis	0.04	0.05	0.07	0.07
Stuttgart	3	LK Schwäbisch Hall	0.04	0.05	0.06	0.06
Stuttgart	3	LK Heilbronn	0.05	0.06	0.06	0.08
Stuttgart	3	SK Heilbronn	0.05	0.06	0.08	0.08
Stuttgart	3	LK Enzkreis	0.04	0.05	0.06	0.08
Stuttgart	3	SK Pforzheim	0.05	0.06	0.06	0.09
Stuttgart	3	LK Calw	0.04	0.05	0.04	0.08
Stuttgart	3	LK Tübingen	0.05	0.07	0.05	0.08
Stuttgart	3	LK Reutlingen	0.05	0.06	0.05	0.07

Table 3.24: Percentage changes in house price index - Top 7 agglomerations and surrounding tiers

	OLS	OLS	FE	RE
log(Median income)	2.05***	2.09***	3.18***	3.14***
	(13.46)	(13.63)	(21.37)	(22.72)
log(Lag Population density (person per km^2))	0.88***	0.88***	3.06***	0.52***
	(13.53)	(13.59)	(7.74)	(4.07)
log(Land area (km^2))	0.22***	0.22***	5.01***	0.29***
	(8.00)	(8.04)	(3.01)	(4.80)
log(arable land (sqkm) per capita)	0.23***	0.25***	-0.81***	-0.15
	(4.46)	(4.69)	(-4.12)	(-1.47)
Green coverage	-4.36***	-3.81***	-7.90***	-9.32***
	(-3.24)	(-2.78)	(-7.06)	(-9.11)
log(Construction cost index)	1.74***	1.87***	-0.99***	-0.44***
	(9.45)	(9.66)	(-8.68)	(-4.16)
year=2015		-0.04		
		(-0.85)		
year=2016		-0.06		
		(-1.15)		
year=2017		-0.08		
		(-1.47)		
year=2018		-0.12**		
		(-2.21)		
Constant	-24.02***	-24.87***	-70.26***	-23.58***
	(-22.02)	(-21.45)	(-6.36)	(-24.66)
N	1890.00	1890.00	1890.00	1890.00
R^2	0.54	0.54	0.50	.
F(4, 1879)		1.28		
Prob > F		0.27		
chi2(6)				153.31
Prob > chi2				0.00

t statistics in parentheses
dependent variable: Land value per m^2
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.25: Non-spatial estimation results, tests

3.7.2 Figures

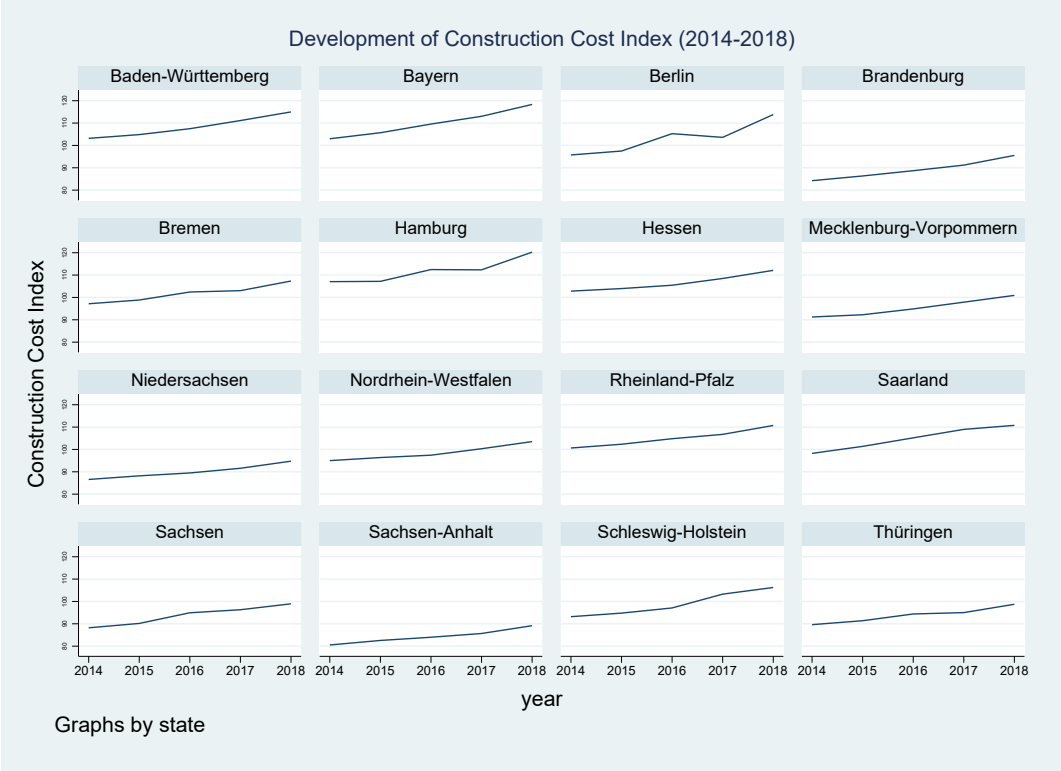


Figure 3.6: Construction cost by state, 2014-2018

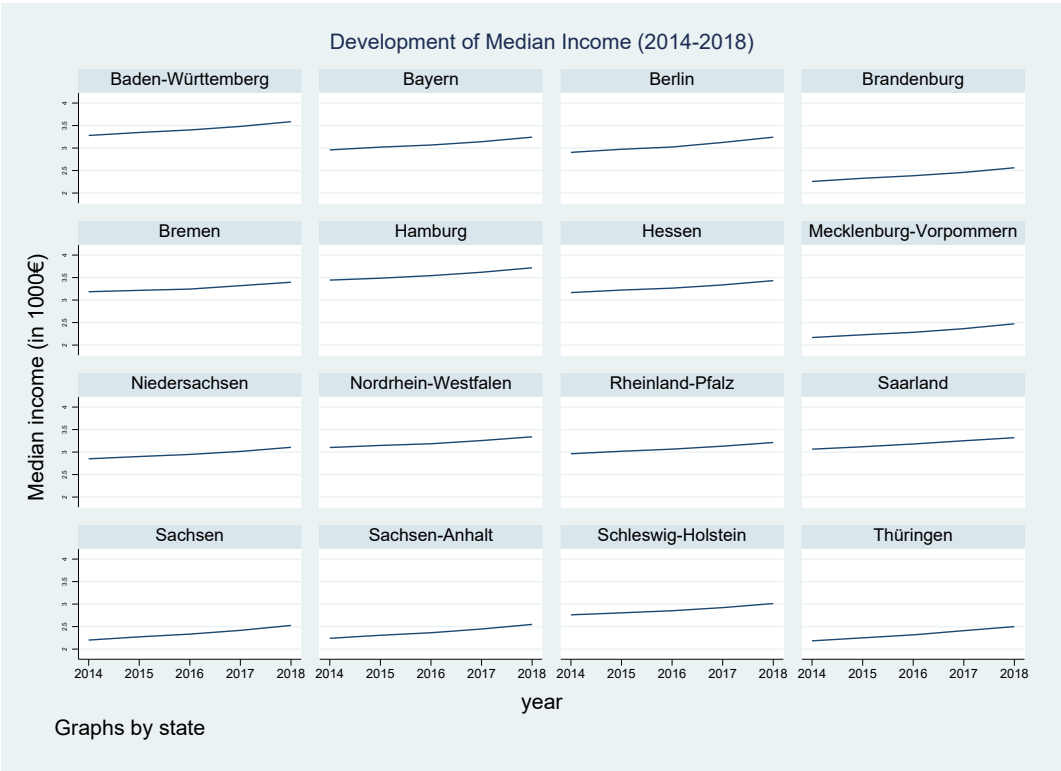


Figure 3.7: Median income by state, 2014-2018

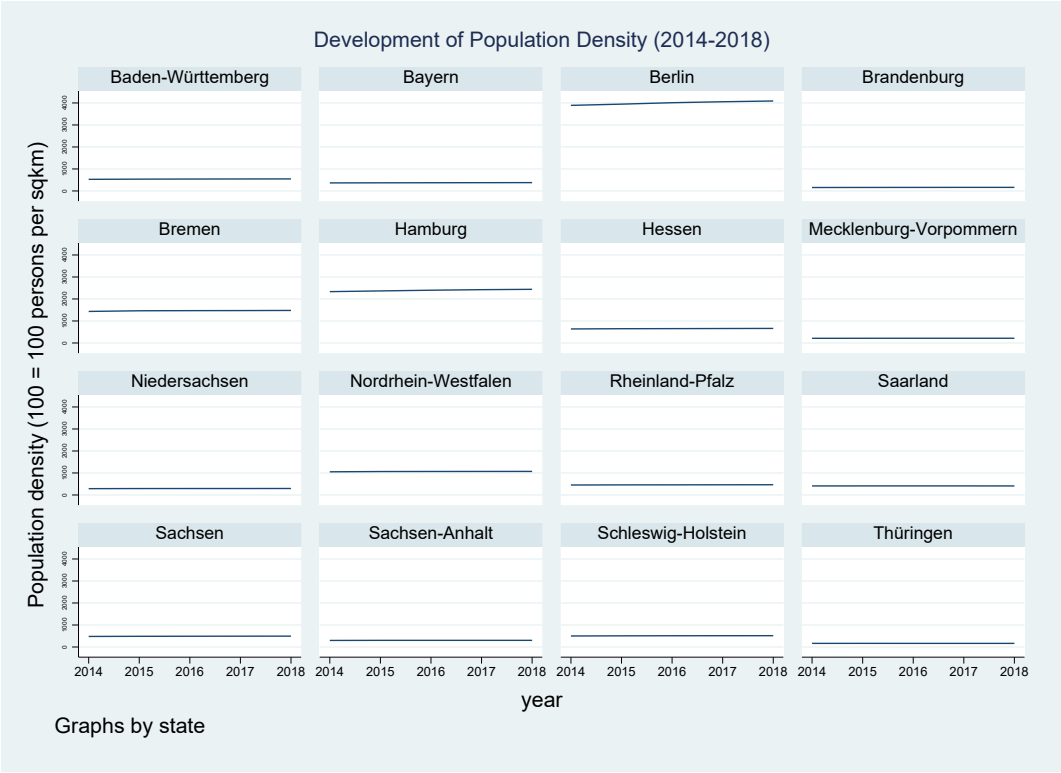


Figure 3.8: Population density by state, 2014-2018

Chapter 4

Effects of Preferential Tax Treatment on German Homeownership

4.1 Introduction

Governments across the globe strive to increase homeownership rates. High homeownership rates are desirable for various reasons. Homeownership is often considered for old-age provision, especially when publicly funded pension rights are low. On the micro-level, homeownership is often considered favorable compared to renting by means of positive externalities. It may positively affect wealth accumulation, is associated with better education for children and is often found to be positively correlated with engagement in communities and better neighborhood maintenance (Coulson and Li, 2013; Mathä et al., 2017; Andrews and Sánchez, 2011).

This chapter is a quantitative exercise to analyze two effects of preferential tax treatment on German homeownership: Taxation of imputed rents and mortgage interest deduction. More specifically, the objective of this chapter is twofold: First, to study the effects of two different tax policies in terms of preferential treatment of owner-occupied housing capital for the German economy, with special focus on homeownership rates, I use the general equilibrium life-cycle model by Gervais (2002)[1] and calibrate it to the German economy. Second, the implications drawn from the counterfactual experiments for Germany are compared to those of Gervais (2002) for the U.S. and discussed in light of recent advances in literature. The reason I take taxation of imputed rents and mortgage interest deduction as two main factors is because unlike the U.S., Germany does not currently employ those tax policies to improve homeownership.

A recent work by Kaas et al. (2021) is closely related to my work. It analyzes the impacts of different policy changes on the homeownership rate in Germany in a lifecycle model with uninsurable income risk, endogenous homeownership and social housing. While not considering imputed rental income, Kaas et al. (2021) focus on the reduction of the real-estate transfer tax (RETT), mortgage interest deduction and considers the elimination of the social housing sector. Moreover, while all rental housing is owned by financial institutions in Gervais (2002), in Kaas et al. (2021) homeowners can rent out housing capital, too. Additionally, Kaas et al. (2021) assumes preferences to be risk dependent and varying by age. Bequests are distributed randomly. Nevertheless, for simplicity I use the more basic approach

[1] Gervais (2002) has been refined, among others, by Chambers et al. (2009), Floetotto et al. (2016) and Sommer and Sullivan (2018)

by Gervais (2002) and focus on two tax policies that have potentially high distortionary impact on tenure choice: the deductibility of mortgage interest payments and tax exemption of imputed rental income.

I study the German economy as there are three salient macroeconomic facts for Germany. First, mean net value of homeowners' main residence makes up 38 percent of total net wealth in 2013 (Mathä et al., 2017).[2] With mean contributions of housing capital to total net wealth in euro area countries of 30 percent (Cyprus) - 74 percent (Solvakia), Germany ranks second lowest (Mathä et al., 2017). Second, with 44 percent Germany's homeownership rate ranks lowest of all euro area countries in 2013 and at the bottom end among developed countries. Using the Eurosystem Household Finance and Consumption Survey 2013, Mathä et al. (2017) reveal variations in homeownership rates between 44 percent (Germany) - 90 percent (Slovakia). Third, since 1995, the German government promoted homeownership either via lump-sum subsidies or not at all: The two subsidies are i) the first time homeowners with children promoting "Baukindergeld", in place since 2018 and ii) the "Eigenheimzulage" (EZ) (1995-2005)[3].

The given facts suggest that the German tax code does not favor owner-occupiers (only implicitly by not taxing imputed rents) and the share of housing capital in total net wealth in Germany is smaller compared to other countries in the Euro zone. Nevertheless, housing with its twofold characteristics as consumption as well as investment good, represents the largest asset of most households' portfolio. The corresponding mortgages on the other hand make up most of households liabilities. Thus, housing market policies may not only have considerably large effects on households' investment and consumption behavior but also on real economic activity and financial markets. A combination of a relatively low percentage of housing capital stock with a low homeownership rate for Germany sheds further light on the feasible effects of different tax policies on the homeownership rate and positive effects that relate to homeowners compared to renters. In contrast to the U.S. and European countries, such as the Netherlands and Belgium, German homeowners cannot deduct their mortgage interest payments. However, housing capital is indirectly treated preferential in Germany as imputed rents[4] are not taxed. Thus, the main difference to the U.S. tax code is that mortgage interest payments are not deductible in Germany.

Distortions gauged by preferential treatment of owner-occupied housing through the tax code are widely discussed in literature. On the one hand, Poterba and Sinai (2008), Rosen (1979a), Rosen (1985) and Albouy and Hanson (2014), among others, use the partial equilibrium user cost approach to study the impact of mortgage interest deductibility and other tax subsidies to homeowners on income tax liabilities and the user cost of owner-occupied housing. This literature finds that undertaxation of owner-occupiers results in a substantial amount of foregone tax revenues, reduces the user cost of housing compared to a neutral tax system and as a consequence leads to overconsumption of housing services. On

[2]Schmalwasser and Schidlowski (2006) suggest that housing capital makes up 47 percent of the total capital stock in 2006. For the U.S., (Gervais, 2002) reports a share of housing capital in total capital of 55 percent. According to (Harding et al., 2007), the share for the U.S. is only approximately one third.

[3]According to the KfW, the former subsidy gives families 12,000 Euro per child if the household income does not exceed 90,000 before taxes. The latter supported homebuyers with around 20,000 Euros over 8 years. Daminger and Dascher (2020) study the impact of a 12 year subsidy removal of the EZ on city shape and societal changes such as rising rents and female labor force participation.

[4]The benefit from the return on investment when owner-occupying a house instead of gaining rental income when renting it out (European Comission, 2012).

the other hand, using dynamic general equilibrium setups, one can analyze the effects on optimal household choices at the extensive margin (regarding the housing tenure choice).

Although there are numerous studies for the U.S., only a few studies examine preferential tax treatment of housing in the Euro-Area and in particular for Germany. Applying the user-cost approach, Fatica and Prammer (2018) find preferential treatment of owner-occupied housing in the Euro-Area to significantly reduce the user cost of housing leading to an excess consumption of owner-occupied housing services. Frick et al. (2010) is another work that analyzes the impact of preferential tax treatment of housing capital in Germany with focus on distributional effects. Exploiting a reform on the Real Estate Transfer Tax (RETT) in 2006, several empirical studies focus on price effects of RETT rather than the impact on homeownership rates. For example Petkova and Weichenrieder (2017) use aggregated state level data and Dolls et al. (2021) use an extensive micro-level listings dataset on housing transactions. Both find price reductions after a one percentage point increase in the RETT. Petkova and Weichenrieder (2017) in addition find a negative effect on the amount of transactions of single-family housing.

The framework by Gervais (2002) allows one to study the impacts on individuals' behavior as well as on the composition of the aggregate capital stock, long run welfare and distributional consequences for the German economy. The model explicitly focuses on the relationship between tenure choice and tax code, which one can interpret as the main channel of distorting individual decisions.[5] Similar to Gervais (2002), I conduct two experiments with different tax policies. First, I introduce mortgage interest deductibility in addition to the tax exemption of imputed rental income and second, I allow imputed rents to be taxed at the same rate as labor income. This procedure delivers several important implications. When owning is preferred over renting, individuals are induced to faster accumulate wealth in their first periods of life. This is done by individuals to meet the downpayment requirements and minimum housing size constraints as soon as possible in order to purchase a house. In the model, this is the case when imputed rents are taxed at a lower rate than other sources of income. Additionally, if mortgage interest payments are not fully deductible then equity is strictly preferred to debt. Contrary, when they are fully deductible, both equity and debt are equivalent and as a result reinforce the over-accumulation of housing capital in the presence of untaxed imputed rents. These results are taken into account by individuals when taking their tenure decision. From the welfare perspective, over-accumulating wealth in early stages of life induces individuals to experience welfare losses as smooth consumption profiles are preferred, while taxing imputed rental income leads to substantial welfare gains in the long run.

The remainder of this chapter consists of five sections. Section 4.2 describes the specific characteristics of the German housing market and the fiscal policy interventions considered in the chapter. Section 4.3 introduces the key implications of the model by Gervais (2002). Section 4.4 describes the calibration of the benchmark economy and the behavior of individuals in the baseline economy. Section 4.5 analyses different tax codes with more or less

[5] Although more recently authors have endogenized house prices and rents (Chambers et al. (2009); Díaz and Luengo-Prado (2008)), introduced progressive income taxation (Sommer and Sullivan, 2018), and specifically analyzed the transitional dynamics from one tax code to another (Floetotto et al., 2016), Gervais (2002) approach enables through its simplicity to focus on the most important distortion channel - the tenure decision - modeled by a minimum downpayment constraint on purchases of imperfectly divisible housing capital.

favorable treatment of owner-occupied housing and Section 4.6 concludes.

4.2 Housing Market Policies

Numerous policy interventions aim towards promoting homeownership by creating a gap between the relative cost of owner-occupied housing and renting. This section describes fundamental differences of the German residential market compared to other European countries' residential markets as potential reasons for the low homeownership rate. I then discuss permanent government interventions into the housing market through the tax code: Mortgage interest deduction and the tax exemption of imputed rents of owner-occupied housing.

4.2.1 Why is the German homeownership rate so low?

Figure 4.1 displays the well known fact that Germany's homeownership rate is with around 50 percent at the bottom end of international rankings. Homeownership rates are seen as an indicator for the level of wealth and a basis for investment decisions (Voigtländer, 2009).

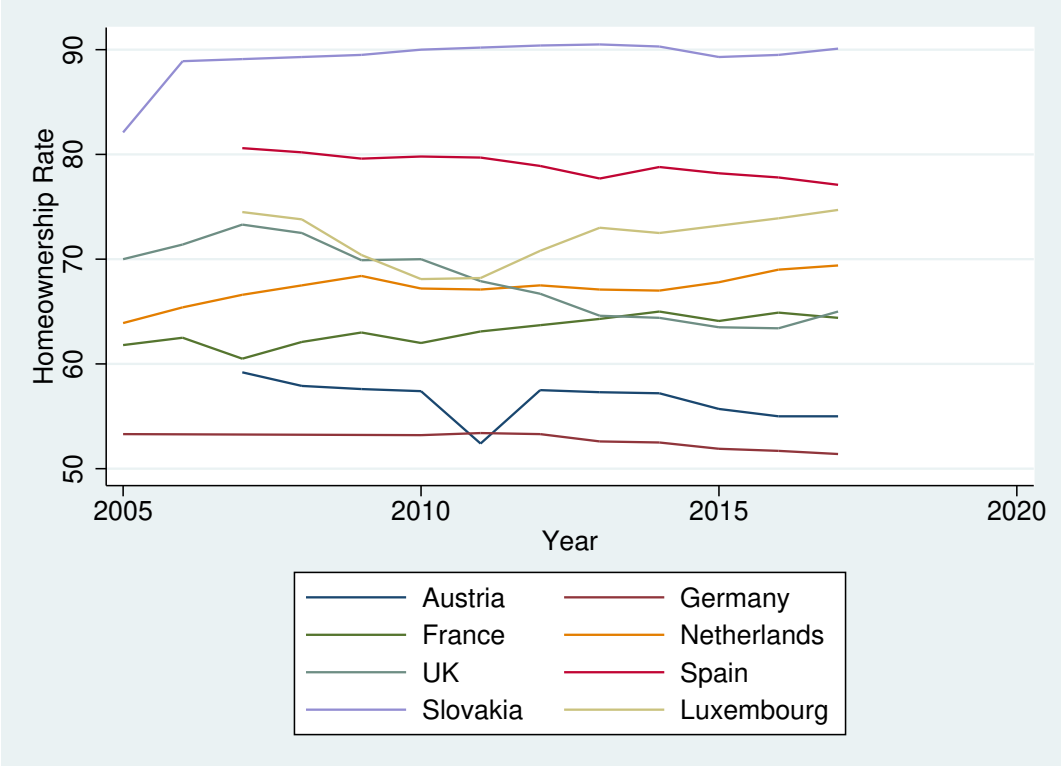


Figure 4.1: Homeownership rates - selected European Countries (Source: Eurostat)

However comparing price-to-income ratios (in Figure 4.2) as an indicator for the affordability of housing and the GDP per capita (in Table 4.1) as a measure of wealth of different European countries, Germany ranks at the higher end of the distribution. Thus, taking the homeownership rate as an indicator for wealth appears to be misleading in the German case.

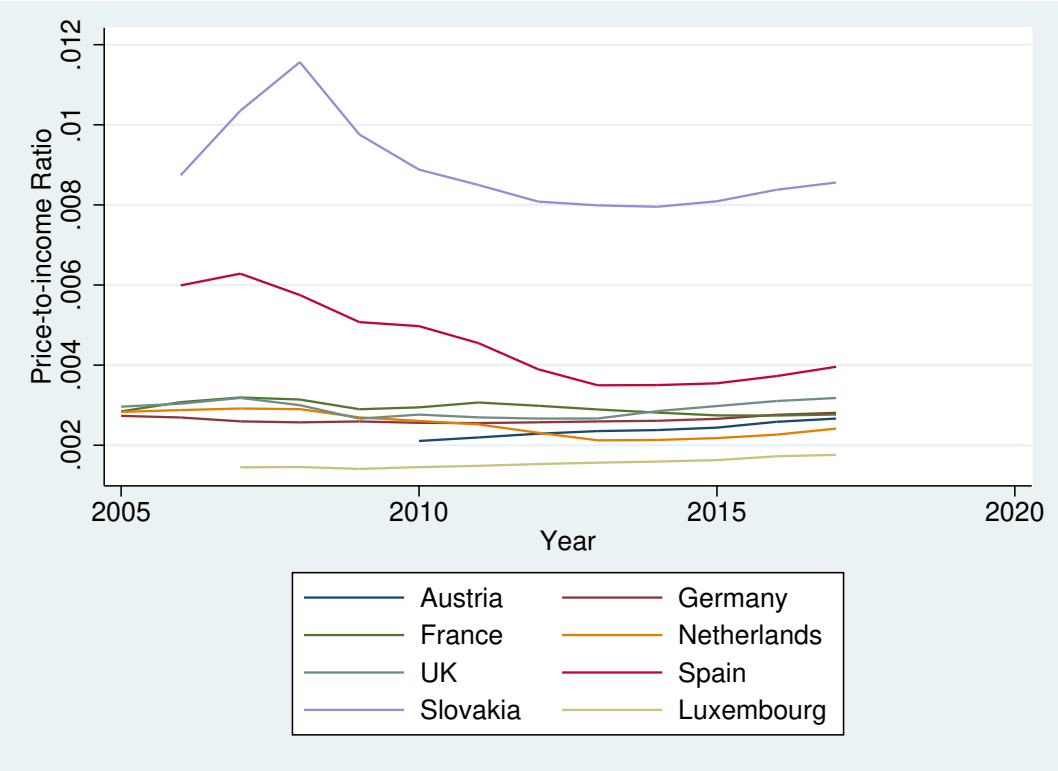


Figure 4.2: Price-to-income ratios - selected European countries (Sources: OECD, Eurostat)

Country	GDP per capita [6]	Average annual wages[7]
Austria	113	50,349
France	97	43,755
Germany	113	47,585
Luxembourg	223	63,062
Netherlands	122	52,877
Slovak Republic	77	24,328
Spain	86	38,507
UK	101	43,732
US	137	60,558

Table 4.1: GDP (Source: OECD)

What are potential institutional and policy factors that hold Germany's homeownership rate low in contrast to those of the U.S. and several countries of the euro zone? First, although imputed rents are not taxed, the tax benefits of homeowners in Germany are less favorable than in neighboring European countries as mortgage interest is not tax deductible for owner-occupiers. Second, the extensive social housing sector with broad eligibility requirements accounts for a large portion of the housing stock. Third, Germany's high real estate transfer tax ranging between $3-5$ percent may provoke high barriers towards homeownership and low turnover rates (Voigtländer, 2009; Kaas et al., 2021).

This chapter focuses on the first potential factor for a low German homeownership rate: The absence of mortgage interest deduction (MID). In addition, it explores the effects of taxing imputed rents that are currently exempt from taxation.

[6] Index using the price levels and PPPs of 2010
[7] In 2017 constant prices at 2017 USD PPPs

4.2.2 Tax regime and alternatives

The two tax policies in the housing market that are believed to be important for influencing individuals' tenure decisions are: MID and the tax exemption of imputed rents of owner-occupied housing. Housing capital can be seen either as a form of investment good or as a consumption good. Landlords investing into housing capital pay taxes on the income received from rents. In contrast, the implicit income or the rents saved by owner-occupiers are not taxed. As landlords usually pass on their expenditures to their tenants, this creates a bias towards homeownership compared to renting (Voigtländer (2009); Floetotto et al. (2016)). As mentioned previously, the German tax code is less advantageous for homeowners compared to other countries. Important implications of the model to analyze whether a more favorable tax treatment of owner-occupied housing would help to increase German homeownership are outlined in the next section.

4.3 Model

I build on the life-cycle housing tenure choice model with tax frictions by Gervais (2002). As the model itself is not new it is outlined for expositional purpose in the Appendix. However, before I introduce some key implications of the model by Gervais (2002) framework below, I want to be upfront about three apparent shortcomings of the model. First, it does not model progressive income taxation. Second, it calibrates the same tax rate for income and capital. Third, it normalizes house prices. Although more recently authors have endogenized house prices and rents (Chambers et al. (2009); Díaz and Luengo-Prado (2008)), introduced progressive income taxation (Sommer and Sullivan, 2018), and specifically analyzed the transitional dynamics from one tax code to another (Floetotto et al., 2016), Gervais (2002) approach enables through its simplicity to focus on the most important distortion channel - the tenure decision - modeled by a minimum downpayment constraint on purchases of imperfectly divisible housing capital.

4.3.1 Housing tax provisions and benefits from homeownership

The link between tax code and the tenure decision as well as the financing decision of an individual is clarified below. The tenure and financing decision is self-evident when savings of the individual are not large enough to fulfill the downpayment constraint. On the other hand, when savings are sufficient then both the minimum housing size and downpayment constraint (Equations (4.13) and (4.14)) are not binding. In this case a household prefers owning over renting, provided that the taxation of imputed rents is lower than the tax rate on other sources of capital income.

Tenure and financing decisions

Consider an individual with savings large enough to have the choice between owning and renting a home. Define h for now as the size of the home an individual would rent. The question now is to specify the benefit or cost an individual would face owner-occupying the same house. Given today's and tomorrow's net worth, the decision to become a homeowner increases the amount of owner-occupied housing by h units. This as a consequence increases

the (implicit) capital income of the individual by $(1-\tau_{ir})(p-\delta_h)h$, where τ_{ir} is the tax rate on imputed rents, p is the price of one unit of housing services in terms of consumption and δ_h is the deprectiation rate of housing capital. For the case that housing can not be financed exclusively by the individual's net worth one has to pay mortgage interests net of deductibility accounting to $(1-\tau_y\tau_m)ib$, where τ_y is the tax rate on labor income and the return on financial assets, τ_m represents the deductible fraction of mortage interest payments from taxable income. Interest rate and amount of mortgage are denoted by i and b, respectively. But also the opportunity costs of housing investment have to be considered. Those correspond to the after-tax return on investment in financial assets of $(h-b)$ units, which is stated as $(1-\tau_y)i(h-b)$.
Accordingly, after transformations and using the no-arbitrage constraint (Equation (4.19)), the net benefit from homeownership is given by

$$\pi(h,b;\omega) = \underbrace{[(1-\tau_{ir})ih-(1-\tau_y)ih]}_{\text{asset benefit}} - \underbrace{[(1-\tau_y\tau_m)ib-(1-\tau_y)ib]}_{\text{borrowing benefit/penalty}} \tag{4.1}$$

where $\omega \in \Omega$ denotes a given policy arrangement.
The net benefit from owner-occupied housing is referred to as the asset benefit minus the borrowing penalty/benefit, whereby the asset benefit equals the opportunity cost of holding the asset subtracted from the implicit rental income from homeownership. This is the tax saving due to investing in housing instead of other financial assets. Obviously this is higher than zero as long as the tax rate on imputed rental income is lower than that on other income. The borrowing penalty is defined as the cost of the mortgage minus the opportunity cost of borrowing. Provided that mortgage interest is not fully deductible there is a borrowing penalty. Writing the penalty as $\tau_y(1-\tau_m)ib$ it is clear that the penalty would be zero in case of full mortgage interest deductibility ($\tau_m = 1$).
Under consideration of the definition of the equity fraction of the house as $\phi \equiv (h-b)/h$, another way of writing the net benefit of homeownership is

$$\pi(h,b;\omega) = [(\tau_y\tau_m - \tau_{ir}) + \phi\tau_y(1-\tau_m)]ih. \tag{4.2}$$

Due to the restriction of the level of mortgage interest deductibility, the first term is positive when taxation of implicit rental income is lower than that of other kinds of income. As before, the second term is strictly positive except when $\tau_m = 1$. As a result, it can be noted that households with an adequate amount of savings strictly prefer owning over renting if $\tau_y > \tau_{ir}$. A second result can be derived from Equation (4.2). A higher equity fraction leads to more net benefit from owner occupied housing. This strictly increasing relationship leads to the fact that individuals that can overcome the downpayment constraint strictly prefer equity to debt. This is only the case when mortgage interest is not fully deductible, since otherwise ,if $\tau_m = 1$, equity is equivalent to debt. In the latter case, the benefit per unit of owner-occupied housing is the same for more and less wealthy households. This is the way in which deductibility of mortgage interest payments shows distributional effects. Further, this leads to the conclusion that the lack of taxation of imputed rents is the driving factor in explaining the rate of homeowners (Gervais, 2002).

Savings decision

Individuals have the possibility to increase their rate of return after taxation through investing in housing capital, only when the tax rate makes households prefer owning over renting. In this case, there is a wedge between the rates of return on housing capital and other financial assets. For a given h and b the return on savings is specified as

$$R(y;h,b) = \frac{(1-\tau_{ir})ih + (1-\tau_y)ia - (1-\tau_y\tau_m)ib}{y}, \tag{4.3}$$

where a is the amount invested in financial assets and net worth y is defined as $a+h-b$. Specifying $\tau_{ir} = 0$ and $\tau_m > 0$, individuals strongly tend to accumulate wealth as well as shifting more consumption to future periods in order to meet the downpayment constraint and receive the benefit from higher returns on housing capital. Furthermore, the preferential tax treatment of housing capital causes individuals to overconsume housing capital. From Equation (4.3), it is obvious that this is the case when $\tau_{ir} < \tau_y$. Then the rate of return on savings is increasing in h.
An important finding is that by eliminating the deductibility of mortgage interest the difference between the two rates of return is significantly reduced.

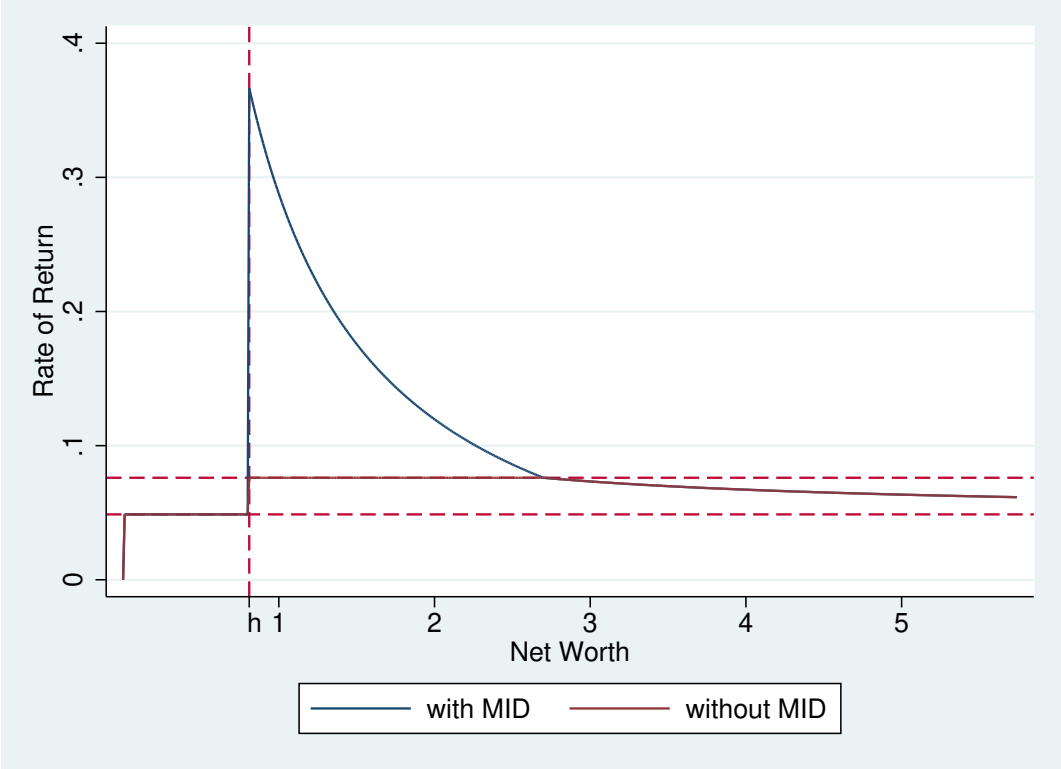


Figure 4.3: Rate of return on savings when $\tau_{ir} = 0$, with and without mortgage interest deductibility

In Figure 4.3 an optimal size of mortgage is assumed, which is minimal in the case with no mortgage interest deductibility (see second result in Section 4.3.1). As a result of this, individuals do not invest in financial assets as long as they are not free of debt. This leads to three stages in the return on savings: As long as savings are not sufficient to meet the

downpayment constraint only financial assets are hold. After purchasing a house until the point when net worth is bigger than the house value, the rate of return on savings equals the interest rate i (housing equity is not taxed in this case). During the last stage the rate of return is a weighted average of both the return on housing and financial assets (Gervais, 2002).

4.4 Calibrating a Benchmark Model for Germany

This section illustrates the calibration of model parameters to the German economy and compares the results to those from Gervais (2002) for the U.S.[8] The calibrated parameters are given in Table 4.2.

Preferences	β	0.99
	θ	0.35
Technology	A	1.0172
	α	0.37
	$\underline{h}$	2.75
	$\underline{s}$	2.5
	δ_k	0.1
	δ_h	0.04
Tax system	τ_y	0.359
	τ_m	0
	τ_{ir}	0
Downpayment	γ	0.3

Table 4.2: Model parameters for the German economy

4.4.1 Demographics and labor income distribution

Identical to Gervais (2002), in the replicated model for Germany one period corresponds to one full year of an individuals lifetime. Furthermore, it is assumed that an individual lives for J=52 model periods. The retirement age in Germany is between 63 and 65 years[9]. Therefore, model period 41, corresponding to 64 years in reality, represents the retirement age. A new generation is assumed to be born in real-life at age 24, which corresponds to model period one and is expected to die at age 75, which corresponds to model period 52. Survey data from the SOEP (2019) from the German Institute for Economic Research (DIW) is used to generate the labor income distribution for the five representative individuals. For this, the mean labor income of males for each labor income quintile at each age is calculated and normalized such that average income is equal to 1[10].

[8] Following Gervais (2002), numerical solving methods are applied to solve for a competitive equilibrium as defined in the Appendix. For the model implementation in MATLAB I used the Fortran code file (Gervais, 1999a) and the solution algorithm (Gervais, 1999b) that correspond to Gervais (2002).

[9] Starting 2012 until 2029 the retirement age is raised gradually from 65 to 67 or 63 to 65 depending on length and type of employment. Early entry into retirement is possible with deductions on the state pension (Deutsche Rentenversicherung, 2021).

[10] I use annual individual labor earnings data from the years 2000-2015. First, I only use males with a positive labor income. Second, the remaining observations are sorted according to the variable age, earnings are adjusted for inflation by the CPI (Consumer Price Index) of the corresponding survey year and after that, earnings are assigned to the corresponding income quintiles for each age. In the last step, the mean labor income for each quintile at each age is built and normalized.

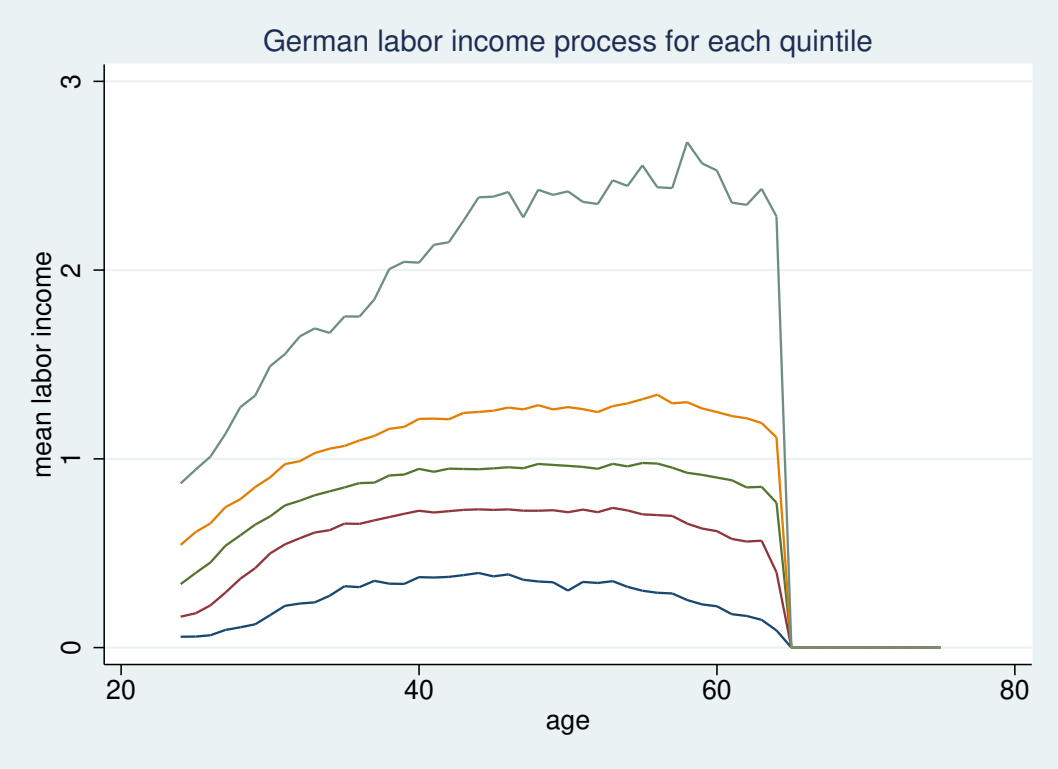


Figure 4.4: German labor income process for each quintile (SOEP v.34)

The (normalized) labor income profiles for five representative individuals (income quintiles) are shown in Figure 4.4. The German labor income distribution shows that the profiles for each quintile increases over life time until 5-10 years before retirement.[11]

4.4.2 Preferences

In line with Gervais (2002), the discount factor is calibrated such that the capital-output ratio equals 3.2, the target value from the data (Derbyshire et al., 2013). The resulting value of 0.99 for β coincides with Kaas et al. (2021) and Gadatsch et al. (2016).
θ represents the share of housing services in total expenditures. I set this parameter to reproduce a share of housing capital in total capital of around 47 percent (Schmalwasser and Schidlowski, 2006) in the benchmark model. In contrast to Gervais (2002), consumer durables will not be included into housing capital, since neither mortgage interest on housing nor mortgage interest on consumer durables are deductible from taxable income in Germany (Federal Ministry of Finance, 2019b). Therefore, I believe that Gervais' justification that households take out bigger loans to finance their consumer durables as in the U.S. is not applicable to Germany. The resulting share of housing in total consumption expenditures, θ, of 35 percent matches with the share of housing in consumption expenditures on living, energy and maintenance from 2010-2015 according to data from the German Federal Statistical Office (German Federal Statistical Office (Destatis), 2018).

[11] One could also include pension subsidies and other forms of income after retirement.

4.4.3 Downpayment

In line with (Gervais, 2002), I calibrate the downpayment fraction by means of average Loan-to-Value Ratios (LTV) instead of targeting the LTV in the model. In Germany there is no regulatory maximum on the LTV ratio. Geiger et al. (2016) report that the LTVs in Germany are on average around 70 percent. Thus, I set the downpayment fraction of 30 percent in the benchmark model to meet the average LTV. This downpayment fraction coincides with suggested downpayment ratios (20-30%) of various German banks.

4.4.4 Technology

The section describes the calibration of the technology parameters $A, \alpha, \underline{h}, \underline{s}, \delta_h$ and δ_k.

δ_h is calibrated by Gervais (2002) as the weighted average of the depreciation rate of housing and consumer durables. To be consistent in the definition of housing capital the consumer durables will be excluded for Germany (Section 4.4.2). The depreciation rate for housing capital, i.e. residential capital in this case, is calibrated following Kollmann et al. (2015)[12]. It follows a depreciation rate of 0.04 p.a. for housing capital.

Gervais (2002) calculates a weighted average of the depreciation of business structures and producer durables to calibrate δ_k. Due to a lack of appropriate data on the depreciation of capital for Germany, δ_k is set according to values used in existing research. According to the calibration of Pariès and Notarpietro (2008) and Kollmann et al. (2015)[13], the depreciation rate of business capital δ_k is set equal to 0.1.

I calibrate the minimum housing sizes for owning and renting to pin down the homeownership rate of Germany. Niehues and Voigtländer (2016) state that since 2010 the homeownership rate is roughly constant at 45 percent. Other sources suggest a homeownership rate for Germany of slightly over 51 percent in 2015 (Eurostat, 2017b). Therefore, the minimum housing sizes are calibrated in order to replicate an ownership rate of around 48 percent, which is the average of the two prevalent values.

The capital share in production is α. As the model assumes constant returns to scale, the production elasticity of the second input factor (L) denotes to $1-\alpha$. For Germany and under the assumptions of constant returns to scale, α thus can be calculated over the labor share (Havik et al., 2014). I calculate the labor share according to Meyer and Meyer (1994) as

$$LS = Comp \cdot \frac{ET}{EE} \cdot (VA), \tag{4.4}$$

where $Comp$ denotes the compensation of employees, ET the total employment, EE total employees and VA represents value added at current prices. Using OECD data from 2008-2016 from OECD (2017), I calculated a labor share of 0.63 and a resulting capital share of 0.37, which are the same values as in Havik et al. (2014). Therefore, α for Germany is set equal to 0.37.

Lastly, according to Gervais (2002) the technology level is calibrated in order to receive a wage rate at unity and to replicate the capital-output ratio found in the data. Derbyshire et al. (2013) find a capital-output ratio of 3.2 both for 1995 and 2002. Thus, I adjust A in order to approximate a capital-output ratio of 3.2.

[12] Where the quarterly depreciation rate for housing capital is set equal to 0.01.
[13] They calibrate on the base of quarterly data, therefore the depreciation rate has to be annualized.

4.4.5 Tax system

In the German taxation system, housing capital is not treated as preferential as in the U.S.. Mortgage interest payments from mortgages, which are secured against owner-occupied housing are not deductible from taxable income. Conversely, mortgage interest payments secured against residential capital, which is rented out, are deductible. But the latter is not considered within the model. Identical to the U.S. tax system, imputed rents are not taxed (European Comission, 2012; Johannesson-Linden and Gayer, 2012; Federal Ministry of Finance, 2019b). Hence, in the benchmark model $\tau_m = 0$ and $\tau_{ir} = 0$.

The income tax rate τ_y is a proportional tax rate on labor income and the return on financial assets. The tax rate for income is calibrated according to Drygalla (2016), who calculated the tax rates for labor and capital according to Mendoza et al. (1994). The method of Mendoza et al. (1994) uses national account data and actual tax payments to calculate effective tax rates for macroeconomic models. An advantage compared to other calibration methods is the consideration of social security contributions as a form of income taxation in Mendoza et al. (1994). This is important as both taxes on wages and salaries as well as social security contributions constitute to the labor income tax in Germany.

However, Drygalla (2016) and Mendoza et al. (1994) calibrate separate tax rates for labor and capital income. In order to receive a combined tax rate for both capital income and labor income as in Gervais (2002), I proportionally combined the tax rates for capital and labor from Drygalla (2016) using data from the German Federal Statistical Office on disposable income from 1999 to 2012 (Statistisches Bundesamt (Destatis), 2017). I calculate the shares of taxable capital income and taxable labor income in total taxable income to multiply each share with the corresponding tax rate. This procedure results in a tax rate τ_y of 0.359.

4.5 Results

4.5.1 Behavior in the benchmark model

The behavior of individuals in the benchmark model can be split into three groups of individuals. The upper class consisting only of quintile five, the middle class (quintiles 2-4) and the poorest income quintile. The poorest consume the smallest possible amount of housing services over their whole lifetime and thus never own a home. The lower middle class individuals start consuming the minimum amount of housing services in combination with a low consumption level of the composite good. Thus, they can save enough to become a homeowner at some point. At this point individuals are constrained by the minimum housing size. Therefore they move into the smallest possible house. Getting wealthier over the years, at least the richer individuals of the middle class move into bigger houses. Also the consumption of the upper class individuals is constrained when they are young. But unlike the individuals belonging to the middle class, upper class individuals are not constrained by the minimum size of housing services. As they can afford the downpayment after a few years, they first move into the largest house they can afford. As a result of getting wealthier during the next years, they are neither constrained by the minimum housing size nor the downpayment constraint. Thus, they increase both consumption and the size of the house

they live in.

However, there are some differences in the outcomes for the U.S. generated by Gervais (2002). First, the tenure decision of purchasing a house is shifted backwards a few periods. Second, individuals tend to finance their home often without a mortgage and third, individuals in the poorest income quintile tend to consume non-positive amounts of the composite good in the first periods. The presumably main reason for outcomes one and two are the relatively high calibrated minimum housing sizes in order to replicate the low ownership rate of Germany. The calibration of the minimum housing sizes to target the owner-occupancy rate may be seen as a shortcoming of the model. Nevertheless, I think it is a good way to account for the indivisibility of housing. It appears that the purchase of houses by individuals is shifted backwards several years to replicate the lower homeownership rate in contrast to the U.S. economy. According to Kaas et al. (2021) this trend is partially consistent with the fact that in Germany households become homeowners later in the life-cycle. There is evidence that the homeownership in Germany increases between ages of below 35 and 66-75 around twice as much as in other comparable European countries (Kaas et al., 2021). This coincides with a lower loan-to-value ratio for the German economy in this model. Households accumulate net worth over a longer time and thus may need a smaller mortgage to finance their home. A second reason is that, according to the German tax code, in the benchmark model for Germany mortgage interest payments are not deductible from taxable income. From result 2 in Section 4.3.1, one knows that equity is strictly preferred to debt. This in combination with the delayed tenure decision induces a smaller fraction of individuals to mortgage finance their home. The third outcome can be supported by the non-convexity gauged by minimum housing size constraints and tenure decision and does not, as one might think, reflect the behavior of non-maximizing individuals. As explained above the minimum size of housing services is higher for Germany. Since individuals need to consume at least the minimum amount of housing services individuals of the poorest income quintile behave optimal in the form that they consume the smallest amount of rented housing services possible. In order to be able to afford this amount in the current as well as in the following period, they need to save net worth for the following period and tend to consume a negative amount of the composite good until they get more productive and wealthier.

I would like to discuss further implications regarding the behavior in the benchmark model. Assets are accumulated by all individuals during their productive years in order to use them up for consumption during retirement period. Also, some individuals switch back to debt finance their house instead of holding the whole asset as equity, to ensure consumption of goods and housing services in the very last periods of their life. This coincides with the findings of Gervais (2002). As induced by the model itself, individuals do not hold financial assets while paying back their mortgage. The model is such that all individuals die with zero net worth with certainty.

Walras' law is satisfied for a tolerance level of 1E-5 and for a tolerance level of 1E-3 when negative consumption is eliminated, i.e. that negative consumption is set equal to zero before calculating the aggregate quantities. The business capital market is cleared at a tolerance level of 1E-6. The budget constraint is approximately zero for all individuals at all ages.

	Benchmark model	Experiment 1 ($\tau_m = 1$)	Experiment 2 ($\tau_{ir} = \tau_y$)
Quantities			
Total Output (Y)	1.221	1.215	1.276
Total capital	4.948	4.906	4.938
Business capital (K)	2.564	2.528	2.883
Total housing	2.384	2.378	2.055
Owner housing (H)	1.807	1.814	0.000
Rental housing (H^f)	0.577	0.563	2.055
Relative quantities			
Total capital/Y	3.301	3.281	3.316
K/(total capital)	0.518	0.515	0.584
$H/(H + H^f)$	0.758	0.763	0.000
G/Y	0.243	0.244	0.245
$(C + pX)/Y$	0.378	0.378	0.402
$pX/(pX + C)$	0.353	0.357	0.282
Prices			
i(%)	7.626	7.784	6.373
w	1.000	0.995	1.045
P	0.116	0.118	0.104
Homeownership rate	0.481	0.488	[0.0;0.0]
Income tax rate (τ_y)	0.359	0.362	0.326

Table 4.3: Statistics for the three tax codes

4.5.2 Experiments

To study the impact of the two existing forms of preferential tax treatment of housing in Germany, two revenue-neutral experiments are conducted. Revenue-neutral in this context means the assumption of constant remaining government expenditures, which are financed by the tax revenues even if fiscal policy is changing.

Following Gervais (2002), a welfare measure is specified in order to compare different fiscal policy arrangements. Usually an individual's welfare is defined as the lifetime utility, which is denoted by

$$W(\omega) \equiv \sum_{j=1}^{J} \beta^{j-1} u(c_j, x_j) \tag{4.5}$$

for a given fiscal policy $\omega \in \Omega$.

The difference in welfare between two different policies is denoted as κ. This is the value of consumption, as percentage of average lifetime consumption $\bar{c}$, that needs to be handed to a new born individual as compensation in every period of life, ensuring that it is indifferent between two policies. Thus, κ is defined such that

$$W(\omega_1) = W(\omega_2, \kappa) = \sum_{j=1}^{J} \beta^{j-1} u(c_j + \kappa\bar{c}, x_j). \tag{4.6}$$

One then has to search for the average lifetime consumption in the benchmark model that would be required as compensation to make the individual indifferent between the tax code in the experiment and the benchmark model. Below, Experiment 1 introduces mortgage

interest deductibility and Experiment 2 removes all policy interventions that support preferential tax treatment of owner-occupied housing.

Experiment 1 - Introducing mortgage interest deductibility

In order to simulate the introduction of mortgage interest deductibility τ_m is set equal to 1. To maintain revenue neutrality, the income tax rate (τ_y) is adjusted to 0.3624.

Aggregate quantities: Overall, the introduction of mortgage interest deductibility has small distributional consequences. The deductibility of mortgage interest has no significant impact on the amount of housing capital. However, the relative advantage of owner-occupied housing has increased even more provided that downpayment and minimum housing size constraints do not bind. The difference between the rates of return on housing capital and other financial assets has also increased. As a result, the wedge in the rates of return on owner-occupied and rental housing increases the owner-occupied housing stock at the expense of a lower amount of rental housing capital. The homeownership rate increases by 0.7 percentage points.
The wedge influences households behavior in two ways, causing the homeownership rate to increase. First, households (especially those in the high income quintiles) ensure to meet the downpayment constraint earlier in life by reducing consumption of goods and housing services as well as by accumulating wealth more quickly. Second, individuals increase their debt financing, which in turn enables them to have higher consumption levels after buying a home as well as to buy larger houses. The average loan-to-value ratio increases by 31 percent from 3.82 percent to 5.55 percent. However, from Section 4.3.1 one knows that equity is equivalent to debt in this case.[14] Furthermore, the business capital stock decreases. And as one would expect the interest rate increases, since to maintain revenue neutrality the income tax rate has to be lifted, which creates a lower desire to save as disposable income shrinks.

While given the issues discussed in Section 4.5 the effects are significantly smaller in size the directions of the results are comparable to those found by Gervais (2002) for the U.S. economy.

Welfare effects: The welfare results for Experiment 1 are presented in Table 4.4 for each income quintile. The table shows the compensation in percent of the individuals average lifetime consumption in the benchmark model per period that would make the individual indifferent between the two tax codes. For Experiment 1 the results imply that consumption in the benchmark model could be lowered by on average 0.36 percent.[15] Thus, there are welfare losses due to introduction of mortgage interest deductibility. While the homeownership rate is increased, all income quintiles would nevertheless prefer to live in an economy without mortgage interest deduction. This results from the desire of individuals to smooth their consumption profile over life-time. In conclusion, incentivised by the introduction of MID, welfare losses occur as a consequence of over-accumulation of net worth to faster overcome the constraints towards homeownership.

[14] In Experiment 1 (with mortgage interest deductibility) individuals are indifferent between mortgage and equity. Thus the loan-to-value ratio is not well defined. The ratio is calculated under the assumption that individuals pay back their entire mortgage before they invest in financial assets again.

[15] Following Gervais (2002) this number is calculated by dividing the average compensation by the average life-time consumption.

	Consumption Compensation (%)
First quintile	0
Second quintile	0
Third quintile	-0.42
Fourth quintile	-0.36
Fifth quintile	-0.13

Table 4.4: Welfare effects Experiment 1 (Germany)

Distributional Consequences: Re-distributional effects can expected to be small given that a tax code without mortgage interest deductibility is preferred. Supporting the small re-distributional effects, the wealth GINI coefficient, a measure for wealth concentration, decreases by less than one percent from the Benchmark model to Experiment 1 (41.67 to 41.63 percent).

Experiment 2 - Taxing imputed rents

The second experiment evaluates the effects of removing all preferential tax treatment of owner-occupied housing. For this, the tax rate on imputed rental income is set equal to the income tax rate ($\tau_y = \tau_{ir}$). Both tax rates are adjusted to maintain revenue neutrality. The rate of mortgage interest deduction has to be set equal to 1. Otherwise individuals would not receive normal deduction.[16]

Aggregate quantities: From Table 4.3, one can see a crowding out effect from housing capital towards business capital due to the preferential tax treatment of housing compared to the benchmark model and Experiment 1. As in Experiment 2 no individual prefers owning strictly over renting, the ownership rate is not well defined. One can assume that every individual that is indifferent between owning and renting decides to own. Then, the homeownership rate remains zero for Experiment 2. This would suggest that homeowners in Germany own because of the tax code. Whether this is a meaningful result is left for discussion. Although this result is probably caused in part by the problems mentioned in Section 4.5, one can expect a significant number of homeowners to own because of the tax code. The taxation of imputed rents lowers the income tax rate by around 10 percent and therefore individuals dispose over substantially more income. This induces individuals to save more, resulting into a lower interest rate and in turn a higher stock of business capital. An important implication from this experiment is that now the rates of return on owner-occupied housing and business capital are equalized.

Welfare effects: Welfare results for Experiment 2 are presented in Table 4.5. For the second Experiment, welfare gains are identified compared to both the benchmark model and Experiment 1. Individuals from all quintiles experience welfare gains. To be indifferent between the benchmark model and Experiment 2, a per period consumption compensation of 3.63 percent of the benchmark models' average lifetime consumption would be required[17].

[16]Normal deduction is "defined as the deduction that would result if mortgage interest payments were in fact deductible against housing capital revenues instead of other types of income." (Gervais (2002)) Therefore the inequality $\tau_m >= \tau_{ir}/\tau_y$ has to be satisfied.

[17]Again, this number is calculated by dividing the average compensation by the average life-time consumption.

	Consumption Compensation (%) vs. Benchmark	Consumption Compensation (%) vs. Experiment 1
First quintile	0.47	0.83
Second quintile	1.27	1.56
Third quintile	3.28	3.5
Fourth quintile	2.27	2.52
Fifth quintile	1.92	1.96

Table 4.5: Welfare effects Experiment 2 (Germany)

Equal taxation of all sources of income implies that rates of return are equalized for owner-occupied housing and other forms of capital. Average rates of return on savings over the lifetime are illustrated for the different models in Figure 4.5. Under Experiment 1 - under mortgage interest deductibility - and to a smaller degree under the Benchmark model, individuals have the desire to accumulate savings faster at younger ages to become homeowners and thus receive a higher rate of return on savings. However, the incentive to overconsume housing is removed in Experiment 2, when the wedge between rates of return on owner-occupied housing and other assets is eliminated.
These findings coincide with the resulting consumption profiles (Figure 4.6). The evolution of the consumption bundle for Experiment 2 remains much flatter over time than for the other settings. Also, in contrast to Experiment 1 and the Benchmark model, younger individuals consume more when imputed rents are taxed since they do not tend to give up consumption in the first years to accumulate savings. Consequently, the consumption profile is smoother both across time and consumption goods under Experiment 2.

Distributional Consequences: The GINI coefficient in Experiment 2 is 6.1 percent lower than in the benchmark model. In combination with the welfare results, this suggests that individuals rather live in a world in which wealth is less concentrated among the rich.

4.5.3 Discussion of Results

This chapter focuses on the relationship between tenure choice and tax code in a relatively simple model framework by Gervais (2002). Given the recent advances in literature on this topic the upcoming section aims to discuss some of the results in context of these advances and the underlying model's limitations.

First, the models' tax code assumes an average tax rate on income and capital instead of taking progressive income taxation into account. In light of Chambers et al. (2009)' results, I would expect the results for Germany to change in the following direction: With progressive income taxation and under the assumption of revenue neutrality, the marginal tax rate in the baseline model would be lower on average and for poorer individuals, while higher income households would likely have to pay higher taxes. On average, one would expect individuals to save less. Lower income quintiles increase savings while due to the higher tax burden high income households are forced to lower savings, housing capital and consumption of the composite good. As a result, interest rates should increase and average income decrease. In turn, this leads to a lower homeownership rate compared to an average tax rate. Moreover, one would expect the value of MID to increase with income and corresponding marginal tax

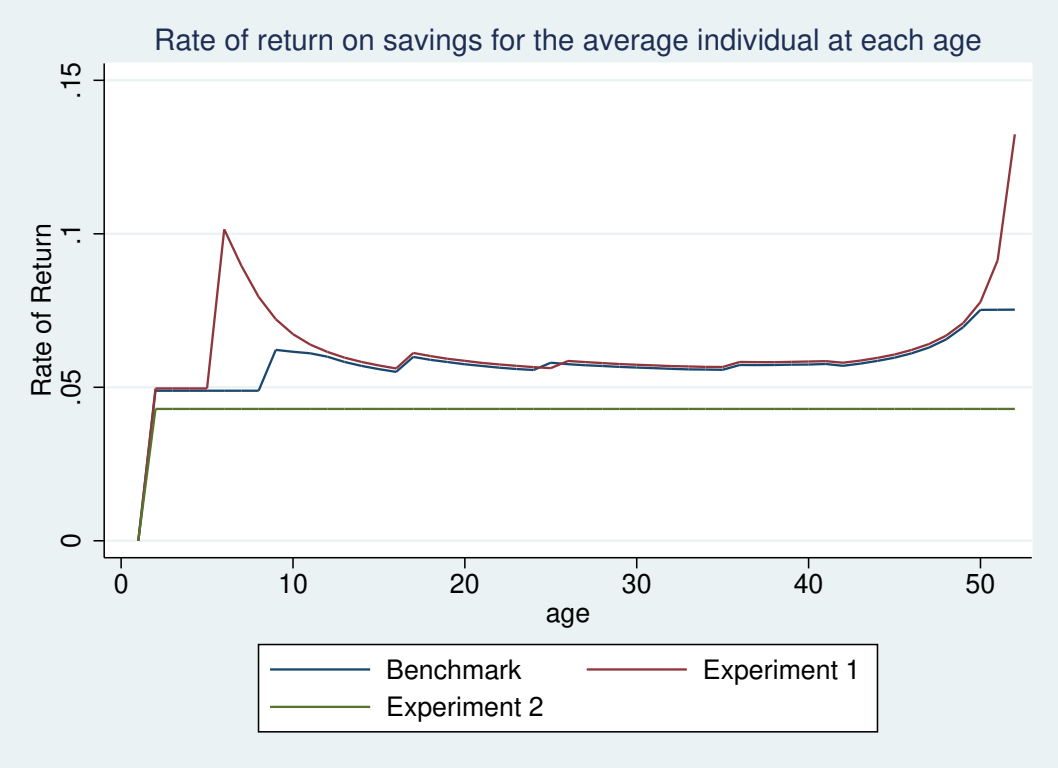


Figure 4.5: Rate of return on savings for the average individual at each age

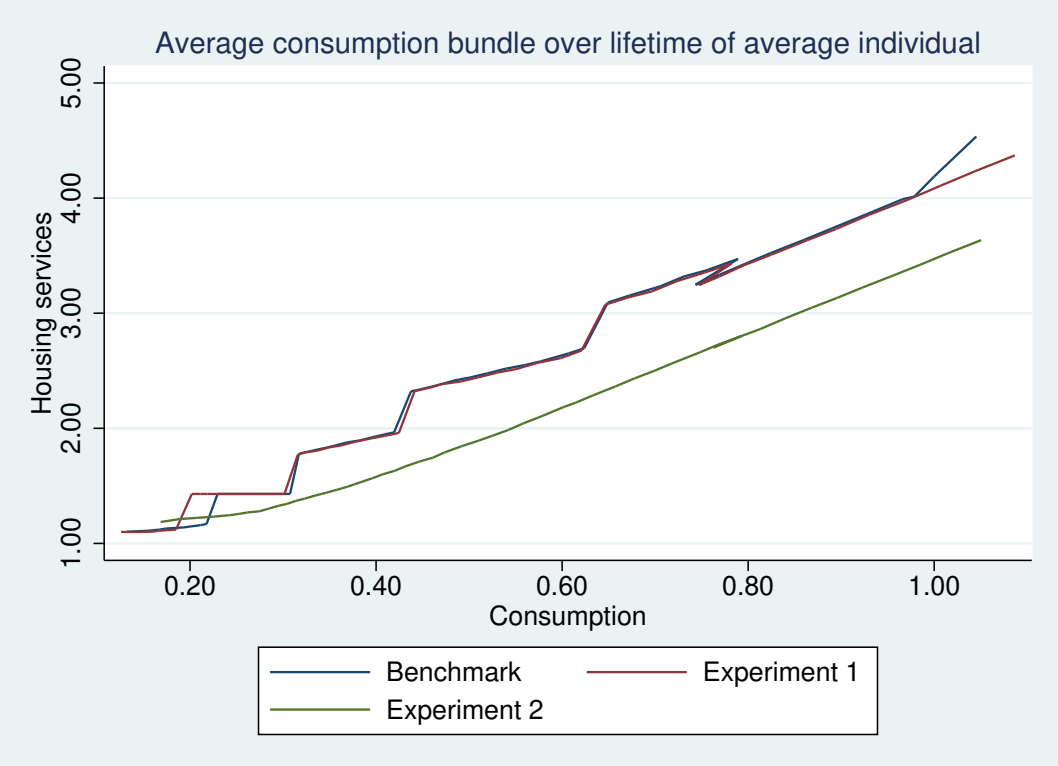


Figure 4.6: Average consumption bundle over lifetime of average individual

rates (Sommer and Sullivan, 2018). According to Chambers et al. (2009), a less progressive income taxation reduces the effects of owner-occupied housing favoring tax codes. This suggests my results to be a lower bound.

Second, all rental housing is owned by financial institutions (i.e. the corporate sector) in the model. Equation (4.19) ensures that the rental price to interest ratio is fixed. In other words, the supply of rental units is totally elastic when rental prices change. The more dampened the change in rental price the lower the reactions in the household sector. As in this case all rental income is held by financial institutions, such effects are completely muted (Chambers et al., 2009).

Lastly, I would like to discuss redistribution channels that are muted by holding house prices fixed. An introduction of MID while holding house prices fixed reduces the cost of homeownership and increases marginal tax rates. I find a slight increase in homeownership rates as a result to the reduced user cost of housing. Sommer and Sullivan (2018) allow house prices to adjust. They find an increase in homeownership after eliminating MID. Two important mechanisms after the change in tax-code are in place that this chapter abstracts from: First, falling house prices reduce downpayment requirements, which allows credit-constrained lower income households to become homeowners. Second, the lower house prices allow unconstrained homeowners to reduce mortgage debt and increase housing consumption.

4.6 Conclusion

Studying the effect of preferential tax treatment of housing capital in Germany, i.e. the impact of untaxed imputed rents and mortgage interest deductibility, the model emphasizes the importance of the relationship between tenure choice and tax policy. My results suggest that this interaction distorts the decisions of individuals over lifetime. The favorable tax code in the general equilibrium life-cycle framework with heterogeneous agents generates a wedge between the rate of return on housing capital and business capital. A downpayment constraint on non-divisible housing capital purchases ensures that individuals face a tenure decision. Although simulations of different tax codes reveal that distributional effects are relatively small, individuals would prefer to live in an economy with less preferential tax treatment of housing capital. Either removing mortgage interest deductibility or taxing imputed rents leads to significant gains of welfare in the long run perspective. Those gains arise for individuals in all income quintiles. Furthermore, both preferential treatments of housing capital have distorting impact on individual decisions. When imputed rents are not taxed, the rate of return on capital is higher the more housing capital is hold. This increases the incentive to become a homeowner and to overconsume housing. Mortgage interest deductibility amplifies this behavior, by making individuals indifferent between holding equity and debt. Overall, individuals prefer a tax code, where imputed rents are taxed or mortgage interest deduction would be removed. Results reveal that the findings of Gervais (2002) for the U.S. are similar for the German economy, but to a lesser extent as justified previously by inconvexities induced through minimum housing sizes. For the German economy, calibration of high minimum housing sizes is required to replicate the low homeownership rate.

Given that both eliminating mortgage interest deductibility and the taxation of imputed

rents would result in higher welfare for Germany, would the introduction of such tax reform still be reasonable in order to promote homeownership? What implications should be taken from those results? While the introduction of mortgage interest deduction suggests an increase of the homeownership rate it leads to welfare losses for the economy in the long run compared to the benchmark model. The taxation of imputed rents improves welfare in the long-run. However, impacts on the homeownership rate are not clear in this case. Hence, both aggregate and wealth effects should be considered before implementing a new tax policy. Importantly, the motives behind the reform and corresponding effects on different subgroups of individuals have to be considered. According to Floetotto et al. (2016), the implementation of a tax on imputed rents primarily influences the richest income groups. Thus a tax reform towards the taxation of imputed rents in the first place harms the richest individuals, whereas the elimination of mortgage interest deductibility primarily leads to losses in the middle-income groups.

4.7 Appendix

4.7.1 Model economy

Households

Overlapping generations of finite living individuals populate the model economy. Households gain utility from a consumption good which is composite and housing services. The utility function of an individual entering the economy is given by

$$\sum_{j=1}^{J} \beta^{j-1}(logc_j + \theta logx_j) \ , \beta > 0 \tag{4.7}$$

where c_j denotes consumption of the composite good, x_j the consumption of housing services of an individual of age j, β represents the time discount factor and an individuals' lifetime is J. The technology for housing capital and services is also part of the household's problem. Each individual has the possibility to either own or rent. In the case of owning, an agent receives housing services directly from its housing capital, where it is assumed that one unit of housing capital generates one unit of housing services ($x_j = h_j$). h_j denotes the units of housing capital of an agent of age j.

The tenure decision is constrained by a minimum downpayment rate γ of the value of the house an individual wants to purchase as well as by the minimum size of owner-occupied houses $\underline{h}$, which reflects that housing capital is not perfectly divisible. By borrowing against the house the remaining cost can be financed with a mortgage of amount b_j. Alternatively, an individual with insufficient wealth can circumvent those constraints if it decides to rent rather than own. Rented housing services are denoted by s_j, which are limited by a minimum amount of $\underline{s}$, where $\underline{s} < \underline{h}$. Therefore, the total amount of housing services is then characterized by $x_j = h_j + s_j$, reflecting that both types of housing services are perfect substitutes in consumption. The price of one unit of housing services regarding consumption is denoted as p. Furthermore it is assumed that housing capital depreciates at a rate of δ_h (units per unit of capital) per period. This assumption leads homeowners to incur a maintenance cost accounting to the amount of depreciation costs and ensures that their house never depreciates below the minimum level of house size.

Furthermore, the income dynamics on the households side need to be specified. As mentioned before each individuals' life lasts for J periods, consisting of both a working and a retirement period. The age of retirement is denoted by j^*. Agents differ intra- and intergenerational. They are endowed with one unit of working time each period of their life before retirement, which they supply and transform into z_j efficiency units of labor. A wage rate of w is paid for each efficient labor unit. Both the average productivity level and the population size are normalized to unity at every point in time.

Another way for individual agents to accumulate wealth is the holding of the three accessible assets: housing (net of mortgages), business capital equity and deposits at financial institutions. The rate of return of the latter two is equalized by a no-arbitrage condition. Therefore, the two assets are the same from a household's perspective and the sum of both assets is denoted by a_j.

The balance sheet of a household is summarized in Table 1, where a_j consists of deposits

and capital equity:

Assets	Liabilities
Owner-occupied housing (h_j)	Mortgage (b_j)
Financial assets (a_j)	Net worth ($y_j = a_j + h_j - b_j$)

Table 4.6: Household's balance sheet (Gervais, 2002)

Financial Institutions

For simplification, all rental housing units are owned by financial institutions. This means that all housing held by agents coincides with owner-occupied housing. Furthermore, financial institutions play the intermediate role for all borrowing and lending.

Production technology

Output is produced following the Cobb-Douglas production technology:

$$f(K, N) = AK^{\alpha}N^{1-\alpha} \tag{4.8}$$

The variable K denotes the amount of business capital used for production, N is specified as the size of the working population and A is a technology parameter. It is possible to transform output goods free of costs into consumption or investment goods (residential and business). According to this, the price of all three types of goods will be equal and normalized to unity.

Structure of taxation

This section outlines the structure of taxation for the U.S. as in Gervais (2002) that is different to the tax code of the German economy. Since the impact of different fiscal policy arrangements is studied a tax code has to be established. In the model individuals can earn three types of income, whereby two types refer to capital income. Clearly, the remaining one is labor income. Capital income consists of interest payments produced by financial assets and imputed rents generated by housing capital. Thus, owner-occupied housing as a fixed asset is used to produce housing services and to generate imputed rents (OECD, 2007).
The tax code enables the government to tax three types of income as well as to deduct an arbitrary fraction of mortgage interest payments from taxable income. Instruments used for this are τ_y, the tax rate on the return on financial assets and labor income as well as τ_{ir}, representing the tax rate on imputed rents and τ_m as the deductible fraction from taxable income of mortgage interest payments.

Household's decision problem

Households are confronted both with intra- and intertemporal decisions. Those decisions take place simultaneously. First, in the intertemporal stage, they choose how much savings they transfer to the next period. Second, households decide intratemporally the amount of consumption of the composite good and housing services during the current period as well

as last periods savings' composition (Gervais, 2002).
Since only one state variable, the net-worth of today or yesterday´s savings, is needed to describe individual j´s situation with productivity z_j the household's optimization problem is relatively simple. As there is no uncertainty, the amount of savings today is chosen being aware of the fact that it will be optimized tomorrow. Therefore, given net worth at age j, an individual chooses the net worth of next period in order to maximize future discounted utility and the problem is recursively formulated as

$$V_j(y_j; z_j) \equiv \max_{y_{j+1} \epsilon \Gamma} \{G_j(y_j, y_{j+1}; z_j) + \beta V_{j+1}(y_{j+1}; z_{j+1})\} \tag{4.9}$$

where $V_j(y_j; z_j)$ is defined as the value of an individual behaving optimal from period j until J, entering period j with net worth y_j and productivity level z_j. Net worth of tomorrow is chosen from the feasible set Γ.
G_j is the return function of an individual of age j and is specified as the maximum achievable utility given its net worth of today and tomorrow which solves the intra-temporal problem:

$$G_j(y_j, y_{j+1}; z_j) \equiv \max_{(c_j, x_j, a_j, h_j, b_j)} \{lnc_j + \theta lnx_j\} \tag{4.10}$$

subject to

1. a budget constraint

$$c_j + px_j + y_{j+1} \leq (1-\tau_y)z_j w + y_j + (1-\tau_{ir})(p-\delta_h)h_j + (1-\tau_y)ia_j - (1-\tau_y\tau_m)ib_j \tag{4.11}$$

where

$$\begin{aligned} y_j &= a_j + h_j - b_j \\ x_j &= s_j + h_j \end{aligned} \tag{4.12}$$

2. housing constraints

$$\begin{aligned} h_j &\geq \underline{h} \\ s_j &\geq \underline{s} \end{aligned} \tag{4.13}$$

3. net worth constraints

$$\begin{aligned} y_j &\geq \gamma h_j \\ y_j &\geq h_j - b_j \end{aligned} \tag{4.14}$$

4. further contraints

$$\begin{aligned} &c_j \geq 0, j = 1, 2, ..., J \\ &z_j = 0, j \geq j^* \\ &a_1 = h_1 = 0 \end{aligned} \tag{4.15}$$

The expenditures on consumption goods, housing services and the savings for the next period are stated on the left hand side of Equation (4.11). The revenues on the right side consist of after tax labor income, net worth as well as after tax imputed rents (net of depreciation) generated through owner-occupied housing, after-tax income on financial assets and the subtraction of the deductible fraction of mortgage payments.
An interesting fact is that if $\tau_{ir} = 0$, housing services disappear from the budget constraint except for the maintenance cost. This basically means, homeowners pay themselves the

rent by transferring money from one side of the budget constraint to the other. Housing constraints were explained before. The first net worth constraint simply derives from the downpayment requirement. The second net worth constraint ensures that financial assets are non-negative.

Financial institutions' decision problem

The financial institutions' problem is formulated in a simple two-period way. A new cohort is born every period. The institutions use the earnings from accepted deposits to issue loans and buy residential capital in the first period. In the second period of their "lives" they gain proceeds for rental accommodations as well as interests from issued loans to pay their interests on deposits. After that they sell their capital (undepreciated) to new financial institutions in the same period as they only exist for two periods.
It is assumed that the interest rate on loans issued is the same as the interest financial intermediaries pay on deposits.
Defining the amount of rental housing in period t as H_t^f, the total amount of deposits as D_t^f as well as the total amount of loans issued and the total amount of housing service provided as B_t^f and S_t^f, respectively, the new financial institutions´problem in period t is given as

$$\max_{(B_{t+1}^f, S_{t+1}^f, H_{t+1}^f, D_{t+1}^f)} (pS_{t+1}^f - \delta_h H_{t+1}^f + iB_{t+1}^f - iD_{t+1}^f) \tag{4.16}$$

subject to

$$H_{t+1}^f + B_{t+1}^f \leq D_{t+1}^f \tag{4.17}$$

$$S_{t+1}^f \leq H_{t+1}^f. \tag{4.18}$$

The first constraint ensures, that financial institutions can only dispose over the amount of deposits to buy residential capital and issue loans. The second constraint states that they cannot provide more housing services than they dispose over residential capital. To make sure that financial intermediaries are indifferent between asset holdings and liabilities, the following no-arbitrage condition needs to be satisfied:

$$i = p - \delta_h \tag{4.19}$$

This guarantees that the maximization problem is well defined and in equilibrium financial institutions will make zero profits. (Gervais, 2002)

Definition of a competitive equilibrium

This definition is adopted from Gervais (2002). For a given set of tax rates $\Omega = \tau_y, \tau_{ir}, \tau_m$ a steady-state competitive equilibrium for a given set of policy is a set of:

1. Value functions $V_j(y_j; z_j)$
2. Individuals decision rules $c_j(y_j; z_j)$, $x_j(y_j; z_j)$, $a_j(y_j; z_j)$, $h_j(y_j; z_j)$, $b_j(y_j; z_j)$ for each age j=1,2,..,J
3. Age-dependent, time-invariant measure of agent types $\lambda_j(y_j; z_j)$

4. A set of relative prices p, i, w and

5. Aggregate quantities $G, Y, K, N, D^f, B^f, H^f, S^f$

such that

1. given prices and fiscal policy, individual decision rules solve the dynamic program given by (1)-(7);

2. inputs are priced competitively: $i = f_K(K, N) - \delta_k$ and $w = f_N(K, N)$;

3. given prices and the fiscal policy, D^f, B^f, H^f, S^f solves the financial institutions' problem ((8) and (9));

4. the goverment maintains a balanced budget every period

$$G = \sum_{j=1}^{J} \int_{\lambda_j} [\tau_y z_j w + \tau_y i a(y_j; z_j) + \tau_{ir} i h(y_j; z_j) - \tau_y \tau_m i b(y_j; z_j)] d\lambda_j(y_j; z_j),$$

5. markets clear:

   i) asset markets clear:

$$K = \sum_{j=1}^{J} \int_{\lambda_j} [a(y_j; z_j) - b(y_j; z_j)] d\lambda_j(y_j; z_j) - H^f$$
$$D^f = \sum_{j=1}^{J} \int_{\lambda_j} a(y_j; z_j) d\lambda_j(y_j; z_j) - K$$
$$B^f = \sum_{j=1}^{J} \int_{\lambda_j} b(y_j; z_j) d\lambda_j(y_j; z_j)$$

   ii) the goods market clears:

$$f(K, N) = \sum_{j=1}^{J} \int_{\lambda_j} [c(y_j; z_j) + \delta_h h(y_j; z_j)] d\lambda_j(y_j; z_j) + \delta_k K + \delta_h H^f + G$$

   iii) the rental market for housing services clears:

$$\sum_{j=1}^{J} \int_{\lambda_j} [x(y_j; z_j) + h(y_j; z_j)] d\lambda_j(y_j; z_j) = S^f = H^f.$$

Chapter 5

Conclusion

This dissertation comprises three chapters. Chapter 2 and 3, focus on discovering and understanding the development of house and land markets in German counties. While Chapter 2's objective is to estimate the size of the land component in the housing bundle for German counties, Chapter 3 concentrates on exploring the spatial dimension and interdependence of German counties' land and house prices. Unlike the foregoing chapters, Chapter 4 focuses on the impact of different tax policies on German homeownership rates, welfare and individual decisions over the life-cycle in a deterministic life-cycle model with heterogeneous agents. The present chapter, sums up the main outcomes of this dissertation, discusses advantages and limitations of the individual chapters, elaborates on some ideas for future research and formulates a couple of policy implications.

Chapter 2 estimates residential land values for 379 of 402 German counties and county-free cities for the period 2014-2018. Using the two-step residual method to build the land value database, I show that land values increased on average by 27 percent. However, average increases in structure cost and house prices only amount to 14 and 20 percent, respectively. This finding implies that upward movements in land values are a crucial factor in the rise of housing prices. Further, larger land shares in home values, especially in locations with inelastic housing supply, suggest a rise in the importance of land values as a key determinant of house price movements in the future. Intracountry differences in the increase of land and house prices are greatest between large agglomerations (e.g. Munich, Berlin, Hamburg, Ruhr-area, Dresden, Stuttgart) and counties in more remote areas. Nevertheless, I find land price increases in almost all counties. Moreover, the historically induced disparities between new and old Federal States are mirrored in differences in the size and growth of land and home values between East and West German counties. I find a significant difference in the change of land share in home value in West German states compared to the economically less developed new Federal States.

Chapter 3 builds on the preceding Chapter 2 by focusing on intra-country differences in German land and housing prices that were shown in Chapter 2. More precisely, I use the land value per m^2 estimates from Chapter 2 and the house price index from vdpResearch for single-/double-family housing of German counties for the period 2014-2018 to study intra-German spatial dependence patterns in land and house prices, with special focus on explaining the impact of agglomeration economies on residential land prices. Estimation results show that counties with higher median income and larger population density have higher land and house prices. Moreover, the restrictions on the supply of land also play an

important role in explaining the variations in land prices. The spatial models reveal that this effect also spills over to neighboring counties for Germany. On the one hand, in the sense that counties located next to high income and high population density counties tend to have higher land prices than more peripheral regions. On the other hand, counties located next to counties with high land and house prices usually have high land and house prices as well. These findings support a proportional relationship between agglomeration effects and residential land markets. While I find evidence for agglomeration effects also on a more local level, the results provide less evidence for spatial interaction effects on land prices for Top 7 German agglomerations. Furthermore, the results show stronger spillover interactions in land prices than for house prices. Finally, comparing the results for two different land price measurements (residential land and building land), the size of spillover effects turns out to be larger for residential land.

In Chapter 4, I calibrate the general equilibrium life-cycle model by Gervais (2002) in order to fit the German economy. I then conduct two counterfactual experiments to discover the impact of tax policies that favorably treat owner-occupied housing on homeownership rates, life-cycle decisions of households and welfare. When imputed rents are not taxed, the model generates a wedge between the rates of return on business and housing capital. Individuals face a higher rate of return the more housing capital they hold. This incentivises individuals to become homeowners as well as to over-consume housing. Allowing households to deduct mortgage interest, causes individuals in the model set up to be indifferent between equity and debt. As a result, the incentive to buy housing capital is even further increased. Despite, an increase in housing capital consumption under preferential tax treatment of owner-occupied housing, I find distributional effects in the model for the German economy to be small. Moreover, although marginal consumers would choose to own rather than rent, from a welfare perspective, individuals from almost all income quintiles are better off when owner-occupied housing is treated less favorable in the tax code.

Some of the findings of the preceding chapters need to be interpreted with caution, as the methods and data used in the chapters of this dissertation dispose of various short-comings. On this account, the subsequent paragraphs discuss limitations of this research.

Land price measurements on German county level are rare. The Federal Statistical Office publishes the price of vacant land sales. Local advisory committees for land value are responsible for determining land values decentralized based on some centralized calculation guidelines. But, one can argue that an increasing number of vacant land transactions may be in urban outskirts rather than in the center of cities. This could lead to significant systematic bias (in largely urbanized counties) when constructing a land price index. Moreover, next to irregular release dates and a lack of centralized availability of expert assessed land values, calculation margins of local advisory committees seem to be quite large, hampering Germany wide land price comparisons. To this end, I think the land prices constructed in Section 2 are a valid alternative presentation of residential land prices for Germany. Though, one has to be clear about several deficiencies in the data and the residual method used to construct the land price measurement in Chapter 2. First, the database is too small to use only new houses for the land price construction. Consequently, I cannot avoid assumptions on depreciation of existing structures' replacement costs when estimating the land's share in home value or use a more advanced approach to construct land values such as the real option approach by

Davis et al. (2021) that uses only new houses. A simple option model in Davis et al. (2021) showed that the residual method tends to underestimate the land component for houses aged 20 years and older as next to depreciation of the structure the option value to tear down an existing structure increases with its age. I try to account for this using age-specific depreciation rates. Second, I use listings rather than transaction data to estimate the land prices. This could create a systematic upward bias in land prices if listings prices significantly diverge from transaction prices. Third, I do not use transaction prices of vacant land sales as in literature on spatial transaction based approaches (Nichols et al., 2013; Haughwout et al., 2008; Albouy et al., 2018). This, I think is a short-coming in the sense that Chapter 2's land value measurement does not reflect values of land currently available to be developed. But, using data on existing and new buildings could deliver a more representative estimate for land values of residential land in both new and old neighborhoods. Lastly, observed listings are not a random sample and sample sizes vary by county, which reduces some counties' estimates reliability given small sample sizes.

A simple improvement of the residential land price estimates would be the replacement of listings with transaction data. Access to a larger database on housing transactions would allow to apply methods that only use newer houses to eliminate the need for assumptions on depreciation of replacement costs (Davis et al., 2017, 2021). The robustness analysis on critical assumptions of the residual method in Chapter 2 shows results to be sensitive to the use of different depreciation rates. Moreover, more extensive construction cost data for houses could improve the construction cost estimates and would allow to estimate a longer time series. A larger transactions database and details on location of these transactions could further be interesting in order to estimate less aggregated land prices, e.g. on municipality or zip code level as has been done for the U.S. (Davis et al., 2021). Information on exact locations of transaction, either developed or undeveloped could help comparing land price estimates based on developed housing and vacant land.

The theory suggests, that house and land prices are spatially clustered. As land price measurements are rare for Germany, this is also true for studies on the spatial interaction of land and housing markets. Otto and Schmid (2018) conduct a spatiotemporal analysis using data on German land sales of land ready for construction. Möller (2009) use the same dataset on building land sales to study the relationship between the price for building land and the inter-temporal value of employment under consideration of spatial dependencies between West German labor market regions (NUTS 3). Yet, the main emphasis of Chapter 3 is on both exogenous and endogenous spillover mechanisms in residential land and housing markets that abstracts from the temporal dimension given the short time span of the land value per m^2 data from Chapter 2. A longer time series would help to account for spatiotemporal effects. Moreover, data on commuting-to-work flows that cross county borders would allow me to compare the results to a spatial weighting pattern based on travel-to-work patterns that could be seen as a proxy for the economic relationship between two counties (Otto and Schmid, 2018; Fingleton, 2008; Möller, 2009). One could include other explanatory variables or use another house price index as a robustness check. Further, one could estimate models that allow for spatial spillovers among the error terms by means of comparison.

Given the prevalent view that house prices are indeed a local phenomenon and that the

location component will likely become even more important in future house price developments, the following questions on the spatial dimension of house and land prices could be interesting for future research: Do large cities and their neighbors experience more housing price growth than more remote spatially dependent housing markets? What city-specific characteristics are driving land and housing prices most? Moreover, in recent times, one should pay more attention to climate conditions and other environmental or natural amenities. Are people willing to pay more for natural amenities that increase their quality of life? For Germany in particular, this would for example raise the question as to what extent the proximity to the alps, the German low mountains or larger water bodies such as the German North and Baltic sea or Lake landscapes plays a prominent role in housing and land markets' developments. Further, besides including other dependent or control variables as well as weighting matrices, taking not only cross-county borders but also borders to other European countries within the Schengen area into consideration could deliver interesting outcomes in regards of the impact of commuting patterns and agglomeration network effects on German house and land markets.

Despite the distinctive features of German housing and rental markets, there are only a few studies on preferential tax treatment of housing for Germany. Chapter 4 conducts a simple counterfactual analysis based on the general equilibrium life-cycle framework by Gervais (2002) to study the impact of mortgage interest deduction and taxation of imputed rental income. However, it neglects several features of more recent heterogeneous agent life-cycle models that study preferential treatment of owner-occupied housing. Besides its deterministic character, the model abstracts for example from progressive income taxation, assumes joint capital and income tax rates, holds prices fixed and neglects the social housing market aspects and pension systems. These abstractions mute transmission channels through which these tax experiments could work in reality. Also, Chapter 4 could conduct further counterfactual experiments on tax policies besides mortgage interest deduction and taxation of imputed rental income.

Housing markets are not only driven by local markets but also by macroeconomic factors and business cycles. The literature suggests that housing market activities caused the recent Great Recession. However, the German housing markets were one of the few that did not experience the boom and bust cycles in the period between 2008-2010 (Voigtländer, 2014; Fehr and Hofmann, 2020). Since the choice of homeownership affects individual households over the life-cycle and has further implications for business cycles, a further research on preferential tax treatment of housing that incorporates both dimensions of life- and business-cycles could shed further light in understanding macro-economic, political and institutional policies for housing markets. Thus, besides incorporating features such as uninsurable income tax, progressive taxation, endogeneous homeownership and social housing, one could combine the framework from Chapter 4 with stochastic business cycle models that include housing. Both Silos (2007) and Iacoviello and Pavan (2013) have combined life- and business-cycle components in a stochastic setting but lack to include housing tax policies and explicit tenure choice as in Gervais (2002) or Kaas et al. (2021).

Despite the discussed weaknesses of data and methodologies applied in this dissertation, the chapters, nevertheless, address some of the key aspects of German housing and land markets. Yet, a lot of work remains to be done to understand the spatial behavior of

German land markets, improve German land price estimates and determine policies that may broadly increase German homeownership rates.

The results of this dissertation have implications for housing policies on national but also on regional level. The fact that I find spillover effects in land and housing markets between neighboring counties as well as a positive correlation of population density, median income and land prices raises the question of whether peripheral counties may be better off investing in public goods and services to increase attractiveness. The findings further show that the land component drives movements in house prices and swings in land values will likely influence house price cycles more in the future than they did in the past. This implication especially affects dense areas with high demand and inelastic housing supply. In turn, this could lead to large swings in house prices as a consequence of large changes in demand. A lot of housing policies, such as the introduction of the "Baukindergeld", rent control laws or more restrictions on property purchases as second home focus, for example, on the affordability of rental and owner-occupied housing for the demand side. While such policies may be successful in the short-run, from a long-run spatial equilibrium point of view it may be assumed that effectiveness of demand side policies is limited as demand is likely to stay high as long as the productivity advantages and other forces of attraction of a local market remain. Thus, one may consider ways to increase the supply of residential land where it is scarce. Surely, there are planning restrictions or topographical limitations but one could for example reduce vacancy of existing residential space. In 2018, the average German vacancy rate was 8.2 percent and varied among the federal states between 5.6 percent in Hamburg and 15.5 percent Sachsen-Anhalt (German Federal Statistical Office, 2020b). Nevertheless, in order to increase homeownership rates, preferential tax treatment of housing that reduces barriers towards homeownership for the demand side could help. However, one not only has to consider both aggregate effects and the impact on wealth but also the impact of such policies on different subgroups of the population.

Overall, the dissertation outlines several economic, structural and political factors that have significant impacts on the German housing and land markets by constructing a novel database on residential land prices for German counties, analyzing land and house price variations over time and space, conducting a quantitative exercise on the impact of two tax policies on German homeownership.

References

Ahlfeldt, G. M. and McMillen, D. P. (2014). Land Values in Chicago, 1913–2010: A City's Spatial History Revealed. *Land Lines*, 26(2):15–21.

Ahlfeldt, G. M. and McMillen, D. P. (2020). New estimates of the elasticity of substitution between land and capital. *LSE Working Paper*.

Albouy, D., Ehrlich, G., and Shin, M. (2018). Metropolitan land values. *Review of Economics and Statistics*, 100(3):454–466.

Albouy, D. and Hanson, A. (2014). 'Are houses too big or in the wrong place? Tax benefits to housing and inefficiencies in location and consumption'. *Tax policy and the economy*, 28(1):63–96.

Almy, R. (2014). Valuation and assessment of immovable property. OECD Working Papers on Fiscal Federalism 19, OECD Publishing.

Andrews, D. and Sánchez, A. C. (2011). The evolution of homeownership rates in selected OECD countries: Demographic and public policy influences. *OECD Journal: Economic Studies*, 2011(1):1–37.

Anselin, L. (1988). *Spatial econometrics: methods and models*. London: Kluwer.

Baltagi, B. H., Fingleton, B., and Pirotte, A. (2014). Spatial lag models with nested random effects: An instrumental variable procedure with an application to English house prices. *Journal of Urban Economics*, 80:76–86.

Barr, J., Smith, F. H., and Kulkarni, S. J. (2018). What's Manhattan worth? A land values index from 1950 to 2014. *Regional Science and Urban Economics*, 70:1–19.

Basu, S. and Thibodeau, T. G. (1998). Analysis of spatial autocorrelation in house prices. *The Journal of Real Estate Finance and Economics*, 17(1):61–85.

BKI (2016). *BKI Baukosten 2016 Neubau - Teil 1. Statistische Kostenkennwerte für Gebäude*. BKI Baukosteninformationszentrum Deutscher Architektenkammern GmbH, Stuttgart.

Boelmann, B. and Schaffner, S. (2019). FDZ Data description: Real-Estate Data for Germany (RWI-GEO-RED) - Advertisements on the Internet Platform ImmobilienScout24. *RWI Projektberichte*.

Bonnet, O., Chapelle, G., Trannoy, A., and Wasmer, E. (2021). Land is back, it should be taxed, it can be taxed. *European Economic Review*, 134, forthcoming.

BORIS-D (2020). Bodenrichtwertinformationssystem für Deutschland. `https://www.bodenrichtwerte-boris.de/borisde/?lang=de`. Accessed: 2020-08-26.

Bostic, R. W., Longhofer, S. D., and Redfearn, C. L. (2007). Land leverage: decomposing home price dynamics. *Real Estate Economics*, 35(2):183–208.

Brady, R. R. (2011). Measuring the diffusion of housing prices across space and over time. *Journal of Applied Econometrics*, 26(2):213–231.

Brady, R. R. (2014). The spatial diffusion of regional housing prices across US states. *Regional Science and Urban Economics*, 46:150–166.

Bundesamt für Kartographie und Geodäsie, Frankfurt am Main (GeoBasis-DE / BKG) (2019). Verwaltungsgebiete - Shape files. `http://www.bkg.bund.de`. Accessed: 2020-05-13.

Camagni, R., Capello, R., and Caragliu, A. (2017). Static vs. dynamic agglomeration economies: Spatial context and structural evolution behind urban growth. In *Seminal studies in regional and urban economics*, pages 227–259. Springer.

Can, A. (1990). The measurement of neighborhood dynamics in urban house prices. *Economic geography*, 66(3):254–272.

Can, A. (1992). Specification and estimation of hedonic housing price models. *Regional science and urban economics*, 22(3):453–474.

Chambers, M., Garriga, C., and Schlagenhauf, D. E. (2009). Housing policy and the progressivity of income taxation. *Journal of Monetary Economics*, 56(8):1116–1134.

Chen, Y. (2015). A new methodology of spatial cross-correlation analysis. *PloS one*, 10(5):e0126158.

Ciccone, A. (2002). Agglomeration effects in Europe. *European economic review*, 46(2):213–227.

Ciccone, A. and Hall, R. E. (1996). Productivity and the density of economic activity. *The American economic review*, pages 54–70.

Clapp, J. M. and Tirtiroglu, D. (1994). Positive feedback trading and diffusion of asset price changes: evidence from housing transactions. *Journal of Economic Behavior & Organization*, 24(3):337–355.

Cohen, J. P., Ioannides, Y. M., and Thanapisitikul, W. W. (2016). Spatial effects and house price dynamics in the USA. *Journal of Housing Economics*, 31:1–13.

Combes, P.-P., Duranton, G., and Gobillon, L. (2019). The costs of agglomeration: House and land prices in French cities. *The Review of Economic Studies*, 86(4):1556–1589.

Combes, P.-P., Duranton, G., Gobillon, L., and Roux, S. (2010). Estimating agglomeration economies with history, geology, and worker effects. In *Agglomeration economics*, pages 15–66. University of Chicago Press.

Combes, P.-P. and Gobillon, L. (2015). The empirics of agglomeration economies. In *Handbook of regional and urban economics*, volume 5, pages 247–348. Elsevier.

Corrado, L. and Fingleton, B. (2012). Where is the economics in spatial econometrics? *Journal of Regional Science*, 52(2):210–239.

Coulson, N. E. and Li, H. (2013). Measuring the external benefits of homeownership. *Journal of Urban Economics*, 77:57–67.

Daminger, A. and Dascher, K. (2020). City Skew and Homeowner Subsidy Removal.

Davis, M. A. and Heathcote, J. (2007). The price and quantity of residential land in the United States. *Journal of Monetary Economics*, 54(8):2595–2620.

Davis, M. A., Larson, W. D., Oliner, S. D., and Shui, J. (2021). The price of residential land for counties, ZIP codes, and census tracts in the United States. *Journal of Monetary Economics*, 118:413–431.

Davis, M. A., Oliner, S. D., Pinto, E. J., and Bokka, S. (2017). Residential land values in the Washington, DC metro area: New insights from big data. *Regional Science and Urban Economics*, 66:224–246.

Davis, M. A. and Palumbo, M. G. (2008). The price of residential land in large US cities. *Journal of Urban Economics*, 63(1):352–384.

Derbyshire, J., Gardiner, B., and Waights, S. (2013). Estimating the capital stock for the NUTS2 regions of the EU27. *Applied economics*, 45(9):1133–1149.

Deutsche Rentenversicherung (2021). Das Renteneintrittsalter. `https://www.deutsche-rentenversicherung.de/DRV/DE/Rente/Kurz-vor-der-Rente/Wann-kann-ich-in-Rente-gehen/wann-kann-ich-in-rente-gehen_node.html`. Accessed: 2021-05-05.

Díaz, A. and Luengo-Prado, M. J. (2008). On the user cost and homeownership. *Review of Economic Dynamics*, 11(3):584–613.

Diewert, W. E., Haan, J. d., and Hendriks, R. (2015). Hedonic Regressions and the Decomposition of a House Price Index into Land and Structure Components. *Econometric Reviews*, 34(1-2):106–126.

Dolls, M., Fuest, C., Krolage, C., and Neumeier, F. (2021). Who bears the burden of real estate transfer taxes? Evidence from the German housing market.

Drygalla, A. (2016). *Monetary and fiscal policy analyses in estimated DSGE models*. PhD thesis.

Dubin, R. A. (1988). Estimation of regression coefficients in the presence of spatially autocorrelated error terms. *The Review of Economics and Statistics*, pages 466–474.

Dubin, R. A. (1992). Spatial autocorrelation and neighborhood quality. *Regional science and urban economics*, 22(3):433–452.

Effenberger, K.-H. (2015). Projektbericht Entwicklungsdynamik EFH Arbeitsbaustein 4: Differenzierung der EFH-Bestände. *Leibniz-Institut für ökologische Raumentwicklung*.

Elhorst, J. P. (2010). Applied spatial econometrics: raising the bar. *Spatial economic analysis*, 5(1):9–28.

Epple, D., Gordon, B., and Sieg, H. (2010). A new approach to estimating the production function for housing. *American Economic Review*, 100(3):905–24.

European Central Bank (2003). *Structural Factors in the EU Housing Markets*.

European Central Bank (2018). Recent house price increases and housing affordability. *ECB Economic Bulletin Issue 1*.

European Comission (2012). Quarterly Report on the Euro Area. Volume 11, No. 4.

Eurostat (2013). Handbook on Residential Property Price Indices (RPPIs). Eurostat methodologies & working papers, Publications Office of the European Union, Publications Office of the European Union, Luxembourg.

Eurostat (2017a). Commercial Property Price Indicators: Sources, Methods and Issues. Eurostat statistical reports, Publications Office of the European Union, Publications Office of the European Union, Luxembourg.

Eurostat (2017b). Housing statistics.

Fatica, S. and Prammer, D. (2018). Housing and the tax system: how large are the distortions in the euro area? *Fiscal Studies*, 39(2):299–342.

Federal Ministry of Finance (2019a). Die neue Grundsteuer - Fragen und Antworten. `https://www.bundesfinanzministerium.de/Content/DE/FAQ/2019-06-21-faq-die-neue-grundsteuer.html`. Accessed: 2021-05-05.

Federal Ministry of Finance (2019b). Einkommen - und Lohnsteuer.

Fehr, H. and Hofmann, M. (2020). Tenure choice, portfolio structure and long-term care–Optimal risk management in retirement. *The Journal of the Economics of Ageing*, 17:100240.

Fingleton, B. (2008). Housing supply, housing demand, and affordability. *Urban studies*, 45(8):1545–1563.

Fingleton, B. and Le Gallo, J. (2008). Estimating spatial models with endogenous variables, a spatial lag and spatially dependent disturbances: finite sample properties. *Papers in Regional Science*, 87(3):319–339.

Floetotto, M., Kirker, M., and Stroebel, J. (2016). Government intervention in the housing market: Who wins, who loses? *Journal of Monetary Economics*, 80:106–123.

Frick, J. R., Grabka, M. M., Smeeding, T. M., and Tsakloglou, P. (2010). Distributional effects of imputed rents in five European countries. *Journal of Housing Economics*, 19:167–179.

Gadatsch, N., Hauzenberger, K., and Stähler, N. (2016). Fiscal policy during the crisis: A look on Germany and the Euro area with GEAR. *Economic Modelling*, 52:997–1016.

Gedal, M. and Ellen, I. G. (2018). Valuing urban land: Comparing the use of teardown and vacant land sales. *Regional Science and Urban Economics*, 70:190–203.

Geiger, F., Muellbauer, J., and Rupprecht, M. (2016). The housing market, household portfolios and the German consumer. *ECB working paper No. 1904*.

German Federal Statistical Office (2020a). 31231-0001: Residential buildings, dwellings, living floor space: Germany, reference date, number of dwellings. `https://www-genesis.destatis.de/genesis//online?operation=table&code=31231-0001&bypass=true&levelindex=0&levelid=1620205617250#abreadcrumb`. Accessed: 2021-05-05.

German Federal Statistical Office (2020b). Anteil unbewohnter Wohnungen nach Bundesländern. `https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Wohnen/Tabellen/unbewohnte-wohnungen-nach-bundeslaendern.html`. Accessed: 2021-04-16.

German Federal Statistical Office (Destatis) (2018). Laufende Wirtschaftsrechnungen Einkommen, Einnahmen und Ausgaben privater Haushalte.

Gervais, M. (1999a). Housing taxation and capital accumulation - Fortran code. Mimeo.

Gervais, M. (1999b). Housing taxation and Capital accumulation Algorithm. Mimeo.

Gervais, M. (2002). Housing taxation and capital accumulation. *Journal of Monetary Economics*, 49(7):1461–1489.

Gibbons, S. and Overman, H. G. (2012). Mostly pointless spatial econometrics? *Journal of Regional Science*, 52(2):172–191.

Glaeser, E. L. (2019). *Agglomeration economics*. University of Chicago Press.

Glaeser, E. L. and Gyourko, J. (2003). The impact of building restrictions on housing affordability. *Economic Policy Review*, 9(2).

Glaeser, E. L., Gyourko, J., and Saks, R. E. (2006). Urban growth and housing supply. *Journal of economic geography*, 6(1):71–89.

Glaeser, E. L., Kolko, J., and Saiz, A. (2001). Consumer city. *Journal of economic geography*, 1(1):27–50.

Göbel, S. D. (2020). Housing Market Report Germany Full year 2019. Jones Lang Lasalle SE.

Gong, Y., de Haan, J., and Boelhouwer, P. (2020). Cross-city spillovers in Chinese housing markets: From a city network perspective. *Papers in Regional Science*.

Gröbel, D. S., Galm, K., and Hücker, A. (2020). Housing Market Overview Germany Big 8 2nd half of 2019. Technical report, JLL.

Guo, J. and Qu, X. (2019). Spatial interactive effects on housing prices in Shanghai and Beijing. *Regional Science and Urban Economics*, 76:147–160.

Gyourko, J., Mayer, C., and Sinai, T. (2013). Superstar cities. *American Economic Journal: Economic Policy*, 5(4):167–99.

Gyourko, J. and Saiz, A. (2006). Construction costs and the supply of housing structure. *Journal of regional Science*, 46(4):661–680.

Halleck Vega, S. and Elhorst, J. P. (2015). The SLX model. *Journal of Regional Science*, 55(3):339–363.

Harding, J. P., Rosenthal, S. S., and Sirmans, C. (2007). Depreciation of housing capital, maintenance, and house price inflation: Estimates from a repeat sales model. *Journal of urban Economics*, 61(2):193–217.

Haughwout, A., Orr, J., and Bedoll, D. (2008). The price of land in the New York metropolitan area. *Current Issues in Economics and Finance*, 14(3).

Havik, K., Morrow, K. M., Orlandi, F., Planas, C., Raciborski, R., Roeger, W., Rossi, A., Thum-Thysen, A., and Vandermeulen, V. (2014). The Production Function Methodology for Calculating Potential Growth Rates & Output Gaps. *European Economy - Economic Papers 2008 - 2015, No. 535*.

Helbich, M., Brunauer, W., Vaz, E., and Nijkamp, P. (2014). Spatial heterogeneity in hedonic house price models: The case of Austria. *Urban Studies*, 51(2):390–411.

Holly, S., Pesaran, M. H., and Yamagata, T. (2010). A spatio-temporal model of house prices in the USA. *Journal of Econometrics*, 158(1):160–173.

Holly, S., Pesaran, M. H., and Yamagata, T. (2011). The spatial and temporal diffusion of house prices in the UK. *Journal of Urban Economics*, 69(1):2–23.

Iacoviello, M. and Pavan, M. (2013). Housing and debt over the life cycle and over the business cycle. *Journal of Monetary Economics*, 60(2):221–238.

Johannesson-Linden, A. and Gayer, C. (2012). Possible reforms of real estate taxation: Criteria for successful policies. *European Economy, Occasional Papers, Volume 119*.

Kaas, L., Kocharkov, G., and Preugschat, E. (2019). Wealth inequality and homeownership in Europe. *Annals of Economics and Statistics*, (136):27–54.

Kaas, L., Kocharkov, G., Preugschat, E., and Siassi, N. (2021). Low homeownership in Germany - A quantitative exploration. *Journal of the European Economic Association*, 19(1):128–164.

Kelejian, H. H. and Prucha, I. R. (1998). A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. *The Journal of Real Estate Finance and Economics*, 17(1):99–121.

Kelejian, H. H. and Prucha, I. R. (1999). A generalized moments estimator for the autoregressive parameter in a spatial model. *International economic review*, 40(2):509–533.

Kelejian, H. H., Prucha, I. R., and Yuzefovich, Y. (2004). Instrumental variable estimation of a spatial autoregressive model with autoregressive disturbances: Large and small sample results. *Advances in Econometrics: Spatial and Spatio-Temporal econometrics*, pages 163–198.

Knoll, K., Schularick, M., and Steger, T. (2017). No price like home: Global house prices, 1870-2012. *American Economic Review*, 107(2):331–53.

Koetter, M. and Poghosyan, T. (2010). Real estate prices and bank stability. *Journal of Banking & Finance*, 34(6):1129–1138.

Kofner, S. (2014). The German housing system: fundamentally resilient? *Journal of Housing and the Built Environment*, 29(2):255–275.

Kolbe, J., Schulz, R., Wersing, M., and Werwatz, A. (2012). Location, location, location: Extracting location value from house prices. *SFB 649 Discussion Paper*.

Kolbe, J., Schulz, R., Wersing, M., and Werwatz, A. (2015). Identifying Berlin's land value map using adaptive weights smoothing. *Computational Statistics*, 30(3):767–790.

Kolbe, J., Schulz, R., Wersing, M., and Werwatz, A. (2019). Land value appraisal using statistical methods. DFG Research Unit 2569 FORLand, Humboldt-Universität zu Berlin.

Kollmann, R., Ratto, M., Roeger, W., Vogel, L., et al. (2015). What drives the German current account? And how does it affect other EU member states? *Economic Policy*, 30(81):47–93.

Krugman, P. R. (1991). *Geography and trade*. MIT press.

Kuethe, T. H. and Pede, V. O. (2011). Regional housing price cycles: a spatio-temporal analysis using US state-level data. *Regional studies*, 45(5):563–574.

Lee, L.-f. and Yu, J. (2010a). Estimation of spatial autoregressive panel data models with fixed effects. *Journal of Econometrics*, 154(2):165–185.

Lee, L.-f. and Yu, J. (2010b). Some recent developments in spatial panel data models. *Regional Science and Urban Economics*, 40(5):255–271.

LeSage, J. and Pace, R. (2009). Introduction to Spatial Econometrics. Boca Raton: Taylor and Francis CRC Press.

LeSage, J. P. and Pace, R. K. (2014). The biggest myth in spatial econometrics. *Econometrics*, 2(4):217–249.

Mathä, T. Y., Porpiglia, A., and Ziegelmeyer, M. (2017). Household wealth in the euro area: The importance of intergenerational transfers, homeownership and house price dynamics. *Journal of Housing Economics*, 35:1–12.

McMillen, D. P. (1996). One hundred fifty years of land values in Chicago: A nonparametric approach. *Journal of Urban Economics*, 40(1):100–124.

Meen, G. (1999). Regional house prices and the ripple effect: a new interpretation. *Housing studies*, 14(6):733–753.

Meijers, E. J. and Burger, M. J. (2017). Stretching the concept of "borrowed size". *Urban Studies*, 54(1):269–291.

Meijers, E. J., Burger, M. J., and Hoogerbrugge, M. M. (2016). Borrowing size in networks of cities: City size, network connectivity and metropolitan functions in Europe. *Papers in Regional Science*, 95(1):181–198.

Mendoza, E. G., Razin, A., and Tesar, L. L. (1994). 'Effective tax rates in macroeconomics: Cross-country estimates of tax rates on factor incomes and consumption'. *Journal of Monetary Economics*, 34(3):297–323.

Meyer, F. J. M. and Meyer, J. L. (1994). An International Sectoral Data Base for Fourteen OECD Countries (Second Edition). *OECD Economics Department Working Papers No. 145*.

Möbert, J. (2020). Berlin housing market Rent cap may decouple real estate cycle from economic supercycle for a number of years. *Deutsche Bank Research - Germany Monitor*.

Möller, J. (2009). Regional variations in the price of building land: a spatial econometrics approach for West Germany. *The Annals of Regional Science*, 43(1):113–132.

Nichols, J. B., Oliner, S. D., and Mulhall, M. R. (2013). Swings in commercial and residential land prices in the United States. *Journal of Urban Economics*, 73(1):57–76.

Niehues, J. and Voigtländer, M. (2016). Wohneigentumsquote: Geringe Dynamik in der Wohneigentumsbildung. *IW-Kurzbericht*.

OECD (2007). Owner occupied housing.

OECD (2017). OECD.stats - National account data.

O'sullivan, A. (2007). *Urban economics*. McGraw-Hill/Irwin Boston, MA.

Otto, P. and Schmid, W. (2018). Spatiotemporal analysis of German real-estate prices. *The Annals of Regional Science*, 60(1):41–72.

Pariès, M. D. and Notarpietro, A. (2008). Monetary policy and housing prices in an estimated DSGE for the US and the euro area. *ECB Working Paper No. 972*.

Partridge, M. D., Rickman, D. S., Ali, K., and Olfert, M. R. (2009). Agglomeration spillovers and wage and housing cost gradients across the urban hierarchy. *Journal of International Economics*, 78(1):126–140.

Petkova, K. and Weichenrieder, A. J. (2017). Price and quantity effects of the German real estate transfer tax.

Pijnenburg, K. (2017). The spatial dimension of US house prices. *Urban Studies*, 54(2):466–481.

Poterba, J. and Sinai, T. (2008). Tax expenditures for owner-occupied housing: Deductions for property taxes and mortgage interest and the exclusion of imputed rental income. *American Economic Review*, 98(2):84–89.

Poterba, J. M. and Sinai, T. (2011). Revenue Costs and Incentive Effects of the Mortgage Interest Deduction for Owner-Occupied Housing. *National Tax Journal*, 64(June):531–564.

Roback, J. (1982). Wages, rents, and the quality of life. *Journal of political Economy*, 90(6):1257–1278.

Rosen, H. S. (1979a). Housing decisions and the US income tax: An econometric analysis. *Journal of Public Economics*, 11(1):1–23.

Rosen, H. S. (1985). Housing subsidies: Effects on housing decisions, efficiency, and equity. In Auerbach, A. J. and Feldstein, M., editors, *Handbook of Public Economics Vol. 1*. North-Holland Publishing Company.

Rosen, S. (1979b). Wage-based indexes of urban quality of life. *Current issues in urban economics*, pages 74–104.

Schaer, C. (2018). Mayor suggests locking out foreign investors from Berlin real estate. *Handelsblatt*.

Schmalwasser, O. and Schidlowski, M. (2006). Kapitalstockrechnung in Deutschland. *Wirtschaft und Statistik*, 11(2006):1107–1123.

Silos, P. (2007). Housing, portfolio choice and the macroeconomy. *Journal of Economic Dynamics and Control*, 31(8):2774–2801.

SOEP (2019). Socio-Economic Panel (SOEP), data from 1984-2017. SOEP Socio-Economic Panel Study.

Sommer, K. and Sullivan, P. (2018). Implications of US tax policy for house prices, rents, and homeownership. *American Economic Review*, 108(2):241–74.

Statistisches Bundesamt (2012). Statistik der Kaufwerte for Bauland. Technical report, Destatis, Wiesbaden.

Statistisches Bundesamt (Destatis) (2012). Statistik der Kaufwerte für Bauland, Qualitätsbericht.

Statistisches Bundesamt (Destatis) (2017). VGR des Bundes - Verfügbares Einkommen der privaten Haushalte: Deutschland, Jahre, Einkommensarten.

Statistisches Bundesamt (Destatis) (2020). Preisindizes für die Bauwirtschaft, Fachserie 17 Reihe 4.

Statstische Ämter des Bundes und der Länder (2021). 61511-01-03-4: Veräußerungsfälle, veräußerte Fläche, Kaufsumme, durchschnittlicher Kaufwert nach Baulandarten - Jahressumme - regionale Tiefe: Kreise und krfr. Städte. `https://www.regionalstatistik.de/genesis//online?operation=table&code=61511-01-03-4&bypass=true&levelindex=0&levelid=1620204967791#abreadcrumb`. Accessed: 2021-05-05.

Steuertipps (2021). Abschreibung / Gebäude. https://www.steuertipps.de/lexikon/a/abschreibung-gebaeude. Accessed: 2021-05-05.

Tideman, N. and Plassmann, F. (2018). The effects of changes in land value on the value of buildings. *Regional Science and Urban Economics*, 69:69–76.

United States Census Bureau (2016). Core-Based Statistical Areas. https://www.census.gov/topics/housing/housing-patterns/about/core-based-statistical-areas.html. Accessed: 2021-05-09.

Voigtländer, M. (2009). 'Why is the German homeownership rate so low?'. *Housing Studies*, 24(3):355–372.

Voigtländer, M. (2014). The stability of the German housing market. *Journal of Housing and the Built Environment*, 29(4):583–594.