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**Spatial distribution of
housing liquidity**



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Francisco Amaral, Mark Toth and Jonas Zdrzalek

ABSTRACT

SPATIAL DISTRIBUTION OF HOUSING LIQUIDITY*

Francisco Amaral, Mark Toth, and Jonas Zdrzalek

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This paper examines the relationship between location, liquidity, and prices in housing markets. We construct spatial datasets for German and U.S. cities and show that liquidity and prices decline with distance to the city center. To rationalize these results, we build a structural model with spatial search frictions. We argue that location preferences concentrate buyers in central areas, making markets tighter, more liquid, and driving up prices. Counterfactuals show that suppressing search frictions raises welfare and prices, especially in peripheral areas. Our findings highlight the importance of demand-side preferences and search frictions for understanding liquidity and asset prices.

Keywords: housing liquidity, housing prices, cities, spatial equilibrium, housing demand, asset pricing

JEL Classification: G12, G51, R21, R30

Francisco Amaral (corresponding author)
University of Zurich; Swiss Finance Institute
Rämistrasse 71, CH-8006 Zürich
Email: francisco.amaral@df.uzh.ch
www.uzh.ch

Mark Toth
University of Bonn
Regina-Pacis-Weg 3, D-53113 Bonn
Email: mark-toth@uni-bonn.de
www.uni-bonn.de

Jonas Zdrzalek
Kiel Institute for the World Economy,
University of Cologne
Kiellinie 66, D-24105 Kiel
Email: jonas.zdrzalek@ifw-kiel.de
www.ifw-kiel.de

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1 Introduction

Transactions in real estate markets are impeded by search frictions and typically take months to complete. This makes real estate a particularly illiquid asset class (see, for example, Ngai and Tenreyro, 2014; Piazzesi, Schneider, and Stroebel, 2020). Given the large relative size of housing in household balance sheets, variation in housing liquidity has substantial aggregate economic consequences (see, for example, Head, Lloyd-Ellis, and Sun, 2014; Garriga and Hedlund, 2020). Moreover, houses are tied to their locations, and although housing market liquidity varies across space as much as it does over the business cycle, we know little about the mechanisms that drive this spatial variation. We argue that location preferences, shaped by the desire to live closer to the city center, interact with search frictions to generate systematic spatial differences in both liquidity and prices.

Scarcity of data has so far limited our knowledge about the spatial variation in housing liquidity. We fill this gap by building spatial datasets on housing prices and several measures of housing liquidity for cities in Germany and the United States. We empirically show that with increasing distance to the city center, housing prices decline, time to sell rises, and the spread between asking and transaction prices widens – even after controlling for property characteristics, income, and demographics. While the result that prices decrease with distance to the city center is established in the literature (see Duranton and Puga, 2015), we are the first to document that liquidity also decreases with distance to the city center. According to our estimates, the spatial variation in housing liquidity exceeds the variation associated with commonly used determinants, such as property size or age. We also show that city-center housing markets are more liquid despite a much higher density of supply. In addition, we provide empirical evidence that rental yields increase with distance to the city center, consistent with illiquidity in peripheral markets being priced in.

To rationalize our empirical results, we develop a structural housing search model in which spatial search frictions are the key determinant of market outcomes. These frictions are particularly strong in the city center, where many buyers simultaneously compete for a limited number of dwellings. The resulting congestion raises market tightness and substantially increases liquidity, defined as the time it takes to sell housing units, in

central locations. By contrast, in the outskirts, where fewer buyers search, markets are thinner and liquidity is lower. Sellers in these less tight markets therefore accept lower prices, generating systematic spatial patterns of both liquidity and prices. We estimate the structural parameters of our model and show that the model reproduces the observed distribution of liquidity and prices with high precision for both Germany and the United States. Counterfactual analysis further quantifies the welfare and price impacts of search frictions: on average, welfare is reduced by 3%, equivalent to 1.5% of housing prices, due to lower matching probabilities and higher vacancy rates. This welfare loss is particularly large in peripheral areas. Moreover, search frictions sharply steepen the spatial price gradient, tripling the gap between the city center and the outskirts. Taken together, our findings demonstrate that spatial search frictions jointly determine liquidity and prices in housing markets, providing new insights into the role of frictions in decentralized markets and their relevance in light of the recent “great rotation” toward illiquid, private assets (Koijsen, Shah, and Van Nieuwerburgh, 2025).

Empirics. In our empirical analysis, we combine the universe of real estate transactions from German cities (introduced in Amaral et al., 2023) with an extensive set of real estate advertisements assembled by a private company¹ using a nearest-neighbor algorithm. We obtain geocoded datasets on housing liquidity and prices from 2012 to 2024 for Hamburg, Munich, Cologne, Frankfurt, and Duesseldorf. For the United States, we use ZIP-Code-level data from Redfin on housing liquidity and prices from 2012 to 2023, combined with data on local housing characteristics and demographics from the American Community Survey and data on neighborhood quality from Chetty et al. (2025). With these datasets, we cover two large and fundamentally distinct housing markets: the German housing market has a low homeownership rate and low turnover, while the U.S. housing market has a high homeownership rate and high turnover.

Our primary measure of liquidity is the time that properties stay on the market as on-line listings, the standard measure in the housing literature (see Han and Strange, 2015). We find that within-city spatial differences in time on the market are substantial and systematic. Conditional on property and neighborhood characteristics, housing units in the outskirts remain on the market approximately 20% longer than those in the city

¹We are very grateful to Sebastian Hein from *VALUE Marktdaten* for giving us access to the data and support throughout the process of writing the paper.

center, both in German and U.S. cities. This spatial variation is an order of magnitude larger than that associated with commonly used determinants of housing liquidity, such as property size or age.² We also show that the spread between asking and sales price, an alternative measure of liquidity that we construct analogously to the bid-ask spread in stock or bond markets, becomes more negative with distance to the city center. Furthermore, we use buyers' contact clicks for listings as a proxy measure for market tightness and show that they decline with distance to the city center. These patterns suggest that liquidity is higher in central locations, despite a higher density of housing supply, underscoring the dominance of demand-side factors. All of our empirical results hold in an extensive series of robustness checks. Among these, a time series analysis shows that the liquidity gradient flattens during the COVID-19 pandemic, but starts to recover thereafter. This finding is in line with the flattening of the price gradient during the COVID-19 pandemic as a consequence of the shift to working from home (see, for example, Gupta et al., 2022). Lastly, using data on job accessibility across U.S. ZIP Codes from Delventhal and Parkhomenko (2024), we show that our findings can be extended to locations beyond city centers which attract a large enough number of commuters.³

Model. In our theoretical analysis, we model a housing market with search frictions, building on an established model structure from Krainer (2001). With this setup, we take a similar approach as prominent recent papers on housing market search, such as Piazzesi, Schneider, and Stroebel (2020) and Guren and McQuade (2020). We assume that households want to minimize their distance to a central location due to travel costs, given their idiosyncratic valuations for individual properties which they can observe by searching.⁴ Our model thus allows us to examine the interaction of location preferences and search frictions. We show that as the cost of travel increases with distance to the city center, market tightness, defined as the number of potential buyers per seller, decreases. This is reflected in a lower probability of sale and therefore a longer time on the market outside of the city center. Sellers act as price setters for spatially differentiated goods and, consistent with the lower probability of sale, decrease their listing prices. Importantly,

²We review the existing papers on the determinants of time on the market in Supplemental Appendix C.4, noting that none of these studies has examined the role of distance to the city center.

³We are very grateful to Andrii Parkhomenko for providing us access to the data.

⁴Conceptualizing location preferences via travel costs is in line with the canonical monocentric city model (Alonso, 1964; Mills, 1967; Muth, 1969). As an alternative interpretation of this travel cost, we also consider an opportunity cost of travel to the city center in terms of foregone wages.

they trade off the listing price and the time to sell a housing unit (as emphasized in, for example, Guren, 2018). It is therefore not optimal for sellers to adjust prices downward so far that spatial liquidity differences disappear. Hence, liquidity and prices are endogenously co-determined by travel costs which reflect fundamental demand-side location preferences. Analogously to our additional empirical findings regarding job accessibility centers, this mechanism equally applies to other locations beyond a single city center.

We estimate the structural parameters of our model for German and U.S. cities via the method of simulated moments, using the datasets from our empirical analysis. The resulting spatial liquidity and price distributions are quantitatively accurate. Then, we conduct a counterfactual analysis to quantify the effects of search frictions on welfare and housing prices. We compare our frictional market equilibrium model with an efficient model in which we abstract from search frictions, as well as a constrained-efficient model in which we include search frictions but abstract from sellers' price-setting behavior internalizing these frictions. When comparing our baseline model to the fully efficient model, we find that search frictions decrease welfare by 3% on average. These welfare losses are mostly driven by high vacancies due to excess search in the market equilibrium, especially in peripheral areas. On the other hand, welfare losses in the baseline model compared to the constrained-efficient model are negligible: sellers' price-setting behavior does not notably distort welfare according to our structural estimates. Hence, our model implies that housing policies which aim to reduce sellers' pricing power are mostly ineffective in terms of welfare gains. A reduction of vacancies, however, especially in the outskirts, provides large room for welfare gains according to our model. Recent literature discusses vacancy taxes (see, for example, Han, Stacey, and Chen, 2023; Segú, 2020), to which we can add that such taxes should be focused on peripheral areas for maximal effectiveness. Lastly, regarding prices, we find that search frictions amplify spatial differences, as search frictions are particularly strong in the outskirts. The spatial price gradient is 3 times as steep in the market equilibrium as in the efficient model.⁵

In an extension of the model, we introduce a bargaining process which creates spreads between asking and sales prices that we can directly compare to our alternative empirical measure of liquidity akin to the bid-ask spread. We show that the time on the market and this spread are interchangeable measures of liquidity in the model by reflecting the

⁵This comparison is not possible for the constrained-efficient model which abstracts from price-setting.

same structural relationships. Finally, in an additional model experiment, we replicate the empirical flattening of liquidity and price gradients due to the shift to working from home induced by the COVID-19 pandemic. Overall, our results show how accounting for the interaction between location preferences and search frictions significantly enhances our understanding of the cross-sectional variation in housing liquidity and prices.

Related literature. We are the first to establish that housing liquidity decreases with distance to the city center. This adds to the well-known fact that housing prices decrease with distance to the city center (for recent research on spatial price gradients, see Bruneel-Zupanc et al., 2025; Gupta et al., 2022; Albouy, Ehrlich, and Shin, 2018).

Our paper also contributes to the growing literature on the spatial variation in housing liquidity. Gerardi, Qian, and D. Zhang (2025), Jiang, Kotova, and A. L. Zhang (2024), and Vanhapelto and Magnac (2024) examine differences in housing liquidity across cities, rather than within cities as we do. Piazzesi, Schneider, and Stroebel (2020) show how segmented search behavior is important to understand within-city spatial differences in housing liquidity and prices. We complement their work by quantifying the effects of search frictions on the spatial distribution of prices and the associated welfare effects. This approach is related to the literature on search frictions in OTC markets (see, for example, Duffie, Gârleanu, and Pedersen, 2005; Lagos and Rocheteau, 2009).

We also contribute to the literature on monocentric city models⁶ by showing that taking into account search frictions significantly improves our understanding of the urban spatial price gradient. Lastly, by integrating space into a framework with trading frictions, we contribute to, first, the well-established literature on housing market search (see Han and Strange, 2015), and second, the emerging literature on urban finance which combines elements of structural urban models with elements of structural macro-finance models (see, for example, Koijen, Shah, and Van Nieuwerburgh, 2025; Favilukis, Mabilie, and Van Nieuwerburgh, 2023).

The rest of this paper is organized as follows. Section 2 describes our data and our measurement of spatial variables and liquidity. Section 3 presents our empirical analysis. Section 4 describes our model framework and presents analytical and quantitative results. Section 5 presents our counterfactual analysis. Section 6 concludes.

⁶See Duranton and Puga (2015) for an overview. From a theoretical perspective, the spatial equilibrium condition in our model refers to expected utility rather than realized utility, which is in line with modern quantitative urban models (see Redding (2023) for an overview).

2 Data and measurement

To study the spatial distribution of housing liquidity and prices, we construct two new spatial datasets for large cities in Germany and the United States. For Germany, we use property-level data covering Hamburg, Munich, Cologne, Frankfurt, and Duesseldorf. Berlin is excluded from our sample due to missing information on addresses. For the United States, we use ZIP-Code-level data covering the 30 largest MSAs.

2.1 Data for German cities

We combine administrative records on the universe of housing transactions in our sampled cities with a comprehensive dataset on housing advertisements. We focus our analysis on apartments, which allows us to examine the role of location consistently within a city, since other types of housing are typically scarce in German city centers. We also consider single-family housing in robustness checks.

Our transaction dataset covers the universe of residential housing transactions in large German cities over several decades. This dataset, introduced in Amaral et al. (2023), is based on data from local real estate committees (*Gutachterausschuesse*). Collecting information on all real estate transactions from notaries, these committees register information on sales prices, contract dates, addresses, and an extensive list of property characteristics which we document in Supplemental Appendix A.1.

We obtain data on real estate advertisements via *VALUE Marktdaten* who scrape and process real estate advertisements from online platforms and real estate agencies. The company's algorithm ensures that ads with both shorter and longer durations are scraped, preventing potential bias from user-influenced advertisement ordering.⁷ We observe the dates on which ads were posted and removed, addresses (if available), further information on location such as ZIP Code or neighborhood, asking prices, and property characteristics. The dataset covers the period between 2012 and 2024, which, in combination with the longer time span covered by the transaction data, limits our sample to this period.

We match the two datasets using a nearest-neighbor algorithm based on location, contract and listing dates, asking and sales prices, housing sizes, and building year of properties. As we do not observe the addresses of all listings, we match only about one-

⁷Note that if an advertisement is posted multiple times across different platforms or within the same platform, this is taken into account when assigning identifiers to advertisements.

third of the transactions with corresponding listings. Our final dataset consists of about 80 thousand observations. In Supplemental Appendix A.1, we provide further details on the matching process and show that the matched sample is representative of the universe of transactions.

2.2 Data for U.S. cities

For the United States, we gather ZIP-Code-level data on median time on the market and median sales prices from Redfin.⁸ To obtain control variables for our empirical analysis, we gather ZIP-Code-level data on average housing size, average building year, income composition, and racial composition from the American Community Survey (U.S. Census Bureau, 2012–2023a; U.S. Census Bureau, 2012–2023b; U.S. Census Bureau, 2012–2023c) as well as ZIP-Code-level data on neighborhood quality from Chetty et al. (2025).

We focus our analysis on single-family homes, the most common housing type in U.S. cities. In Supplemental Appendix D.3, we show that our results also hold for condominiums, multi-family houses, and townhouses. Our dataset covers the 30 largest MSAs from 2012 to 2023 at a monthly frequency. Supplemental Appendix A.2 describes our data preparation procedure in further detail.

2.3 Measurement of spatial variables

We measure spatial variation in our data using the distance to the city center, an established measure in the urban economics literature (see Duranton and Puga, 2015). For Germany, we choose historic city centers for our baseline analysis.⁹ In a robustness check, we show that selecting the centroid of the business district with the highest land value (via the *Bodenrichtwerte* land value measurements from the *Gutachterausschuesse* real estate committees)¹⁰ yields nearly identical city centers as the ones we choose by

⁸Redfin is a real estate brokerage company that obtains its data directly from local listing services, especially those based in the largest MSAs (see: <https://www.redfin.com/news/data-center/>). We do not use data from Zillow, the most popular provider of U.S. real estate data, as Zillow does not provide access to data on time on the market at a more granular level than MSA. However, as we show in Supplemental Appendix A.2, the differences in coverage between Zillow and Redfin for the 30 largest MSAs are very small and should not affect our results. Moreover, we show that our results are robust to using data from Realtor.com, another online listing platform (<https://www.realtor.com/research/data/>).

⁹We choose the following historic city centers: Hamburg: *Alsterhaus*, Munich: *Marienplatz*, Cologne: *Koelner Dom*, Frankfurt: *Konstablerwache*, Duesseldorf: *Marktplatz*.

¹⁰Retrieved from the *BORIS-D* database (<https://www.bodenrichtwerte-boris.de/>).

hand. We calculate kilometer distances between city centers and locations of properties transacted within the corresponding city boundaries. For the United States, we define the center of an MSA as the location of its city hall (as done in, for example, Gupta et al., 2022). We calculate kilometer distances between MSA centers and ZIP Code centroids located within the corresponding MSA boundaries.¹¹ In a robustness analysis, we create a job access index using data from Delventhal and Parkhomenko (2024) which we use to find locations with high job access as alternative focal points beyond city centers.

As an alternative spatial measure, we use travel time estimates. The spatial structure of cities can feature rivers or other factors that influence local transportation. Such features could be more accurately represented via the travel time rather than the kilometer distance to the city center. Via openrouteservice,¹² we request the typical travel time to the city center by car. For robustness, we also request car and public transport travel times via the Google Maps Directions API.¹³

2.4 Measurement of liquidity

Our main measure of housing liquidity is the time on the market, the standard measure for liquidity in the housing literature. For the German dataset, we define this time as the period between the start and the end of an advertisement and report the number of weeks a property has been advertised if it sells on day T of being advertised, that is, $T/7$ weeks. For the U.S. dataset, we directly obtain the time on the market via Redfin. This time refers to the median number of advertised days for housing units sold within a ZIP Code area in a calendar month. Table 1 presents summary statistics for the German and U.S. datasets. In Supplemental Appendix B, we present summary statistics by city. Overall, we observe that the German market is generally less liquid than the U.S. market, with properties typically taking almost twice as long to sell.

We also construct additional liquidity measures using the richer German dataset. First, we calculate the spread between the asking price and the sales price, akin to the bid-ask spread in stock or bond markets. We call this measure the *asking price discount*. We also construct this measure at the ZIP-Code level for the United States with the Redfin

¹¹Population-weighted ZIP Code centroids retrieved from <https://catalog.data.gov/dataset/zip-code-population-weighted-centroids>. MSA boundaries retrieved from <https://www2.census.gov/geo/tiger/TIGER2021/CBSA/>.

¹²<https://openrouteservice.org/>.

¹³<https://developers.google.com/maps/documentation/directions>.

data. Second, we use the number of contact clicks per ad as a proxy variable for market tightness. This measure refers to the number of times that potential buyers directly contacted a seller who placed an advertisement.

Table 1: *Summary statistics for both datasets*

Dataset	Time on the market in weeks				Sales price in 1,000 € or \$				
	Mean	SD	P25	P75	Mean	SD	P25	P75	N
Germany	13.51	16.71	2.40	17.80	374	274	189	478	84,292
U.S.	7.60	7.87	3.50	9.64	446	502	205	530	682,100

Notes: N is the number of transactions for the German dataset. For the U.S. dataset, it represents the number of ZIP-Code-year-month pairs.

3 Empirical analysis

In this section, we document new stylized facts on the spatial variation in housing liquidity within German and U.S. cities and replicate established stylized facts on the spatial variation in housing prices.

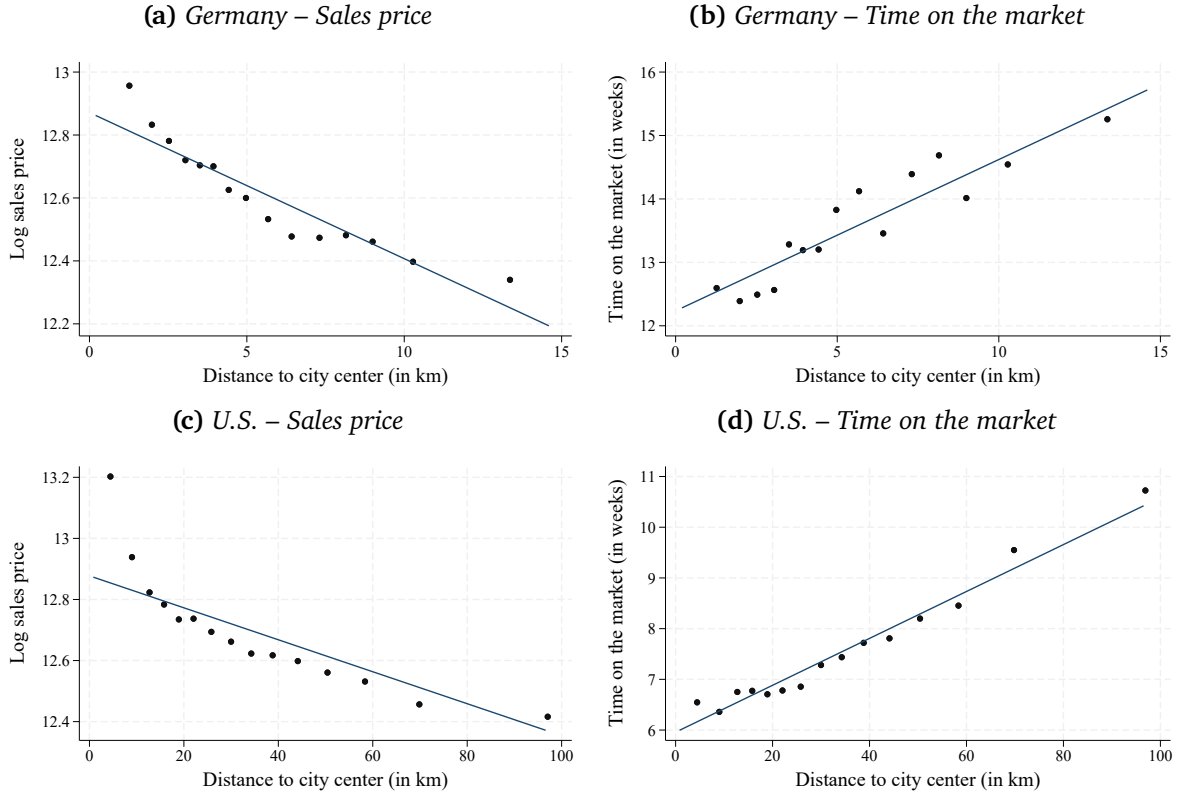
3.1 Spatial variation in liquidity and prices

Regression framework. In our baseline analysis, we use hedonic regressions. This approach allows us to rule out that spatial liquidity or price differences are driven by systematic spatial variation in housing characteristics or demographics. We estimate

$$y_I = \alpha \times distance_I + \beta \times X_I + f_{ct} + \varepsilon_I, \quad (1)$$

where for the German dataset, I indexes transactions, with every transaction I being assigned to a city c and a calendar quarter t , while for the U.S. dataset, $I = it$ includes an index i for ZIP Codes, with every ZIP Code i being assigned to an MSA c , and an index t for time measured in months. The dependent variable y_I refers to the time on the market or sales prices. The explanatory variable $distance_I$ is the (time-invariant) distance to the city center, measured as a kilometer distance in the baseline specification and as a travel time in the alternative specification.

Figure 1: Liquidity and price gradients for Germany (2012–2024) and the U.S. (2012–2023)



Notes: These binned scatter plots display the results of Regression (1) with log sales price and time on the market as the outcome variables, using 15 equally-sized distance bins. The binned scatter plots are based on the complete regression specification, as shown in columns three and six of Tables 2 and 3. The binned scatter plots are produced following Cattaneo et al. (2024).

For regressions using the German dataset, the control vector X_i includes an extensive set of property characteristics, such as size, building year, number of bathrooms, or type of heating. For regressions using the U.S. dataset, X_i includes the share of 1-room, 2–3-room, 4–5-room, 6–7-room, and 8-or-more-room dwellings; the share of housing units built after 2010, in 2000–2009, 1980–1999, 1960–1979, 1940–1959, and in 1939 or earlier; median household income; the share of households with annual income above \$150,000; the homeownership rate; and the share of Black households. The observations of these control variables are at the yearly level. A yearly observation is assigned to all months within that year. In addition, we control for state fixed effects and for spatial differences in neighborhood quality from Chetty et al. (2025), measured by the fraction of children born between 1978 and 1983 in a given ZIP Code area who were incarcerated by April 1, 2010. For U.S. regressions with liquidity as the left-hand-side variable, we also control for the price level in 2011 to capture unobserved housing characteristics. Note that

by considering within-city variation, we furthermore rule out bias due to confounding across-city variation in unobserved variables. Lastly, f_{ct} captures city-time fixed effects to account for common time trends in liquidity or prices within a city, and ε_l denotes the error term. To address spatial correlation in the error terms, we cluster standard errors at the city-year level.

Table 2: *Time on the market and distance to the city center, Germany (2012–2024)*

	(1)	(2)	(3)	(4)	(5)	(6)
	TOM	TOM	TOM	TOM	TOM	TOM
Distance to center (in km)	0.34*** (0.04)	0.24*** (0.03)	0.20*** (0.03)			
Travel time to center (in min)				0.15*** (0.02)	0.10*** (0.01)	0.08*** (0.01)
City $\times$ Year-quarter FE	✓	✓	✓	✓	✓	✓
Property characteristics		✓	✓		✓	✓
Borough FE			✓			✓
N	84,292	84,292	84,292	84,292	84,292	84,292
Adj. R^2	0.04	0.13	0.13	0.04	0.13	0.13
Mean(TOM)	13.51	13.51	13.51	13.51	13.51	13.51

Notes: This table displays the output of Regression (1) on time on the market (TOM), measured in weeks. The first three columns show the results for distance to the city center measured in kilometers, while the last three columns show the results for car travel time to the city center measured in minutes. The list of property characteristics is available in Supplemental Appendix A.1. Regressions are based on the matched sample for all cities covering the period between 2012 and 2024. Standard errors (in parentheses) are clustered at the city-year level. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

Results. In Figure 1, we present binned scatter plots based on Regression (1). The left-hand panels display a clear negative relationship between sales prices and distance to the city center. This negative price gradient has been documented in the literature for cities in the United States (Harris, 2024) and across the globe (Liotta, Viguié, and Lepetit, 2022). The right-hand panels display a clear positive relationship between time on the market and distance to the city center, which constitutes our novel finding of a *negative liquidity gradient*. By showing the results for both German and U.S. cities, we demonstrate that these stylized facts hold for very different housing markets as well as different city structures – U.S. cities are typically larger and more sprawled than European cities (see, for example, Nechyba and Walsh, 2004).

Table 3: *Time on the market and distance to the city center, U.S. (2012–2023)*

	(1)	(2)	(3)	(4)	(5)	(6)
	TOM	TOM	TOM	TOM	TOM	TOM
Distance to center (in km)	0.04*** (0.005)	0.03*** (0.005)	0.05*** (0.004)			
Travel time to center (in min)				0.04*** (0.007)	0.03*** (0.006)	0.06*** (0.005)
Median income		-0.09 (0.110)	-0.14 (0.088)		-0.08 (0.105)	-0.09 (0.085)
MSA $\times$ Year-month FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Property characteristics			✓			✓
Demographic controls			✓			✓
<i>N</i>	682,100	682,100	682,100	682,100	682,100	682,100
ZIP Codes	4,943	4,943	4,943	4,943	4,943	4,943
Adj. R^2	0.29	0.29	0.32	0.29	0.29	0.32
Mean(TOM)	7.60	7.60	7.60	7.60	7.60	7.60

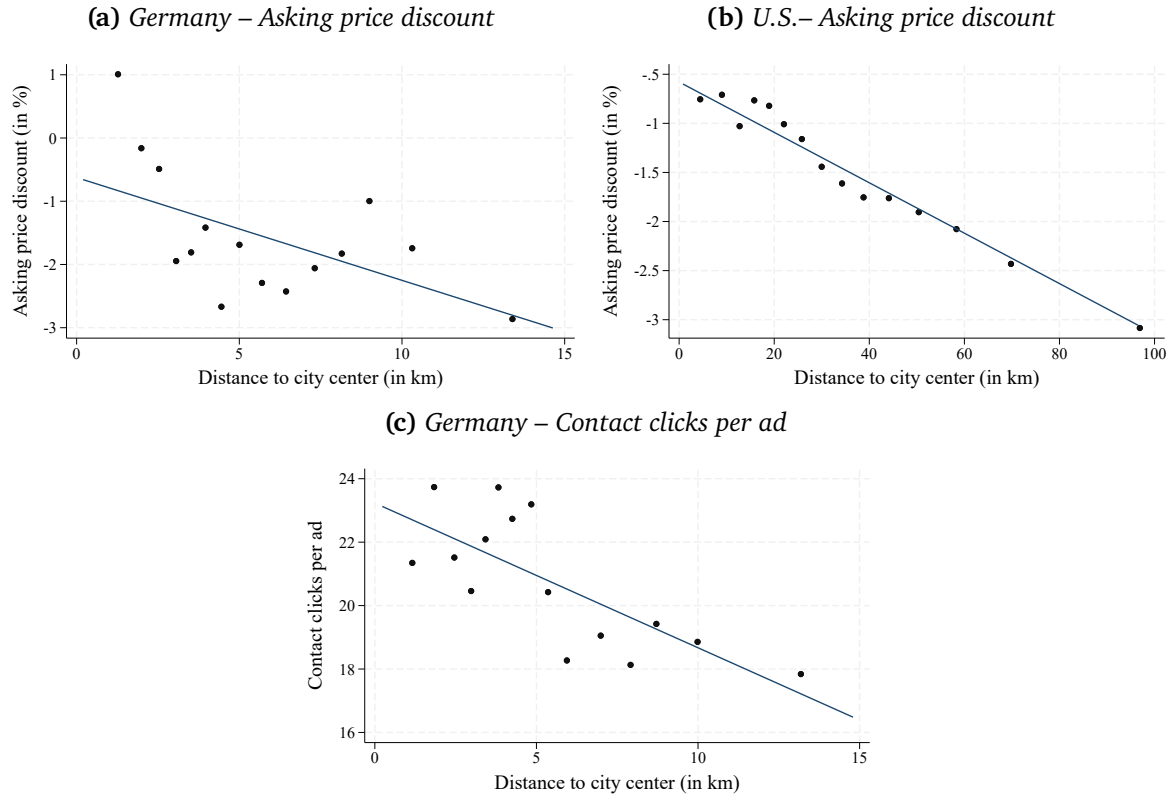
Notes: This table displays the output of Regression (1) on time on the market (TOM), measured in weeks. The first three columns show the results for distance to the city center measured in kilometers, while the last three columns show the results for car travel time to the city center measured in minutes. Regressions are based on data for single-family houses for the 30 largest MSAs covering the period between 2012 and 2023. Standard errors (in parentheses) are clustered at the MSA-year level. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

Next, we quantify the relation between time on the market and distance to the city center using several alternative specifications of Regression (1). Tables 2 and 3 present the results for Germany and the U.S. across model specifications, ranging from the most parsimonious model, which only includes city-time fixed effects, to the most comprehensive model, which features the full set of control variables. The coefficient on kilometer distance or travel time is consistently significant at the 1% level for both German and U.S. cities across all specifications.¹⁴ The coefficients remain highly significant but become slightly smaller when property characteristics are included as controls – the housing stock in city centers often exhibits features that enhance its liquidity, such as apartments being smaller and newer. The results remain robust when focusing solely on within-borough (*Stadtbezirk*) variation in German cities and when controlling for local median household

¹⁴Note that differences in average travel times between Germany and the U.S. lead to different relative magnitudes of the kilometer distance and travel time coefficients.

income, neighborhood quality, and demographic characteristics in U.S. cities.¹⁵

Figure 2: Alternative liquidity measures for Germany (2012–2024) and the U.S. (2012–2023)



Notes: These binned scatter plots visualize the results of Regression (1) with asking price discount and contact clicks per ad as the outcome variables, using 15 equally-sized distance bins. The binned scatter plots are produced following Cattaneo et al. (2024).

In terms of magnitude, properties in the outskirts take approximately 20% longer to sell compared to those in the city center after taking into account spatial variation in property characteristics, income, and demographics. In German cities, this amounts to approximately two and a half weeks, while in U.S. cities, it corresponds to about two weeks.¹⁶ As we show later in our model, these results reflect large spatial differences in market tightness with substantial effects on welfare and prices. Moreover, as we illustrate in Supplemental Appendix C.1, the spatial variation in U.S. housing market liquidity is as large as the variation over time. The cyclical variation in time on the market amounts to up to three weeks, which has been shown to have important implications for business

¹⁵In Supplemental Appendix J.1, we show that the variance of time on the market also increases with distance to the city center. This result confirms a prediction of our structural model in the second part of the paper.

¹⁶These results are based on a specification of Regression (1) in which the “city center” is defined as all observations within a 3 km radius of the city center in Germany and a 10 km radius in the U.S., while the “outskirts” are defined as areas beyond 13 km for German cities and beyond 40 km for U.S. cities.

cycle dynamics (Garriga and Hedlund, 2020). Moreover, as we show in Supplemental Appendix C.4, distance to the city center is more strongly associated with time on the market than are other property characteristics such as size or building year.¹⁷ Lastly, despite large differences in terms of city structure between German and U.S. cities, when considering the actual travel time to the city center with all controls (Column 6 in both tables), time on the market changes at almost the same rate across space in both countries.

3.2 Spatial variation in other liquidity measures

We now show that other dimensions of liquidity in housing markets – beyond the time on the market – also decline with distance to the city center. Figure 2 presents binned scatter plots based on Regression (1). First, the spread between the asking price and the sales price decreases with distance to the city center in both German and U.S. cities. In both countries, this spread is on average negative, indicating that final transaction prices tend to fall below initial asking prices. This finding suggests that sellers in the outskirts have a harder time selling at their asking prices. Second, market tightness, proxied by contact clicks per ad, decreases with distance to the city center in German cities.¹⁸ Both of these effects are statistically significant, as shown in Supplemental Appendices C.6 and C.7 with detailed regression results. Supplemental Appendix D.9 shows that these results also hold for rental yields. Importantly, spatial liquidity differences cannot be explained by housing supply: as we show in Supplemental Appendix C.7, the density of the residential housing stock decreases with distance to the center. Altogether, our findings underscore the importance of demand-side factors in shaping spatial patterns of housing liquidity.

¹⁷Note that even though we estimate a strong and significant relationship between distance to the city center and time on the market, our results for Germany yield low R-squared values. This is consistent with prior studies summarized in Supplemental Appendix C.4. The limited explanatory power largely reflects unobserved bargaining dynamics between buyers and sellers, which, however, does not bias our estimated relationships as long as these unobservables are not systematically correlated with distance to the city center. Supporting evidence comes from the substantially higher R-squared in our U.S. analyses which are aggregated at the ZIP code level, suggesting that much of the idiosyncratic heterogeneity averages out once data are aggregated locally.

¹⁸Data retrieved from RWI - Leibniz-Institut für Wirtschaftsforschung and ImmobilienScout24 (2024). Recall from Section 2.4 that we can construct this measure only for German cities.

3.3 Robustness analyses

Results for individual cities. In the previous section, we have presented results for pooled samples of German and U.S. cities. Given that cities vary in size and other spatial characteristics, it is possible that our results are driven by a subsample of cities. As we show in Supplemental Appendix D.1, this is not the case. We find negative liquidity and price gradients for all cities in the German dataset and negative liquidity gradients for all cities as well as negative price gradients for most cities in the U.S. dataset. Our empirical analysis is not focused on heterogeneity in coefficients across cities, rather, it aims to detect systematic patterns across the cities in our sample. Our structural model in the second part of the paper then serves to explain these systematic patterns. Nevertheless, according to our model, potential drivers of the heterogeneity in coefficients could be related to the cost of travel to the city center.

COVID. The COVID-19 pandemic and the subsequent shift to remote work significantly flattened the price gradient in the United States (Gupta et al., 2022). In contrast, the impact on the price gradient in Europe has been comparably muted (Biljanovska and Dell’Ariccia, 2025). We test whether remote work influenced liquidity gradients by splitting our samples into pre- and post-2020 periods. For both Germany and the U.S., the liquidity gradient flattened during the COVID-19 pandemic but started to recover thereafter, as documented in Supplemental Appendix D.2. Our structural model is able to replicate this development, which we show in Supplemental Appendix J.6. The extent to which the flattening is persistent depends on the future evolution of remote work levels and preferences to live near city centers.

Different housing types. In our baseline analysis, we focus on the most common housing types in German and U.S. cities: apartments and single-family houses, respectively. In this robustness check, documented in Supplemental Appendix D.3, we demonstrate that our results for German and U.S. cities remain robust when alternative housing types are considered (single-family homes for German cities and condominiums, multi-family homes, and townhouses for U.S. cities).

Alternative city definitions. To ensure that our U.S. results are not specific to the rather broad definition of MSAs, we replicate our baseline analysis using functional urban area boundaries from Moreno-Monroy, Schiavina, and Veneri (2021), which define cities

based on commuting flows following the EU-OECD definition in Dijkstra, Poelman, and Veneri (2019).¹⁹ In Supplemental Appendix D.4, we show that our results hold when using functional urban area boundaries for U.S. cities.

Alternative city center definitions. In our baseline analysis, our definition of city center is based on historic locations for German cities and city halls for U.S. cities. We conduct a robustness analysis with alternative city centers. For Germany, we use the centroid of the business district with the highest land value in 2023, as given by the *Bodenrichtwerte* land values produced by the *Gutachterausschuesse* real estate committees.²⁰ This definition follows the concept of a central business district in the canonical monocentric city model. For the United States, we do not have appraisal data available and therefore use the locations with the highest job access index as alternative city centers. The results, documented in Supplemental Appendix D.5, show practically unchanged spatial gradients.

Non-parametric estimation. Although our main results are highly significant and robust to a multitude of controls and fixed effects, we still rely on the functional form of the OLS regression specified in Equation (1). To ensure that our results are not compromised by misspecification, we employ nonparametric methods. When applying these methods, we test whether liquidity and prices are on average lower in the outskirts than in the city center, where we match at the level of housing units based on observable characteristics. Accordingly, we can only produce these results for German cities.

First, we use augmented inverse probability weighting to estimate the average difference in outcome variables between city center and outskirts, while using LASSO regression in the first stage to estimate the probability of treatment. Second, we use propensity score matching based on our full set of apartment characteristics. Third, we use inverse probability weights from a logistic regression to estimate average differences. The results are documented in Table 4, comparing the first 3 bins of the distance to the city center with the 13th, 14th, and 15th (out of 15) bins. All non-parametric methods confirm our baseline OLS results both in terms of direction as well as in terms of magnitude. The relatively high number of observations and detailed information on properties explain

¹⁹This robustness analysis is not possible for German cities, as we only have data available that refers to apartments transacted within the administrative city boundaries.

²⁰For this analysis, we have to exclude Munich, as we do not have access to its local *Bodenrichtwerte* appraisals.

the similar effect magnitudes across methods.

Table 4: Average differences between city center and outskirts, Germany (2012–2024)

Method	Difference in TOM	Difference in log prices	N
OLS	1.89*** (0.227)	-0.40*** (0.004)	33,717
LASSO	2.11*** (0.378)	-0.43*** (0.006)	33,717
Propensity score	1.99*** (0.446)	-0.43*** (0.013)	33,717
Inverse probability	2.20*** (0.328)	-0.43*** (0.005)	33,717

Notes: This table shows the estimated average difference between city center and outskirts for time on the market (TOM), measured in weeks, and log sales prices for different non-parametric methods. The different methods are described in the main text. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

Properties that do not get sold. Our baseline results could be biased if the number of advertisements that did not result in a sale varies systematically across space. To assess this, we run an algorithm to identify such advertisements in the German data. Supplemental Appendix D.6 shows that the percentage of ads that do not result in a sale is small and increases slightly with distance to the city center. In addition, we conduct a survival analysis that includes ads which did not result in a sale, and find that the probability of sale decreases with distance to the city center. By excluding unsold properties from our main analysis, we may, if anything, be underestimating the steepness of the spatial liquidity gradient.

Systematic overvaluation. A potential alternative explanation for lower liquidity in the outskirts is the presence of less-informed sellers, possibly due to an older population that is less engaged with housing markets. Specifically, if sellers in peripheral areas systematically overvalue their properties by setting unrealistically high asking prices, this may lead to longer marketing durations. A further implication is a wider gap between asking and transaction prices in these areas – an empirical pattern that we indeed observe. However, as demonstrated in Supplemental Appendix D.7, this overvaluation mechanism cannot explain the observed differences in housing market liquidity. We show that the spatial gradient in the time on the market remain practically unchanged when controlling for the asking price discount, and vice versa. This result is not surprising, given that real estate listing platforms are widely accessible, which implies that market participants in the outskirts are, on average, probably as informed as those in the city center.

3.4 Discussion of external validity

Our empirical analysis shows that liquidity and prices decrease with distance to the city center. In this section, we discuss to which extent these results can be generalized to other settings, considering alternative focal points beyond the city center and other markets.

In our empirical analysis, we implicitly assume that the cities in our sample exhibit a monocentric structure. However, the mechanism we propose in the theoretical part of the paper extends beyond the monocentric structure. In particular, our theoretical mechanism only requires the existence of focal points that attract sufficiently large numbers of commuters. We test whether our empirical results hold when considering alternative focal points. Using data on commuting distances and the number of employees across ZIP Codes from Delventhal and Parkhomenko (2024), we construct an index of job accessibility at the ZIP-Code level as an inverse-distance-weighted average of accessible jobs. We identify the ZIP Codes with the highest job accessibility within a given MSA, which we refer to as *focal ZIP Codes*, and calculate the distance from each ZIP Code to the nearest focal ZIP Code. We then test whether we also find liquidity and price gradients in this alternative setting. The results, presented in Supplemental Appendix D.8, confirm that both gradients are also present when measuring distances to nearest focal ZIP Codes. This finding is robust to varying the number of focal ZIP Codes per MSA.

Second, we test whether our results also hold beyond the owner-occupied housing market. If the observed liquidity and price gradients are driven by differences in local market tightness, as suggested by our results in Section 3.2, we should expect to observe similar patterns in the rental market. To test this, we use German rental listings data from ValueAG for the same cities and time period as in our baseline analysis. The results, calculated using the baseline specification of Regression (1), are presented in Table 5. We find that the time on the market for rental housing units increases with distance to the city center, while net rents (defined as monthly rental prices excluding utilities) decrease. In Columns 3 and 6, we show that these results also hold when relying on within-ZIP-Code variation, which partially isolates confounding variation due to spatial differences in income and demographics.²¹

²¹Note that due to the high number of observations for rentals, we are able to use these more granular location fixed effects compared to those in our baseline analysis.

Table 5: *Liquidity and price gradients in the rental market, Germany (2012–2024)*

	(1)	(2)	(3)	(4)	(5)	(6)
	TOM	TOM	TOM	Net rent	Net rent	Net rent
Distance to center (in km)	0.17*** (0.02)	0.17*** (0.02)	0.21*** (0.08)	-0.02*** (0.00)	-0.03*** (0.00)	-0.02*** (0.00)
City $\times$ Year-quarter FE	✓	✓	✓	✓	✓	✓
Property characteristics		✓	✓		✓	✓
ZIP Code FE			✓			✓
N	957,249	957,249	957,249	957,249	957,249	957,249
Adj. R^2	0.23	0.26	0.27	0.40	0.90	0.91
Mean(dependent variable)	6.72	6.72	6.72	6.52	6.52	6.52

Notes: This table displays the output of Regression (1) on time on the market (TOM) and log net rental value (net rent). All columns show the results for distance to the city center measured in kilometers. The list of property characteristics is available in Supplemental Appendix A.1. Regressions are based on the cleaned sample of rental listings from ValueAG for all cities covering the period between 2012 and 2024. Standard errors (in parentheses) are clustered at the city-year level. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

4 Theoretical analysis

We give structure to the stylized empirical facts documented in the previous sections by building a spatial search model of a city’s housing market. We start from a frictional search market for housing (see, for example, Ngai and Tenreyro, 2014; Piazzesi, Schneider, and Stroebel, 2020; Guren and McQuade, 2020), using the established basic setup from Krainer (2001). We introduce space following the monocentric city model going back to Alonso (1964), Mills (1967), and Muth (1969). The spatial distribution of housing in the static monocentric city model is endogenous. Here, we take the spatial distribution of housing as exogenously given to focus on liquidity, an inherently dynamic object.

4.1 Structural framework

Model environment. Time is discrete and measured in days. A large number N of infinitely-lived agents live in a monocentric city. The agents are risk neutral,²² financially unconstrained, and discount with factor $\beta \in (0, 1)$. All agents travel to the city center for work and leisure activities. The daily travel cost $\tau(d)$ is associated with a distance to

²²Risk neutrality is standard in housing search models, analogously to labor market search models (see, for example, Rogerson, Shimer, and Wright, 2005).

the city center $d \in \mathcal{D} = [\underline{d}, \bar{d}]$, where $\partial \tau / \partial d > 0$. There are two goods in the economy, housing and a composite consumption good which is not modeled explicitly. All costs and benefits in the model are expressed in terms of the composite consumption good.

Housing. The housing stock is exogenously given and consists of N housing units with given distances to the city center. Before deciding whether to purchase a housing unit, an agent draws an idiosyncratic valuation ε , referred to as *housing dividend* in the following. The housing dividend is a random variable with cumulative distribution function F and probability density function f . Having decided to purchase a property, the agent receives the corresponding dividend in every period until they are unmatched. The dividend is independently and identically distributed across agents, space, and time. An agent can only occupy one housing unit at a time, can only search for new housing units after they have been unmatched, and cannot rent out their property.

Search process. We focus on a stationary search equilibrium and omit time indices. In the first model period, every agent is endowed with a housing unit. In every following period, a match between an agent and a housing unit persists with probability π . With probability $1 - \pi$, an agent is unmatched, which can be interpreted as a moving shock. In this case, the agent puts their property up for sale and searches for a new one.²³ Agents are therefore sellers and buyers simultaneously.²⁴ In a given model period, first, sellers post prices, and second, buyers randomly visit housing units that are on the market. When visiting a housing unit, a buyer observes their dividend draw, the property's distance to the city center, and the posted price. The buyer either agrees on the price and moves into the property in the next period or does not agree on the price and continues to search. In Supplemental Appendix G, we extend the search process with a bargaining process,

²³While searching, agents do not necessarily own and live in properties defined formally within the model framework, as they can sell their unmatched property before having found a new property to live in. For this case, we assume that they live in rental units owned by absentee landlords. These properties are rented out at a fixed rental rate normalized to zero, such that this rental rate fully operates in the background of the model and all other costs and benefits in the model are to be understood as deviations from this rental rate. Since this rental rate is small compared to housing prices and expected travel costs for the time of living in a property, we do not explicitly take it into account in our quantitative exercises in Sections 4.5 to 5. Another interpretation of this assumption is that agents live in relatives' (etc.) housing units while searching if they have already sold their previously unmatched property. The travel cost incurred during the period of living in rental units or being "unhoused" is negligible, as is the rental cost in the first interpretation of this assumption.

²⁴An agent can only occupy one housing unit at a time, but can have multiple housing units on the market as a seller. Such a scenario occurs if an agent is unmatched, finds a new property, is unmatched again, but has not yet sold their old property/properties. Due to the large number of agents, the probability of a single agent accumulating all housing units is approximately zero.

following Carrillo (2012).

Seller's problem. Risk neutrality, a standard assumption in search models, allows us to analyze buyer and seller decisions separately due to linear additivity of agents' value functions. A seller chooses a posted price $p(d)$ to maximize their present value

$$\Pi(d) = \gamma(d)p(d) + (1 - \gamma(d))\beta\Pi(d). \quad (2)$$

With probability of sale $\gamma(d)$, the seller receives $p(d)$. With probability $1 - \gamma(d)$, they try to sell the housing unit again in the next period, obtaining a discounted continuation value $\beta\Pi(d)$. The probability of sale $\gamma(d)$ reflects expected demand, or market tightness, given $p(d)$. Sellers take into account the effect of posted prices on local market tightness. They act as local price setters.²⁵

Buyer's problem. A matched buyer, that is, a buyer who has purchased a property and is either currently occupying the housing unit or will occupy the housing unit in the next period, obtains value

$$V(d, \varepsilon) = \beta \left(\varepsilon - \tau(d) + \pi V(d, \varepsilon) + (1 - \pi)(\Pi(d) + W) \right), \quad (3)$$

where W denotes the value of search. With a delay of one period, the buyer receives the dividend ε and incurs the travel cost $\tau(d)$. With probability π , the buyer keeps on living in the housing unit for another period and receives the discounted continuation value $\beta V(d, \varepsilon)$. With probability $1 - \pi$, the buyer becomes unmatched and receives the discounted resale value $\beta\Pi(d)$ and the discounted value of search

$$\beta W = \beta \mathbb{E}_{d, \varepsilon} \left[\max \left[V(d, \varepsilon) - p(d), \beta W \right] \right], \quad (4)$$

where a buyer either accepts a posted price and receives a discounted net value of $\beta(V(d, \varepsilon) - p(d))$, or continues to search and receives $\beta^2 W$.²⁶

²⁵This assumption, which we take over from the original Krainer (2001) model, serves as the basis for one of our counterfactual exercises in Section 5. The assumption is not required to generate our key theoretical result, which is that buyer reservation dividends increase with distance to the city center. Specifically, a constrained-efficient model version in Section 5 in which sellers do not set prices and buyers simply search for their preferred housing units also yields reservation dividends that increase with distance to the city center.

²⁶To calculate the expectation over distances, we assume that it is formed using the whole set of distances $\mathcal{D}$, even if only a subset of distances is covered by the market in a given period. In other words, we assume

4.2 Equilibrium

Seller's optimization. Rearranging the seller profit expression (2), we have that

$$\Pi(d) = \tilde{\gamma}(d)p(d), \quad (5)$$

where $\tilde{\gamma}(d) = \gamma(d)/(1 - \beta(1 - \gamma(d)))$ is the discount-factor-adjusted probability that a seller can sell their property in the current period or in any future period. It reflects the expected demand that is relevant for the seller from the perspective of the current period. The first-order condition for profit maximization is then similar to that of a typical price setter, but with a probabilistic sale of a single good and without production costs:

$$\tilde{\gamma}(d) + p(d) \frac{\partial \tilde{\gamma}}{\partial p(d)|_d} = 0, \quad (6)$$

where the derivative $\partial \tilde{\gamma}(d)/\partial p(d)|_d$ is a reformulation of the derivative $\partial \gamma(d)/\partial p(d)|_d$.²⁷ It captures the tradeoff between price and probability of sale that the seller faces: if the seller changes their price, the probability of sale also changes. We show in Supplemental Appendix E that a seller's first-order condition provides a local maximum for their profit.

Buyer's optimization. Via the definition of the value of search (4), a buyer has to be indifferent between buying a property and continuing to search at some reservation dividend $\varepsilon^*(d)$:

$$V(d, \varepsilon^*(d)) - p(d) = \beta W. \quad (7)$$

The solution of this equation for a given distance to the city center characterizes the corresponding reservation dividend. The optimality condition (7) defines a cutoff rule

that buyers act as if housing units at all distances to the city center will be available on the market in the next period. This modeling choice is a consequence of focusing on a stationary equilibrium. With a large number of properties, this holds approximately true in every period.

²⁷Specifically, this derivative reads

$$\frac{\partial \tilde{\gamma}}{\partial p(d)|_d} = \frac{\partial \gamma}{\partial p(d)|_d} \left(\frac{1 - \frac{\beta \gamma(d)}{1 - \beta(1 - \gamma(d))}}{1 - \beta(1 - \gamma(d))} \right),$$

where the denominator reflects that if the seller marginally changes their posting price, the probability of sale changes in the current period, but also in the next period with probability $1 - \gamma(d)$ which is discounted with factor β , and so forth, ad infinitum. The numerator adjusts for the fact that the probability $1 - \gamma(d)$ with which the probability of sale changes in the next period, changes as well.

for a stochastic event. Individual buyers can draw higher housing dividends than $\varepsilon^*(d)$, in which case they accept the equilibrium price $p(d)$ and obtain a net utility above βW .

Notion of spatial equilibrium. The buyers' optimality condition (7) implies reservation dividends with which buyers are indifferent between purchases at all distances to the city center, as the discounted value of search βW does not vary across space. The buyer indifference condition is hence also a spatial equilibrium condition. Note that precisely because equilibrium expected net buyer utility is constant, required dividend draws have to offset travel costs. Hence, this spatial equilibrium condition is also to be interpreted as a spatial no-arbitrage condition for housing (see, for example, Glaeser and Gyourko, 2008), such that there is no arbitrage opportunity for buyers across space.

Probability of sale. The equilibrium probability of sale at some distance to the city center is equal to the probability that a buyer's idiosyncratic dividend draw is above the reservation dividend at this distance:

$$\gamma(d) = \text{Prob}(\varepsilon \geq \varepsilon^*(d)) = 1 - F(\varepsilon^*(d)). \quad (8)$$

Thus, for the derivative in the seller's optimality condition (6) we have that

$$\frac{\partial \gamma}{\partial p(d)|_d} = -f(\varepsilon^*(d)) \frac{\partial \varepsilon^*}{\partial p(d)|_d}. \quad (9)$$

To characterize this derivative, we rearrange the buyer's value (3) and obtain the linear expression

$$V(d, \varepsilon) = \frac{\beta}{1 - \pi\beta} \left(\varepsilon - \tau(d) + (1 - \pi)(\Pi(d) + W) \right). \quad (10)$$

Using the indifference condition (7), we isolate the reservation dividend:

$$\varepsilon^*(d) = \frac{1 - \pi\beta}{\beta} p(d) + \tau(d) - (1 - \pi)\Pi(d) + (\pi - \pi\beta)W. \quad (11)$$

Hence, the derivative in the first-order condition of the seller is

$$\frac{\partial \gamma}{\partial p(d)|_d} = -f(\varepsilon^*(d)) \frac{1 - \pi\beta}{\beta}, \quad (12)$$

where $\partial\Pi/\partial p(d)|_d = 0$ due to the envelope theorem. Now, we have all required information to define an equilibrium of the model.

Equilibrium definition. A *stationary spatial search equilibrium* consists of value functions $\{V, \Pi\}$, a value of search W , a posting price function p , a reservation dividend function ε^* , and a sale probability function γ that satisfy equations (2), (4), (6), (7), (8) for all distances to the city center $d \in \mathcal{D}$, given parameters $\{\beta, \pi, \underline{d}, \bar{d}\}$, a cumulative distribution function for idiosyncratic dividends F with probability density function f , and a travel cost function τ .

4.3 Analytical results

Before calibrating and estimating the model's structural parameters, we first derive analytical results that rationalize our findings from the empirical part of the paper as general properties of our model. We show that the equilibrium expected time on the market increases with distance to the city center, while the equilibrium sales price decreases. We derive these results here for uniformly distributed dividends $\varepsilon \sim U[\underline{\varepsilon}, \bar{\varepsilon}]$ which we later employ in our quantitative exercise. In Supplemental Appendix F, we show that these results hold with more general assumptions about the dividend distribution, and with the exponential distribution as a specific example of an alternative dividend distribution. In Supplemental Appendix G, we show that the expected time on the market is interchangeable with the asking price discount as an alternative concept of liquidity within the extended version of our model with bargaining. In Supplemental Appendix H, we provide proofs of the equilibrium's existence and uniqueness for our extended model with bargaining and our baseline model as a nested case of the extended model.

4.3.1 Reservation dividends across space

First, as an auxiliary result, we derive that buyer reservation dividends $\varepsilon^*(d)$ increase with distance to the city center. This result is auxiliary in the sense that it is essential to understand the spatial patterns in liquidity and prices, our main results. We show that buyers need higher draws of the dividend to make a purchase the farther a housing unit they visit is away from the city center, due to a higher travel cost $\tau(d)$. To obtain that $\partial\varepsilon^*/\partial d > 0$, we reformulate $p(d)$ and $\Pi(d)$ in terms of $\varepsilon^*(d)$. We plug the resulting terms

into the isolated reservation dividend expression (11) which then only depends on the travel cost and the value of search which does not vary across space. If we differentiate this expression with respect to the distance to the city center, we can express the spatial variation in buyer preferences solely as a function of the spatial variation in travel costs. This allows us to obtain features of our model which turn out to hold irrespective of parameter values.

To start our derivations, we use the seller optimality condition characterized by (6) to express the equilibrium price as a function of the probability of sale:

$$p(d) = \frac{-1}{\partial \gamma(d)/\partial p(d)|_d} \left(\gamma(d) + \frac{\beta}{1-\beta} (\gamma(d))^2 \right), \quad (13)$$

where

$$\gamma(d) = 1 - \frac{\varepsilon^*(d) - \underline{\varepsilon}}{\bar{\varepsilon} - \underline{\varepsilon}} = \frac{\bar{\varepsilon} - \varepsilon^*(d)}{\bar{\varepsilon} - \underline{\varepsilon}} \quad (14)$$

due to equilibrium relation (8) between probabilities of sale and reservation dividends. Then, together with the closed-form relation (12) for the derivative $\partial \gamma(d)/\partial p(d)|_d$,

$$p(d) = \frac{\beta(\bar{\varepsilon} - \varepsilon^*(d))}{1 - \pi\beta} + \frac{\beta^2(\bar{\varepsilon} - \varepsilon^*(d))^2}{(1 - \beta)(1 - \pi\beta)(\bar{\varepsilon} - \underline{\varepsilon})} \quad (15)$$

and, via the definition of the seller profit (2),

$$\Pi(d) = \frac{\beta(\bar{\varepsilon} - \varepsilon^*(d))^2}{(1 - \beta)(1 - \pi\beta)(\bar{\varepsilon} - \underline{\varepsilon})}. \quad (16)$$

Plugging these results into the expression for the reservation dividend (11) and differentiating with respect to the distance to the city center, we get:

$$\frac{\partial \varepsilon^*}{\partial d} \underbrace{\left(2 + 2 \frac{\pi\beta}{1 - \pi\beta} \frac{\bar{\varepsilon} - \varepsilon^*(d)}{\bar{\varepsilon} - \underline{\varepsilon}} \right)}_{>0} = \frac{\partial \tau}{\partial d} > 0, \quad (17)$$

and hence, $\partial \varepsilon^*/\partial d > 0$. Intuitively, buyers want to be compensated for higher travel costs with higher housing dividends. This behavior holds in and of itself, and further takes into account spatial differences in prices and profits (and hence resale values) in the underbraced terms. The auxiliary result provides the starting point for our following

description of the spatial variation in liquidity and prices.

4.3.2 Liquidity and prices across space

Liquidity. In line with the measurement of time on the market in the empirical part of the paper, we define that a property has been on the market for T days if it sells on day number T of being advertised. Via the expected value of the geometric distribution that results from the multiplication of sale probabilities over time, the expected time on the market in days at a given distance to the city center is

$$\mathbb{E}[TOM(d)] = \frac{1}{\gamma(d)} = \frac{\bar{\varepsilon} - \underline{\varepsilon}}{\bar{\varepsilon} - \varepsilon^*(d)}. \quad (18)$$

Therefore,

$$\frac{\partial \mathbb{E}[TOM]}{\partial d} = \underbrace{(\bar{\varepsilon} - \underline{\varepsilon})(\bar{\varepsilon} - \varepsilon^*(d))^{-2}}_{>0} \frac{\partial \varepsilon^*}{\partial d} > 0. \quad (19)$$

Intuition. Reservation dividends increase with distance to the city center, which reflects compensation for a higher cost of travel to the city center. With a higher cutoff value for dividend draws, the probability of sale decreases with distance to the city center, that is, the market thins out. A lower probability of sale implies a higher expected time on the market.²⁸

Prices. Via auxiliary expression (15),

$$\frac{\partial p}{\partial d} = \underbrace{\left(\frac{\beta}{1 - \pi\beta} + \frac{2\beta^2(\bar{\varepsilon} - \varepsilon^*(d))}{(1 - \beta)(1 - \pi\beta)(\bar{\varepsilon} - \underline{\varepsilon})} \right)}_{>0} \left(-\frac{\partial \varepsilon^*}{\partial d} \right) < 0. \quad (20)$$

Intuition. Sellers expect to sell housing units with a higher probability in the city center, as reservation dividends are lower. Being local price setters, they optimally post higher prices, since they know that they are more likely to meet a searcher that is willing to buy. As in the standard monocentric city model, the underlying factor for equilibrium prices to decrease with distance to the city center is the cost of travel to the city center.²⁹

²⁸As an additional result, in Supplemental Appendix J.1, we show that the variance of time on the market increases with distance to the city center and confirm this result empirically.

²⁹In Supplemental Appendix J.2, we show that the model furthermore predicts the price gradient to be steeper than the liquidity gradient due to the dynamic nature of the seller's problem and confirm this

Further remarks. We choose to build on the canonical monocentric city model because it is a well-established framework. Our mechanism does not require a single city center, or any city center whatsoever to function. Our additional empirical analysis with focal ZIP Codes across the United States further illustrates this statement empirically. Whenever there is a location for which homebuyers share a common preference to live nearby, generating spatial patterns in market tightness, our mechanism applies. City centers provide established examples for such focal points, and as such a special case of our mechanism. Note that in practice, the cost of travel to a focal point may sometimes not increase with distance to this focal point due to, for example, rivers or other factors that influence local transportation. In such a case, we would not expect liquidity and prices to decrease with distance to this focal point.

Next, note that we assume all agents to be identical. In principle, different buyer clienteles in the city center and the outskirts could also generate spatial variation in liquidity and prices. However, first, within-city housing market search tends to be integrated via “broad searchers” (Piazzesi, Schneider, and Stroebel, 2020) who search across many locations. Second, in our empirical analysis, we condition on apartment size and on borough fixed effects for German cities, both of which should capture some dimension of buyer heterogeneity. For U.S. cities, we control for ZIP-Code-level demographic characteristics. It is therefore consistent with the empirical part of the paper to abstract from buyer heterogeneity in the model.

Moreover, we assume that buyers randomly visit housing units and observe their idiosyncratic dividends during these visits. If buyers were more likely to visit properties in the city center, this would also affect the time on the market. The result on “broad searchers” from Piazzesi, Schneider, and Stroebel (2020) partly counteracts also this concern. Moreover, in Carrillo (2012), searchers observe part of their dividends before deciding to visit properties, which, however, is estimated to play a quantitatively negligible role in housing purchase decisions. In any case, more search flowing towards the center would increase the probability of sale, just as our mechanism predicts. Hence, under the alternative mechanism of spatial differences in search intensity, the driving force behind spatial differences in liquidity and prices would equally consist of spatial differences in market tightness.

result empirically.

Furthermore, note that if housing units are more heterogeneous in the outskirts and this causes higher search costs, buyers are also less likely to buy properties in the outskirts. If heterogeneity is increasing gradually with distance to the city center, this could provide a mechanism for the decreasing market tightness. Such a systematic gradually evolving spatial pattern in the housing stock is unrealistic. Obviously, travel costs do not increase gradually either in the real world – however, arguably much more so than forms of heterogeneity in the housing stock that induce higher search costs.

Lastly, as we show in Supplemental Appendix J.1, lower market tightness in the outskirts also increases the uncertainty about housing liquidity. We assume risk neutrality of agents for tractability. Risk-averse agents would discount uncertainty about liquidity more in the outskirts than in the city center. Spatial price differences would be reinforced.

4.4 Calibration and estimation of model parameters

Now, we turn to our quantitative exercise and first calibrate and estimate the structural parameters of our model. Since our equilibrium conditions gives us a set of non-linear equations, we solve the model numerically.³⁰ To do so, we discretize the set of distances to the city center: $\mathcal{D}^\Delta = \{d_1^\Delta, \dots, d_z^\Delta\}$, where $\underline{d} = d_1^\Delta$ and $\bar{d} = d_z^\Delta$. To obtain the discretized distances $\mathcal{D}^\Delta$, we group the distances to the city center from the pooled German and U.S. datasets into $z = 15$ bins, using the distance bins from the scatterplots in Figure 1. Since the bins are constructed with equal numbers of observations per bin, the implied number of housing units in the model is equal for all 15 distance bins. This does not mean that housing supply is uniform across space. There are more bins in the city center and fewer bins in the outskirts, hence also more model housing units in the city center and fewer model housing units in the outskirts.³¹

We obtain empirical travel time estimates as explained in Section 2.3 and convert them into travel cost estimates, assuming that $\tau(d^\Delta) = \mu \tilde{\tau}(d^\Delta)$, where $\tilde{\tau}(d^\Delta)$ is the travel time to the city center in minutes. This conversion of travel time into travel costs follows established approaches (see, for example, Ahlfeldt et al., 2015).³² The scaling parameter

³⁰Supplemental Appendix I describes our numerical model solution method.

³¹Moreover, we do not implicitly assume any city shape here. We simply represent the spatial distribution of housing of some underlying city in the form of binned distances to the city center.

³²Note that our linear travel cost enters net utility additively, while the typical implementation in Ahlfeldt et al. (2015)-type models assumes an exponential travel cost that enters net utility multiplicatively. For small numbers (which applies for the modeled daily travel cost), these two approaches are approximately equivalent via a first-order Taylor expansion of the exponential function.

μ measures the cost in model units of traveling 2 minutes by car, as agents travel from their property to the city center and back every day. We follow the canonical monocentric city model and calibrate the travel cost as a physical cost of travel, but also provide an alternative calculation in Supplemental Appendix J.3 in which we think of the travel cost as an opportunity cost due to lost time and thus foregone wages. We convert between model units and euros or dollars via the average apartment sales price.

Calibrated parameters. We set $\beta = \sqrt[365]{0.95} \approx 0.9999$ such that the annual discount factor is 0.95. For German cities, the housing match persistence is given by $\pi = 1 - (1/(30 \times 122)) \approx 0.9997$, as the average holding period in the data is 122 months. This value is based on observations from January 1990 to 2024 to capture the full length of holding periods as well as possible. For Hamburg, we do not have data on holding periods available, thus the calibrated housing match persistence is based on information from Munich, Cologne, Frankfurt, and Duesseldorf. For the U.S., we use a holding period of 120 months as a broadly suitable value for large cities, based on the Redfin data.

Estimated parameters. We estimate the travel cost scaling parameter μ and the uniform distribution bounds $\underline{\varepsilon}$ and $\bar{\varepsilon}$ with the method of simulated moments, using an identity weighting matrix for our three parameters and the average time on the market as the only targeted moment. Hence, by construction, we match the average time on the market in the pooled German city (13.51 weeks) and the pooled U.S. city (7.60 weeks). The average sales price is also matched by construction, as we convert between model units and euros or dollars via the average apartment sales price.

Table 6: *Estimated parameters, pooled German and U.S. cities*

Parameter	Value	Bootstrapped 95% CI
μ^{Germany}	0.00619	[0.00618, 0.00630]
$\mu^{\text{U.S.}}$	0.00420	[0.00417, 0.00422]
$\underline{\varepsilon}^{\text{Germany}}$	-0.437	[-0.443, -0.427]
$\underline{\varepsilon}^{\text{U.S.}}$	0.290	[0.282, 0.290]
$\bar{\varepsilon}^{\text{Germany}}$	0.533	[0.527, 0.541]
$\bar{\varepsilon}^{\text{U.S.}}$	0.702	[0.696, 0.711]

The estimation results are displayed in Table 6. We obtain 95% confidence intervals by drawing 1,000 bootstrapped replications of data inputs sized 1/3 of the entire sample with replacement, estimating the model for each draw, and using the 0.025 quantiles and

0.975 quantiles of the resulting parameter distributions as confidence bounds. Note that the estimated lower bound of the housing dividend distribution is negative for Germany, but positive for the United States. This stems from the level difference in time on the market between the two countries, as the U.S. housing market is substantially more liquid than the German housing market.

The estimated values of μ imply an average daily travel cost for the German cities of €20.45, which is in the range of average daily car operating costs in Germany of around €15 (see Andor et al., 2020). For the United States, the average daily travel cost in the model is \$29.59 which is in the range of daily car operating costs in the U.S. of around \$25 (see Moody et al., 2021).³³ The cited empirical travel cost estimates are broad calculations at the country level and likely vary to a considerable degree at the city level. It is furthermore not entirely clear that the car operating cost per se captures the full travel costs or is the only suitable measure. Our opportunity cost calculation in terms of foregone wages in Supplemental Appendix J.5 provides an alternative measure.

4.5 Model results

Our model results exhibit spatial variation that closely aligns with the data, as displayed in Figure 3.³⁴ As such, we argue for the cost of travel to the city center to be a quantitatively strong fundamental that generates within-city spatial variation in both housing liquidity and housing prices. Nevertheless, the model fails to capture the steep price gradients near the city center, and, for the U.S., the flat price gradient in the outskirts. This leaves explanatory room for factors other than the cost of travel to the city center to systematically drive the within-city variation in apartment prices. Possible factors are, for example, housing supply elasticity (see, for example, Baum-Snow and Han, 2024) or residential amenities (see, for example, Garcia-López and Viladecans-Marsal, 2024). Without further analysis, which goes beyond the scope of this paper, we cannot shed light on this issue.

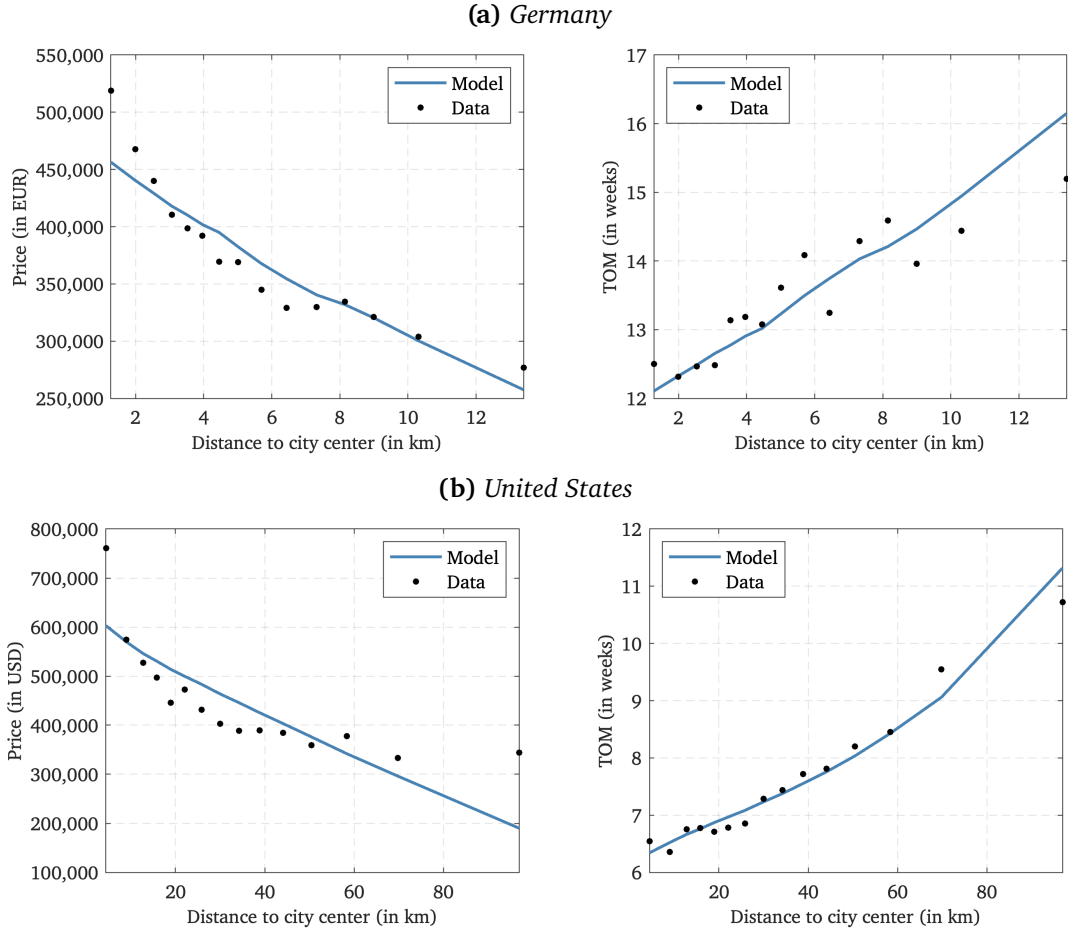
As an additional test of the ability of our model to generate realistic patterns, we replicate the flattened liquidity and price gradient during and after the COVID-19 pan-

³³Most of the average car operating cost consists of fuel costs, depreciation costs, and repair costs which we find plausible to be linear in car travel time. Since empirically we find that public transport travel times are approximately interchangeable with car travel times, we do not repeat this robustness analysis here for the model.

³⁴Supplemental Appendix J.3 provides the spatial distributions of the remaining endogenous variables.

demographic discussed in the empirical robustness analysis. This additional model exercise is documented in Supplemental Appendix J.6 and relies on estimates from Gupta et al. (2022).

Figure 3: Spatial distributions of liquidity and prices: model vs. data



Notes: “TOM” refers to the (expected) time on the market. The data points are calculated using Regression (1) with city-time fixed effects and all controls, as displayed in Figure 1. The binned scatter plots are produced following Cattaneo et al. (2024), using 15 equally-sized distance bins.

5 Housing liquidity, welfare, and spatial asset pricing

In the previous sections, we have established that spatial variation in travel costs leads to spatial variation in market tightness, which in turn creates spatial gradients in housing liquidity and prices. This result holds both qualitatively and quantitatively: empirical variation in travel costs generates spatial gradients in liquidity and prices close to those that we observe in the data. However, we also know from the literature on search markets that asset liquidity affects welfare and prices. Therefore, we now investigate to which

extent housing liquidity affects welfare and housing prices across space. This exercise allows us to gain theoretical insights on housing market welfare and pricing across space. It furthermore allows us to obtain policy implications from our model.

In our model, illiquidity arises from search frictions, and these frictions can affect welfare and prices through two main channels. First, search frictions impose search costs on buyers. Since buyers need to search more in the outskirts, search costs are higher in those areas, which is reflected in a lower market tightness. Second, sellers adjust their posted prices by internalizing spatial differences in market tightness. In particular, in the city center where the market is tighter, sellers have more pricing power and can charge relatively higher prices. These mechanisms are analogous to frictional search in over-the-counter (OTC) markets, where welfare and prices are shaped by search costs and the bargaining power of dealers (see Duffie, Gârleanu, and Pedersen, 2005). Disentangling the two channels allows us to offer a detailed perspective on how spatial differences in liquidity affect welfare and prices across space.

To do so, we conduct a counterfactual analysis, comparing our baseline model with two alternatives: a frictionless model without search, referred to as the *efficient model*, and a model with constrained search, the *constrained-efficient model*.³⁵

Constrained-efficient model. First, following Krainer and LeRoy (2002), we consider a counterfactual constrained-efficient version of our model which is characterized by optimal buyer search behavior given physical search constraints, but no strategic internalization of this search behavior in the price posting of sellers. To implement this allocation, we calculate reservation dividends $\varepsilon^{\text{CE}}(d^\Delta)$ that maximize welfare $\mathbb{W}(d^\Delta)$ at every distance $d^\Delta \in \mathcal{D}^\Delta$ defined as the expected value of being matched, such that

$$\mathbb{W}(d^\Delta) = m(d^\Delta) \left(\mathbb{E}_\varepsilon \left[\varepsilon \mid \varepsilon \geq \varepsilon^{\text{CE}}(d^\Delta) \right] - \tau(d^\Delta) \right), \quad (21)$$

where $m(d^\Delta)$ denotes the probability of being matched and introduces physical constraints into the maximization problem. Without this factor, the optimal reservation dividend

³⁵Note that in our counterfactual analysis, we use the estimated structural parameters from the baseline model. By doing so, we assume that our baseline model, which matches the data on liquidity and prices with high precision, represents reality reasonably well and hence provides us with the starting point. Then, when building a counterfactual model with a different market structure and using the estimated structural parameters (which refer to buyer preferences and travel costs) from our baseline model, we pose the question what would happen if the market structure changes while buyer preferences and travel costs remain the same.

would be the maximum dividend $\bar{\varepsilon}$. However, search implies a tradeoff: if the reservation dividend is high, the probability of being matched is low. Correspondingly, the optimal constrained-efficient reservation dividends imply an optimal level of time on the market and hence illiquidity larger than zero, given physical constraints. This is analogous to a natural unemployment rate. Note that the counterpart of $m(d^\Delta)$ is the steady-state vacancy rate $1 - m(d^\Delta)$. Our baseline model correctly predicts the level as well as the spatial variation in the vacancy rate, which we include in our additional model results in Supplemental Appendix J.3.

Within the welfare definition, the expected idiosyncratic dividend at distance d^Δ is $(\varepsilon^{\text{CE}}(d^\Delta) + \bar{\varepsilon})/2$ with uniformly distributed idiosyncratic dividends, while the travel cost is $\tau(d^\Delta) = \mu \tilde{\tau}(d^\Delta)$.³⁶ Moreover, agents transition from being unmatched to being matched with probability $(\bar{\varepsilon} - \varepsilon^{\text{CE}}(d^\Delta))/(\bar{\varepsilon} - \underline{\varepsilon})$ and keep a housing unit with probability π . The transition probability from being unmatched to being matched is a “flow probability”. The steady-state probability of being matched, a “stock probability”, is therefore

$$m(d^\Delta) = \pi m(d^\Delta) + \pi(1 - m(d^\Delta)) \frac{\bar{\varepsilon} - \varepsilon^{\text{CE}}(d^\Delta)}{\bar{\varepsilon} - \underline{\varepsilon}}, \quad (22)$$

which allows us to calculate welfare in the constrained-efficient model version as

$$\max_{\varepsilon^{\text{CE}}(d^\Delta)} \left(\frac{\pi \frac{\bar{\varepsilon} - \varepsilon^{\text{CE}}(d^\Delta)}{\bar{\varepsilon} - \underline{\varepsilon}}}{1 - \pi + \pi \frac{\bar{\varepsilon} - \varepsilon^{\text{CE}}(d^\Delta)}{\bar{\varepsilon} - \underline{\varepsilon}}} \right) \left(\frac{\varepsilon^{\text{CE}}(d^\Delta) + \bar{\varepsilon}}{2} - \mu \tilde{\tau}(d^\Delta) \right). \quad (23)$$

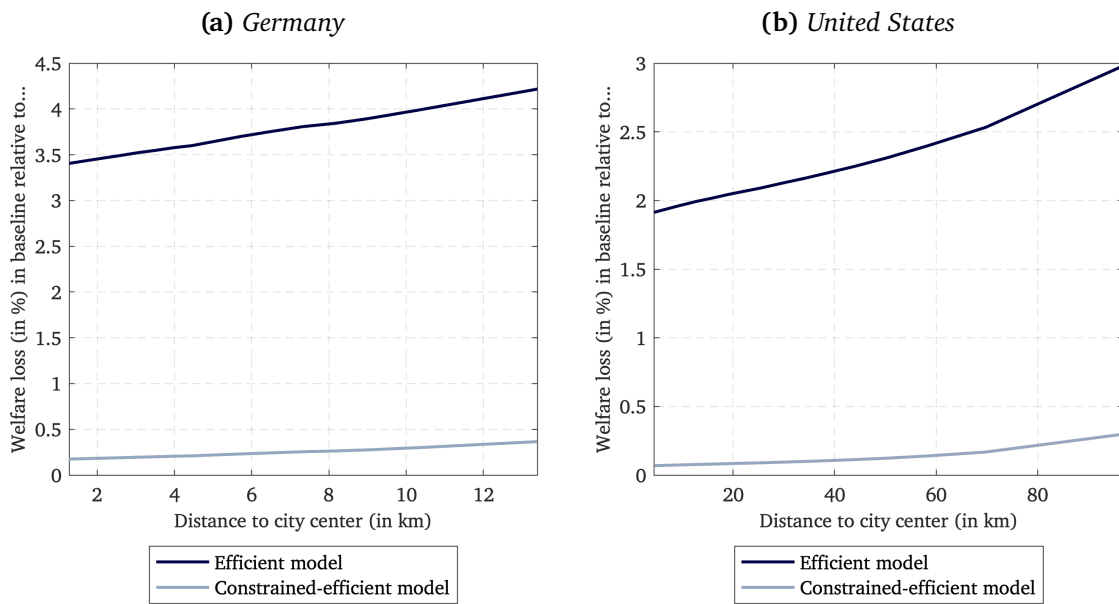
Efficient model. In a fully efficient version of the model, agents do not face search frictions. Matches happen instantaneously and the time on the market is zero everywhere. This translates to $m(d^\Delta) = 1$ at every distance to the city center, such that there are no vacancies. Similarly, every agent can move directly into the housing unit they prefer best. Hence, with the definition from (21), welfare in the efficient model version at distance d^Δ is given by $\bar{\varepsilon} - \mu \tilde{\tau}(d^\Delta)$. Note that in this model, the liquidity gradient is flat by definition.

Welfare analysis. We calculate the spatial distributions of welfare, as defined in (21), in the two counterfactual model versions and compare them to the one in the baseline model in Figure 4. First, we notice that search frictions cause large welfare losses. Compared to the efficient model which abstracts from search frictions entirely, welfare losses in the

³⁶Note that we do not differentiate in notation between the German sample and the U.S. sample here and in the rest of this section to avoid unnecessary notation.

baseline model are on average 3.7% in Germany and 2.2% in the United States.³⁷ The smaller average welfare loss in the U.S. arises due the fact that the U.S. housing market is more liquid, which means that there is less room for welfare gains when eliminating search frictions. On average in both countries, welfare losses amount to 3%.³⁸ These results are well within the range of estimated welfare losses due to frictional illiquidity in other search markets, such as municipal bond markets (see Hugonnier, Lester, and Weill, 2019).

Figure 4: Spatial welfare loss distributions



Notes: Welfare is calculated as defined in (21). The percentages refer to the loss in welfare in the baseline model relative to a counterfactual at every distance to the city center.

The welfare loss in the baseline model relative to the constrained-efficient model is rather small, reaching up to 0.4% in Germany and 0.3% in the United States. The difference in the constrained-efficient model compared to the baseline model lies in the pricing power of sellers. Hence, according to our findings, the interaction of pricing power and search frictions in the housing market causes small welfare losses. Consequently,

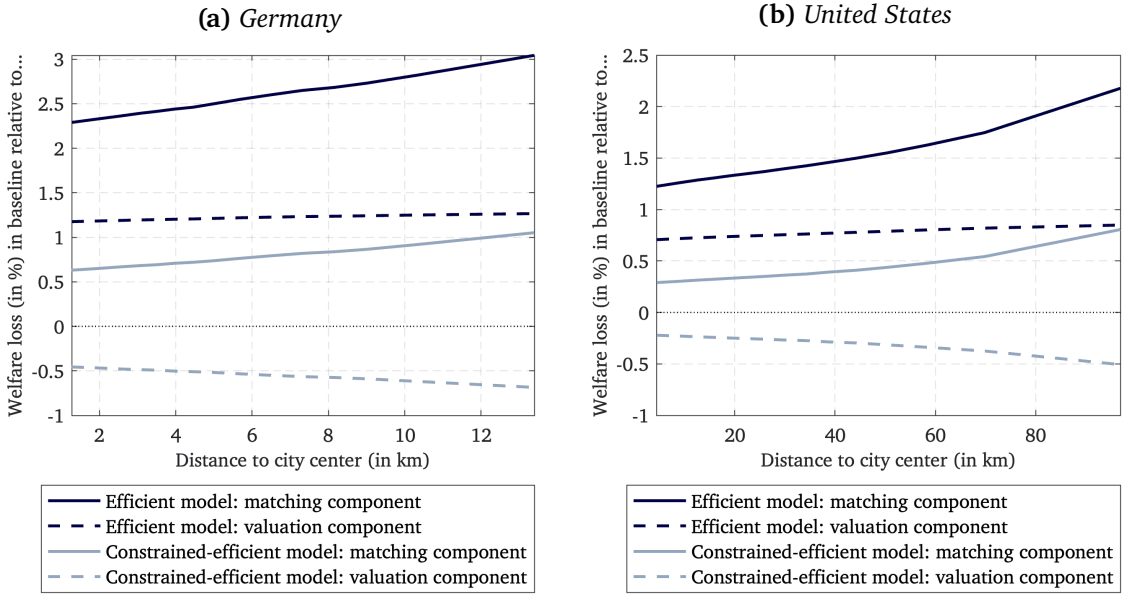
³⁷In Supplemental Appendix J.3, we document that the average welfare loss measured relative to housing prices amounts to 2% in Germany and to 1% in the United States. Hence, on average, welfare losses amount to 1.5% relative to housing prices.

³⁸A possible objection to our welfare calculations is the omission of a rental market in our model. For the U.S., owner-occupied housing is prevalent and owner-occupied and rental housing markets are highly segmented, so this is not a particular concern. For Germany, this is not the case, hence it might be an issue – however, our empirical results from Table 5 show negative liquidity and price gradients for German rental markets, therefore, the same mechanism and the corresponding welfare effects should be present when including a rental market.

there is little room for policy to achieve welfare gains by reducing sellers' pricing power in the owner-occupied housing market according to our model.

To understand the welfare differences, we further decompose welfare losses to assess how much is due to a lower probability of being matched (which we refer to as the “matching component”) and how much is due to lower average dividends (which we refer to as the “valuation component”). This decomposition is shown in Figure 5. We distill two key findings. First, the matching component is the dominant component for welfare losses relative to both counterfactuals.³⁹ The matching probability decreases with search frictions. In other words, at any given point in time, a larger fraction of the housing stock remains vacant, which has large welfare costs. This provides room for policy: for example, vacancy taxes which aim to reduce housing vacancies face large potential welfare gains according to our model.

Figure 5: Spatial welfare loss distributions: decomposition



Notes: Welfare is calculated as defined in (21) and decomposed into the percentage change in the first factor $m(d^\Delta)$ (“matching component”) and the second factor $\mathbb{E}_\varepsilon [\varepsilon \mid \varepsilon \geq \varepsilon^{CE}(d^\Delta)] - \tau(d^\Delta)$ (“valuation component”). The percentages refer to the loss in welfare in the baseline model relative to a counterfactual at every distance to the city center.

³⁹In fact, even though the total welfare loss relative to the constrained-efficient model is small, the isolated welfare loss from the matching component is considerable: in the baseline model, agents search more than in the constrained-efficient model and end up with a lower probability of being matched, which lowers welfare. However, this welfare loss gets canceled out by a welfare *gain* in the valuation component. Reservation dividends in the baseline model are higher than in the constrained-efficient model, such that matched agents have a higher valuation on average. Why? In the constrained-efficient model, agents have to trade off a higher matching frequency with a higher valuation. If agents want to match more often, they need to lower their reservation dividends. It turns out that, with our model calibration, these two factors approximately cancel out, except in the outskirts.

Next, we examine spatial patterns in welfare losses due to frictional illiquidity. As shown in Figure 4, welfare losses increase with distance to the city center. In Germany, agents in the outskirts lose 4.2% welfare in the baseline model relative to the efficient model, whereas agents in the city center lose 3.4%. The difference between these welfare losses amounts to one-fifth of the average welfare loss at 3.7%. In the United States, spatial differences in welfare losses are even larger (1.9% in the center and 3.0% in the outskirts) and amount to half of the average welfare loss at 2.2%. Hence, a welfare calculation which does not take into account these spatial differences would miss a fundamental and large component of variation in welfare losses. Spatial differences in welfare losses stem almost entirely from the matching component: matches are particularly infrequent and vacancies are particularly high in the outskirts in the baseline model. Vacancy-reducing policies therefore have a particularly large scope for welfare gains in the outskirts. In contrast, welfare losses due to the valuation component are relatively stable across space.⁴⁰ Overall, we find that the matching component is key for both the aggregate welfare loss levels and for the spatial variation.

We provide a sensitivity analysis for these results in Supplemental Appendix J.4. We find that, first, bootstrapped 95% confidence intervals for welfare losses are quite narrow and second, the welfare loss estimates are robust to alternative choices for the housing match persistence and the discount factor. As we would expect, when we decrease the match persistence, welfare losses become somewhat larger, since agents have to search more often. A change in the discount factor has close to no effect on the welfare loss estimates.

In summary, we have found that welfare losses in the baseline model relative to more efficient model versions, in particular relative to the efficient model version without search frictions, accrue mostly in the outskirts and mostly due to the matching component of welfare. Due to relatively high reservation dividends in the outskirts, the market equilibrium yields a relatively low probability of sale and therefore relatively high time on the market. This should imply larger relative price differences between the city center and the outskirts in the baseline model compared to the efficient model.

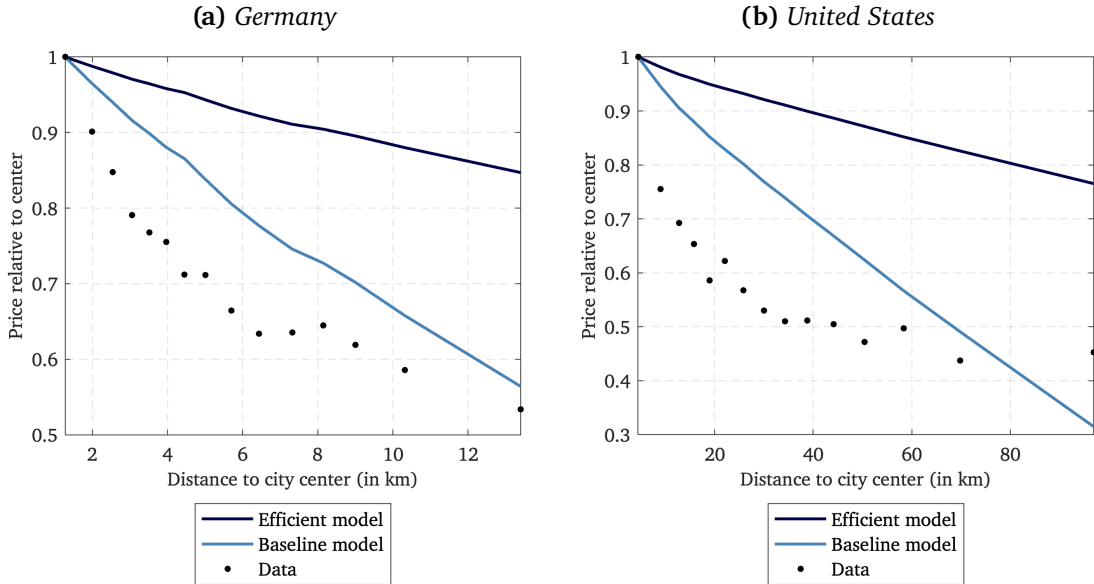
⁴⁰For the constrained-efficient model, the negative welfare loss, that is, the welfare gain, becomes mildly more negative with distance to the city center: there is less scope for pricing power to distort reservation dividends in the outskirts where markets are less tight.

Spatial price gradient comparison. Next, we examine the impact of frictional illiquidity on housing prices. Our constrained-efficient model does not involve prices and thus does not allow for such an analysis. Our efficient counterfactual model describes a frictionless housing market. In such a market, the spatial price gradient merely reflects the cost of travel to the city center. We scale up the daily travel cost $\tau(d^\Delta) = \mu \tilde{\tau}(d^\Delta)$ to an expected lifetime travel cost (where “lifetime” refers to the lifetime of a match) with factor $\beta/(1 - \pi\beta)$, assuming that when an agent becomes unmatched, they immediately find a new match. Then, we have that for the i -th distance to the city center with $i \geq 2$,

$$p^E(d_i^\Delta) - p^E(d_{i-1}^\Delta) = -\frac{\beta}{1 - \pi\beta} \left(\mu \tilde{\tau}(d_i^\Delta) - \mu \tilde{\tau}(d_{i-1}^\Delta) \right), \quad (24)$$

where $p^E(d^\Delta)$ is the price in the efficient model at distance d^Δ . This equation only considers spatial price differences, not levels. To obtain a straightforward comparison to the baseline model prices, we set the price in the city center to 1 and scale the spatial differences in (24) by the price in the distance bin closest to the city center from the baseline model.

Figure 6: Spatial price gradients



Notes: For the data points and the baseline model, all prices are normalized by the price in the first distance bin. For the efficient model, the price in the first distance bin is set to 1 and the spatial differences in prices thereafter, as defined in (24), are normalized by the price in the first distance bin from the baseline model.

We plot the resulting normalized spatial price distributions in Figure 6. Recall that spatial differences in welfare losses are more relevant for the U.S. than for Germany.

Consistently, the relative price distortion in the baseline model compared to the efficient model is larger in the U.S. In the baseline model, U.S. housing prices in the outskirts are 32% of those in the city center, while in the efficient model, this amounts to 77%.⁴¹ Prices therefore decrease by 0.7% per kilometer in the baseline model, but only by 0.2% per kilometer in the efficient model. For Germany, prices decrease by 3.3% per kilometer in the baseline model, but only by 1.1% per kilometer in the efficient model.

Spatial price distortions due to inefficient illiquidity are therefore sizable. For both Germany and the United States, our model implies that the spatial gradient becomes about 3 times as steep due to search frictions and the associated spatial differences in housing market tightness and liquidity. Nevertheless, the magnitude of this result should be interpreted with caution, as our model relies on simplifying assumptions. If we were to endogenize travel costs, for example, the amount of congestion resulting from housing market tightness could spill over to physical congestion and directly influence travel times, hence also travel costs and therefore the spatial price gradient. Considering such mechanisms in detail goes beyond the scope of this paper.

6 Conclusion

In this paper, we use novel spatial datasets from Germany and the United States to demonstrate that housing market liquidity declines with distance to the city center. We develop a spatial search model of the housing market and show that higher travel costs to the city center lead to lower market tightness, which in turn reduces liquidity and depresses sales prices. Moreover, we structurally estimate the extent to which search frictions – operating through search costs and seller pricing power – shape the spatial distribution of welfare and housing prices. We conclude that accounting for search frictions and their impact on housing prices is essential for a more realistic perspective on housing markets. Our findings can also inform research on the link between liquidity and the valuation of real assets. In particular, given the recent “great rotation” (Kojien, Shah, and Van Nieuwerburgh, 2025) toward infrequently traded, heterogeneous private and real assets, our results can help future research identify systematic variation in the

⁴¹Note that, as discussed in the analysis of Figure 3, the model has difficulties in matching the flatter parts of the spatial price distribution in U.S. outskirts. In the U.S. data, prices in the outskirts are 45% of those in the center. Moreover, the model has difficulties in matching the high prices very close to the city center. In the spatial price gradient analysis done here, higher prices in the city center would shrink all relative prices equally, as we normalize by prices in the city center, so this is not an issue.

pricing of such assets.

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Supplemental Appendix for “Spatial distribution of housing liquidity”

Francisco Amaral, Mark Toth, and Jonas Zdrzalek

A Data sources and cleaning procedures

In this section, we present in detail the steps that we took to prepare the data for the empirical analysis.

A.1 German data

Matching algorithm. We start the algorithm by matching each transaction to potential ads based on location. This gives us a pool of potential matching ads for each transaction. We then follow a series of steps to eliminate those ads that are unrealistic matches. First, we exclude advertisements that were published after the contract date and ads that were removed more than one year before the contract date. The algorithm proceeds by matching observations with complete addresses, that is, addresses which include street names and house numbers. However, for apartments, having information on solely the street name and the house number is insufficient for a successful match, as there may be multiple apartment transactions related to the same building. If that is the case, the algorithm excludes ads based on property characteristics in the following order:

1. The living area differs by more than 10%.
2. The floor number differs by more than 2.
3. The building year differs by more than 5 years.

We choose these property characteristics since they have the lowest number of missing values from the set of variables that are covered by both datasets and select numeric values for the criteria that give us reasonable buffers for measurement errors due to incorrect user inputs. If, after this process, we still have more than one potential listing for a particular transaction, we continue to eliminate listings in the following sequential steps until we have only one listing for a particular transaction:

1. We keep the ad(s) that minimize(s) the distance to the transaction in terms of living area.
2. We keep the ad(s) that minimize(s) the distance in terms of floor number.
3. We keep the ad(s) that minimize(s) the spread between the listing price and the sales price.
4. We eliminate listings that were taken out more than three months prior to the actual transaction.

If we still have multiple matches after these steps, we drop them because we have no way of identifying the correct match.

Next, we check if we have assigned an ad to multiple transactions. If this is the case, we keep only the most likely match following the steps described above. When we match based on the building's exact address, we do not exclude matches with different building years. Matching by address is sufficient to identify a building, and typically the building year is the same for all flats within a building. When this is not the case, we attribute the different building years to measurement error, that is, incorrect user-specified information on the advertisement websites. We match the transactions which do not have entries with complete addresses via the same process as for those with complete addresses, but condition sequentially on the following geographical objects: street name, ZIP Code, and neighborhood (*Stadtteil*), until we have a unique match. If there is no unique match, we drop the observation.

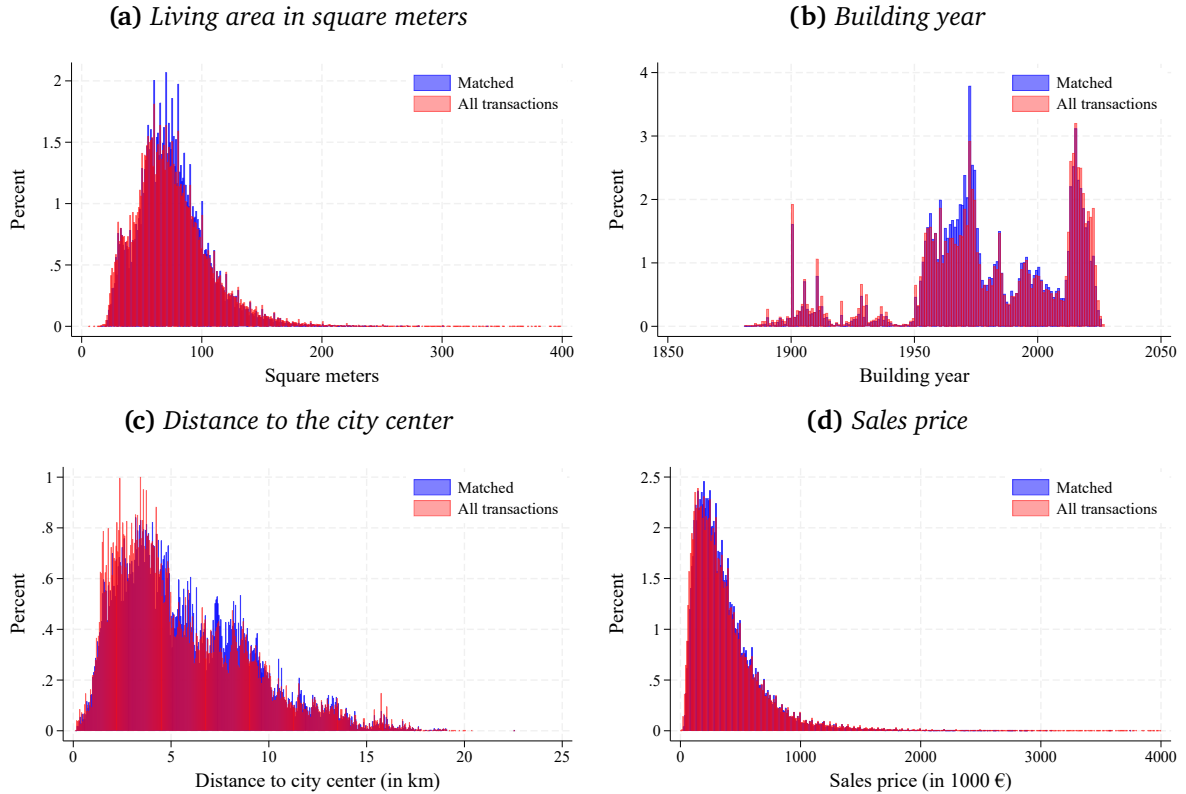
On average, we match about 30% of the transactions across cities. The relatively low proportion of transactions that are matched is largely due to overmatching, that is, the fact that in many cases we end up with more than one potential advertisement for a given transaction after the algorithm has applied all criteria. In Table A1, we provide further information on the matched observations by city.

Table A1: Summary statistics: matched dataset

City	# Transactions	# Ads	# Matched	Avg. sales price (€)	Avg. asking price (€)
Hamburg	80,157	78,342	20,418	356,541	358,604
Munich	57,629	112,135	25,966	493,312	495,710
Cologne	41,338	46,349	14,273	237,462	254,164
Frankfurt	35,493	39,083	12,035	388,445	405,843
Duesseldorf	35,581	34,669	11,611	288,863	303,802

Notes: This table reports summary statistics about the matched transaction and advertisement data for the period 2012–2024.

We show that the matched sample is not biased along several important characteristics of the transacted properties in Figure A1. We plot the distributions from the matched sample and the universe of transactions, with all cities pooled together, of the variables living area, building year, distance to the city center, and sales price. For each of these variables, the two distributions mostly overlap, which indicates that the matched sample is representative of the universe of transactions.

Figure A1: Matched sample and universe of transactions, all German cities pooled

Notes: These plots show histograms of different variables in the matched sample and the universe of transactions. The y-axis measures the frequency in percent of a given value on the x-axis in the respective sample.

Data preparation. We transform several variables to prepare them for regression analysis. We control for the following variables: living area in m^2 , living area squared, number

of rooms, year of construction, “Altbau” or not, “Neubau” or not, physical condition of the building, whether the apartment is in the upper floor of the house or not, whether the apartment is rented out or not, type of heating, source of heating, whether the apartment has a fitted kitchen or not, whether the apartment has an open kitchen or not, whether the bathroom has a shower, whether the bathroom has a bathtub, whether the apartment has a terrace or balcony, whether the apartment has a basement, whether the apartment has a garden, and the number of parking spaces. These control variables are identical for the regressions with rental housing.

We control for the age of the properties by creating a categorical variable that divides the observations into different construction periods. We follow the commonly used categories introduced by the official German appraisers. In particular, we construct the following categories: pre-1950, 1950–1977, 1978–1990, 1990–2005, and post-2005. We use a categorical variable rather than a continuous variable for the building year of the property because the relationship between age and price or liquidity is highly non-linear in the case of the German housing market, as shown in Amaral et al. (2023). In addition, we also include a category for properties that are being occupied for the first time and another category that identifies properties where construction is not yet complete. We divide the heating type of each home into four different categories. We define “brown” dwellings as those that consume energy produced by oil or coal, or use space heating and tile stove heating. We define “standard” dwellings as those that consume energy produced by gas and use central heating. We define “green” properties as those where the energy comes from solar, heat pumps or pellets, or use district heating or CHP. We also use an “other” category, taken directly from the dataset, which includes other energy sources. We use a categorical variable to consider the quality of the furnishings and interiors of the property and a categorical variable to categorize the quality of the construction of the building, both of which are provided directly in the dataset. We create a categorical variable to control for the number of rooms in the property. The variable has four categories: 1 room, 2 rooms, 3 rooms, and 4 or more rooms. We also control for the number of floors on which the apartment is located and the total number of floors in the building where the apartment is located.

A.2 U.S. data

Redfin is both a real estate brokerage and an online platform. Redfin typically has direct access to data from local multiple listing services (MLS) and adds those listings to the platform. However, unlike the well-known Zillow platform (which we cannot use due to a lack of data availability for liquidity variables at the ZIP-Code level), Redfin has a low coverage of for-sale-by-owner (FSBO) listings because Redfin does not allow sellers to post listings themselves. Since FSBOs account for only about 6% of all home sales in the U.S. (see: National Association of Realtors), by including the majority of MLS listings, Redfin covers most of the market. We clean the data by dropping all ZIP Codes for which the time on the market estimates are, on average, based on less than 10 observations and there is one month with less than 5 observations. For a robustness analysis, we collect data on time on the market from another online platform, Realtor.com, which covers most local MLS in the United States, and compare these results to our baseline results. We estimate the time on the market gradient using both datasets. Because the Realtor.com platform only provides data for an “all residential” category, we cannot perform the comparison for different segments separately. Moreover, the dataset from Realtor.com only starts in 2016, so we limit our analysis to the period between 2016 and 2023. In Table A2, we provide outputs for regressions of time on the market on distance to the city center using both the Redfin and Realtor.com data, with very similar results.

For our U.S. control variables on housing characteristics and demographic composition, we use yearly data from the American Community Survey 5-year estimates at the ZIP-Code level from 2012 to 2023. The variables are listed in Section 3.1. Lastly, for the measure of U.S. neighborhood quality, we use data from Chetty et al. (2025). We calculate ZIP-Code-level averages of the fraction of children born between 1978 and 1983 who were incarcerated on April 1st, 2010 (*jail_pooled_pooled_mean*).

Table A2: Time on the market and distance to the city center in the U.S. (2016–2023)

	(1)	(2)	(3)	(4)
	Redfin	Realtor.com	Redfin	Realtor.com
Distance to center (in km)	0.01** (0.006)	0.02*** (0.002)	0.02*** (0.005)	0.02*** (0.002)
Median income			-0.93*** (0.051)	-0.86*** (0.039)
MSA $\times$ Year-Month FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Property characteristics			✓	✓
<i>N</i>	507,490	507,490	507,490	507,490
ZIP Codes	5,673	5,673	5,673	5,673
Adj. R^2	0.20	0.34	0.24	0.40
Mean(TOM)	6.45	7.34	6.45	7.34

Notes: This table shows results for regressions of time on the market on the distance to the city center as specified in Regression (1). Time on the market is measured in weeks. Standard errors (in parentheses) are clustered at the MSA-year level. Median income and property characteristics are control variables. The underlying data bundles all residential housing types into one category. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

B Summary statistics

B.1 German cities

Table B1: *Summary statistics: time on the market and prices in German cities (2012–2024)*

City	Time on the market in weeks				Sales price in €1,000				N
	Mean	SD	P25	P75	Mean	SD	P25	P75	
Hamburg	15.13	17.59	3.10	20.40	357	267	188	437	20,418
Munich	12.34	15.53	2.30	16.30	493	308	285	611	25,966
Cologne	12.42	16.19	2.30	16.20	237	153	130	300	14,273
Frankfurt	15.04	18.23	2.60	20.20	388	253	210	499	12,035
Duesseldorf	12.99	16.28	2.30	17.00	289	225	137	365	11,611

Notes: This table reports summary statistics of time on the market and sales prices by city for the period 2012–2024. All estimates are based on the matched dataset. N is the total number of transactions in the respective matched dataset.

B.2 U.S. cities

Table B2: *Summary statistics: time on the market and prices in U.S. cities (2012–2023)*

MSA	Time on the market in weeks				Sales price in \$1,000				Nr. ZIP Codes	N
	Mean	SD	P25	P75	Mean	SD	P25	P75		
Atlanta-Sandy Springs-Alpharetta, GA	6.70	5.06	3.71	8.57	274	188	150	348	190	26,992
Austin-Round Rock-Georgetown, TX	5.93	4.75	2.93	7.71	413	263	238	502	73	10,509
Baltimore-Columbia-Towson, MD	7.33	5.96	3.64	9.43	406	178	281	497	121	17,477
Boston-Cambridge-Newton, MA-NH	7.49	6.64	2.64	11.36	577	369	350	668	247	24,295
Charlotte-Concord-Gastonia, NC-SC	10.87	7.42	6.43	13.29	256	175	148	315	105	13,508
Chicago-Naperville-Elgin, IL-IN-WI	8.30	5.49	5.00	10.29	288	230	158	348	342	25,102
Cincinnati, OH-KY-IN	10.87	9.51	6.71	13.71	188	105	118	236	123	17,681
Dallas-Fort Worth-Arlington, TX	5.83	3.77	3.43	7.07	285	200	165	348	245	18,665
Denver-Aurora-Lakewood, CO	4.08	6.15	1.21	4.71	455	198	315	561	108	15,480
Detroit-Warren-Dearborn, MI	5.04	4.30	2.50	6.50	210	130	118	285	201	16,703
Houston-The Woodlands-Sugar Land, TX	6.17	4.42	3.14	8.00	266	201	156	302	204	29,363
Las Vegas-Henderson-Paradise, NV	9.44	7.12	6.00	11.21	296	145	200	366	62	8,858
Los Angeles-Long Beach-Anaheim, CA	5.98	4.86	3.93	7.07	934	738	512	1,066	337	30,265
Miami-Fort Lauderdale-Pompano Beach, FL	9.93	5.48	6.79	11.29	533	638	275	560	174	7,709
Minneapolis-St. Paul-Bloomington, MN-WI	6.77	7.31	3.07	8.36	307	146	210	373	196	27,638
New York-Newark-Jersey City, NY-NJ-PA	11.12	9.67	5.43	14.14	627	810	353	698	739	23,776
Orlando-Kissimmee-Sanford, FL	7.81	7.96	3.21	10.57	279	143	179	350	85	11,945
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	7.96	5.97	4.00	10.36	320	184	193	398	270	11,026
Phoenix-Mesa-Chandler, AZ	7.01	3.61	4.86	8.14	338	241	200	410	142	20,050
Pittsburgh, PA	13.62	7.18	8.57	16.57	176	111	102	221	149	21,432
Portland-Vancouver-Hillsboro, OR-WA	4.95	5.23	1.57	6.29	426	185	294	525	110	15,046
Riverside-San Bernardino-Ontario, CA	7.20	4.72	4.43	8.71	375	205	233	478	125	17,534
Sacramento-Roseville-Folsom, CA	4.21	4.07	1.86	5.14	424	208	288	519	85	12,198
San Antonio-New Braunfels, TX	8.11	5.58	4.79	9.86	238	125	151	304	93	13,386
San Diego-Chula Vista-Carlsbad, CA	4.51	4.42	2.14	5.29	788	531	479	895	84	12,239
San Francisco-Oakland-Berkeley, CA	2.77	1.65	1.86	3.14	1,218	857	680	1,504	130	8,610
Seattle-Tacoma-Bellevue, WA	3.27	3.39	1.07	4.43	599	441	330	722	140	11,693
St. Louis, MO-IL	11.85	27.78	5.29	12.86	182	137	94	230	213	25,043
Tampa-St. Petersburg-Clearwater, FL	7.57	5.83	3.14	10.64	281	191	164	345	126	18,144
Washington-Arlington-Alexandria, DC-VA-MD-WV	6.23	5.16	3.14	7.79	541	295	340	658	248	23,122

Notes: This table reports summary statistics of time on the market and sales prices by MSA for the period 2012–2023. N is the number of ZIP-Code-year-month observations in the respective subset of data.

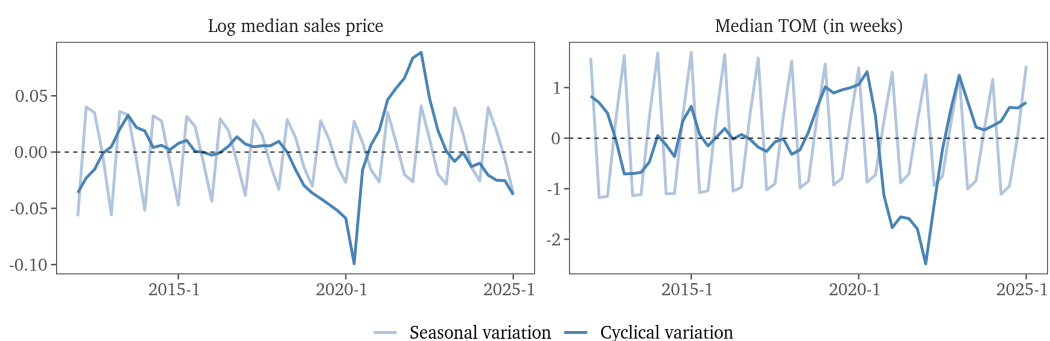
C Additional empirical results

C.1 Time series of housing liquidity and prices in the U.S.

As we mention in the main text, our documented within-city spatial variation in housing liquidity and prices is comparable to the variation over time. Figure C1 displays Redfin time series of U.S.-level quarterly log median sales prices and time on the market, decomposed via a Hodrick–Prescott filter with standard penalty parameter $\lambda = 1,600$. The cyclical variation is obtained by isolating the cyclical component of a seasonally adjusted time series (provided by Redfin via X-13ARIMA-SEATS) from the Hodrick–Prescott filter. The seasonal variation is obtained by isolating the cyclical component of the unadjusted time series from the Hodrick–Prescott filter and subtracting the cyclical time series.

As becomes evident from the figure, the seasonal variation in prices amounts to about 10%, while the variation over the business cycle amounts to 10-15%. This is comparable to a spatial price difference in the U.S. over 20-30km (with prices changing by 0.5% per kilometer, see Table D7). For the time on the market, the seasonal variation amounts to about 2 weeks, while the variation over the business cycle amounts to 2-3 weeks. This is comparable to a spatial time-on-the-market difference in the U.S. over 40-60km (with the time on the market changing by 0.05 weeks per kilometer, see Table D6).

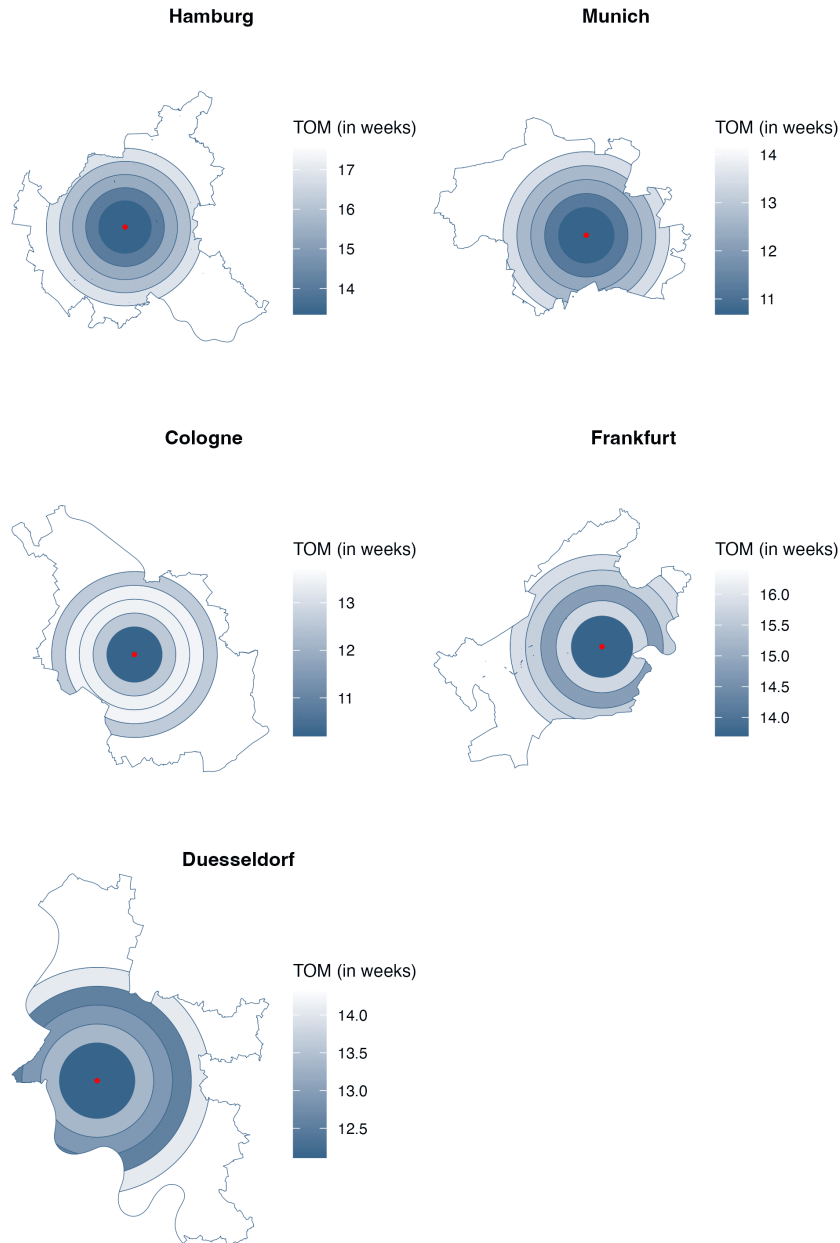
Figure C1: Variation in U.S. housing market variables around long-run trends



Notes: These plots display decomposed time series of U.S.-level quarterly log median sales prices and time on the market (TOM).

C.2 Spatial distribution of time on the market in German cities

Figure C2: Time on the market across space, Germany (2012–2024)



Notes: These maps display the spatial distribution of time on the market (TOM) by city from our matched German dataset, averaged within rings around city centers. Shapefile data sources:

Hamburg: <https://suche.transparenz.hamburg.de/dataset/stadtteil-profile-hamburg10>.

Munich: https://opendata.muenchen.de/dataset/vablock_stadtbezirke_opendata.

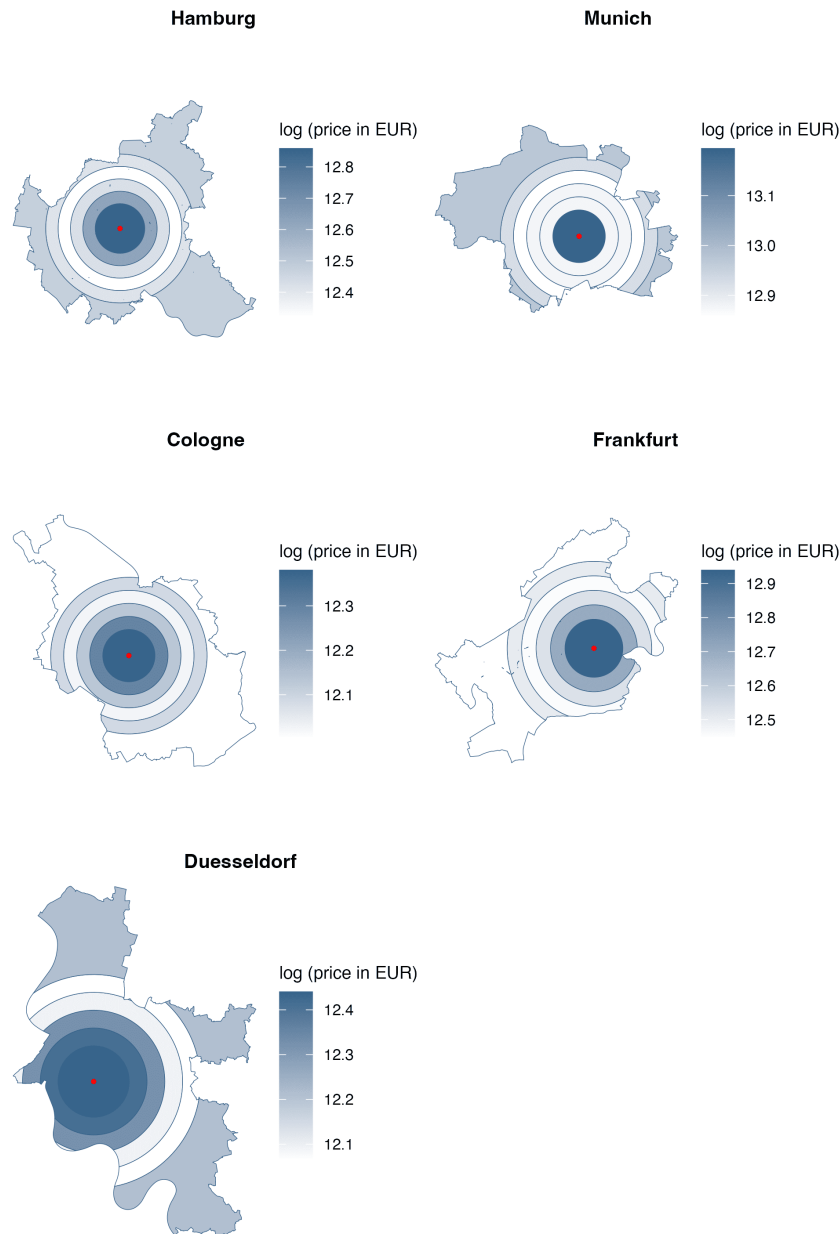
Cologne: <https://offenedaten-koeln.de/dataset/stadtbezirke-koeln>.

Frankfurt: https://geowebdienste.frankfurt.de/WFS_Stadtgebietgliederung.

Duesseldorf: <https://opendata.duesseldorf.de/dataset/stadtteilgrenzen-duesseldorf-2025>.

C.3 Spatial distribution of sales prices in German cities

Figure C3: Sales prices across space, Germany (2012–2024)



Notes: These maps display the spatial distribution of sales prices by city from our matched German dataset, averaged within rings around city centers. Shapefile data sources:

Hamburg: <https://suche.transparenz.hamburg.de/dataset/stadtteil-profile-hamburg10>.

Munich: https://opendata.muenchen.de/dataset/vablock_stadtbezirke_opendata.

Cologne: <https://offenedaten-koeln.de/dataset/stadtbezirke-koeln>.

Frankfurt: https://geowebdienste.frankfurt.de/WFS_Stadtgebietgliederung.

Duesseldorf: <https://opendata.duesseldorf.de/dataset/stadtteilgrenzen-duesseldorf-2025>.

Table C1: Log sales prices and distance to the city center, Germany (2012–2024)

	(1)	(2)	(3)	(4)	(5)	(6)
	Price	Price	Price	Price	Price	Price
Distance to center (in km)	-0.04*** (0.00)	-0.05*** (0.00)	-0.04*** (0.00)			
Travel time to center (in min)				-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)
City × Year-quarter FE	✓	✓	✓	✓	✓	✓
Property characteristics		✓	✓		✓	✓
Borough FE			✓			✓
<i>N</i>	84,292	84,292	84,292	84,292	84,292	84,292
Adj. <i>R</i> ²	0.31	0.86	0.88	0.31	0.86	0.88
Mean(log(price))	12.60	12.60	12.60	12.60	12.60	12.60

Notes: This table shows results for regressions of the log sales price on the distance to the city center as specified in the regression specification (1). “Price” refers to the sales price in log euros. Standard errors (in parentheses) are clustered at the city-year level. The list of property characteristics controls is available in Supplemental Appendix A.1. * : $p < 0.1$; ** : $p < 0.05$; *** : $p < 0.01$.

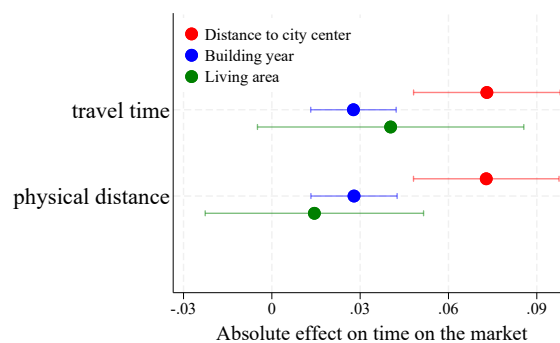
C.4 Additional determinants of housing liquidity in German cities

In our main analysis, we focus on how liquidity varies across space. Nevertheless, houses differ along several other dimensions that may also influence liquidity. In fact, an extensive literature has investigated determinants of housing liquidity. Particularly expensive locations (“prime locations”) are associated with a shorter time on the market (Smith, 2009). By contrast, atypical properties experience both longer times on the market and higher listing prices, due to strong search frictions and thin buyer pools (Haurin et al., 2010). Dwelling size and age exhibit nonlinear effects: larger, appropriately priced homes tend to sell more quickly, while older or functionally obsolete properties often remain longer on the market (see Knight, 2002; Cirman, Pahor, and Verbic, 2015). In what follows, we compare the most important property characteristics – location, size, and age – in explaining variation in time on the market.

In Figure C4, we plot the coefficients for living area (in square meters), building year, and distance to the city center from Regression (1), standardized by their standard deviations and set into absolute values. As is evident from the plot, distance to the city center has the strongest impact on liquidity, whether measured as travel time or physical

distance. Its coefficient is more than twice as large as that of building year. The coefficient for size is not significant.⁴² Overall, this indicates that although liquidity varies with other physical characteristics of the property, location – measured by distance to the city center – is the most important factor. Unfortunately, due to data limitations, we cannot run similar regressions for the United States. However, Smith (2009) uses U.S. data to regress time on the market on property characteristics and shows that including the exact location, as given by the properties' coordinates, strongly increases the predictive power of the regression – even when size and age are already included.

Figure C4: Determinants of time on the market, Germany (2012–2024)



Notes: This plots shows OLS regression coefficients for the combined German sample, as well as their respective 99% confidence intervals, based on regression (1). The coefficients are standardized across the displayed determinants using the respective sample standard deviation. Travel time is measured in car travel minutes from the city center. Physical distance is the kilometer distance to the city center.

Other determinants of time on the market. A large body of empirical work has examined the determinants of time on the market (TOM) in residential real estate. In addition to the property characteristics mentioned in the previous paragraph, U.S. studies highlight the role of pricing strategy and overpricing (Anglin, Rutherford, and Springer, 2003), seller motivation and urgency (Glower, Haurin, and Hendershott, 1998), and financial constraints such as low equity or high indebtedness (Genesove and Mayer, 1997) as key drivers of selling time. Despite these consistent patterns, the explanatory power of empirical TOM models remains limited. Studies typically report low R-squared values, often below 0.20, which reflects that a large share of variation in selling times is left unexplained. This issue has been widely acknowledged in the literature, with a meta-analysis in Sirmans, MacDonald, and Macpherson (2010) noting that TOM is inherently difficult

⁴²The coefficient for size is negative and significant in the more parsimonious specification of the regression, but becomes insignificant once other property characteristics are included.

to predict due to idiosyncratic buyer–seller interactions and unobserved heterogeneity. Even when controlling for pricing, seller characteristics, and credit conditions, much of the observed dispersion in TOM persists, suggesting that random shocks, local demand fluctuations, and negotiation dynamics play a central role. In our estimation, the uncertainty surrounding time on the market does not bias the estimated relationship, provided that unobserved determinants are not systematically correlated with location. Evidence for this is given by the substantially higher R-squared values we obtain in our more aggregated U.S. analyses at the ZIP code level. This suggests that a considerable share of the unobserved heterogeneity averages out once observations are spatially aggregated.

C.5 Alternative travel times

In our main analysis, we use car travel times from openrouteservice. Here, we also present our regression results using travel times obtained from Google Maps. We retrieve car travel times and public transport travel times to the city center. In Tables C2 and C3, we present the results for Germany, using Google car travel times and public transport times, respectively. The results are both quantitatively and qualitatively similar to those in our baseline analysis.

We then perform the same analysis for the United States. The results are shown in Tables C4 and C5. For car travel times, we find that the results remain unchanged compared to the baseline. For public transport, however, we find that both time on the market and price gradients are considerably smaller. This is probably due to the fact that only a small part of the population uses public transport to commute in some U.S. cities, meaning that it serves as a poor proxy for actual commuting costs. In the United States, only about 5% of the population uses public transport to commute to work daily (Burrows, Burd, and McKenzie, 2021).

Table C2: Liquidity and price gradients with Google car travel times, Germany (2012–2024)

	(1)	(2)	(3)	(4)	(5)	(6)
	TOM	TOM	TOM	Price	Price	Price
Google travel time (in min)	0.15*** (0.02)	0.10*** (0.01)	0.08*** (0.02)	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)
City × Year-quarter FE	✓	✓	✓	✓	✓	✓
Property characteristics		✓	✓		✓	✓
Borough FE			✓			✓
<i>N</i>	84,292	84,292	84,292	84,292	84,292	84,292
Adj. <i>R</i> ²	0.04	0.13	0.13	0.30	0.86	0.88
Mean(dependent variable)	13.51	13.51	13.51	12.60	12.60	12.60

Notes: This table displays the output of Regression (1) on time on the market (TOM), measured in weeks, and log sales prices using Google car travel times to measure commuting time to the city center. The list of property characteristics controls is available in Supplemental Appendix A.1. The regressions are based on data for apartments for the five cities in our sample in the period between 2012–2024. Standard errors (in parentheses) are clustered at the city-year level. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

Table C3: Liquidity and price gradients with public transport travel times, Germany (2012–2024)

	(1)	(2)	(3)	(4)	(5)	(6)
	TOM	TOM	TOM	Price	Price	Price
Public transport travel time (in min)	0.09*** (0.01)	0.06*** (0.01)	0.04*** (0.01)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)
City × Year-quarter FE	✓	✓	✓	✓	✓	✓
Property characteristics		✓	✓		✓	✓
Borough FE			✓			✓
<i>N</i>	84,292	84,292	84,292	84,292	84,292	84,292
Adj. <i>R</i> ²	0.04	0.13	0.13	0.29	0.85	0.87
Mean(dependent variable)	13.51	13.51	13.51	12.60	12.60	12.60

Notes: This table displays the output of Regression (1) on time on the market (TOM), measured in weeks, and log sales prices using Google public transport travel times to measure commuting time to the city center. The list of property characteristics controls is available in Supplemental Appendix A.1. The regressions are based on data for apartments for the five cities in our sample in the period between 2012–2024. Standard errors (in parentheses) are clustered at the city-year level. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

Table C4: Liquidity and price gradients with Google car travel times, U.S. (2012–2023)

	(1)	(2)	(3)	(4)	(5)	(6)
	TOM	TOM	TOM	Price	Price	Price
Google car travel time (in min)	0.052*** (0.0079)	0.045*** (0.0074)	0.070*** (0.0061)	-0.004*** (0.0005)	-0.003*** (0.0005)	-0.004*** (0.0003)
MSA × Year-month FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Property characteristics			✓			✓
Demographic controls			✓			✓
<i>N</i>	682,100	682,100	682,100	682,100	682,100	682,100
ZIP Codes	4,943	4,943	4,943	4,943	4,943	4,943
Adj. <i>R</i> ²	0.29	0.29	0.32	0.56	0.62	0.85
Mean(dependent variable)	7.60	7.60	7.60	12.69	12.69	12.69

Notes: This table displays the output of Regression (1) on time on the market (TOM), measured in weeks, and log sales prices using Google car transport travel times to measure commuting time to the city center. The regressions are based on data for single-family houses for the 30 largest MSAs in the U.S. in the period between 2012–2023. Standard errors (in parentheses) are clustered at the MSA-year level. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

Table C5: Liquidity and price gradients with public transport travel times, U.S. (2012–2023)

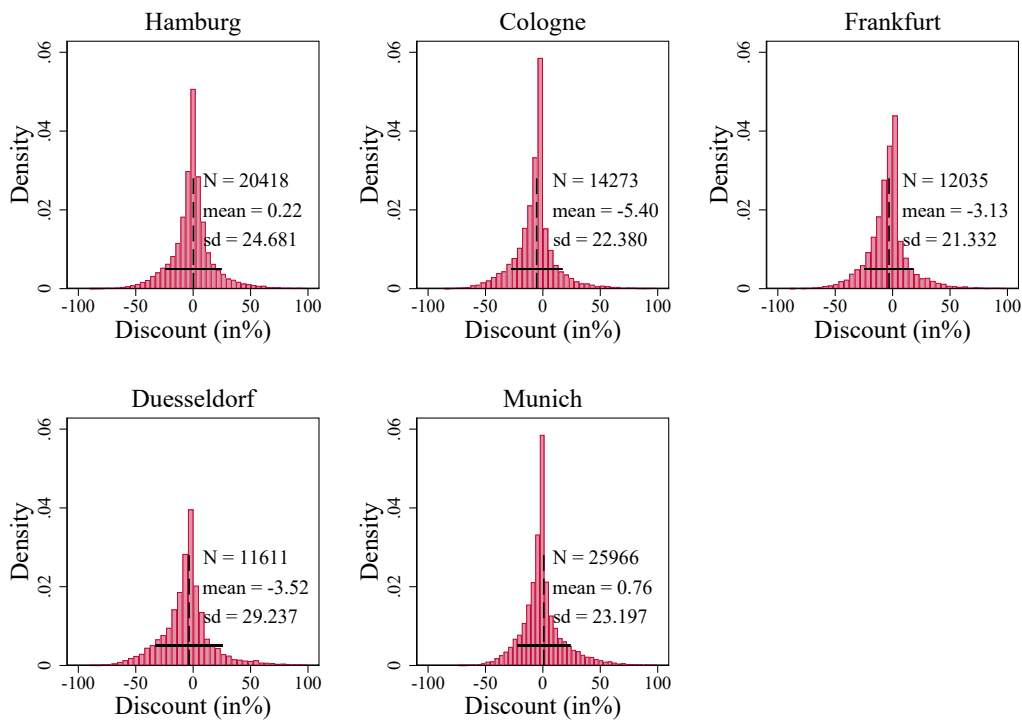
	(1)	(2)	(3)	(4)	(5)	(6)
	TOM	TOM	TOM	Price	Price	Price
Public transport travel time (in min)	-0.000 (0.0022)	-0.001 (0.0020)	0.007*** (0.0010)	-0.001*** (0.0002)	-0.001*** (0.0002)	-0.001*** (0.0001)
MSA × Year-month FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Property characteristics			✓			✓
Demographic controls			✓			✓
<i>N</i>	479,116	479,116	479,116	479,116	479,116	479,116
ZIP Codes	3,485	3,485	3,485	3,485	3,485	3,485
Adj. <i>R</i> ²	0.41	0.42	0.46	0.57	0.65	0.87
Mean(dependent variable)	7.03	7.03	7.03	12.78	12.78	12.78

Notes: This table displays the output of Regression (1) on time on the market (TOM), measured in weeks, and log sales prices using Google public transport travel times to measure commuting time to the city center. The regressions are based on data for single-family houses for the 30 largest MSAs in the U.S. in the period between 2012–2023. Standard errors (in parentheses) are clustered at the MSA-year level. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

C.6 Asking price discount

In Figure C5, we plot a histogram of the asking price discount for our matched German sample by city. The majority of transactions exhibit a negative discount, that is, properties typically sell below their asking prices. The distribution resembles a normal distribution but has a more positive skew and thinner tails. On average, a property is transacted at a sales price below its asking price. There is a clear bunching at an asking price discount of 0%. This finding has been documented for other countries and reflects that the asking price is a relevant anchor for the bargaining process in housing markets, as it is a partial commitment for the seller (Han and Strange, 2016). In Table C6, we present results for regressions of the asking price discount on distance to the city center. For all specifications, there is a negative and highly significant coefficient on the distance to the city center.

Figure C5: Histograms of asking price discount (2012–2024)



Notes: These plots show histograms for the asking price discount in our matched data set.

Table C6: Asking price discount and distance to the city center, Germany (2012–2024)

	(1)	(2)	(3)	(4)	(5)	(6)
	APD	APD	APD	APD	APD	APD
Distance to center (in km)	-0.15*** (0.04)	-0.16*** (0.03)	-0.11** (0.05)			
Travel time to center (in min)				-0.07*** (0.02)	-0.07*** (0.01)	-0.03 (0.03)
City × Year-quarter FE	✓	✓	✓	✓	✓	✓
Property characteristics		✓	✓		✓	✓
Borough FE			✓			✓
<i>N</i>	84,292	84,292	84,292	84,292	84,292	84,292
Adj. <i>R</i> ²	0.02	0.05	0.05	0.02	0.05	0.05
Mean(APD)	-1.56	-1.56	-1.56	-1.56	-1.56	-1.56

Notes: This table shows results for regressions of the asking price discount on the distance to the city center as specified in Regression (1). “APD” refers to the asking price discount in percent. Standard errors (in parentheses) are clustered at the city-year level. The list of property characteristics controls is available in Supplemental Appendix A.1. * : $p < 0.1$; ** : $p < 0.05$; *** : $p < 0.01$.

Table C7: Asking price discount and distance to the city center, U.S. (2012–2023)

	(1)	(2)	(3)	(4)	(5)	(6)
	APD	APD	APD	APD	APD	APD
Distance to center (in km)	-0.02*** (0.002)	-0.01*** (0.002)	-0.03*** (0.001)			
Travel time to center (in min)				-0.02*** (0.002)	-0.02*** (0.002)	-0.03*** (0.002)
Median income		0.28*** (0.041)	0.28*** (0.034)		0.28*** (0.041)	0.26*** (0.032)
MSA $\times$ Year-month FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Property characteristics			✓			✓
Demographic controls			✓			✓
<i>N</i>	682,034	682,034	682,034	682,034	682,034	682,034
ZIP Codes	4,943	4,943	4,943	4,943	4,943	4,943
Adj. R^2	0.49	0.49	0.51	0.49	0.49	0.52
Mean(APD)	-1.49	-1.49	-1.49	-1.49	-1.49	-1.49

Notes: This table displays the output of Regression (1) on asking price discount (APD), measured in percent of the asking price. The regressions are based on data for single-family houses for the 30 largest MSAs in the U.S. in the period between 2012–2023. Standard errors (in parentheses) are clustered at the MSA-year level. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

C.7 Market tightness in German cities

Next, we present results for regressions of contact clicks per ad on distance to the city center. The data is from RWI - Leibniz-Institut für Wirtschaftsforschung and ImmobilienScout24 (2024). Since in this dataset we do not have the exact location of each apartment, but only the ZIP Code, we calculate distances to the city center using the centroids of ZIP Code areas. For the same reason, we cannot present results with ZIP Code fixed effects. In addition to year-quarter- and city fixed effects, we control for the following property characteristics: size in square meters, number of rooms, bathrooms, kitchens, and balconies, floor number of the apartment, building year category, type of heating system, whether the building is a landmark, and whether the apartment is owner-occupied or rented. The results are documented in Table C8. The number of contact clicks per ad decreases significantly with distance to the city center, confirming

the results from the binned scatterplot in the main text.

Moreover, as mentioned in the main text, these results on market tightness are unlikely to be driven by an increasing supply of housing with distance to the city center. In Figure C6, we plot the amount of residential built-up volume by distance to the city center in the German cities from our sample and the 5 largest U.S. cities, retrieved via the Global Human Settlement Layer Database (Pesaresi and Politis, 2023; Pesaresi et al., 2024). We observe that the amount of residential built-up volume in fact decreases with distance to the city center, generally speaking.

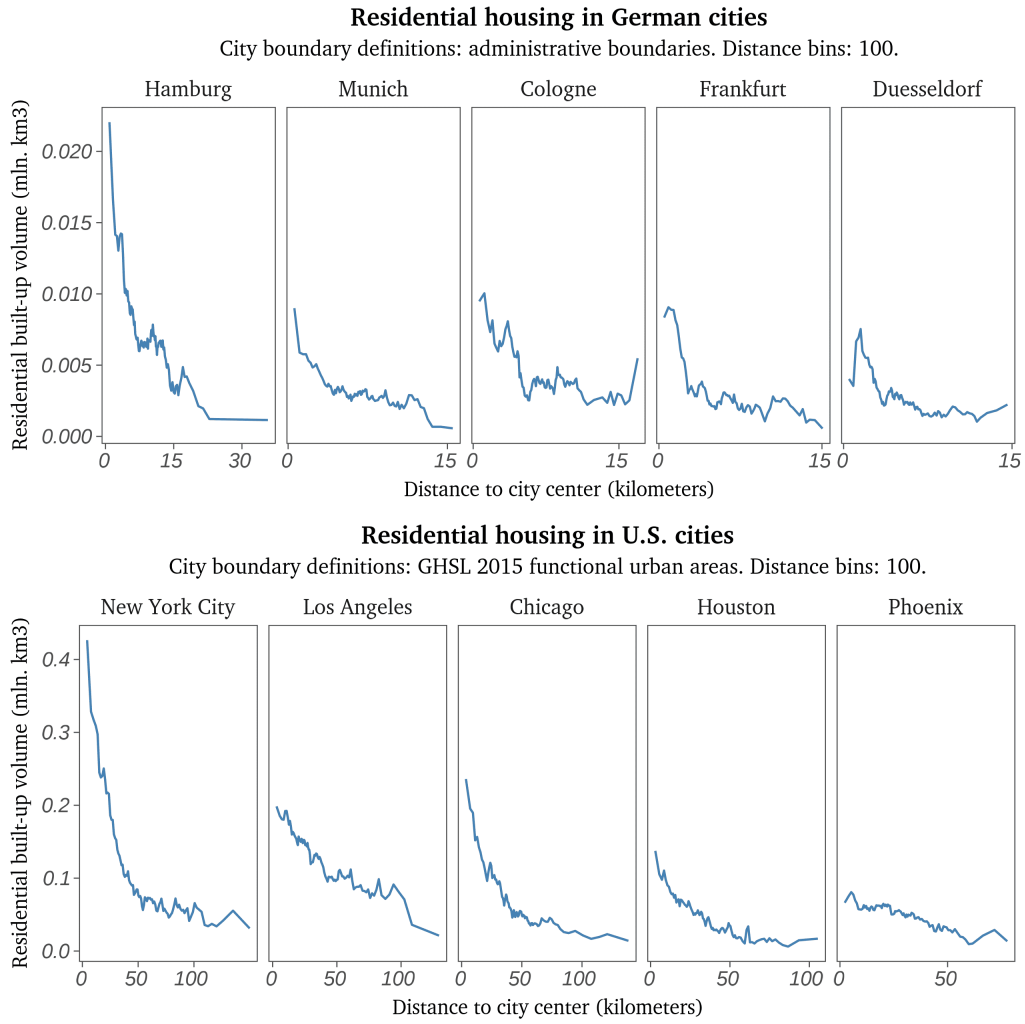
To get these measures, we first subtract the non-residential layer of built-up volume (*GHS-BUILT-V-NRES*) from the total layer of built-up volume (*GHS-BUILT-V-RES+NRES*) to obtain residential built-up volume across $100\text{m} \times 100\text{m}$ grid cells. We select all grid cells within the respective city boundary and calculate the distance to the city center for each grid cell (using the city centers defined in Section 2.3). Then, we create 100 distance bins for these grid cells and sum up the residential built-up volume by distance bin. We select the year 2015 to show results for the definition year of functional urban areas for U.S. cities (see Moreno-Monroy, Schiavina, and Veneri, 2021), also retrieved via the GHSL database (*GHS-FUA*), which define cities based on commuting flows, following the EU-OECD definition from Dijkstra, Poelman, and Veneri (2019). For consistency, we also show built-up volume in 2015 for German cities, even though here we use administrative boundaries, as in the main empirical exercise.

Table C8: *Contact clicks and distance to the city center, Germany (2012–2024)*

	(1)	(2)
	Clicks	Clicks
Distance to center (in km)	-0.49*** (0.11)	-0.46*** (0.11)
City $\times$ Year-quarter FE	✓	✓
Property characteristics		✓
<i>N</i>	192,512	192,512
Adj. R^2	0.20	0.20
Mean(clicks)	20.72	20.72

Notes: This table shows results for regressions of contact clicks per advertisement on the distance to the city center as specified in Regression (1). “Clicks” refers to the contact clicks per ad as defined in the text. Standard errors (in parentheses) are clustered at the city-year level. The list of property characteristics controls is available in Supplemental Appendix A.1. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

Figure C6: Residential built-up volume by distance to city center (2015)



Notes: These plots display the amount of residential built-up volume by distance to the city center in the German cities from our sample and the 5 largest U.S. cities.

C.8 Log time on the market

Next, we show that our baseline results are robust to using the log of time on the market as the left-hand-side variable. The results for Germany are reported in Table C9, and those for the U.S. in Table C10. Using the log of time on the market, which is less sensitive to potential outliers, does not change our main findings: we continue to find a positive and highly significant time-on-the-market gradient across all specifications.

Table C9: Log time on the market and distance to city center, Germany (2012–2024)

	(1)	(2)	(3)	(4)	(5)	(6)
	Log TOM	Log TOM	Log TOM	Log TOM	Log TOM	Log TOM
Distance to center (in km)	0.04*** (0.00)	0.03*** (0.00)	0.03*** (0.00)			
Travel time to center (in min)				0.02*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
City × Year-quarter FE	✓	✓	✓	✓	✓	✓
Property characteristics		✓	✓		✓	✓
Borough FE			✓			✓
<i>N</i>	84,292	84,292	84,292	84,292	84,292	84,292
Adj. <i>R</i> ²	0.05	0.12	0.12	0.05	0.12	0.12
Mean(TOM)	1.77	1.77	1.77	1.77	1.77	1.77

Notes: This table displays the output of Regression (1) on log time on the market (TOM). The list of property characteristics controls is available in Supplemental Appendix A.1. The regressions are based on data for apartments for the five cities in our sample in the period between 2012–2024. Standard errors (in parentheses) are clustered at the ZIP Code level. * : $p < 0.1$; ** : $p < 0.05$; *** : $p < 0.01$.

Table C10: Log time on the market and distance to city center, U.S. (2012–2023)

	(1)	(2)	(3)	(4)	(5)	(6)
	Log TOM	Log TOM	Log TOM	Log TOM	Log TOM	Log TOM
Distance to center (in km)	0.004*** (0.0005)	0.003*** (0.0004)	0.005*** (0.0003)			
Travel time to center (in min)				0.005*** (0.0006)	0.004*** (0.0006)	0.006*** (0.0004)
Median income		-0.037*** (0.0107)	-0.053*** (0.0087)		-0.037*** (0.0104)	-0.048*** (0.0083)
MSA × Year-month FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Property characteristics			✓			✓
Demographic controls			✓			✓
<i>N</i>	682,100	682,100	682,100	682,100	682,100	682,100
ZIP Codes	4,943	4,943	4,943	4,943	4,943	4,943
Adj. <i>R</i> ²	0.61	0.62	0.64	0.61	0.62	0.65
Mean(TOM)	1.74	1.74	1.74	1.74	1.74	1.74

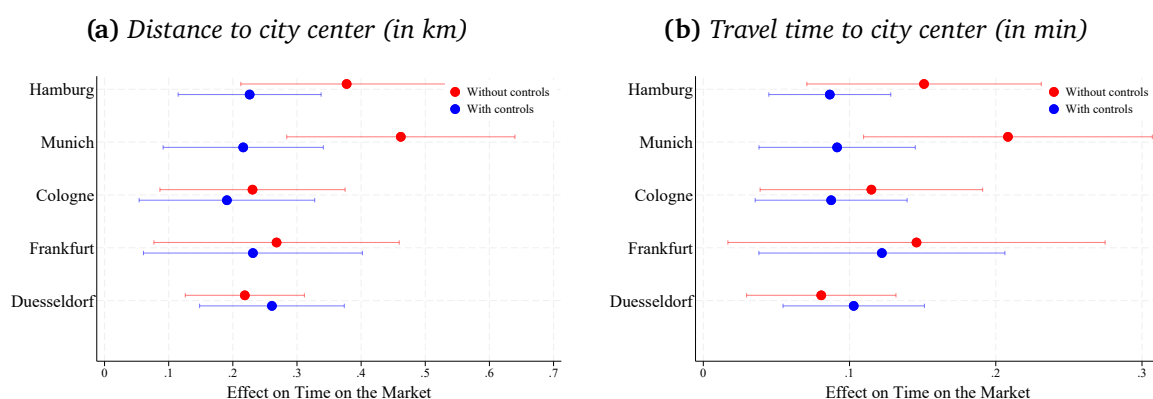
Notes: This table displays the output of Regression (1) on log time on the market (TOM). The regressions are based on data for single-family houses for the 30 largest MSAs in the U.S. in the period between 2012–2023. Standard errors (in parentheses) are clustered at the city-year level. * : $p < 0.1$; ** : $p < 0.05$; *** : $p < 0.01$.

D Robustness analysis

D.1 Results for individual cities

Germany. We run Regression (1) for each city separately and report the coefficients with the corresponding 95% confidence intervals by city bundled in Figure D1. For all cities, the coefficients for both kilometer distance and car travel time are positive and highly significant. The coefficient magnitudes are similar across cities, especially after including controls.

Figure D1: Time on the market and distance to city center by city (2012–2024)



Notes: These plots show the OLS regression coefficients of distance to the city center as specified in (1) with 95% confidence intervals with the standard errors clustered at the year level. All regressions include year-quarter fixed effects. See Supplemental Appendix A.1 for a full list of property characteristics controls.

United States. We also test whether we can find the time on the market gradient for individual MSAs. For all cities, we find a positive time on the market gradient with significance at the 1% level, with the exception of San Francisco-Oakland-Berkeley, CA. For San Francisco-Oakland-Berkeley, CA, the Realtor.com data show a larger inventory than the Redfin data, suggesting that the latter do not provide good coverage. In fact, with the Realtor.com data, we find a positive slope for San Francisco. Spatial price gradients are negative and significant at the 1% level for almost every MSA. For Sacramento-Roseville-Folsom, CA and San Antonio-New Braunfels, TX, we find positive price gradients, which is due the fact that they have especially low prices in the city center. This has already been documented in Gupta et al. (2022).

Table D1: TOM and price gradient by MSA, 2012–2023

MSA	TOM gradient	Price gradient	P-value TOM	P-value Price	N
Atlanta-Sandy Springs-Alpharetta, GA	0.075	-0.009	0.00	0.00	27,202
Austin-Round Rock-Georgetown, TX	0.131	-0.016	0.00	0.00	10,509
Baltimore-Columbia-Towson, MD	0.113	-0.002	0.00	0.00	17,413
Boston-Cambridge-Newton, MA-NH	0.065	-0.010	0.00	0.00	35,411
Charlotte-Concord-Gastonia, NC-SC	0.109	-0.011	0.00	0.00	13,508
Chicago-Naperville-Elgin, IL-IN-WI	0.048	-0.012	0.00	0.00	49,092
Cincinnati, OH-KY-IN	0.058	-0.006	0.00	0.00	17,681
Dallas-Fort Worth-Arlington, TX	0.045	-0.004	0.00	0.00	34,548
Denver-Aurora-Lakewood, CO	0.170	-0.002	0.00	0.00	15,480
Detroit-Warren-Dearborn, MI	0.027	-0.001	0.01	0.01	28,146
Houston-The Woodlands-Sugar Land, TX	0.061	-0.003	0.00	0.00	29,363
Las Vegas-Henderson-Paradise, NV	0.063	-0.002	0.00	0.00	8,782
Los Angeles-Long Beach-Anaheim, CA	0.033	-0.001	0.01	0.06	48,366
Miami-Fort Lauderdale-Pompano Beach, FL	0.026	-0.000	0.00	0.13	23,083
Minneapolis-St. Paul-Bloomington, MN-WI	0.116	-0.007	0.00	0.00	28,208
New York-Newark-Jersey City, NY-NJ-PA	0.016	-0.004	0.01	0.00	86,390
Orlando-Kissimmee-Sanford, FL	0.103	-0.005	0.00	0.00	12,230
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	0.062	-0.005	0.00	0.00	38,705
Phoenix-Mesa-Chandler, AZ	0.056	-0.004	0.00	0.00	20,294
Pittsburgh, PA	0.078	-0.007	0.00	0.00	21,432
Portland-Vancouver-Hillsboro, OR-WA	0.147	-0.009	0.00	0.00	15,542
Riverside-San Bernardino-Ontario, CA	0.036	-0.005	0.00	0.00	17,818
Sacramento-Roseville-Folsom, CA	0.042	0.003	0.00	0.00	12,091
San Antonio-New Braunfels, TX	0.079	0.006	0.00	0.00	13,386
San Diego-Chula Vista-Carlsbad, CA	0.080	-0.000	0.00	0.69	12,095
San Francisco-Oakland-Berkeley, CA	-0.015	-0.011	0.00	0.00	18,716
Seattle-Tacoma-Bellevue, WA	0.063	-0.015	0.00	0.00	20,158
St. Louis, MO-IL	0.264	-0.006	0.00	0.00	25,000
Tampa-St. Petersburg-Clearwater, FL	0.115	-0.007	0.00	0.00	18,144
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.069	-0.009	0.00	0.00	35,537

Notes: This table reports the output of regressions of time on the market in weeks on distance to the city center, median income, property characteristics, and year-quarter fixed effects by MSA. The underlying data is for single-family houses from Redfin. See the text for information on the data sources. Standard errors are clustered at the year level. N stands for the number of ZIP-Code-year-month observations.

D.2 COVID

This section of the supplemental appendix examines how the liquidity gradient shifted in Germany and the U.S. following the onset of COVID-19 and the widespread adoption of remote work. Tables D2 and D3 report the baseline regression results for the periods before and after 2020. In both countries, the liquidity gradient became significantly flatter, consistent with the increase in working from home. Figures D2a and D2b show how the coefficient on distance to the city center evolved between 2018 and 2023. In both Germany and the U.S., the liquidity gradient nearly disappeared in 2021 and 2022, but began to rise again afterward.

Table D2: TOM gradients before and after COVID, Germany (2012–2024)

	(1)	(2)	(3)
	Full sample	Pre-2020	Post-2020
Distance to center (in km)	0.24*** (0.03)	0.26*** (0.03)	0.13*** (0.04)
City $\times$ Year-quarter FE	✓	✓	✓
Property characteristics	✓	✓	✓
<i>N</i>	84,292	60,377	23,914
Adj. R^2	0.13	0.14	0.29
Mean(TOM)	13.51	13.46	13.61

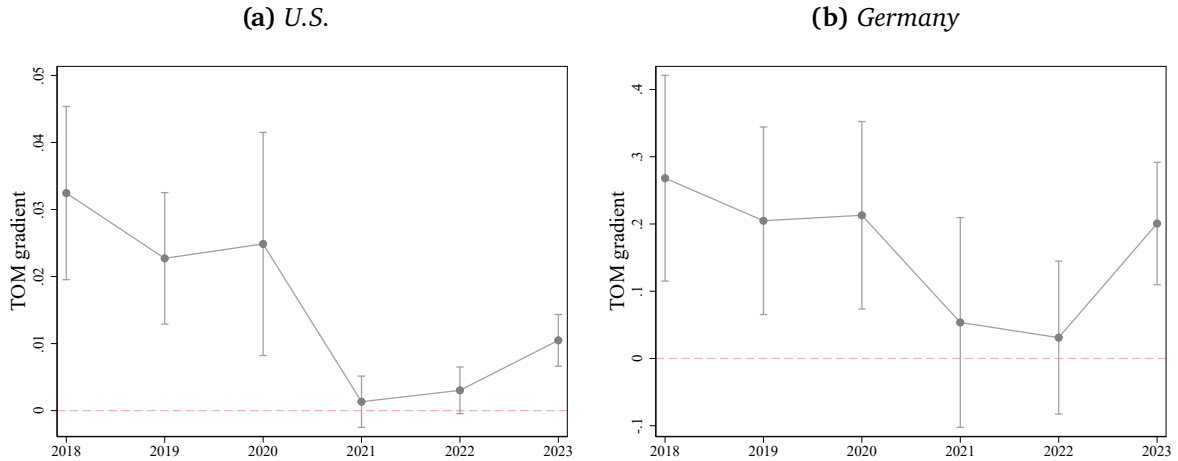
Notes: This table displays the output of Regression (1) on time on the market (TOM), measured in weeks. The list of property characteristics controls is available in Supplemental Appendix A.1. Regressions are based on the matched sample for all cities covering the period between 2012 and 2024. Standard errors (in parentheses) are clustered at the city-year level. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

Table D3: TOM gradients before and after COVID, U.S. (2012–2023)

	(1)	(2)	(3)
	Full sample	Pre-2020	Post-2020
Distance to center (in km)	0.05*** (0.004)	0.06*** (0.005)	0.02*** (0.005)
Median income	-0.16* (0.091)	-0.23* (0.138)	-0.71*** (0.099)
MSA $\times$ Year-month FE	✓	✓	✓
State FE	✓	✓	✓
Property characteristics	✓	✓	✓
Demographic controls	✓	✓	✓
<i>N</i>	754,331	494,322	260,009
ZIP Codes	5,453	5,453	5,446
Adj. R^2	0.29	0.29	0.21
Mean(TOM)	7.63	8.86	5.28

Notes: This table displays the output of Regression (1) on time on the market (TOM), measured in weeks. Regressions are based on data for the 30 largest MSAs covering the period between 2012 and 2023. Standard errors (in parentheses) are clustered at the city-year level. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

Figure D2: Variation over time in the TOM gradient, U.S. and Germany (2018–2023)



Notes: These plots display outputs by year of Regression (1) on time on the market (TOM), measured in weeks. Regressions are based on data for the 30 largest MSAs for the U.S. and for the 5 German cities covered by our sample. 90% Confidence bands are constructed using standard errors clustered at the city-year level.

D.3 Different housing types

This section of the supplemental appendix presents the results for the liquidity gradient across different housing types. Table D4 reports the coefficient on distance to the city center from Regression (1), using time on the market as the dependent variable for our sample of five German cities: single-family houses (columns 1 and 2) and apartments (columns 3 and 4). To ensure comparability across housing types and due to data availability, we rely on listings data from RWI - Leibniz-Institut für Wirtschaftsforschung and ImmobilienScout24 (2024) for this analysis. The results closely mirror our baseline findings for Germany. Tables D5, D6, and D7 present the results for the 30 largest MSAs in the U.S. Table D5 reports the results for the pooled sample, which includes data on single-family houses, condos, townhouses, and multi-family houses. Table D6 reports the results for time on the market separately by housing type, and Table D7 does so for prices.

Table D4: Time on the market and distance to the city center by housing type, Germany (2012–2024)

	(1)	(2)	(3)	(4)
	Single-family	Single-family	Apartment	Apartment
Distance to center (in km)	0.074*** (0.018)	0.066*** (0.018)	0.068*** (0.016)	0.059*** (0.019)
City × Year-quarter FE	✓	✓	✓	✓
Property characteristics		✓		✓
<i>N</i>	129,427	129,427	192,512	192,512
Adj. <i>R</i> ²	0.04	0.06	0.05	0.07
Mean(dependent variable)	4.87	4.87	4.80	4.80

Notes: This table displays the output of Regression (1) on time on the market (TOM), measured in weeks. Property characteristics controls are: living area, building year category, type of property, type of heating system and whether the house is under monument protection. Regressions are based on the full sample of listings from RWI - Leibniz-Institut für Wirtschaftsforschung and ImmobilienScout24 (2024) for all cities in our sample covering the period between 2012 and 2024. Standard errors (in parentheses) are clustered at the city-year level. * : $p < 0.1$; ** : $p < 0.05$; *** : $p < 0.01$.

Table D5: *Time on the market and distance to city center, U.S.: all housing types (2012–2023)*

	(1)	(2)	(3)	(4)	(5)	(6)
	TOM	TOM	TOM	TOM	TOM	TOM
Distance to center (in km)	0.02*** (0.005)	0.02*** (0.005)	0.04*** (0.004)			
Travel time to center (in min)				0.02*** (0.007)	0.02*** (0.007)	0.05*** (0.005)
Median income		-0.53*** (0.090)	-0.20** (0.081)		-0.53*** (0.085)	-0.17** (0.078)
MSA × Year-month FE	✓	✓	✓	✓	✓	✓
Property type FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Property characteristics			✓			✓
Demographic controls			✓			✓
<i>N</i>	1,342,681	1,342,681	1,341,818	1,342,681	1,342,681	1,341,818
ZIP Codes	5,128	5,128	5,115	5,128	5,128	5,115
Adj. R^2	0.26	0.26	0.28	0.26	0.26	0.28
Mean(TOM)	7.64	7.64	7.64	7.64	7.64	7.64

Notes: This table displays the output of Regression (1) on time on the market (TOM), measured in weeks. The first three columns show the results for distance to the city center measured in kilometers, while the last three columns show the results for the car travel time to the city center measured in minutes. Regressions are based on data for the 30 largest MSAs covering the period between 2012 and 2023. Standard errors (in parentheses) are clustered at the MSA-year level. * : $p < 0.1$; ** : $p < 0.05$; *** : $p < 0.01$.

Table D6: *Time on the market and distance to the city center by property type, U.S. (2012–2023)*

	(1)	(2)	(3)	(4)
	Single-family	Condos	Multi-family	Townhouse
Distance to center (in km)	0.05*** (0.004)	0.02*** (0.005)	0.05*** (0.010)	0.03*** (0.003)
Median income	-0.14 (0.088)	-0.28* (0.147)	-0.94*** (0.321)	-0.13 (0.104)
MSA $\times$ Year-month FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Property characteristics	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
<i>N</i>	682,100	321,653	93,061	244,860
ZIP Codes	4,943	2,422	918	1,837
Adj. R^2	0.32	0.35	0.15	0.30
Mean(TOM)	7.60	7.84	9.52	6.75

*Notes: This table displays the output of Regression (1) on time on the market (TOM), measured in weeks. The four columns show the results for distance to the city center measured in kilometers. Regressions are based on data for each property type separately for the 30 largest MSAs covering the period between 2012 and 2023. Standard errors (in parentheses) are clustered at the MSA-year level. * : $p < 0.1$; ** : $p < 0.05$; *** : $p < 0.01$.*

Table D7: Log sales prices and distance to the city center by property type, U.S. (2012–2023)

	(1)	(2)	(3)	(4)
	Single-family	Condos	Multi-family	Townhouse
Distance to center (in km)	-0.005*** (0.000)	-0.003*** (0.000)	-0.005*** (0.001)	-0.004*** (0.001)
Median income	0.110*** (0.010)	0.198*** (0.014)	0.214*** (0.027)	0.313*** (0.018)
MSA $\times$ Year-month FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Property characteristics	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
<i>N</i>	682,641	321,867	93,061	244,968
ZIP Codes	4,955	2,428	918	1,840
Adj. R^2	0.74	0.69	0.83	0.72
Mean(log(price))	12.69	12.34	12.80	12.49

Notes: This table displays the output of Regression (1) on log sales prices. The four columns show the results for distance to the city center measured in kilometers. Regressions are based on data for each property type separately for the 30 largest MSAs covering the period between 2012 and 2023. Standard errors (in parentheses) are clustered at the MSA-year level. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

D.4 Alternative city definitions

In this section of the supplemental appendix, we present the results based on the sample of the 30 largest FUAs (functional urban areas) for U.S. cities (see Moreno-Monroy, Schiavina, and Veneri, 2021), retrieved via the GHSL database (Schiavina et al., 2019), which define cities based on commuting flows, following the EU-OECD definition from Dijkstra, Poelman, and Veneri (2019). Columns 1 and 2 of Table D13 show the results using distance to the MSA city center definition, while columns 3 and 4 show the results using distance to the FUA city center definition, which measures the location with the highest residential built-up volume within the FUA.

Table D8: Price and liquidity gradients for functional urban areas, U.S. (2012–2023)

	(1) TOM	(2) Price	(3) TOM	(4) Price
Distance to MSA center (in km)	0.020*** (0.004)	-0.004*** (0.000)		
Distance to FUA center (in km)			0.026*** (0.003)	-0.007*** (0.000)
Median income	-0.080 (0.070)	0.208*** (0.013)	-0.061 (0.072)	0.190*** (0.013)
FUA × Year-month FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Property characteristics	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
<i>N</i>	656,126	656,126	656,126	656,126
ZIP Codes	4,736	4,736	4,736	4,736
Adj. <i>R</i> ²	0.46	0.75	0.46	0.76
Mean(dependent variable)	7.15	12.74	7.15	12.74

*Notes: This table displays the output of Regression (1) on time on the market (TOM), measured in weeks, and log sales prices. The four columns show the results for distance to the city center measured in kilometers. In the first two columns, the distance is measured to the city hall of the respective MSA, while in the last two columns, the distance is measured to the location with the highest residential built-up volume within the functional urban area (FUA). The regressions are based on data for single-family dwellings in the 30 largest FUAs for the period 2012–2023. Standard errors (in parentheses) are clustered at the FUA-year level. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.*

D.5 Alternative city centers

In this section of the supplemental appendix, we present the results for the baseline Regression (1) using distance to alternative definitions of the city center. Table D9 shows the results for Germany. Table D13 shows the results for the U.S. in Columns 1 and 2, which we report together with our results on focal locations as multiple alternative city centers.

Table D9: Price and liquidity gradients using alternative city centers, Germany (2012–2024)

	(1)	(2)	(3)	(4)	(5)	(6)
	TOM	TOM	TOM	Price	Price	Price
Distance to center (in km)	0.31*** (0.05)	0.25*** (0.03)	0.20*** (0.03)	-0.04*** (0.00)	-0.05*** (0.00)	-0.04*** (0.00)
City $\times$ Year-quarter FE	✓	✓	✓	✓	✓	✓
Property characteristics		✓	✓		✓	✓
Borough FE			✓			✓
<i>N</i>	58,326	58,326	58,326	58,326	58,326	58,326
Adj. R^2	0.05	0.13	0.13	0.23	0.84	0.86
Mean(dep. variable)	14.03	14.03	14.03	12.45	12.45	12.45

Notes: This table displays the output of Regression (1) on time on the market (TOM), measured in weeks, and log sales prices. The six columns show the results for distance to the city center measured in kilometers. The distance is measured to the centroid of the business district with the highest land value (Bodenrichtwert) in the city. The list of property characteristics controls is available in Supplemental Appendix A.1. The regressions are based on data for apartments in Hamburg, Cologne, Frankfurt, and Duesseldorf for the period 2012–2024. Standard errors (in parentheses) are clustered at the city-year level. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

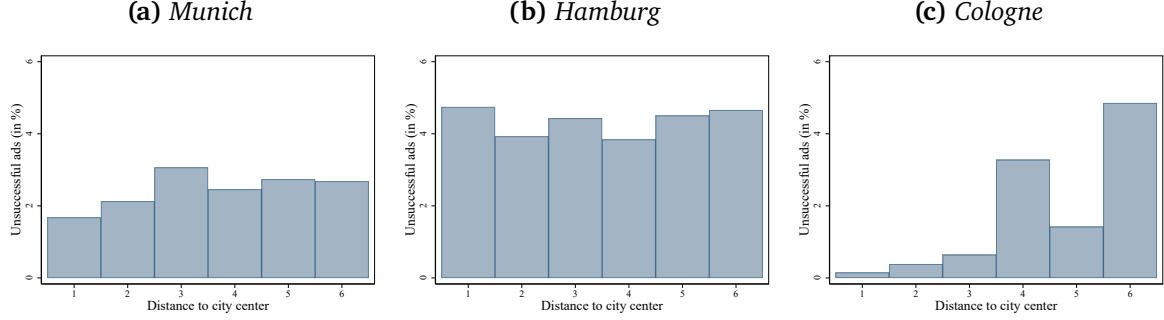
D.6 Properties that do not get sold

We identify listed properties that do not get sold via three steps. First, we match all ads with transactions that occurred within the same neighborhood (*Stadtteil*). Each ad is then associated with a set of potential transactions in the neighborhood. Out of these ads, we identify those as “unsuccessful” that are associated with transactions one year after or before the ad was published. Second, we identify ads as “unsuccessful” that are associated with transactions for which the living area of the matched apartment differs by more than 50%. Third, we identify ads as “unsuccessful” for which the remaining potential matches have a living area and building year that deviate by more than 10% and 10 years.

While this algorithm will identify listings that, with a very high probability, did not end up in a sale, it does not identify all listings that did not end up in a sale. As such, the algorithm presents a lower bound of “unsuccessful” ads. However, we do not have reasons to believe that this lower bound is systematically biased across space, which is the variation we want to explore. We focus only on the three largest cities in our German sample – Hamburg, Munich, and Cologne – because, for the other cities, the number of “unsuccessful” ads is too small to conduct a meaningful statistical analysis.

We first analyze the spatial distribution of unsuccessful ads, measured as the percentage of unsuccessful ads in terms of total ads at the city level, displayed in Figure D3. In all three cities, the relative number of unsuccessful ads is not larger in the city center. If anything, we see that this number slightly increases with distance to the city center.

Figure D3: *Unsuccessful ads and distance to the city center, Germany (2012–2024)*



Notes: These plots display the percentage of ads that do not result in a sale by distance to the city center with 6 equally-sized distance bins. The algorithm to identify the “unsuccessful” ads is described in the text.

To conduct a more formal assessment, we run a survival analysis on time on the market. In other words, we test for the relationship between expected time on the market and distance to the city center by estimating the following hazard function for time on the market:

$$h(TOM_{it}) = h_0(TOM) \times \exp [\gamma \times \text{distance}_i + \delta \times X_i + f_t + g_c + \varepsilon_{it}], \quad (D1)$$

where $h_0(TOM)$ is the baseline hazard rate which depends on the assumption on the functional form of the distribution of error terms ε_{it} . The hazard rate $h(TOM_{it})$ denotes the probability of property i being sold at time t , conditional on the seller listing the property in that point in time, the property characteristics are X_i , time fixed effects are f_t , and city fixed effects are g_c . We estimate the hazard rate using various error term distributions and present the results in Table D10. The first row of the table displays the effect of distance to the city center on the hazard rate of time on the market, given by its hazard ratio. Across all specifications, it is significantly larger than one, meaning that a greater distance to the city center is associated with a longer expected time on the market. In other words, an ad has a higher chance of “surviving” in the outskirts than in the city center.

Table D10: *Expected time on the market and distance to city center, Germany (2012–2024)*

	Exponential	Weibull	Cox
Distance to center (in km)	1.013*** (0.0032)	1.012*** (0.0037)	1.014*** (0.0037)
City $\times$ Year FEs	✓	✓	✓
Property characteristics	✓	✓	✓
<i>N</i>	56,279	56,279	56,279

Notes: This table displays the output of Regression (1) for three different duration models of time on the market, measured in weeks. The first row displays the estimated hazard ratio for the predicted distance to the city center. The regressions are based on data for apartments in Hamburg, Cologne and Munich. The list of property characteristics controls is available in Supplemental Appendix A.1. Standard errors are in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

D.7 Systematic overvaluation

In this section of the appendix, we present the regression results for the robustness analysis regarding systematic overvaluation of apartments in the outskirts. Tables D11 and D12 report the estimates from Regression (1) on time on the market (measured in weeks) and asking price discount (measured as a percentage of the asking price) for Germany and the U.S. The first and third columns in both tables are based on the specification with the full set of controls used in our baseline analysis. Columns two and four additionally include controls for the asking price discount and the time on the market, respectively. As shown, the coefficients remain largely unchanged across all specifications for both Germany and the U.S.

Table D11: Liquidity gradients, Germany (2012–2024)

	(1) TOM	(2) TOM	(3) APD	(4) APD
Distance to center (in km)	0.241*** (0.0260)	0.241*** (0.0261)	-0.162*** (0.0279)	-0.158*** (0.0275)
Asking price discount (in %)		-0.006 (0.0036)		
Time on the market (in weeks)				-0.014 (0.0084)
City × Year-quarter FE	✓	✓	✓	✓
Property characteristics	✓	✓	✓	✓
<i>N</i>	84,292	84,292	84,292	84,292
Adj. <i>R</i> ²	0.13	0.13	0.05	0.05
Mean(dependent variable)	13.51	13.51	-1.56	-1.56

*Notes: This table presents the results of Regression (1) on time on the market (TOM), measured in weeks, and asking price discount (APD), measured as a percentage of the asking price. The list of property characteristics controls is available in Supplemental Appendix A.1. The second and fourth columns additionally control for time on the market and the asking price discount, respectively. The regressions are based on the matched sample for all cities, covering the period from 2012 to 2024. Standard errors (in parentheses) are clustered at the city-year level. * : $p < 0.1$; ** : $p < 0.05$; *** : $p < 0.01$.*

Table D12: Liquidity gradients, U.S. (2012–2023)

	(1)	(2)	(3)	(4)
	TOM	TOM	APD	APD
Distance to center (in km)	0.046*** (0.0039)	0.036*** (0.0036)	-0.026*** (0.0014)	-0.023*** (0.0013)
Asking price discount (in %)		-0.395*** (0.0202)		
Time on the market (in weeks)				-0.059*** (0.0101)
MSA $\times$ Year-month FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Property characteristics	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
<i>N</i>	682,034	682,034	682,034	682,034
ZIP Codes	4,943	4,943	4,943	4,943
Adj. R^2	0.32	0.34	0.51	0.53
Mean(dependent variable)	7.59	7.59	-1.49	-1.49

Notes: This table presents the results of Regression (1) on time on the market (TOM), measured in weeks, and asking price discount (APD), measured as a percentage of the asking price. The second and fourth columns additionally control for time on the market and the asking price discount, respectively. Regressions are based on data for single-family houses for the 30 largest MSAs covering the period between 2012 and 2023. Standard errors (in parentheses) are clustered at the city-year level. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

D.8 Focal ZIP Codes

In this section of the supplemental appendix, we present the results of Regression (1), allowing for multiple city centers within an MSA for the U.S. Columns 1 and 2 of Table D13 show the results when defining a single city center based on the job access index using data from Delventhal and Parkhomenko (2024). To obtain the job access index, we calculate the distance-weighted average of the number of jobs that can be accessed from a ZIP Code and normalize such that 1 represents the maximum available number of jobs across all ZIP Codes. Columns 3 and 4 show the results when defining 3 focal ZIP Codes per MSA as the three ZIP Codes with the highest job access index. Columns 5 and 6 display the results when defining 5 focal ZIP Codes. Our results hold for any definition of focal ZIP Codes.

Table D13: *Time on the market and distance to job centers, U.S. (2012–2023)*

	(1) TOM	(2) TOM	(3) TOM	(4) TOM	(5) TOM	(6) TOM
Distance to largest job center (in km)	0.02*** (0.005)	0.02*** (0.003)				
Distance to nearest job center (in km)			0.02*** (0.006)	0.03*** (0.003)		
Distance to nearest job center (in km)					0.02*** (0.007)	0.02*** (0.004)
MSA $\times$ Year-month FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Property characteristics		✓		✓		✓
Demographic controls		✓		✓		✓
<i>N</i>	595,732	595,732	595,732	595,732	595,732	595,732
ZIP Codes	4,311	4,311	4,311	4,311	4,311	4,311
Adj. R^2	0.39	0.44	0.39	0.44	0.39	0.44
Mean(TOM)	7.27	7.27	7.27	7.27	7.27	7.27

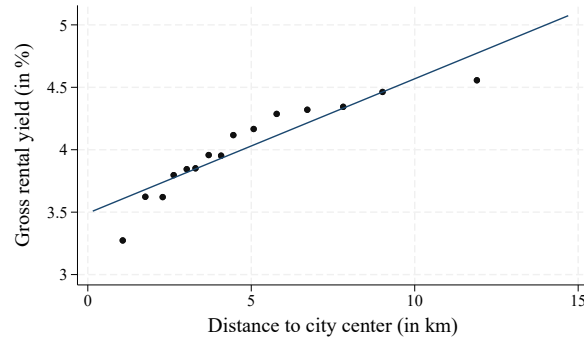
Notes: This table displays the output of Regression (1) on time on the market (TOM), measured in weeks, using focal points from the job access index instead of the city center. Columns 3 and 4 assume 3 different focal ZIP Codes, while columns 5 and 6 assume 5 different focal ZIP Codes. The regressions are based on data for single-family dwellings in the 30 largest MSAs for the period 2012–2023. Standard errors (in parentheses) are clustered at the MSA-year level. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

D.9 Spatial distribution of rental yields

In this section of the supplemental appendix, we present results on the spatial distribution of rental yields. We use listings data for investment properties, that is, properties advertised with both a rental income and a listing price, to construct property-level estimates of rental yields. These estimates reflect gross rental yields; however, as long as maintenance and utility costs do not vary systematically with distance to the city center, this does not affect our results.

Our dataset comprises approximately 51,000 observations across all cities in our German sample. We then estimate Regression (1), using gross rental yield as the dependent variable. In Figure D4, we plot the binned scatter results, and in Table D14 we report the regression estimates, including specifications in which the dependent variable is the logarithm of gross rental yield.

Figure D4: Rental yields and distance to city center, Germany (2012–2024)



Notes: These binned scatter plots visualize the results of Regression (1) with gross rental yield as the outcome variable, using 15 equally-sized distance bins. The binned scatter plots are produced following Cattaneo et al. (2024)

Across all specifications, our results are robust and show that rental yields increase significantly with distance to the city center. The differences between central and peripheral locations are sizable: properties on the outskirts exhibit rental yields more than 1 percentage point higher than those in the city center. Overall, these findings provide additional evidence that market liquidity decreases with distance from the city center.

Table D14: Rental yields and distance to city center, Germany (2012–2024)

	(1)	(2)	(3)	(4)
	Rental yield	Rental yield	Log rental yield	Log rental yield
Distance to center (in km)	0.10*** (0.01)	0.11*** (0.01)	0.03*** (0.00)	0.03*** (0.00)
City × Year-quarter FE	✓	✓	✓	✓
Property characteristics		✓		✓
<i>N</i>	51,545	51,545	51,545	51,545
Adj. <i>R</i> ²	0.38	0.43	0.47	0.53
Mean(dependent variable)	4.02	4.02	1.31	1.31

Notes: This table displays the output of Regression (1) on gross rental yield, measured as the ratio of annual gross rental income to listings price in percent. In columns 3 and 4, the left hand side variable is log gross rental yields. The regressions are based on data for apartments for the five large German cities in our sample between 2012 and 2024. The list of property characteristics controls is available in Supplemental Appendix A.1. The second and fourth columns additionally control for time on the market and the asking price discount, respectively. The regressions are based on the matched sample for all cities, covering the period from 2012 to 2024. Standard errors (in parentheses) are clustered at the ZIP Code level. * : $p < 0.1$; ** : $p < 0.05$; *** : $p < 0.01$.

E Local maximum in the seller's optimization problem

To save on notation, we show that the first-order condition of the seller's profit maximization problem provides a local maximum via

$$\frac{\partial \Pi}{\partial p(d)|_d} = \gamma(d) + p(d) \frac{\partial \gamma}{\partial p(d)|_d} - \beta \Pi(d) \frac{\partial \gamma}{\partial p(d)|_d} = 0 \quad (\text{E1})$$

rather than the reformulated expression (6) in the main text. The second-order condition for a local maximum is

$$\frac{\partial^2 \Pi}{\partial p^2(d)|_d} = 2 \frac{\partial \gamma}{\partial p(d)|_d} + \frac{\partial^2 \gamma}{\partial p^2(d)|_d} (p(d) - \beta \Pi(d)) < 0. \quad (\text{E2})$$

From (12), we know that

$$\frac{\partial \gamma}{\partial p(d)|_d} = -f(\varepsilon^*(d)) \frac{1 - \pi\beta}{\beta} \leq 0 \quad (\text{E3})$$

and therefore

$$\frac{\partial^2 \gamma}{\partial p^2(d)|_d} = -f'(\varepsilon^*(d)) \frac{1 - \pi\beta}{\beta} \frac{\partial \varepsilon^*}{\partial p(d)|_d} = -f'(\varepsilon^*(d)) \left(\frac{1 - \pi\beta}{\beta} \right)^2. \quad (\text{E4})$$

Hence, for (E2) to hold, we need that

$$-2f(\varepsilon^*(d)) \frac{1 - \pi\beta}{\beta} - f'(\varepsilon^*(d)) \left(\frac{1 - \pi\beta}{\beta} \right)^2 (p(d) - \beta \Pi(d)) < 0 \quad (\text{E5})$$

or

$$f'(\varepsilon^*(d)) > \frac{-2f(\varepsilon^*(d)) \frac{1 - \pi\beta}{\beta}}{\left(\frac{1 - \pi\beta}{\beta} \right)^2 (p(d) - \beta \Pi(d))}, \quad (\text{E6})$$

where $p(d) - \beta \Pi(d) > 0$ follows immediately from (6) and (12). In particular, for $\varepsilon \sim U[\underline{\varepsilon}, \bar{\varepsilon}]$,

$$f'(\varepsilon^*(d)) = 0 > \frac{-2 \frac{1}{\bar{\varepsilon} - \underline{\varepsilon}} \frac{1 - \pi\beta}{\beta}}{\left(\frac{1 - \pi\beta}{\beta} \right)^2 (p(d) - \beta \Pi(d))}. \quad (\text{E7})$$

F Analytical results with more general dividend distributions

In this section, we show that the buyer reservation dividend $\varepsilon^*(d)$ increases with distance to the city center d with more general assumptions on the cumulative distribution function of buyer dividends F than with the uniform distribution applied in the main text. As in Section 4.3, we start from the expression for the equilibrium price (F1):

$$p(d) = \frac{-1}{\partial \gamma(d) / \partial p(d)|_d} \left(\gamma(d) + \frac{\beta}{1-\beta} (\gamma(d))^2 \right),$$

Plugging in the equilibrium relations between probabilities of sale and reservation dividends (8) and (12), we have that

$$p(d) = \frac{\beta}{1-\pi\beta} \frac{1-F(\varepsilon^*(d))}{f(\varepsilon^*(d))} + \frac{\beta^2}{(1-\beta)(1-\pi\beta)} \frac{(1-F(\varepsilon^*(d)))^2}{f(\varepsilon^*(d))}. \quad (\text{F1})$$

and, via the seller optimality condition (6),

$$\Pi(d) = \frac{\beta}{(1-\beta)(1-\pi\beta)} \frac{(1-F(\varepsilon^*(d)))^2}{f(\varepsilon^*(d))}. \quad (\text{F2})$$

Plugging these results into the linear expression for buyer dividends (11) yields

$$\begin{aligned} \varepsilon^*(d) = & \frac{1-F(\varepsilon^*(d))}{f(\varepsilon^*(d))} + \frac{\beta}{1-\beta} \frac{(1-F(\varepsilon^*(d)))^2}{f(\varepsilon^*(d))} - \frac{(1-\pi)\beta}{(1-\beta)(1-\pi\beta)} \frac{(1-F(\varepsilon^*(d)))^2}{f(\varepsilon^*(d))} \\ & + \tau(d) + (\pi - \pi\beta)W. \end{aligned} \quad (\text{F3})$$

Taking the derivative with respect to d gives us

$$\begin{aligned} \frac{\partial \varepsilon^*}{\partial d} \left(1 + \frac{(f(\varepsilon^*(d)))^2 + f'(\varepsilon^*(d))(1-F(\varepsilon^*(d)))}{(f(\varepsilon^*(d)))^2} \right. \\ \left. + \frac{2(1-F(\varepsilon^*(d)))(f(\varepsilon^*(d)))^2 + f'(\varepsilon^*(d))(1-F(\varepsilon^*(d)))^2}{(f(\varepsilon^*(d)))^2} \right) = \frac{\partial \tau}{\partial d} > 0. \end{aligned} \quad (\text{F4})$$

Hence, for $\partial \varepsilon^* / \partial d > 0$, we need

$$f'(\varepsilon^*(d)) > \frac{-(f(\varepsilon^*(d)))^2 (2 + 2(1-F(\varepsilon^*(d))))}{(1-F(\varepsilon^*(d))) + (1-F(\varepsilon^*(d)))^2}, \quad (\text{F5})$$

that is, $f'(\varepsilon^*(d))$ may be negative, but not too negative. For the uniform distribution in the main text, this holds immediately with $f'(\varepsilon^*(d)) = 0$. Another distribution commonly used in housing search models is the exponential distribution (see, for example, Guren and McQuade, 2020). With an exponential distribution with rate parameter $\lambda > 0$,

$$f'(\varepsilon^*(d)) = -\lambda^2 \exp(-\lambda \varepsilon^*(d)) \quad (\text{F6})$$

and

$$\frac{-(f(\varepsilon^*(d)))^2 (2 + 2(1 - F(\varepsilon^*(d))))}{(1 - F(\varepsilon^*(d))) + (1 - F(\varepsilon^*(d)))^2} = \frac{-2\lambda^2 \exp(-2\lambda \varepsilon^*(d)) - 2\lambda^2 \exp(-3\lambda \varepsilon^*(d))}{\exp(-\lambda \varepsilon^*(d)) + \exp(-2\lambda \varepsilon^*(d))}. \quad (\text{F7})$$

Hence, noting that

$$(1 - F(\varepsilon^*(d))) + (1 - F(\varepsilon^*(d)))^2 = \exp(-\lambda \varepsilon^*(d)) + \exp(-2\lambda \varepsilon^*(d)) > 0, \quad (\text{F8})$$

we have that

$$\begin{aligned} & f'(\varepsilon^*(d)) \left((1 - F(\varepsilon^*(d))) + (1 - F(\varepsilon^*(d)))^2 \right) \\ &= -\lambda^2 \exp(-2\lambda \varepsilon^*(d)) - \lambda^2 \exp(-3\lambda \varepsilon^*(d)) \\ &= -\lambda^2 \left(\exp(-2\lambda \varepsilon^*(d)) + \exp(-3\lambda \varepsilon^*(d)) \right) < 0, \end{aligned} \quad (\text{F9})$$

while in the numerator of (F7),

$$\begin{aligned} & -(f(\varepsilon^*(d)))^2 (2 + 2(1 - F(\varepsilon^*(d)))) \\ &= -2\lambda^2 \left(\exp(-2\lambda \varepsilon^*(d)) + \exp(-3\lambda \varepsilon^*(d)) \right) < 0. \end{aligned} \quad (\text{F10})$$

Therefore,

$$\begin{aligned} & f'(\varepsilon^*(d)) \left((1 - F(\varepsilon^*(d))) + (1 - F(\varepsilon^*(d)))^2 \right) \\ &> (f(\varepsilon^*(d)))^2 (2 + 2(1 - F(\varepsilon^*(d)))) \end{aligned} \quad (\text{F11})$$

as $2 > 1$ and both sides are negative, such that

$$f'(\varepsilon^*(d)) > - \frac{(f(\varepsilon^*(d)))^2 (2 + 2(1 - F(\varepsilon^*(d))))}{(1 - F(\varepsilon^*(d))) + (1 - F(\varepsilon^*(d)))^2} \quad (\text{F12})$$

as desired. Even though the exponential distribution's probability density function has a negative slope, it is not too negative, such that our key result that reservation dividends increase with distance to the city center still holds. The results that liquidity and prices decrease with distance to the city center follow from this result, as shown in the main text.

G Extended model with bargaining

We extend our model with a bargaining process, following Carrillo (2012). With this addition, the model features asking prices and sales prices, which allows us to form a model notion of an asking price discount (APD), as in the supplementary empirical results. In this model, the asking price discount will always be weakly negative. In the data, it can reach positive values, however, in most cases, it is indeed weakly negative.

The search process changes as follows. When a buyer visits a housing unit, the buyer and the seller may or may not bargain, which is determined stochastically. With probability θ , the seller does not accept counteroffers, and $p(d)$ is a take-it-or-leave-it offer (“no-counteroffer scenario”, subscript n). The buyer accepts or rejects the offer. If the buyer accepts, the seller receives $p(d)$, and the buyer receives their first housing dividend ε and incurs their first commuting cost $\tau(d)$ in the following period. If the buyer rejects, the seller relists the property, and the buyer visits a new housing unit in the following period. With probability $1 - \theta$, the buyer can bargain by making a take-it-or-leave-it counteroffer $o(d)$ to the seller (“counteroffer scenario”, subscript c). If the buyer makes a counteroffer, the seller accepts or rejects the offer. The outcomes of accepting or rejecting the offer are analogous to those in the no-counteroffer scenario.

Changes in the seller’s problem. The seller maximizes their expected profit $\Pi(d)$ over an asking price $p(d)$ and a reservation value $r(d)$. We assume that buyers have perfect information about sellers’ decision problems. Hence, in the counteroffer scenario, the offer $o(d)$ is equal to the seller’s reservation value $r(d)$, as this offer corresponds to the lowest price the seller is willing to accept. In the following, we denote by $\gamma_n(d)$ the probability that a buyer is willing to buy in the no-counteroffer scenario. The analogous probability in the counteroffer scenario is $\gamma_c(d)$. The expected profit is

$$\begin{aligned} \Pi(d) = & \theta \left(\gamma_n(d)p(d) + (1 - \gamma_n(d))\beta\Pi(d) \right) \\ & + (1 - \theta) \left(\gamma_c(d) \max[r(d), \beta\Pi(d)] + (1 - \gamma_c(d))\beta\Pi(d) \right). \end{aligned} \quad (\text{G1})$$

Changes in the buyer’s problem. The buyer’s search value is given by

$$W = E_{d,\varepsilon} [\theta V_n(d, \varepsilon) + (1 - \theta) V_c(d, \varepsilon)]. \quad (\text{G2})$$

The buyer's value in the no-counteroffer scenario is given by

$$V_n(d, \varepsilon) = \max [V(d, \varepsilon) - p(d), \beta W]. \quad (\text{G3})$$

The buyer's value in the counteroffer scenario is given by

$$V_c(d, \varepsilon) = \max [\delta(d)(V(d, \varepsilon) - o(d)) + (1 - \delta(d))(\beta W), \beta W], \quad (\text{G4})$$

where $\delta(d)$ denotes the probability that the seller accepts the buyer's counteroffer. The seller always accepts the optimal counteroffer $o(d) = r(d)$. Hence, $\delta(d) = 1$ at all distances to the city center in equilibrium.

G.1 Equilibrium in the extended model

Seller's optimization. Since the counteroffer $o(d) = r(d)$ is the lowest price that the seller is willing to accept, the seller's reservation value $r(d) = \beta \Pi(d)$. The expression for the expected profit (G1) then simplifies to

$$\Pi(d) = \theta \gamma_n(d) p(d) + (1 - \theta \gamma_n(d)) r(d). \quad (\text{G5})$$

Optimizing with regard to the asking price $p(d)$ yields

$$p(d) = r(d) - \frac{\gamma_n(d)}{\partial \gamma_n / \partial p(d)|_d}, \quad (\text{G6})$$

and plugging the condition $r(d) = \beta \Pi(d)$ into (G5) yields

$$r(d) = \frac{\beta \theta \gamma_n(d) p(d)}{1 - \beta (1 - \theta \gamma_n(d))}. \quad (\text{G7})$$

The pair of the optimal asking price and reservation value for a given distance to the city center solves equations (G6) and (G7) simultaneously.

Buyer's optimization. Via the buyer value function in the no-counteroffer scenario (G3), we define a reservation dividend $\varepsilon_n^*(d)$ such that a buyer is indifferent between

buying a housing unit and continuing to search:

$$V(d, \varepsilon_n^*(d)) - p(d) = \beta W. \quad (\text{G8})$$

Analogously, via the buyer value function in the counteroffer scenario (G4), we define a reservation dividend $\varepsilon_c^*(d)$ such that

$$V(d, \varepsilon_c^*(d)) - r(d) = \beta W. \quad (\text{G9})$$

Probability of sale. The probability of sale conditional on a bargaining scenario is equal to the probability that the buyer's idiosyncratic dividend is above their respective reservation dividend. Hence, in the no-counteroffer scenario,

$$\gamma_n(d) = 1 - F(\varepsilon_n^*(d)) \quad (\text{G10})$$

and in the counteroffer scenario,

$$\gamma_c(d) = 1 - F(\varepsilon_c^*(d)). \quad (\text{G11})$$

Thus, for the derivative in the seller optimality condition (G6) we have that

$$\frac{\partial \gamma_n}{\partial p(d)|_d} = -f(\varepsilon_n^*(d)) \frac{\partial \varepsilon_n^*}{\partial p(d)|_d}. \quad (\text{G12})$$

By proceeding as in the main text, we get

$$\varepsilon_n^*(d) = \frac{1 - \pi\beta}{\beta} p(d) + \tau(d) - (1 - \pi)\Pi(d) + (\pi - \pi\beta)W \quad (\text{G13})$$

and

$$\frac{\partial \gamma_n}{\partial p(d)|_d} = -f(\varepsilon_n^*(d)) \frac{1 - \pi\beta}{\beta}. \quad (\text{G14})$$

Analogous relations hold for the counteroffer scenario.

G.2 Analytical results in the extended model

Again, we start with auxiliary derivations, applying $\varepsilon \sim U[\underline{\varepsilon}, \bar{\varepsilon}]$. First, Lemma 1 enables us to simplify expressions that contain reservation dividends and probabilities of sale.

Lemma 1. *The buyer reservation dividends in the counteroffer scenario and the no-counteroffer scenario relate as $\varepsilon_c^*(d) = 2\varepsilon_n^*(d) - \bar{\varepsilon}$. The probabilities of sale in these two scenarios relate as $\gamma_c(d) = 2\gamma_n(d)$.*

Proof. Using the buyer indifference conditions (G8) and (G9) together with the linear expression of the buyer value function (10), we have that

$$\varepsilon_n^*(d) = \frac{1 - \pi\beta}{\beta} p(d) + \tau(d) - (1 - \pi)(\Pi(d) + W) + (1 - \pi\beta)W \quad (\text{G15})$$

and

$$\varepsilon_c^*(d) = \frac{1 - \pi\beta}{\beta} r(d) + \tau(d) - (1 - \pi)(\Pi(d) + W) + (1 - \pi\beta)W. \quad (\text{G16})$$

With the seller optimality condition (G6), the equilibrium relation between probabilities of sale and reservation dividends in the no-counteroffer scenario (G10), and the value of the derivative in (G14), we get

$$\varepsilon_n^*(d) - \varepsilon_c^*(d) = \frac{1 - \pi\beta}{\beta} (p(d) - r(d)) = \frac{1 - \pi\beta}{\beta} \left(-\frac{\gamma_n(d)}{\partial \gamma_n / \partial p(d)|_d} \right) \quad (\text{G17})$$

$$= \frac{1 - \pi\beta}{\beta} \left(-\frac{\frac{\bar{\varepsilon} - \varepsilon_n^*(d)}{\bar{\varepsilon} - \underline{\varepsilon}}}{-\frac{1 - \pi\beta}{\beta} \frac{1}{\bar{\varepsilon} - \underline{\varepsilon}}} \right) \quad (\text{G18})$$

which means that

$$\varepsilon_c^*(d) = 2\varepsilon_n^*(d) - \bar{\varepsilon}. \quad (\text{G19})$$

Translating the reservation dividends back into probabilities of sale, we have that

$$\bar{\varepsilon} - (\bar{\varepsilon} - \underline{\varepsilon})\gamma_c(d) = 2(\bar{\varepsilon} - (\bar{\varepsilon} - \underline{\varepsilon})\gamma_n(d)) - \bar{\varepsilon} \quad (\text{G20})$$

and hence $\gamma_c(d) = 2\gamma_n(d)$. □

Lemma 2. *The reservation dividends in the no-counteroffer scenario $\varepsilon_n^*(d)$ and in the counteroffer scenario $\varepsilon_c^*(d)$ increase with distance to the city center d .*

Proof. We know from (G13) that

$$\varepsilon_n^*(d) = \frac{1 - \pi\beta}{\beta} p(d) + \tau(d) - (1 - \pi)\Pi(d) + (\pi - \pi\beta)W.$$

Analogously to the main derivations, we reformulate the asking price $p(d)$ and the expected profit from reselling the property $\Pi(d)$ in terms of the reservation dividend $\varepsilon_n^*(d)$. First, we combine the seller optimality conditions (G6) and (G7) and get

$$p(d) = -\frac{(1 - \beta)\gamma_n(d) + \beta\theta\gamma_n^2(d)}{(1 - \beta)(\partial\gamma_n/\partial p(d)|_d)}. \quad (\text{G21})$$

Expressing the probability of sale $\gamma_n(d)$ and the derivative $\partial\gamma_n/\partial p(d)|_d$ in terms of the reservation dividend $\varepsilon_n^*(d)$ using the equilibrium relations (G10) and (G14), we have that

$$p(d) = \frac{\beta(\bar{\varepsilon} - \varepsilon_n^*(d))}{1 - \pi\beta} + \frac{\beta^2\theta(\bar{\varepsilon} - \varepsilon_n^*(d))^2}{(1 - \beta)(1 - \pi\beta)(\bar{\varepsilon} - \underline{\varepsilon})}. \quad (\text{G22})$$

Next, using the seller's conditions (G5) and (G6), we get

$$\Pi(d) = p(d) + \frac{\gamma_n(d) - \theta\gamma_n^2(d)}{\partial\gamma_n/\partial p(d)|_d}, \quad (\text{G23})$$

which, using (G22) and again expressing the probability of sale and the derivative in terms of the reservation dividend via (G10) and (G14), amounts to

$$\Pi(d) = \frac{\beta\theta(\bar{\varepsilon} - \varepsilon_n^*(d))^2}{(1 - \beta)(1 - \pi\beta)(\bar{\varepsilon} - \underline{\varepsilon})}. \quad (\text{G24})$$

Plugging these results into the linear reservation dividend expression (G13) and taking the derivative with respect to the distance to the city center d on both sides yields

$$\frac{\partial\varepsilon_n^*}{\partial d} \underbrace{\left(2 + 2\frac{\pi\beta\theta}{1 - \pi\beta} \frac{\bar{\varepsilon} - \varepsilon_n^*(d)}{\bar{\varepsilon} - \underline{\varepsilon}}\right)}_{>0} = \frac{\partial\tau}{\partial d} > 0 \quad (\text{G25})$$

and therefore $\partial\varepsilon_n^*/\partial d > 0$. Via Lemma 1, also $\partial\varepsilon_c^*/\partial d > 0$. $\square$

Corollary 1. *The expected profit $\Pi(d)$, the asking price $p(d)$, the seller reservation value $r(d)$, and $\mathbb{E}[\text{Sales price}(d)] = \theta p(d) + (1 - \theta)r(d)$ decrease with distance to the city center d .*

Proof. Using (G24), we have that

$$\frac{\partial \Pi}{\partial d} = -\frac{\partial \varepsilon_n^*}{\partial d} \frac{2\beta\theta(\bar{\varepsilon} - \varepsilon_n^*(d))}{(1 - \beta)(1 - \pi\beta)(\bar{\varepsilon} - \underline{\varepsilon})} < 0, \quad (\text{G26})$$

where $\partial \varepsilon_n^* / \partial d > 0$ via Lemma 2. Next, using (G22), we get

$$\frac{\partial p}{\partial d} = -\frac{\partial \varepsilon_n^*}{\partial d} \left(\frac{\beta}{1 - \pi\beta} + \frac{2\beta^2\theta(\bar{\varepsilon} - \varepsilon_n^*(d))}{(1 - \beta)(1 - \pi\beta)(\bar{\varepsilon} - \underline{\varepsilon})} \right) < 0. \quad (\text{G27})$$

Proceeding as in the proof of Lemma 1, we have that

$$r(d) = p(d) - \frac{\beta(\bar{\varepsilon} - \varepsilon_n^*(d))}{1 - \pi\beta} = \frac{\beta^2\theta(\bar{\varepsilon} - \varepsilon_n^*(d))^2}{(1 - \beta)(1 - \pi\beta)(\bar{\varepsilon} - \underline{\varepsilon})}. \quad (\text{G28})$$

Then,

$$\frac{\partial r}{\partial d} = -\frac{\partial \varepsilon_n^*}{\partial d} \frac{2\beta^2\theta(\bar{\varepsilon} - \varepsilon_n^*(d))}{(1 - \pi\beta)(1 - \beta)(\bar{\varepsilon} - \underline{\varepsilon})} < 0. \quad (\text{G29})$$

$\mathbb{E}[\text{Sales price}(d)] = \theta p(d) + (1 - \theta)r(d)$ decreases with distance to the city center, as both the asking price $p(d)$ and the seller reservation value $r(d)$ decrease with distance to the city center. $\square$

Time on the market. The probability $\gamma_{nc}(d)$ that a housing unit sells in a period is given via the probabilities for the two bargaining scenarios and the corresponding probabilities of sale:

$$\gamma_{nc}(d) = \theta\gamma_n(d) + (1 - \theta)\gamma_c(d). \quad (\text{G30})$$

The expected time on the market at a given distance to the city center is

$$\mathbb{E}[TOM(d)] = \frac{1}{\gamma_{nc}(d)}. \quad (\text{G31})$$

Proposition 1. *The expected time on the market $\mathbb{E}[TOM(d)]$ increases with distance to the*

city center d in the extended model with bargaining.

Proof. Using Lemma 1 and the equilibrium relations between the reservation dividends and the probabilities of sale (G10) and (G11), we can express the expected time on the market in terms of the reservation dividend in the no-counteroffer scenario:

$$\mathbb{E}[TOM(d)] = \frac{1}{(2-\theta)\gamma_n(d)} = \frac{\bar{\varepsilon} - \underline{\varepsilon}}{(2-\theta)(\bar{\varepsilon} - \varepsilon_n^*(d))}. \quad (G32)$$

The derivative of the expected time on the market with respect to the distance to the city center amounts to

$$\frac{\partial \mathbb{E}[TOM]}{\partial d} = \frac{\partial \varepsilon_n^*}{\partial d} \underbrace{\frac{\bar{\varepsilon} - \underline{\varepsilon}}{2-\theta} (\bar{\varepsilon} - \varepsilon_n^*(d))^{-2}}_{>0} > 0. \quad (G33)$$

□

Intuition. See main text.

Asking price discount. The expected asking price discount at a given distance to the city center is

$$\mathbb{E}[APD(d)] = \theta \times APD_n(d) + (1-\theta) \times APD_c(d) = (1-\theta) \times APD_c(d), \quad (G34)$$

where the asking price discount in the no-counteroffer scenario $APD_n(d) = 0$. We define the asking price discount in the counteroffer scenario analogously to our empirical measure as

$$APD_c(d) = \frac{r(d) - p(d)}{p(d)}. \quad (G35)$$

Proposition 2. *Given that the probability of no counteroffer $\theta \in (0, 1)$, the expected asking price discount $\mathbb{E}[APD(d)] < 0$ becomes more negative with distance to the city center d .*

Proof. If $\theta = 1$, then the asking price discount is always equal to zero, as the probability of being in the no-counteroffer scenario is equal to one, and hence the asking price is the same as the sales price at all distances to the city center. This corresponds to the setup in the main model. In the following, we consider $\theta < 1$. Using the expression for

the optimal reservation value $r(d)$ of a seller (G7), we have that

$$APD_c(d) = \frac{\frac{\beta\theta\gamma_n(d)p(d)}{1-\beta(1-\theta\gamma_n(d))} - p(d)}{p(d)} = \underbrace{\frac{1}{1-\beta+\beta\theta\frac{\bar{\varepsilon}-\varepsilon_n^*(d)}{\bar{\varepsilon}-\underline{\varepsilon}}}}_{>0} \underbrace{(\beta-1)}_{<0} < 0. \quad (G36)$$

Hence, the expected asking price discount $\mathbb{E}[APD(d)] = (1-\theta)APD_c(d) < 0$. The derivative of $\mathbb{E}[APD(d)]$ with respect to the distance to the city center amounts to

$$\frac{\partial \mathbb{E}[APD]}{\partial d} = \frac{\partial \mathbb{E}[APD_c]}{\partial d} = \underbrace{\left(1-\beta+\beta\theta\frac{\bar{\varepsilon}-\varepsilon_n^*(d)}{\bar{\varepsilon}-\underline{\varepsilon}}\right)^{-2}}_{>0} \underbrace{\frac{\beta\theta}{\bar{\varepsilon}-\underline{\varepsilon}} \frac{\partial \varepsilon_n^*}{\partial d} (\beta-1)}_{<0} < 0, \quad (G37)$$

provided that $\theta > 0$. □

Intuition. As for the time on the market, the relevant condition for liquidity in the form of the asking price discount to decrease with distance to the city center is that reservation dividends increase with distance to the city center. In principle, both the asking price and the seller reservation value decrease with distance to the city center (see Corollary 1). For the expected asking price discount to become more negative with distance to the city center, we need that the seller reservation value decreases more steeply with distance to the city center than the asking price.⁴³ Why is this condition fulfilled? Recall from the seller optimization that the reservation value is equal to the discounted profit of the next period in equilibrium, as otherwise, the seller would always reject the buyer's optimal counteroffer. For the asking price discount to become more negative with distance to the city center, we, therefore, need that the expected profit decreases more steeply than the

⁴³Formally,

$$\frac{\partial \mathbb{E}[APD]}{\partial d} = (1-\theta) \frac{\partial \left(\frac{r-p}{p}\right)}{\partial d} = (1-\theta) \left(\frac{\partial r}{\partial d} \frac{1}{p(d)} - \frac{\partial p}{\partial d} \frac{r}{(p(d))^2} \right), \quad (G38)$$

such that for the expected asking price discount to decrease with distance to the city center, we need

$$\underbrace{\frac{\partial r / \partial d}{r(d)}}_{<0} < \underbrace{\frac{\partial p / \partial d}{p(d)}}_{<0}, \quad (G39)$$

where both sides of the expression are < 0 due to Corollary 1.

asking price.⁴⁴ A formal proof of this statement follows shortly. Intuitively, we can express the expected profit in terms of the probability of sale and the asking price. Since both the probability of sale and the asking price decrease with distance to the city center and the expected profit is composed of the two, the expected profit decreases more steeply than the asking price alone. *Proof: the expected profit decreases more steeply with distance to the city center than the asking price.* Via (G5), we can express the expected profit as

$$\Pi(d) = \theta \gamma_n(d) p(d) + (1 - \theta \gamma_n(d)) \beta \Pi(d),$$

since the seller's reservation value $r(d) = \beta \Pi(d)$ via the optimal counteroffer of the buyer. Then,

$$\Pi(d) = \frac{\theta \gamma_n(d) p(d)}{1 - \beta + \theta \beta \gamma_n(d)} \quad (\text{G41})$$

and

$$\frac{\partial \Pi}{\partial d} = \frac{(1 - \beta + \theta \beta \gamma_n(d)) \left(\theta \frac{\partial \gamma_n}{\partial d} p(d) + \theta \gamma_n(d) \frac{\partial p}{\partial d} \right) - \theta^2 \beta \frac{\partial \gamma_n}{\partial d} \gamma_n(d) p(d)}{(1 - \beta + \theta \beta \gamma_n(d))^2}. \quad (\text{G42})$$

The proportional derivative of $\Pi(d)$ with respect to d is then

$$\frac{\partial \Pi / \partial d}{\Pi(d)} = \underbrace{\frac{\partial \gamma_n / \partial d}{\gamma_n(d)}}_{<0} + \underbrace{\frac{\partial p / \partial d}{p(d)}}_{<0} - \underbrace{\frac{(\theta \beta)(\partial \gamma_n / \partial d)}{1 - \beta + \theta \beta \gamma_n(d)}}_{<0}. \quad (\text{G43})$$

Statement (G40) says that

$$\frac{\partial \Pi / \partial d}{\Pi(d)} < \frac{\partial p / \partial d}{p(d)}, \quad (\text{G44})$$

for which to hold we need that

$$\frac{\partial \gamma_n / \partial d}{\gamma_n(d)} < \frac{(\theta \beta)(\partial \gamma_n / \partial d)}{1 - \beta + \theta \beta \gamma_n(d)}. \quad (\text{G45})$$

⁴⁴Formally,

$$\frac{\partial r / \partial d}{r(d)} = \frac{\partial (\beta \Pi) / \partial d}{\beta \Pi(d)} = \frac{\partial \Pi / \partial d}{\Pi(d)} < \frac{\partial p / \partial d}{p(d)}. \quad (\text{G40})$$

As $\partial \gamma_n / \partial d < 0$, this expression simplifies to

$$\frac{1}{\gamma_n(d)} > \frac{\theta \beta}{1 - \beta + \theta \beta \gamma_n(d)}, \quad (\text{G46})$$

or equivalently

$$1 - \beta > 0, \quad (\text{G47})$$

which is true, since $\beta \in (0, 1)$. Therefore, $\frac{\partial \Pi / \partial d}{\Pi(d)} < \frac{\partial p / \partial d}{p(d)}$, as required. $\square$

Relation between time on the market and asking price discount. Via the proofs of Propositions 1 and 2, we can directly derive that housing units that spend more time on the market also sell at more negative discounts. Thus, lower liquidity in one measure corresponds to lower liquidity in the other measure.

Corollary 2. *Given that the probability of no counteroffer $\theta \in (0, 1)$, the model correlation between the expected asking price discount $\mathbb{E}[APD(d)]$ and the expected time on the market $\mathbb{E}[TOM(d)]$ is negative.*

Proof. We start by expressing the asking price discount in terms of the time on the market. Then, we evaluate the derivative of the asking price discount with respect to the time on the market at a given distance to the city center. First, from the proofs of Propositions 1 and 2 we have that

$$\mathbb{E}[APD(d)] = \frac{\beta - 1}{1 - \beta + \frac{\beta \theta}{(2 - \theta) \mathbb{E}[TOM(d)]}} \quad (\text{G48})$$

The derivative of the expected time on the market with respect to the expected asking price discount, given a distance to the city center d is then

$$\frac{\partial \mathbb{E}[APD]}{\partial \mathbb{E}[TOM(d)]|_d} = \underbrace{\left(1 - \beta + \frac{\beta \theta}{(2 - \theta) \mathbb{E}[TOM(d)]}\right)^{-2} \frac{\beta \theta}{2 - \theta} \left(\mathbb{E}[TOM(d)]\right)^{-2}}_{>0} \underbrace{(\beta - 1)}_{<0} < 0, \quad (\text{G49})$$

provided that $\theta \in (0, 1)$. A higher time on the market therefore corresponds to a more negative asking price discount. $\square$

H Equilibrium existence and uniqueness

We show existence and uniqueness of an equilibrium in the extended model. The main model is obtained by setting the probability of the no-counteroffer scenario $\theta = 1$.

H.1 Equilibrium existence

First, we show the existence of a solution. Evidently, we find a solution numerically, nevertheless, we prove its existence formally, following Krainer (2001). As in (10), we can express the buyer's value in the extended model as

$$V(d, \varepsilon) = \frac{\beta}{1 - \pi\beta} \left(\varepsilon - \tau(d) + (1 - \pi) (\Pi(d) + W) \right). \quad (\text{H1})$$

Hence, $V(d, \varepsilon)$ is linear in ε and there exist reservation dividends as defined in the buyer indifference conditions (G8) and (G9). In what follows, we express the other endogenous variables in terms of the buyer's reservation dividends, the model parameters, and the travel cost function to prove uniqueness of the solution. The fact that reservation dividends exist then implies that a solution also exists, as the remaining objects listed in the previous sentence are exogenous.

H.2 Equilibrium uniqueness

To show uniqueness, we follow Vanhapelto and Magnac (2024), showing that two possible ways of expressing the value of search allow for only one pair of the buyer reservation dividends $\{\varepsilon_n^*(d), \varepsilon_c^*(d)\}$ at every distance to the city center such that both of these expressions hold. The first expression decreases in the buyer reservation dividends, whereas the second expression increases. Hence, given a set of parameters and a travel cost function, the model's solution is unique, as we express all endogenous variables in terms of parameters, the exogenous travel cost, and the endogenous buyer reservation dividends.

Expression 1. We set up the first expression for the value of search in terms of the buyer reservation dividends via the definitions (G2), (G3), and (G4):

$$W = \mathbb{E}_{d, \varepsilon} \left[\theta \max [V(d, \varepsilon) - p(d), \beta W] + (1 - \theta) \max [V(d, \varepsilon) - r(d), \beta W] \right], \quad (\text{H2})$$

and hence

$$W = \frac{1}{1-\beta} \mathbb{E}_{d,\varepsilon} [\theta \max [V(d, \varepsilon) - p(d) - \beta W, 0] + (1-\theta) \max [V(d, \varepsilon) - r(d) - \beta W, 0]]. \quad (\text{H3})$$

Next, we express the relations within the max operators in terms of the buyer reservation dividends. Note that when the buyer indifference conditions (G8) and (G9) hold, we have that

$$\beta W = V(d, \varepsilon_n^*(d)) - p(d) = V(d, \varepsilon_c^*(d)) - r(d). \quad (\text{H4})$$

Inserting the linear buyer value (H1), we get

$$\beta W = \frac{\beta}{1-\pi\beta} \left(\varepsilon_n^*(d) - \tau(d) + (1-\pi)(\Pi(d) + W) \right) - p(d) \quad (\text{H5})$$

and

$$\beta W = \frac{\beta}{1-\pi\beta} \left(\varepsilon_c^*(d) - \tau(d) + (1-\pi)(\Pi(d) + W) \right) - r(d). \quad (\text{H6})$$

Hence,

$$\frac{\beta}{1-\pi\beta} \varepsilon_n^*(d) = \frac{\beta}{1-\pi\beta} \tau(d) - \frac{\beta(1-\pi)}{1-\pi\beta} \Pi(d) + \frac{\pi\beta(1-\beta)}{1-\pi\beta} W + p(d) \quad (\text{H7})$$

and

$$\frac{\beta}{1-\pi\beta} \varepsilon_c^*(d) = \frac{\beta}{1-\pi\beta} \tau(d) - \frac{\beta(1-\pi)}{1-\pi\beta} \Pi(d) + \frac{\pi\beta(1-\beta)}{1-\pi\beta} W + r(d). \quad (\text{H8})$$

Again using (H1), we can express the sum within the first max operator from (H3) as

$$V(d, \varepsilon) - p(d) - \beta W = \frac{\beta}{1-\pi\beta} \varepsilon + -\frac{\beta}{1-\pi\beta} \tau(d) + \frac{\beta(1-\pi)}{1-\pi\beta} \Pi(d) - p(d) - \frac{\pi\beta(1-\beta)}{1-\pi\beta} W.$$

Then, via (H7), we get

$$V(d, \varepsilon) - p(d) - \beta W = \frac{\beta}{1-\pi\beta} \varepsilon - \frac{\beta}{1-\pi\beta} \varepsilon_n^*(d) = \frac{\beta}{1-\pi\beta} (\varepsilon - \varepsilon_n^*(d)). \quad (\text{H9})$$

Analogously, using (H8), we have that

$$V(d, \varepsilon) - r(d) - \beta W = \frac{\beta}{1 - \pi\beta} (\varepsilon - \varepsilon_c^*(d)). \quad (\text{H10})$$

We can then express the value of search from (H3) as

$$W = \frac{1}{1 - \beta} \mathbb{E}_{d, \varepsilon} \left[\theta \max \left[\frac{\beta}{1 - \pi\beta} (\varepsilon - \varepsilon_n^*(d)), 0 \right] + (1 - \theta) \max \left[\frac{\beta}{1 - \pi\beta} (\varepsilon - \varepsilon_c^*(d)), 0 \right] \right] \quad (\text{H11})$$

which decreases in $\varepsilon_n^*(d)$ and $\varepsilon_c^*(d)$.

Expression 2. We set up the second expression via the buyer indifference conditions. First, using the linear form of the buyer value (H1), we can express the indifference condition for the no-counteroffer scenario (G8) as

$$W = \frac{1}{\pi - \pi\beta} \left(\varepsilon_n^*(d) - \tau(d) + (1 - \pi)\Pi(d) - \frac{1 - \pi\beta}{\beta} p(d) \right). \quad (\text{H12})$$

We can express the price and the profit in terms of the reservation dividend in the no-counteroffer scenario via (G22) and (G24), such that

$$W = \frac{1}{\pi - \pi\beta} \left(2\varepsilon_n^*(d) - \bar{\varepsilon} - \tau(d) - \frac{(\pi - \pi\beta)\beta\theta(\bar{\varepsilon} - \varepsilon_n^*(d))^2}{(1 - \beta)(1 - \pi\beta)(\bar{\varepsilon} - \underline{\varepsilon})} \right). \quad (\text{H13})$$

Hence,

$$\frac{\partial W}{\partial \varepsilon_n^*(d)|_d} = \frac{2}{\pi - \pi\beta} + \frac{2\beta\theta(\bar{\varepsilon} - \varepsilon_n^*(d))}{(1 - \beta)(1 - \pi\beta)(\bar{\varepsilon} - \underline{\varepsilon})} > 0. \quad (\text{H14})$$

Via Lemma 1, also $\partial W / \partial \varepsilon_c^*(d)|_d > 0$. Since Expression 1 for the value of search decreases in both reservation dividends and Expression 2 increases in both reservation dividends, there can only be a single pair of reservation dividends $\{\varepsilon_n^*(d), \varepsilon_c^*(d)\}$ at a given distance to the city center such that Expression 1 and Expression 2 hold simultaneously. With W being constant across space, it immediately follows that this holds for all distances to the city center.

I Model solution method

We are not able to solve the model in closed form, as we obtain a nonlinear system of equations via the equilibrium conditions. Hence, we solve the model numerically. The equilibrium condition (4), which describes the value of search W as an expectation over distances to the city center and idiosyncratic dividends, and the equilibrium conditions (2), (6), (7), and (8), which have to hold for all distances to the city center $d^\Delta \in \mathcal{D}^\Delta$, constitute the relevant system of $1 + z \times 4$ equations. Solving the system as it is via standard solvers brings up problems of numerical instability due to the high degree of non-linearity involved. Hence, we instead iterate over the value of search to find a value that is consistent with (2), (6), (7), and (8) at each $d^\Delta \in \mathcal{D}^\Delta$.

We implement the iteration as follows. First, we initialize an arbitrary guess for the value of search. Given this guess, we solve (2), (6), (7), and (8) for all $d^\Delta \in \mathcal{D}^\Delta$. We update the guess via

$$\tilde{W} = \frac{1}{z} \sum_{d^\Delta \in \mathcal{D}^\Delta} \gamma(d^\Delta) \left(V(d^\Delta, \frac{\varepsilon^*(d^\Delta) + \bar{\varepsilon}}{2}) - p(d^\Delta) \right) + (1 - \gamma(d^\Delta)) (\beta W), \quad (I1)$$

using that a buyer purchases a housing unit at d^Δ with probability of sale $\gamma(d^\Delta)$ and continues to search with probability $1 - \gamma(d^\Delta)$, which follows the alternative definition of the value of search in Krainer and LeRoy (2002) and is simply a rewritten version of the expectation in (4). This expression only requires information from (2), (6), (7), and (8). The new guess for the value of search is then set to $\tilde{W}$, and the whole process is repeated until $W = \tilde{W}$ up to a fixed iteration tolerance. In principle, convergence is not necessarily guaranteed by the standard contraction mapping theorem, even though $(1 - \gamma(d^\Delta))\beta < 1$, as the entire right-hand side of (I1) depends on W . In practice, convergence is not a problem and we obtain fast and reliable solutions, which allows us to estimate the model's structural parameters without problems.

J Additional model results

J.1 Variance of time on the market across space

An additional prediction of our model mentioned in Section 4.3 is that the variance of time on the market increases with distance to the city center. To see this, consider the variance of the geometric distribution that results from the multiplication of sale probabilities over time, together with the equilibrium relation (8) between probabilities of sale and reservation dividends:

$$\text{Var}[TOM(d)] = \frac{1 - \gamma(d)}{(\gamma(d))^2} = \frac{\frac{\varepsilon^*(d) - \underline{\varepsilon}}{\bar{\varepsilon} - \underline{\varepsilon}}}{\left(\frac{\bar{\varepsilon} - \varepsilon^*(d)}{\bar{\varepsilon} - \underline{\varepsilon}}\right)^2} = (\bar{\varepsilon} - \underline{\varepsilon}) \frac{\varepsilon^*(d) - \underline{\varepsilon}}{(\bar{\varepsilon} - \varepsilon^*(d))^2}. \quad (J1)$$

Taking the derivative with respect to the distance to the city center yields

$$\frac{\partial \text{Var}[TOM(d)]}{\partial d} = \frac{\partial \varepsilon^*}{\partial d} (\bar{\varepsilon} - \underline{\varepsilon}) \underbrace{\frac{(\bar{\varepsilon} - \varepsilon^*(d))^2 + 2(\bar{\varepsilon} - \varepsilon^*(d))(\varepsilon^*(d) - \underline{\varepsilon})}{(\bar{\varepsilon} - \varepsilon^*(d))^4}}_{>0} > 0 \quad (J2)$$

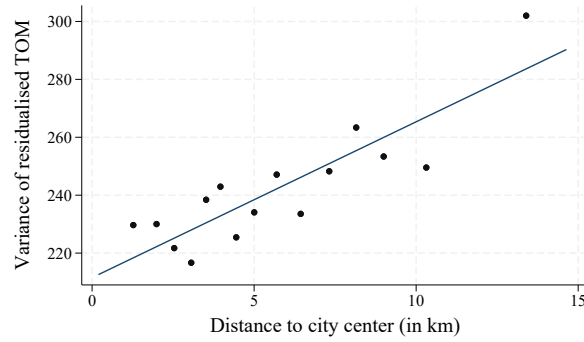
with auxiliary result (17) that the reservation dividend $\varepsilon^*(d)$ increases with distance to the city center. Intuitively, with a lower probability of a successful sale in the outskirts, a higher variability in success rates can realize, and therefore also a higher variability in time on the market.

We test this prediction of the model using transaction-level data from Germany. To focus on the relationship between distance to the city center and the variance of time on the market we estimate Regression (1) with time on the market as the dependent variable. We then use the squared residuals as our measure of time on the market variance, having accounted for differences in property characteristics. Finally, in Figure J1, we plot the squared residuals against distance to the city center. The Figure shows that the variance increases with distance to the city center, thereby confirming the model's prediction.

J.2 Steepness of price vs. liquidity gradient

Another prediction of our model mentioned in Section 4.3. is that the price gradient is steeper than the liquidity gradient. For this comparison, we express both gradients in

Figure J1: Variance of time on the market and distance to the city center, Germany (2012–2024)



Notes: This binned scatter plot shows the relation between the variance of the residualized time on the market and distance to the city center, using 15 equally-sized distance bins. The binned scatter plot is produced following Cattaneo et al. (2024).

absolute values and in relative terms for immediate comparison. For the expected time on the market, this gradient is

$$\left| \frac{\partial \mathbb{E}[TOM] / \partial d}{\mathbb{E}[TOM(d)]} \right| = \left| \frac{\partial \gamma / \partial d}{\gamma(d)} \right|, \quad (J3)$$

by definition of the time on the market. Using the probability of sale $\gamma(d)$ here instead of the reservation dividend $\varepsilon^*(d)$ simplifies the comparison to the expression for the relative price gradient. Using (12) and (F1), the relative price gradient amounts to

$$\left| \frac{(\partial \gamma / \partial d) \left(1 + 2 \left(\beta / (1 - \beta) \right) \gamma(d) \right)}{\gamma(d) + \left(\beta / (1 - \beta) \right) (\gamma(d))^2} \right| > \left| \frac{\partial \gamma / \partial d}{\gamma(d)} \right|. \quad (J4)$$

This is due to the factor 2 in front of $(\beta / (1 - \beta))$, which results from the expression for expected profit in which the seller obtains a value of selling the property in the next period with probability $(\gamma(d))^2$. This option of selling the property in the future is priced in today. For a given increase in the expected time on the market when going further away from the city center, the corresponding price decreases more. The demand-driven level of liquidity, given a stationary equilibrium, will also determine market conditions in the following period in case the seller is not able to sell their housing unit in this period. With a successful sale in the next period, the seller then obtains the discounted profit.

Table J1: *Standardized TOM and price gradients, Germany and U.S.*

Country	Dataset	TOM gradient	Price gradient
Germany	Condos full sample	0.048	-0.202
U.S.	Single-family FUA (full sample)	0.029	-0.146
U.S.	Single-family MSA (50km radius)	0.048	-0.276
U.S.	Single-family MSA (full sample)	0.134	-0.074

Note: This table presents regression coefficients of time on the market (TOM) and log sales price on property characteristics with time and location fixed effects based on Regression (1). The coefficients are standardized by the sample standard deviation of the respective variable. For Germany, the fixed effects are at the year-quarter-city level. For the U.S., the fixed effects are at the year-month-MSA or year-month-FUA level. More information on data sources is provided in the main text.

Table J1 provides empirical comparisons of the steepness of the price and liquidity gradients for Germany and the United States. The theoretical prediction that the price gradient is steeper than the liquidity gradient holds empirically, except in the U.S. at the MSA level across the full sample. This is likely due to the spatial boundaries of some MSAs reaching very far out, which makes the estimates noisier. With functional urban area boundaries, the result holds, as well as when restricting the U.S.-MSA sample to a 50km radius around the MSA center.

J.3 Additional model results

Figure J2: *Spatial distributions of additional variables, Germany*

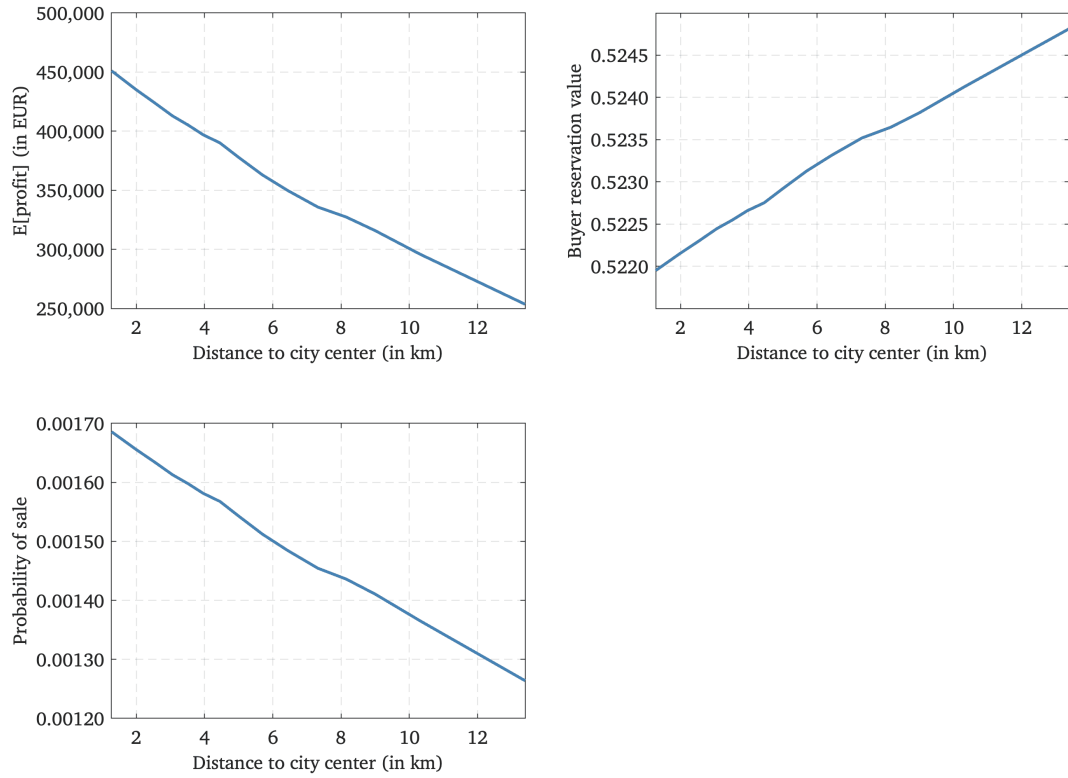


Figure J3: *Spatial distributions of additional variables, United States*

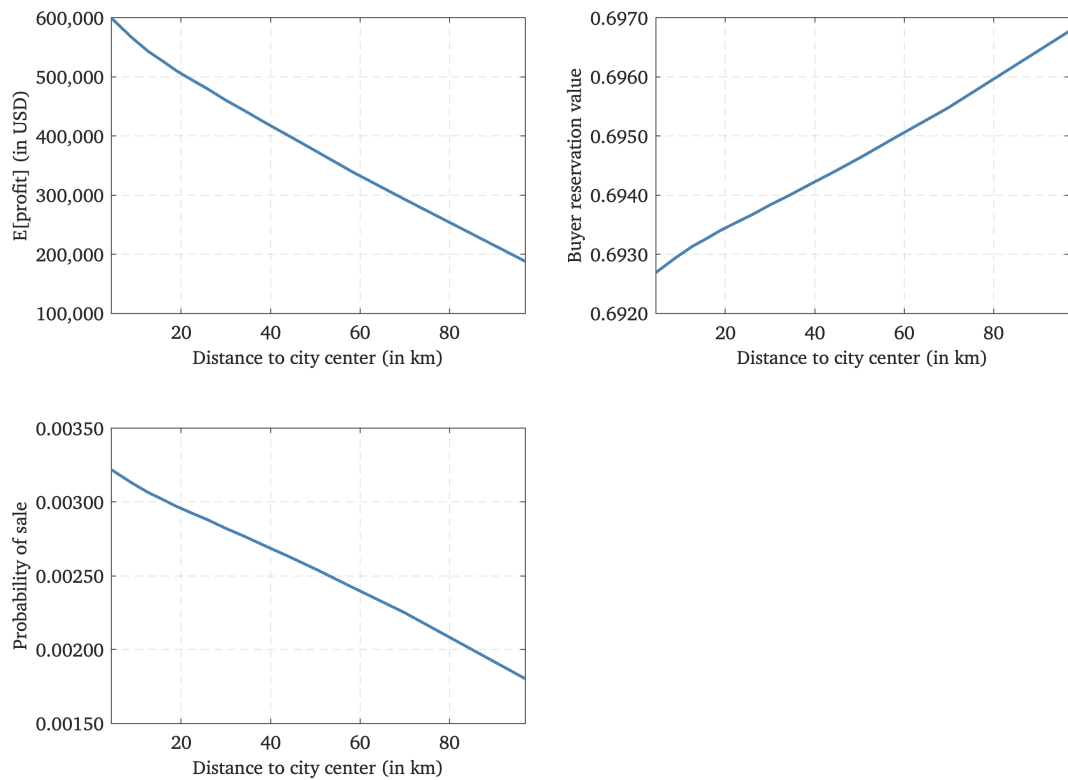
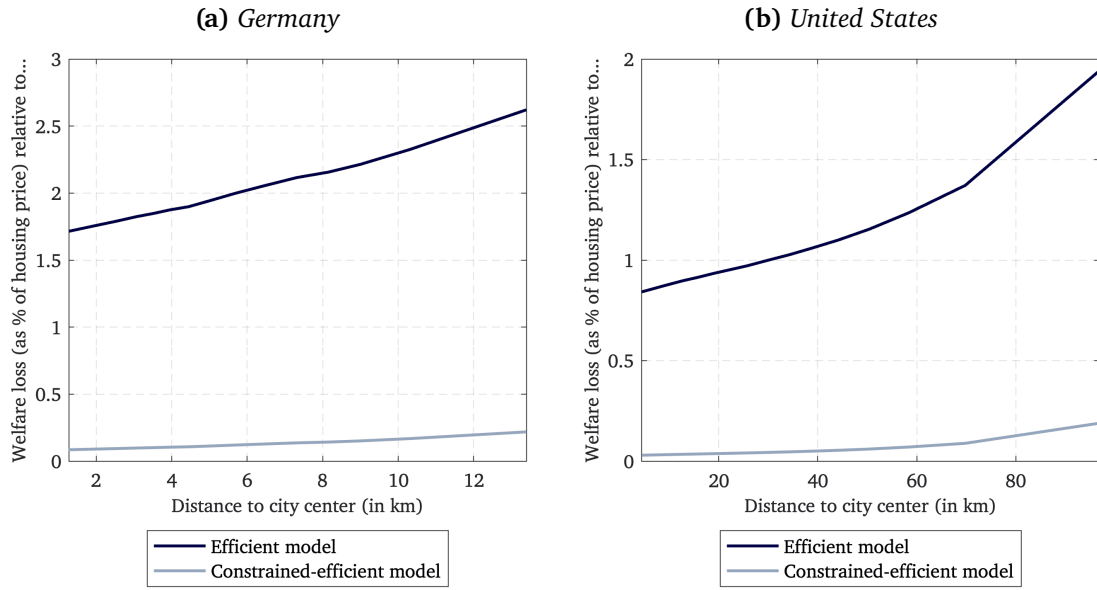
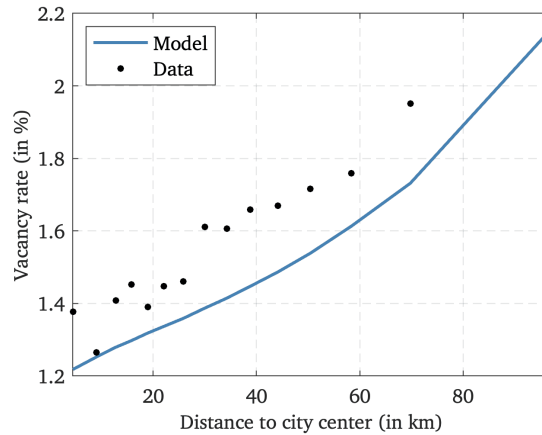


Figure J4: Spatial welfare loss distributions in terms of housing prices



Notes: These plots show the welfare loss in the baseline model compared to the counterfactual model versions by distance to the city center. Welfare is calculated as defined in (21) and scaled up to an expected lifetime value with factor $\beta/(1 - \pi\beta)$. The percentages refer to the absolute loss in welfare in the baseline model compared to a counterfactual as a fraction of the housing price at every distance to the city center.

Figure J5: Spatial distribution of homeowner vacancy rate, United States



Notes: This plot shows the distribution of the homeowner vacancy rate, that is, the vacancy rate in the owner-occupied housing market, across distances to the city center from our baseline model and from the data. Note that neither the spatial variation nor the level of vacancy rates are targeted in the model calibration. The model vacancy rates are calculated as defined via the probability of being matched, defined in (22). The data points are calculated using the ZIP-Code level yearly American Community Survey data from 2012–2023 introduced in Supplemental Appendix A.2, using Regression (1) with all fixed effects and controls.

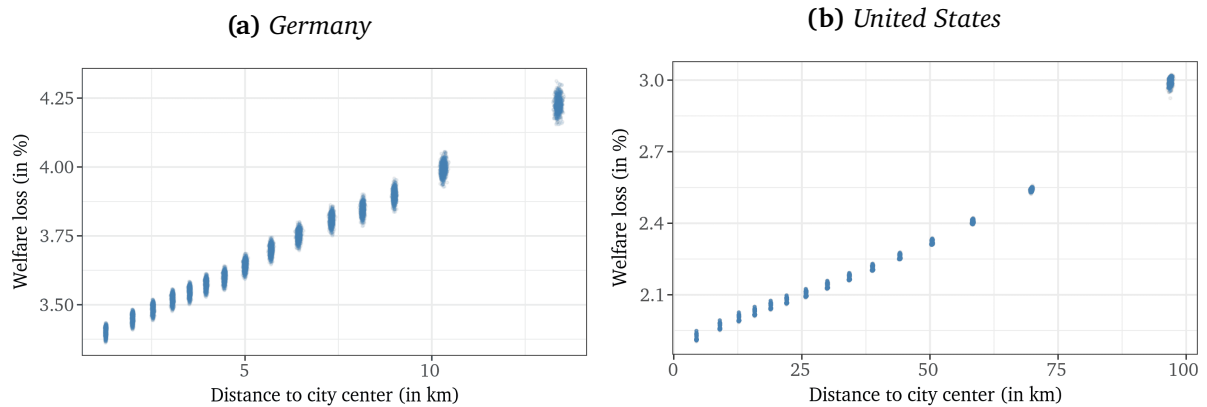
J.4 Model sensitivity analysis

In this subsection, we provide a sensitivity analysis for our welfare estimates. First, in Figure (J6), we plot the welfare loss in the baseline model relative to the efficient model

with bootstrapped confidence bounds. As described in the main text, the confidence intervals are narrow, which leaves us confident about our estimates from this side.

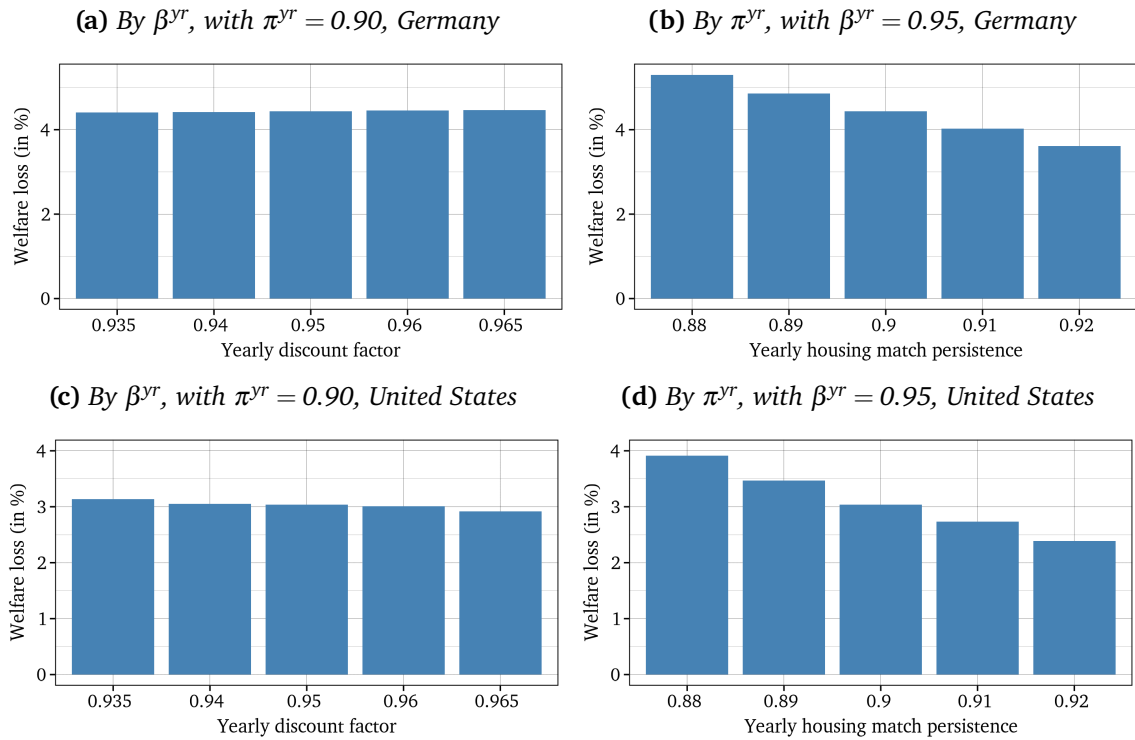
Second, in the main calibration, we set the yearly discount factor to 0.95, a standard value. Nevertheless, we check if our illiquidity discount estimates are sensitive to our choice of the discount factor. Moreover, we cannot calculate holding periods for apartments that were transacted before the beginning of our German sample in January 1990, while the holding period for the U.S. is only a rough estimate obtained via Redfin. Hence, we also check if our illiquidity discount estimates change if we use different housing match persistence probabilities. In Figure J7, we plot the welfare loss in the outskirts, varying the yearly discount factor β^{yr} between 0.935 and 0.965 and the yearly housing match persistence π^{yr} between 0.88 and 0.92. Each bar represents a recalibration of the model. As explained in the main text, the choice of the discount factor leaves the welfare loss estimates unaffected, while a lower match persistence increases the welfare loss.

Figure J6: Bootstrapped welfare loss estimates



Notes: These plots show the welfare loss in the baseline model compared to the efficient model version by distance to the city center. Welfare is calculated as defined in (21). The percentages refer to the loss in welfare in the baseline model relative to the efficient model at every individual distance. The individual dots depict the 1,000 bootstrapped replication draws.

Figure J7: Sensitivity analysis for outskirts welfare loss



Notes: These plots show the welfare loss in the baseline model compared to the efficient model version at the outermost distance to the city center, with varying yearly discount factors and housing match persistence probabilities. Welfare is calculated as defined in (21). The percentages refer to the loss in welfare in the baseline model relative to the efficient model at every distance to the city center.

J.5 Alternative travel cost interpretation

In the main model, we think of a physical cost of car travel when estimating the parameter μ , consistent with the canonical monocentric city model. μ then reflects a conversion of travel time in minutes, fed into the model from our travel time estimates, to the associated travel cost in model units. Alternatively, we can think of the travel cost in the model as an opportunity cost which results from lost time due to traveling to the city center. We also conceptualize this opportunity cost as translating travel time to the city center in minutes linearly into a monetary cost. To do so, we must specify what a minute of travel time is worth to agents in the model. We do this using the average hourly wage in Germany and the United States. For Germany, we retrieve wage statistics via the German Statistical Office (GENESIS database, variable code: 81000-090⁴⁵). For the United States, we retrieve wage statistics via FRED (variable code: CES0500000003, primary source:

⁴⁵ <https://www.destatis.de/DE/Themen/Wirtschaft/Volkswirtschaftliche-Gesamtrechnungen-Inlandsprodukt/Publikationen/Downloads-Inlandsprodukt/statistischer-bericht-2180120.html>

U.S. Bureau of Labor Statistics (2025)). We keep the wage rates nominal on purpose for a direct comparison to the nominal travel cost estimates in the main calibration. We obtain a gross hourly wage in Germany from 2012 to 2024 of €28.33 and in the United States from 2012 to 2023 of \$27.49.

Then, we calculate the average travel time in our sample, multiplied by 2, to get a measure of daily travel time. In our model, agents travel to and from the city center for 34 minutes per day on average in Germany and for 84 minutes per day in the United States. Measured in terms of an opportunity cost, if we assume that the value of time lost can be expressed in terms of wages, agents in Germany lose $(34/60) \times €28.33 = €16.05$ per day, while agents in the United States lose \$38.49 per day. The actual losses should be somewhat lower, since these are gross wages, and net wages are typically considerably below gross wages. Moreover, the same words of caution as for the travel cost estimates apply: these calculations are at the country level and likely vary to a considerable degree at the city level, and it is not clear to what extent wages capture the opportunity cost experienced when commuting. Hence, we conclude that, roughly speaking, opportunity costs can serve as an alternative interpretation of travel costs.

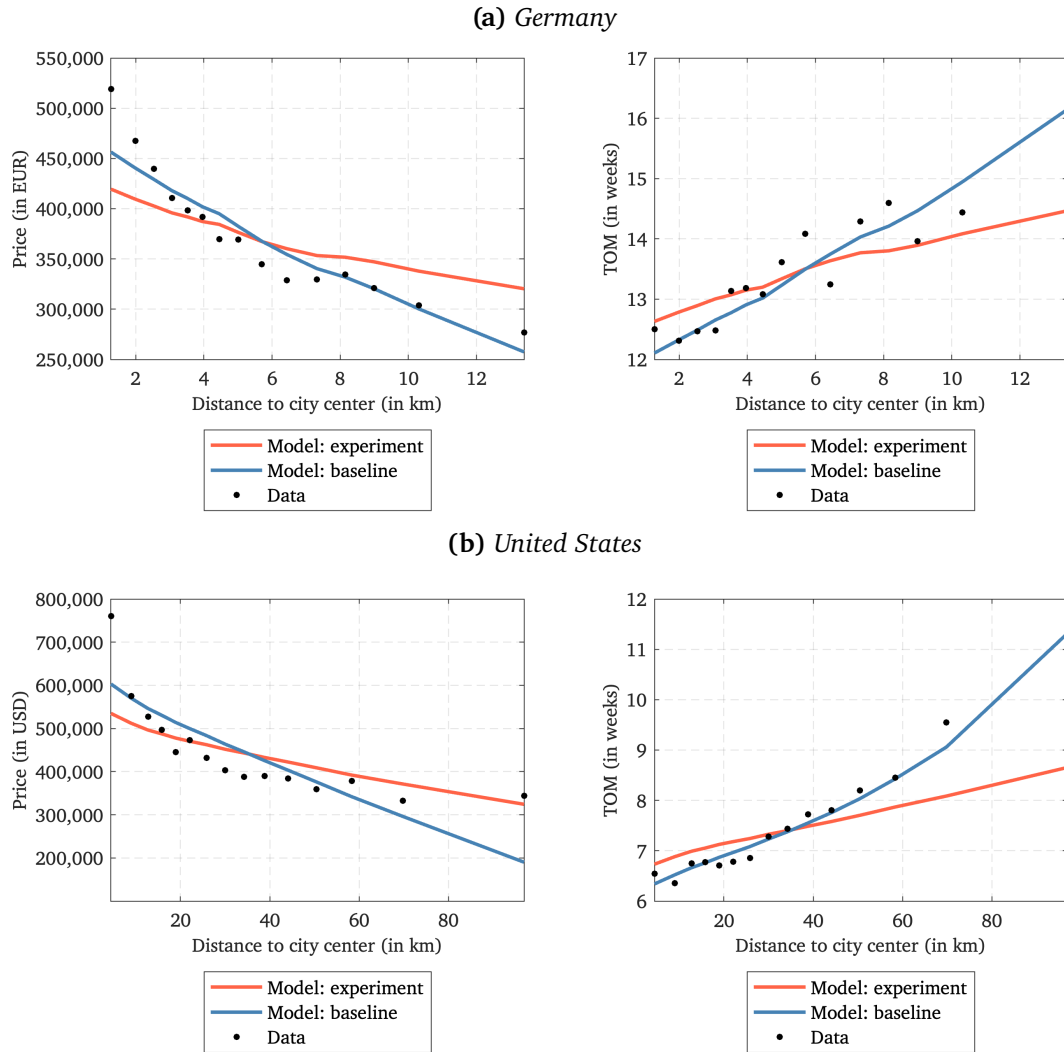
J.6 COVID experiment in the model

We test whether our baseline model can replicate the flattening of the price gradient as documented in Gupta et al. (2022) and produce a flattened liquidity gradient as we document in our empirical results. The COVID-19 pandemic induced a shift to working from home. The experiment consists of varying the travel time input, which generates a travel cost curve within the model, such that it reflects the shift in commuting patterns induced by working from home.

Per se, we have no information available on the change in time traveled to the city center across space within cities. Hence, we impose restrictions on the changes that we make by using the results from Gupta et al. (2022). To get the result that prices decrease in the city center and increase in the outskirts compared to before, the travel cost within our model must increase in the city center and decrease in the outskirts compared to before. A straightforward way to implement this is to let the average travel cost stay the same while changing its spatial distribution. Then, we must only specify one number which changes in the experiment. We impose that, keeping the average travel

time constant, the slope of the linearly approximated travel time input curve is multiplied by some factor between 0 and 1. We add back the residuals between the original travel time input curve and its linear approximation to the new tilted curve. With a factor of 1/2, we approximately replicate the price decrease of 5-10% in the city center and the price increase of 15-20% in the outskirts estimated for New York City in Gupta et al. (2022) and our flattened liquidity gradients from Supplemental Appendix D.2, see Figure J8.

Figure J8: Results of COVID experiment in the model



Notes: “TOM” refers to (expected) time on the market. The data points are calculated using Regression (1) with city-time fixed effects and all controls, as for Figure 1. The binned scatter plots are produced following Cattaneo et al. (2024), using 15 equally-sized distance bins.

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