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Spatial distribution of housing liquidity

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ABSTRACT

SPATIAL DISTRIBUTION OF HOUSING LIQUIDITY*

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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. We build and estimate a spatial housing search model and demonstrate that travel costs determine the spatial distribution of liquidity and prices. In a counterfactual analysis, we find that frictional illiquidity reduces prices in the outskirts by 7% relative to the center and explains 19% of the spatial price differences. Our findings highlight the importance of demand-side preferences for asset pricing.

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

JEL Classification: G12, G51, R21, R30

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1 Introduction

Transactions in housing markets are impeded by search frictions and typically take months to complete (see, for example, Ngai and Tenreyro, 2014; Piazzesi, Schneider, and Stroebel, 2020). This makes housing a particularly illiquid asset class, with sizable implications for business cycles, in particular during the Great Recession (Head, Lloyd-Ellis, and Sun, 2014; Garriga and Hedlund, 2020). Moreover, in contrast to other assets, housing is tied to its location. Although housing market liquidity varies across space as much as it varies across the business cycle (Jiang, Kotova, and Zhang, 2024), we know little about the determinants of this spatial variation. In this paper, we show that location preferences explain spatial differences in housing liquidity and prices. Our results imply that demand-side preferences determine equilibrium prices of heterogeneous, illiquid assets.

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 liquidity and prices for cities in two of the largest housing markets in the world. We empirically show that housing prices and various measures of housing liquidity decrease with distance to the city center in both German and U.S. cities, even when taking into account spatial differences in property characteristics, income, and demographics. These spatial differences are comparable in magnitude to cyclical fluctuations in housing prices and liquidity. To rationalize our results, we build a quantitative urban housing model with search frictions. In our model, an increasing cost of travel to the city center decreases market tightness and therefore housing market liquidity. Facing less tight markets, sellers reduce their offered prices. We estimate our model using transaction-level data and reproduce the spatial distribution of liquidity and prices with high precision for every city in our sample. Motivated by the well-established result that liquidity affects asset prices (see, for example, Duffie, Gârleanu, and Pedersen, 2005), we then quantify the impact of spatial liquidity differences on housing prices. In a counterfactual analysis in which we suppress search frictions, we find that search frictions explain 19% of the spatial variation in prices and depress prices in the outskirts relative to the city center by 7%. This illiquidity discount is in the range of related measures for housing markets (Piazzesi, Schneider, and Stroebel, 2020) and other highly illiquid assets (e.g. Gavazza, 2016). Overall, we show how buyers' preferences can simultaneously determine prices and liquidity, consistent with demand-based asset pricing (Koijen and Yogo, 2019).

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 company[1] using a nearest-neighbor algorithm. We end up with 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 to obtain control variables. 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 online listings, the standard measure in the housing liquidity literature (Han and Strange, 2015). Our empirical results show that other measures of liquidity display the same pattern, and our theoretical results indicate that time on the market can be seen as a proxy for other liquidity measures.

We find that within-city differences in the time on the market are substantial and systematic. Conditional on property characteristics and neighborhood characteristics, housing units stay on the market for 15% longer in the outskirts compared to the city center in both German and U.S. cities. This constitutes a negative liquidity gradient in urban housing markets, a novel finding which adds to the well-documented negative price gradient (see Duranton and Puga, 2015). We also show that the spread between asking and sales price, a measure that we construct analogously to the bid-ask spread, 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 it declines with distance to the city center. 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 as a consequence of the shift to working from home in this period (see Gupta et al., 2022). Lastly, using data on job accessibility across U.S. ZIP Codes from Delventhal and Parkhomenko (2024),[2] we show that our findings can be extended to locations beyond city centers which attract a large enough number of commuters.

Building on an established housing search framework (Krainer, 2001), we model search fric-

[1]We 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.

[2]We thank Andrii Parkhomenko for providing us access to the data.

tions which give rise to frictional illiquidity in the housing market. We assume that households want to minimize their distance to a central location, which gives rise to a spatial distribution of travel costs.[3] Our model thus allows us to examine the interaction of search frictions and location preferences. 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, which leads to a lower probability of sale. This is reflected in a longer time on the market outside of the city center. Sellers act as local monopolists for differentiated goods and decrease their listing prices as market tightness decreases with distance to the city center. Importantly, they trade off the listing price and the time to sell a housing unit. It is hence not optimal for sellers to adjust prices downwards such that spatial liquidity differences disappear. Hence, liquidity and prices are endogenously co-determined by travel costs which reflect fundamental demand-side location preferences. Moreover, this mechanism can be generalized to other locations beyond the city center for which homebuyers share a common preference to live nearby, analogously to our additional empirical findings.

We estimate the structural parameters of our model using our transaction-level German data via the method of simulated moments. The only spatial input required for our model to generate quantitatively accurate spatial liquidity and price distributions is the spatial distribution of travel time to the city center, translated into a monetary travel cost within the model. Leveraging the quantitative accuracy of our model, we conduct a counterfactual analysis to quantify spatial differences in the effects of search frictions on housing prices. To do so, we compute an efficient welfare-maximizing allocation that abstracts from search frictions. We compare the spatial distribution of liquidity and prices from this allocation to the one from our baseline allocation with search frictions. According to our model, frictional search results in excess illiquidity in the outskirts relative to the city center. The frictional spatial price gradient is thus inefficiently steep. Prices are 7% lower in the outskirts relative to the city center due to frictional illiquidity.

Furthermore, by comparing our modeled price gradients from the two scenarios with the German price data, we find that search frictions explain 19% of the empirical price gradient. In an extension of the model, we introduce a bargaining process which creates spreads between asking and sales prices analogous to our additional empirical measure. We show that the time on the market and this spread are interchangeable measures of liquidity in the model. Lastly, in an additional model experiment, we replicate the flattening of the liquidity gradient due to

[3]This is in line with the canonical monocentric city model (Alonso, 1964; Muth, 1969; Mills, 1967) in which housing prices depend on the cost of travel to the city center.

the shift to working from home induced by the COVID-19 pandemic. Overall, our results show how accounting for the interaction between location and search frictions significantly enhances our understanding of the cross-sectional variation in housing liquidity and prices.

Related literature. From an empirical perspective, we are the first to establish that not only housing prices, but also various housing liquidity measures decrease with distance to the city center. From a theoretical perspective, we are the first to quantify location-dependent effects of frictional illiquidity on housing prices as a function of spatial fundamentals.

Our paper adds to the growing literature on the spatial variation in housing liquidity. In Piazzesi, Schneider, and Stroebel (2020), spatial within-city liquidity differences are driven by the search behavior of buyer clienteles. We show how, given search behavior, location preferences also generate within-city liquidity differences. Jiang, Kotova, and Zhang (2024) and Vanhapelto (2022) focus on a more aggregate comparison and highlight differences in housing market liquidity across regions.

We also contribute to the literature on the spatial price gradient (see, for example, Gupta et al., 2022; Albouy, Ehrlich, and Shin, 2018) by being the first to document the spatial liquidity gradient. Moreover, as we show in our counterfactual analysis, taking into account the spatial liquidity gradient significantly improves our understanding of the spatial price gradient. In addition, we provide a more general equilibrium condition than those used in the literature. In our model, buyers have the same net utility across space in expectation, which contrasts with standard spatial equilibrium conditions where the realized net utility of buyers equalizes across space (see, for example, Duranton and Puga, 2015).

In our model, we endogenize the spatial distribution of search frictions and examine its connection to housing prices, thus contributing to the literature on asset pricing models that endogenize trading frictions (starting with Duffie, Gârleanu, and Pedersen, 2005). We show how demand-side preferences determine both liquidity and prices. In addition, by structurally estimating a spatial illiquidity discount for housing, we also contribute to the literature on the pricing of liquidity in asset markets, which has traditionally been focused on bond markets and stock markets (Amihud, Mendelson, and Pedersen, 2012). We quantify the spatial illiquidity discount by comparing the frictional equilibrium allocation of our model to a counterfactual efficient allocation in the spirit of Gavazza (2016).

Lastly, by integrating space into framework with trading frictions, we contribute to 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, Mabille, and Van Nieuwerburgh, 2023; Mabille, 2023; Favilukis and Van Nieuwerburgh, 2021).

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.

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 metropolitan statistical areas (MSAs).

2.1 Data for German cities

We combine administrative records on the universe of housing transactions in our 5 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.

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 various property characteristics.

We obtain data on apartment 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 ad ordering influenced by users. We observe the dates on which ads were posted and removed, addresses (if available), information on location such as ZIP Code or neighborhood, asking prices, and various 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, apartment sizes, and building year of properties. As we do not observe the addresses of all listings, we match only about one third of the transactions with corresponding listings. Our final dataset consists of more than 80 thousand observations. In 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.[4] 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 as well as ZIP-Code-level data on social mobility and 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 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. 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.[5] 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) yields nearly identical city centers as the ones we choose by hand. We calculate kilometer distances between city centers and locations of apartments 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,

[4]Redfin is a real estate brokerage company that obtains its data directly from local listing services, especially those based in the largest MSAs. 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 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.

[5]Hamburg: *Alsterhaus*, Munich: *Marienplatz*, Cologne: *Koelner Dom*, Frankfurt: *Konstablerwache*, Duesseldorf: *Marktplatz*.

for example, Gupta et al., 2022). We calculate kilometer distances between MSA centers and ZIP Code centroids located within the corresponding MSA boundaries. In a robustness analysis, we also create a job access index using data from Delventhal and Parkhomenko (2024) which we use to find alternative city centers, either one or multiple per city.

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, we request the typical travel time to the city center by car, defined analogously to the distance measures from the previous paragraph.

2.4 Measurement of liquidity

Our main measure of housing liquidity is the time on the market. 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 an apartment has been advertised if it sells on day T, 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 houses sold within a ZIP Code area in a calendar month. Table 1 presents summary statistics for the German and U.S. datasets. In Appendix C, we present summary statistics by city. The German market is generally less liquid than the U.S. market, with properties typically taking almost twice as long to sell.

Table 1: *Summary statistics for both datasets*

	Time on the market in weeks				Sales price in 1000 € or $				
Dataset	Mean	SD	P25	P75	Mean	SD	P25	P75	N
Germany	12.47	16.36	2.30	16.20	386	302	187	490	87502
U.S.	7.60	7.87	3.50	9.64	446	502	205	530	682641

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.

We also provide additional liquidity measures using the richer German dataset. First, we construct a measure of the spread between the asking price and the sales price, akin to the bid-ask spread in stock markets or bond markets. We call this measure the *asking price discount*. 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.

3 Empirical analysis

In this section, we document new stylized facts about the spatial variation in liquidity and prices in German and U.S. cities.

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 demographic differences. We estimate

$$y_I = \alpha \times \text{distance}_I + \beta \times X_I + f_{ct} + \varepsilon_I, \tag{1}$$

where for the German dataset, I indexes transactions, with every transaction I being assigned to a calendar quarter t and a city c, 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 time on the market or sales prices. The explanatory variable distance_I is the distance to the city center, measured in kilometers in the baseline specification and as the travel time to the city center (in minutes) in the alternative specification.

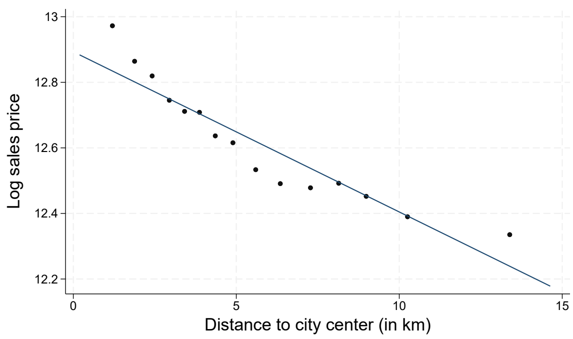
For regressions using the German dataset, the control vector X_I includes an extensive set of dwelling characteristics, such as size or building year, documented in Appendix A.1. For regressions using the U.S. dataset, X_{it} includes average dwelling size, average building year, median household income, the share of households with annual income above 150,000$, the homeownership rate and the share of Black households. In addition, we control for spatial differences in social mobility and neighborhood quality, measured by (i) the probability of reaching the top quintile of the 2014–2015 U.S. household income distribution for individuals born between 1978 and 1983 in a given ZIP Code area and (ii) the fraction of children born in the same period and area who were incarcerated by April 1, 2010. The observations of the U.S. control variables, except for the last two variables on social mobility and neighborhood quality, are at the yearly level. A yearly observation is assigned to all months within that year.

f_{ct} captures city-time fixed effects to account for common time trends in liquidity or prices within a city, and ε_I denotes the error term. To address spatial correlation in the error terms, we cluster standard errors at the borough (*Stadtbezirk*) level for regressions using the German dataset and at the ZIP-Code level for regressions using the U.S. dataset. Note that by considering within-city variation, we rule out bias due to confounding across-city variation in unobserved variables.

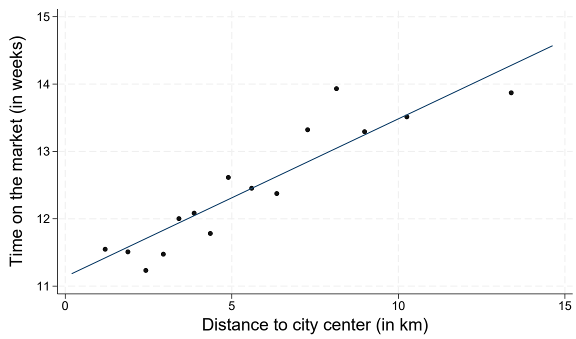
Results. In Figure 1, we present binned scatter plots based on Regression (1).[6] The left-hand panels display a clear negative relationship between sales prices and distance to the city center. This negative price gradient has been documented in the literature for cities in the United States (see, for example, Harris, 2024) and across the globe (see, for example, 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 and city sizes.[7]

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

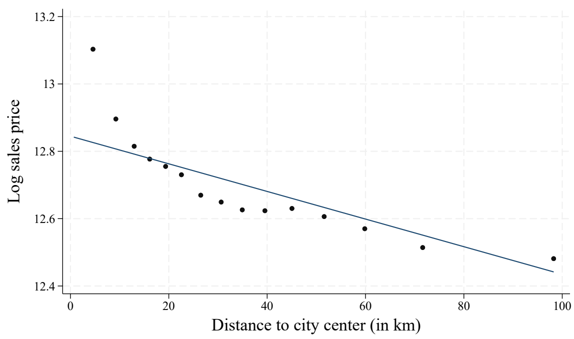
(a) *Germany – Sales price*



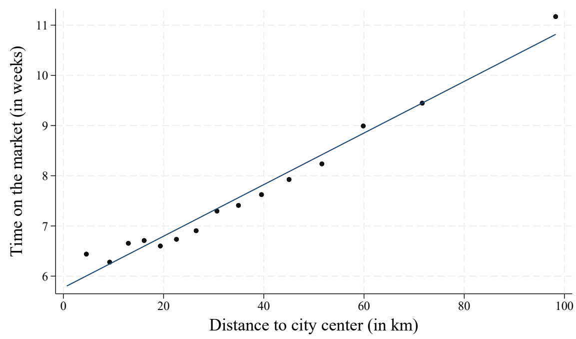
(b) *Germany – Time on the market*



(c) *U.S. – Sales price*



(d) *U.S. – Time on the market*



Notes: These binned scatter plots display the results of Regression (1) *with log sales price and time on the market as the outcome variables and 15 equally-sized distance bins. The regressions include time and location fixed effects and control for property characteristics. The binned scatter plots are produced following Cattaneo et al. (2024).*

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

[6]For geographical maps of spatial liquidity and price distributions in cities from our German sample, see Appendices B.2 and B.3.

[7]U.S. cities are typically larger and more sprawled than European cities (see, for example, Nechyba and Walsh, 2004).

Germany and the U.S. across model specifications, ranging from the most parsimonious model, which only includes time fixed effects, to the most comprehensive model, which features the full set of control variables. The coefficient on kilometer distance or travel time[8] is consistently significant at the 1% level for both German and U.S. cities across all specifications. 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.[9] The results remain robust when focusing solely on within-borough (*Stadtbezirk*) variation in German cities and when controlling for local median household income, neighborhood quality, and demographic characteristics in U.S. cities.

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

	(1) TOM	(2) TOM	(3) TOM	(4) TOM	(5) TOM	(6) TOM
Distance to center (in km)	0.31***	0.23***	0.17***			
	(0.05)	(0.03)	(0.05)			
Travel time to center (in min)				0.13***	0.09***	0.06***
				(0.02)	(0.01)	(0.02)
City × Year-quarter FE	✓	✓	✓	✓	✓	✓
Property characteristics		✓	✓		✓	✓
Borough FE			✓			✓
N	87497	87497	87497	86162	86162	86162
Adj. R^2	0.05	0.12	0.12	0.05	0.13	0.13
Mean(TOM)	12.47	12.47	12.47	12.26	12.26	12.26

Notes: This table displays the output of Regression (1) *on time on the market (TOM). 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. The list of property characteristics is available in 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 borough (Stadtbezirk) level.* $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

In terms of magnitude, properties in the outskirts take approximately 15% longer to sell compared to those in the city center after taking into account spatial variation in property characteristics, income, and demographics. The within-city spatial variation in housing liquidity

[8]Note that differences in average travel time speed between Germany and the U.S. lead to different relative magnitudes of the physical and travel time coefficients.

[9]In Appendix B.4, we document that the most relevant of these characteristics are still substantially less relevant determinants of housing liquidity than the distance to the city center.

is comparable to the seasonal variation (as studied in, for example, Ngai and Tenreyro, 2014) and the cyclical variation (as studied in, for example, Garriga and Hedlund, 2020), which we document in Appendix B.1. For Germany, this amounts to about three weeks, while for the United States, this amounts to about two weeks.[10]

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

	(1) TOM	(2) TOM	(3) TOM	(4) TOM	(5) TOM	(6) TOM
Distance to center (in km)	0.04***	0.03***	0.04***			
	(0.003)	(0.003)	(0.004)			
Travel time to center (in min)				0.04***	0.04***	0.05***
				(0.003)	(0.003)	(0.004)
Median income		-0.43***	-0.41***		-0.40***	-0.35***
		(0.049)	(0.050)		(0.047)	(0.050)
MSA × Year-month FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Property characteristics			✓			✓
Demographic controls			✓			✓
N	682641	682641	682641	682641	682641	682641
ZIP codes	4955	4955	4955	4955	4955	4955
Adj. R^2	0.29	0.29	0.30	0.29	0.29	0.31
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). 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 single-family houses for the 30 largest MSAs covering the period between 2012 and 2023. Standard errors (in parentheses) are clustered at the ZIP-Code level.* $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

3.2 Spatial variation in other liquidity measures

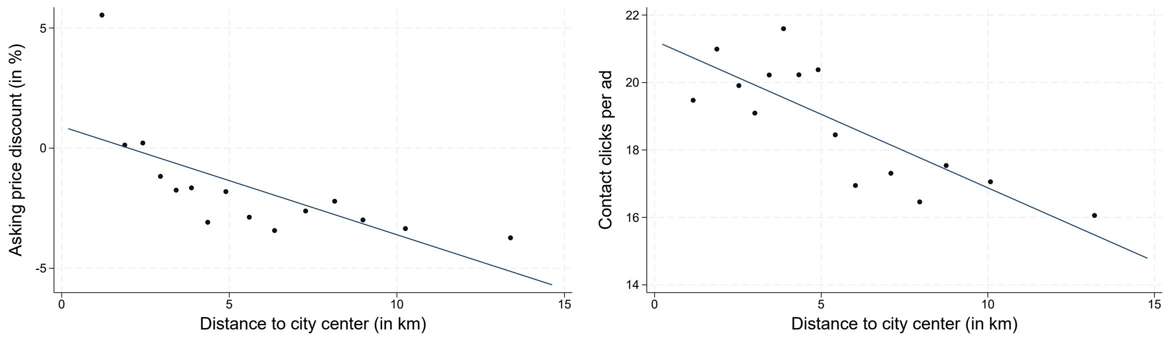
We now focus on the German data to demonstrate that other measures of housing liquidity also decrease with distance to the city center. Figure 2 presents binned scatter plots based on Regression (1) for the matched sample across all German cities. First, the spread between the asking price and the sales price becomes increasingly negative with distance to the city center. Second, market tightness, proxied by contact clicks per ad, decreases with distance to the city

[10]These results are based on a specification of Regression 1 in which "city center" is defined as all observations within a 4 km radius of the city center, while "outskirts" is defined as areas beyond 13 km for German cities and beyond 30 km for U.S. cities.

center. Both of these effects are statistically significant, as demonstrated in Appendices B.5 and B.6 with detailed regression results.

Figure 2: *Spatial gradients of alternative liquidity measures, Germany (2012- 2024)*

(a) *Asking price discount* **(b)** *Contact clicks per ad*



Notes: These binned scatter plots visualize the results of Regression (1) *with asking price discount and contact clicks per ad as the outcome variables and 15 equally-sized distance bins. The regressions include year-quarter and city fixed effects and control for property characteristics listed in Appendix A.1. The binned scatter plots are produced following Cattaneo et al. (2024).*

3.3 Robustness analysis

Results for individual cities. In the previous section, we presented results for pooled samples of German and U.S. cities. Given that cities vary in size and other characteristics, it is possible that our results are driven by a subsample of cities. As we show in Appendix D.1, this is not the case. We find negative liquidity and price gradients for all cities in the German dataset and for 90% of the cities in the U.S. dataset. We do not explicitly analyze heterogeneity in coefficients across cities, but as our model in the second part of the paper suggests, this heterogeneity should be driven by 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, 2023). 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 Appendix D.2. Our model is able to replicate this development, which we document in Appendix H.5. 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 Appendix D.3, we show that our results for German cities remain robust across apartment size categories and our results for the United States remain robust when considering different housing types (condominiums, multi-family homes, and townhouses).

Alternative city definitions. For U.S. cities, we test whether our results hold when using functional urban area (FUA) boundaries from Moreno-Monroy, Schiavina, and Veneri (2021) which define cities based on commuting flows, following the EU-OECD definition from Dijkstra, Poelman, and Veneri (2019). In Appendix D.4, we confirm our results for the FUAs that correspond to the MSAs from the main analysis. This robustness analysis is not possible for German cities, as we only have data available that refers to apartments transacted within the administrative city boundaries.

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.[11] 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 volumes of residential construction as alternative city centers. We obtain these locations via the Global Human Settlement Layers database by the European Commission Joint Research Centre. The results, documented in Appendix D.5., show practically unchanged spatial gradients.

Non-parametric estimation. Although our main results are highly significant and robust to different fixed effects and standard errors, 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. Hence, we can only produce these results for German cities.

First, we use augmented inverse probability weighting to estimate the average difference

[11] For this analysis, we are not using the data for Munich, as we do not have access to its local *Bodenrichtwerte* appraisals.

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.

Table 4: *Average differences between city center and outskirts, Germany*

Method	Difference in TOM	Difference in log prices	N
OLS	1.91*** (0.218)	-0.44*** (0.004)	35002
LASSO	2.02*** (0.342)	-0.46*** (0.006)	35002
Propensity score	1.83*** (0.426)	-0.50*** (0.012)	35002
Inverse probability	1.94*** (0.297)	-0.46*** (0.006)	35002

Notes: This table shows the estimated average difference between city center and outskirts for time on the market (TOM) and log sales prices for different non-parametric methods. The time on the market is measured in weeks. The different methods are described in more detail 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 ads that did not end up in a sale varies systematically across space. To check this, we run an algorithm to identify advertisements in the German data that did not end up in a transaction. Appendix D.6 shows that the percentage of ads that did not result in a sale increases with distance to the city center, as our structural model described in the second part of the paper would predict.

3.4 Discussion of external validity

Our empirical analysis shows that liquidity and prices decrease with distance to the city center in owner-occupied residential housing markets. In this section, we examine the extent to which these results can be generalized to other settings, considering alternative focal points beyond the city center, and to 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. Here, we test whether our empirical results hold when considering alternative focal points. Using data on commuting distances and 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 Appendix D.7, 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 residential 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, applying the same cleaning procedures as for the sales listings. 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 solely on within-ZIP-Code variation, which partially isolates confounding variation due to spatial differences in income and demographics.

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

	(1) TOM	(2) TOM	(3) TOM	(4) Net rent	(5) Net rent	(6) Net rent
Distance to center (in km)	0.17***	0.17***	0.21***	-0.02***	-0.03***	-0.02***
	(0.02)	(0.02)	(0.08)	(0.00)	(0.00)	(0.00)
City × Year-quarter FE	✓	✓	✓	✓	✓	✓
Property characteristics		✓	✓		✓	✓
ZIP Code FE			✓			✓
N	957249	957249	957249	957249	957249	957249
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 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 ZIP-Code (PLZ) level. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

4 Theoretical analysis

4.1 Structural framework

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 standard housing search model (Krainer, 2001) and introduce a notion of space following the canonical monocentric city model (Alonso, 1964; Muth, 1969; Mills, 1967). 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.

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, 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 $\tau(d)$ depends on the distance to the city center $d \in \mathscr{D} = [0, \bar{d}\,]$ of an agent's occupied housing unit, where $\partial\tau/\partial d > 0$. We abstract from other economically relevant factors that exogenously vary across space. 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 physically identical housing units.[12] Before deciding whether to purchase a housing unit, an agent draws an idiosyncratic valuation $\varepsilon \sim U\left[\tilde{\varepsilon}-1, \tilde{\varepsilon}\right]$ for this property, referred to as "dividend" in the following.[13] Having decided to purchase the 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 unit 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, which can be interpreted

[12] Due to limitations in data availability, we abstract from spatial differences in housing supply elasticity which could be a complementary mechanism to explain price differences across the city.

[13] The uniform distribution, used in the original Krainer (2001) model, allows us to derive simple analytical statements in Section 4.3. In our quantitative exercise, we estimate the bounds of this distribution using our transaction-level data. To estimate as few parameters as possible and avoid overfitting the model, we scale the uniform distribution to be of measure 1 and to be centered at $\tilde{\varepsilon}-0.5$ (both of which have no inherent meaning and are irrelevant for the model results) such that a single estimated parameter $\tilde{\varepsilon}$ contains all relevant information.

as a moving shock. With probability $1-\pi$, an agent is unmatched, puts their property up for sale, and searches for a new one. Agents are therefore sellers and buyers simultaneously.

Then, first, sellers post prices $p(d)$. Second, buyers randomly visit housing unit 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 in next period or does not agree on the price and continues to search. In Appendix F, we extend the search process with a bargaining process, 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 additivity of agents' value functions.[14] A seller chooses a posted price $p(d)$ to maximize their present value

$$\Pi(d) = \gamma(d)p(d) + \big(1-\gamma(d)\big)\beta\Pi(d). \tag{2}$$

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.

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

$$V(d,\varepsilon) = \beta\Big(\varepsilon - \tau(d) + \pi V(d,\varepsilon) + \big(1-\pi\big)\big(\Pi(d)+W\big)\Big), \tag{3}$$

where W denotes the value of search.[15] 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

[14] Note that an 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. Note that while searching, agents do not own necessarily own properties. For the case that that do not, we make the standard assumption that they live in rental units of absentee landlords which are located in the city center, such that they do not incur travel costs. Renting out unmatched properties is not possible.

[15] The linear specification for buyer values is standard in housing search models, analogously to linear specifications of worker values in labor market search models (see, for example, Rogerson, Shimer, and Wright, 2005).

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

where a buyer either accepts a posted price and receives a net discounted value of $\beta(V(d,\varepsilon) - p(d))$, or continues to search and receives $\beta^2 W$.[16]

4.2 Equilibrium

Seller's optimization. The first-order condition for profit maximization is

$$p(d) = \beta \Pi(d) - \frac{\gamma(d)}{\partial \gamma / \partial p(d)|_d}, \tag{5}$$

where the derivative $\partial \gamma / \partial p(d)|_d$ is evaluated at the equilibrium sales price given a distance to the city center d. We show in Appendix E that this condition provides a maximum.

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 $\varepsilon^*(d)$:

$$V(d, \varepsilon^*(d)) - p(d) = \beta W. \tag{6}$$

The solution of this equation for a given distance to the city center characterizes the corresponding reservation dividend. Note that the optimality condition (6) defines a cutoff rule for a stochastic event. Individual buyers can draw higher reservation values than $\varepsilon^*(d)$, in which case they accept the equilbrium price $p(d)$ and obtain a net utility above βW. The average idiosyncratic dividend at distance to the city center d is $(\varepsilon^*(d) + \tilde{\varepsilon})/2$. Note that precisely because equilibrium expected net buyer utility is constant, where "expected" refers to locations and dividend draws, required dividend draws have to offset travel costs.

Notion of spatial equilibrium. The buyers' optimality condition (6) 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. Morover, 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.

[16]To calculate the expectation over distances, we assume that it is formed using the whole set of distances $\mathscr{D}$, even if only a subset of distances is covered by the market in a given period. In other words, we assume 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 disregarding dynamics and focusing on a stationary equilibrium. With a large number of properties, this holds approximately true in every period.

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:

$$\gamma(d) = Prob(\varepsilon > \varepsilon^*(d)) = \tilde{\varepsilon} - \varepsilon^*(d). \tag{7}$$

Thus, for the derivative in the seller's optimality condition (5) we have that

$$\frac{\partial \gamma}{\partial p(d)|_d} = -\frac{\partial \varepsilon^*}{\partial p(d)|_d}. \tag{8}$$

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

$$V(d,\varepsilon) = \frac{\beta}{1-\pi\beta}\Big(\varepsilon - \tau(d) + \big(1-\pi\big)\big(\Pi(d) + W\big)\Big). \tag{9}$$

Using the indifference condition (6), we isolate the reservation dividend:

$$\varepsilon^*(d) = \frac{1-\pi\beta}{\beta}p(d) + \tau(d) - \big(1-\pi\big)\Pi(d) + \big(\pi - \pi\beta\big)W. \tag{10}$$

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

$$\frac{\partial \gamma}{\partial p(d)|_d} = -\frac{1-\pi\beta}{\beta}, \tag{11}$$

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. In Appendix G, we provide proofs of the equilibrium's existence and uniqueness.

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), (5), (6), (7) for all distances to the city center $d \in \mathscr{D}$, given parameters $\{\beta, \pi, \tilde{\varepsilon}\}$ 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 with distance to the city center. The underlying economic factor behind these results is the cost of travel to the city center. In Appendix F, 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.

4.3.1 Reservation dividends across space

First, as an auxiliary result, we show that buyer reservation dividends $\varepsilon^*(d)$ increase with distance to the city center. Buyers need higher draws of the dividend to make a purchase the farther a housing unit they visit is away from the city center, which reflects a higher travel cost $\tau(d)$. To show that $\partial\varepsilon^*/\partial d > 0$, we reformulate $p(d)$ and $\Pi(d)$ in terms of $\varepsilon^*(d)$. Combining the expression for the expected profit (2) and the seller optimality condition (5), we obtain

$$p(d) = -\frac{(1-\beta)\gamma(d) + \beta\big(\gamma(d)\big)^2}{(1-\beta)\big(\partial\gamma(d)/\partial p(d)|_d\big)}. \tag{12}$$

With equilibrium relations (7) and (11) between probabilities of sale and reservation dividends,

$$p(d) = \frac{\beta}{1-\pi\beta}\big(\tilde{\varepsilon} - \varepsilon^*(d)\big) + \frac{\beta^2}{(1-\beta)(1-\pi\beta)}\big(\tilde{\varepsilon} - \varepsilon^*(d)\big)^2 \tag{13}$$

and, via the seller optimality condition (5),

$$\Pi(d) = \frac{\beta}{(1-\pi\beta)(1-\beta)}\big(\tilde{\varepsilon} - \varepsilon^*(d)\big)^2. \tag{14}$$

Plugging these results into the expression for the reservation dividend (10) and differentiating with respect to the distance to the city center, we get:

$$\frac{\partial\varepsilon^*}{\partial d}\underbrace{\left(2 - 2\frac{\pi\beta}{1-\pi\beta}\big(\tilde{\varepsilon} - \varepsilon^*(d)\big)\right)}_{>0} = \frac{\partial\tau}{\partial d} > 0, \tag{15}$$

and hence, $\partial\varepsilon^*/\partial d > 0$.[17]

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

$$\mathbb{E}\big[TOM(d)\big] = \frac{1}{\gamma(d)} = \frac{1}{\tilde{\varepsilon} - \varepsilon^*(d)}, \tag{16}$$

[17] This should hold for any well-behaved dividend distribution and value function. The uniform dividend distribution and linear value function allow us to obtain straightforward analytical expressions.

again using the equilibrium relation (7) between probabilities of sale and reservation dividends. Therefore,

$$\frac{\partial \mathbb{E}\left[TOM\right]}{\partial d} = \frac{\partial \varepsilon^*}{\partial d} \underbrace{\left(\tilde{\varepsilon} - \varepsilon^*(d)\right)^{-2}}_{>0} > 0. \tag{17}$$

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.

Prices. Via auxiliary expression (13),

$$\frac{\partial p}{\partial d} = -\frac{\partial \varepsilon^*}{\partial d} \underbrace{\left(\frac{\beta}{1-\pi\beta} + \frac{2\beta^2\left(\tilde{\varepsilon} - \varepsilon^*(d)\right)}{\left(1-\beta\right)\left(1-\pi\beta\right)} \right)}_{>0} < 0. \tag{18}$$

Intuition. Sellers expect to sell housing units with a higher probability inside 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. They set distortedly high prices in the tighter local market near the city center relative to the outskirts. 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. In Appendix H.1, 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 result empirically.

Further remarks. First, our choice of building on the standard monocentric city model results from considerations of simplicity. 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.

Next, note that in practice, the cost of travel to the city center may sometimes not increase with distance to the city center 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 the city center.

Moreover, 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, within-city housing market search tends to be integrated via "broad searchers" (Piazzesi, Schneider, and Stroebel, 2020) who search across many locations, hence we are not particularly concerned about this aspect. Moreover, 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 household heterogeneity in the model.

Furthermore, we assume that buyers randomly visit housing units and observe their idiosyncratic dividends during these visits. If buyers, irrespective of clientele, are more inclined to visit properties in the city center, this might also influence the time on the market. The result on "broad searchers" partly counteracts also this concern. Moreover, in Carrillo (2012), searchers observe part of their dividends before visiting properties, which, however, is estimated to play a quantitatively negligible role for housing purchase decisions. Even if we take into account that online services are more developed today, this aspect cannot be quantitatively relevant in our framework in light of this result.

Lastly, by assuming risk neutrality of agents, we can separate buyer and seller decisions. If we were to introduce risk aversion, agents' idiosyncratic housing valuations could matter for their motivation to sell. Idiosyncratically higher-valued properties located in the outskirts could then be kept longer on the market. For this argument to matter, our mechanism has to be present in the first place, unless there is another economic fundamental that can convincingly generate the same spatial variation in reservation dividends quantitatively.

4.4 Model solution method

We evaluate the quantitative performance of our model by estimating it using our German transaction-level data. 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. We discretize the set of distances to the city center: $\mathscr{D}^{\Delta} = \{d_1^{\Delta}, \dots, d_z^{\Delta}\}$. The equilibrium condition (4), which describes the value of search as an expectation over distances to the city center and idiosyncratic dividends, and the equilibrium conditions (2), (5), (6), and (7), which have to hold for all distances to the city center $d^{\Delta} \in \mathscr{D}^{\Delta}$, constitute the relevant system of equations. Solving the model is not trivial due to its high dimensionality,

Algorithm 1 Solution algorithm: stationary spatial search equilibrium

```
Initialize an iteration tolerance η.
Initialize a guess for the value of search W.
Initialize an auxiliary W̃ with |W − W̃| > η.
while |W − W̃| > η do
    Set the guess W equal to W̃.
    for d^Δ ∈ 𝒟^Δ do
        Solve equations (2), (5), (6), and (7), given W.
    end for
    Update W̃.
end while
```

Solution algorithm. Algorithm 1 solves for the unique stationary spatial equilibrium. It starts from a guess for the value of search W and updates the guess via

$$\widetilde{W} = \frac{1}{z} \sum_{d^\Delta \in \mathscr{D}^\Delta} \gamma(d^\Delta)\Big(V\big(d^\Delta, \tfrac{\varepsilon^*(d^\Delta)+\tilde{\varepsilon}}{2}\big) - p(d^\Delta)\Big) + \big(1-\gamma(d^\Delta)\big)\Big(\beta W\Big), \tag{19}$$

where a buyer purchases a housing unit at d^Δ with probability of sale $\gamma(d^\Delta)$ and continues to search with probability $1-\gamma(d^\Delta)$, following the alternative definition of the value of search in Krainer and LeRoy (2002). We obtain our first guess for the value of search by solving the model without space and using the value of search from that solution. The algorithm stops when the guess W is equal to the resulting $\widetilde{W}$, with tolerance η.

4.5 Calibration and estimation of model parameters

To obtain the discretized distance distribution $\mathscr{D}^\Delta$, we group the distances to the city center from the pooled German dataset net of year-quarter fixed effects, city fixed effects, and apartment characteristics controls into $z = 15$ bins with equal numbers of observations. We obtain the corresponding travel time estimates as explained in Section 2.3 and convert them into travel cost estimates, assuming that $\tau(d^\Delta) = \mu \times \tilde{\tau}(d^\Delta)$, where $\tilde{\tau}(d^\Delta)$ is the travel time to the city center by car in minutes. This conversion of travel time into travel cost follows established approaches (see, for example, Ahlfeldt et al., 2015). The scaling parameter μ measures the cost in model units of traveling 2 minutes by car, as agents commute back and forth between their property and the city center every day.

Calibrated parameters. We set $\beta = \sqrt[365]{0.95} \approx 0.9999$ such that the annual discount factor is 0.95. The housing match persistence is given by $\pi = 1 - \frac{1}{30\times 120} \approx 0.9997$, as the average holding period in the data is 120 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.

Table 6: *Estimated parameters, all German cities pooled*

Parameter	Description	Value	Bootstr. 95% CI	Target statistic	Target (model) value
μ	Travel time scaling	0.0051	$[0.0050, 0.0052]$	Avg. car oper. cost	14.17 (14.17) €
$\tilde{\varepsilon}$	Dividend dist. bound	0.56	$[0.55, 0.57]$	Avg. time on mkt.	12.47 (12.46) wk

Estimated parameters. We estimate μ and $\tilde{\varepsilon}$ with the method of simulated moments, matching 2 moments with 2 parameters as displayed in Table 6. With the travel cost scaling parameter μ, we target an average daily car operating cost in Germany of 14.17€ (Andor et al., 2020).[18] We convert between model units and euros via the average apartment sales price, consistent with both the travel cost and the average apartment sales price being expressed in units of the background consumption good. We follow the canonical monocentric city model and calibrate the travel cost as a physical cost of travel, but also provide an alternative calibration in Appendix H.3 in which we think of the travel cost as an opportunity cost due to lost time by traveling to the city center. With the idiosyncratic dividend distribution bound parameter $\tilde{\varepsilon}$, we target the average time on the market. A higher value of $\tilde{\varepsilon}$ mechanically increases idiosyncratic dividend draws and thus shortens the average time on the market. 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 (as done in, for example, Gavazza, 2016).

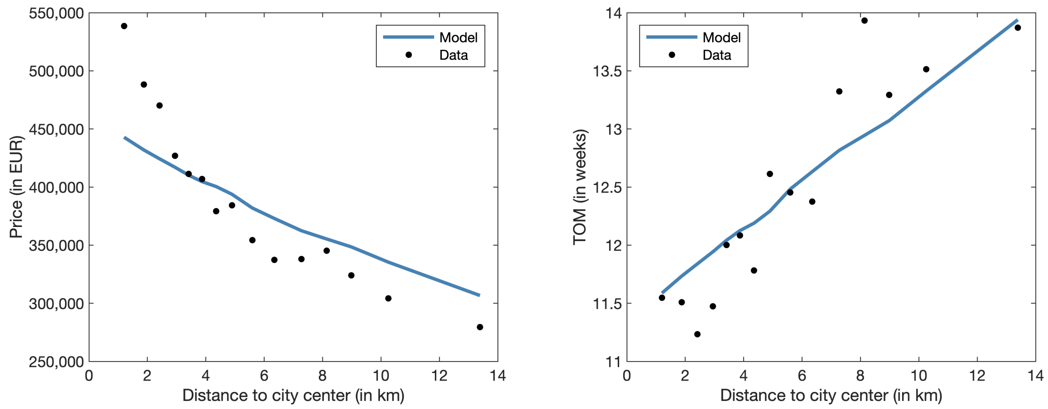
4.6 Model results

Even though we do not target the spatial gradients of time on the market and sales prices, our results exhibit spatial variation that closely aligns with the data, as displayed in Figure 3. The model requires the spatial distribution of the car travel time to the city center as the only spatial input and, using additional city-wide average values, produces accurate spatial liquidity

[18] See supplementary information, Table 3. Most 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.

and price distributions.[19] 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. Appendix H.2 provides the spatial distributions of additional variables and Appendix H.4 provides results for individual German cities. Our results hold for every city.

Figure 3: *Model results: spatial distributions of liquidity and prices, all German cities pooled*



Notes: "TOM" refers to the (expected) time on the market. The data points are calculated using Regression (1) *with year-quarter fixed effects, city fixed effects, and property characteristics controls.*

5 Housing liquidity and spatial asset pricing

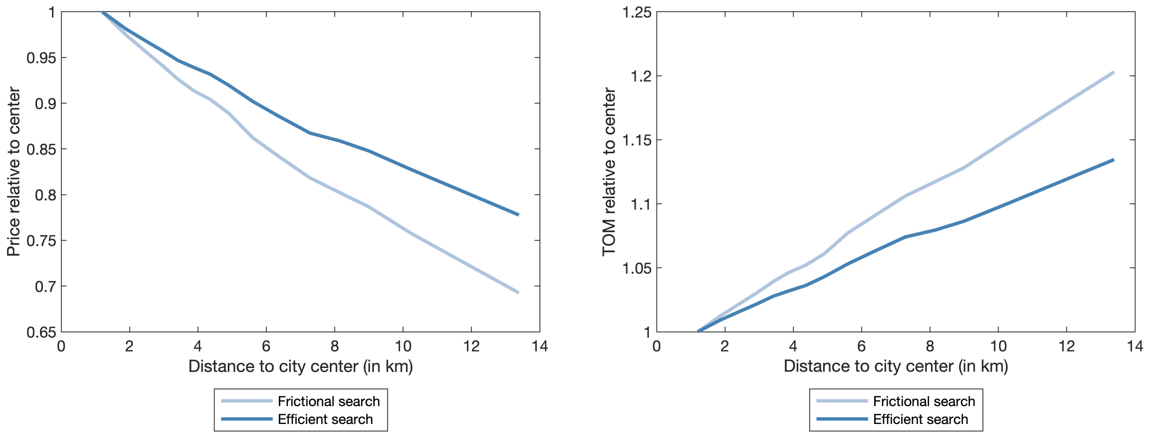
In this section, we quantify how spatial liquidity differences matter for housing prices. Both the fundamental value and the liquidity component of housing prices depend on location, which makes it challenging to disentangle these two variables empirically.[20] Following Krainer and LeRoy (2002), we calculate a counterfactual efficient allocation in our model. We measure how much prices change across space if we remove frictional illiquidity by comparing the frictional baseline allocation to the counterfactual efficient allocation. The efficient allocation is characterized by welfare-maximizing reservation dividends which translate into welfare-maximizing liquidity and prices. Intuitively, an efficient allocation in our model could be best thought of as an allocation in a market with a very large seller side. Buyers in such a market

[19]Nevertheless, the model fails to capture the steep price gradient near the city center. 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, a particularly inelastic housing supply (Baum-Snow and Han, 2024) or a particularly high concentration of residential amenities (Garcia-López and Viladecans-Marsal, 2024) near city centers. Without further analysis, which goes beyond the scope of this paper, we cannot shed light on this issue.

[20]Approaching such issues with other asset classes is more straightforward empirically if the assets' cash flow and maturity are directly observable. In housing markets, the cash flow is a latent variable.

have many outside options, which eliminates the price-setting power of sellers.[21]

Figure 4: *Spatial distributions under frictional and efficient search, all German cities pooled*



Notes: These figures show the equilibrium expected time on the market (TOM) and sales price by distance to the city center sfrom our main model ("frictional search") and the the efficient allocation ("efficient search").

Efficient allocation. Assuming a steady state over all model periods, we choose reservation dividends $\varepsilon^{\text{eff}}(d^{\Delta})$ to maximize welfare

$$\mathbb{W} = \sum_{t=0}^{\infty} \beta^t \left(\frac{1}{z} \sum_{d^{\Delta} \in \mathscr{D}^{\Delta}} \left(m(d^{\Delta}) \left(E_{\varepsilon} \left[\bar{\varepsilon}(d^{\Delta}) \right] - \bar{\tau}(d^{\Delta}) \right) \right) \right), \tag{20}$$

where $m(d^{\Delta})$ denotes the probability of being matched and bars denote averages at given distances to the city center. Agents at distance d^{Δ} have an average dividend of $(\varepsilon^{\text{eff}}(d^{\Delta}) + \tilde{\varepsilon})/2$. All agents at distance d^{Δ} pay the travel cost $\tau(d^{\Delta})$. As there are no further constraints, we can equivalently maximize

$$\widetilde{\mathbb{W}}(d^{\Delta}) = m(d^{\Delta}) \left(\frac{\varepsilon^{\text{eff}}(d^{\Delta}) + \tilde{\varepsilon}}{2} - \tau(d^{\Delta}) \right) \tag{21}$$

for every distance $d^{\Delta} \in \mathscr{D}^{\Delta}$. Agents transition from being unmatched to being matched with probability $\tilde{\varepsilon} - \varepsilon^{\text{eff}}(d^{\Delta})$ and keep a housing unit with probability π. The steady-state probability of being matched is therefore $m(d^{\Delta}) = \pi m(d^{\Delta}) + \pi(\tilde{\varepsilon} - \varepsilon^{\text{eff}}(d^{\Delta}))(1 - m(d^{\Delta}))$, and hence,

$$m(d^{\Delta}) = \frac{\pi\left(\tilde{\varepsilon} - \varepsilon^{\text{eff}}(d^{\Delta})\right)}{1 - \pi + \pi\left(\tilde{\varepsilon} - \varepsilon^{\text{eff}}(d^{\Delta})\right)}. \tag{22}$$

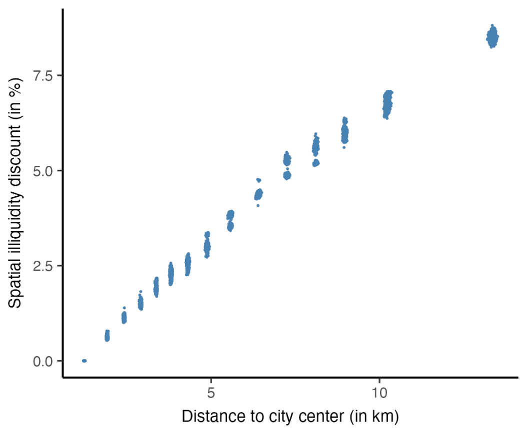
We then calculate the efficient reservation dividend for a given d^{Δ} numerically via

[21] Note that even in the efficient allocation, illliquidity still exists, that is, there is an optimal level of illiquidity larger than zero. This is comparable to the concept of a natural unemployment rate.

$$\underset{\varepsilon^{\text{eff}}(d^{\Delta})}{\text{argmax}} \left(\frac{\pi(\tilde{\varepsilon} - \varepsilon^{\text{eff}}(d^{\Delta}))}{1 - \pi + \pi(\tilde{\varepsilon} - \varepsilon^{\text{eff}}(d^{\Delta}))} \right) \left(\frac{\varepsilon^{\text{eff}}(d^{\Delta}) + \tilde{\varepsilon}}{2} - \tau(d^{\Delta}) \right). \tag{23}$$

In Figure 4, we plot the expected sales prices and time on the market by distance to the city center for the frictional and the efficient allocation, focusing on spatial differences by normalizing with respect to the values at d_1^{Δ}.[22] Search decreases relatively more in the outskirts than in the city center, which leads to a flattened liquidity gradient. We quantify how this flattening transmits to the spatial price gradient, which flattens as well.

Figure 5: *Spatial illiquidity discount, all German cities pooled*



Notes: This figure shows the price discount due to inefficient illiquidity relative to the city center as defined in (24). *The dots display illiquidity discount estimates from the 1,000 bootstrapped replication draws.*

Spatial illiquidity discount. We calculate a price discount due to frictional illiquidity at a distance to the city center d^{Δ} by comparing relative prices $p^{\text{eff}}(d^{\Delta})/p^{\text{eff}}(d_1^{\Delta})$ from the efficient allocation to relative prices $p(d^{\Delta})/p(d_1^{\Delta})$ from the frictional allocation:

$$\Psi(d^{\Delta}) = \frac{p^{\text{eff}}(d^{\Delta})}{p^{\text{eff}}(d_1^{\Delta})} - \frac{p(d^{\Delta})}{p(d_1^{\Delta})}, \tag{24}$$

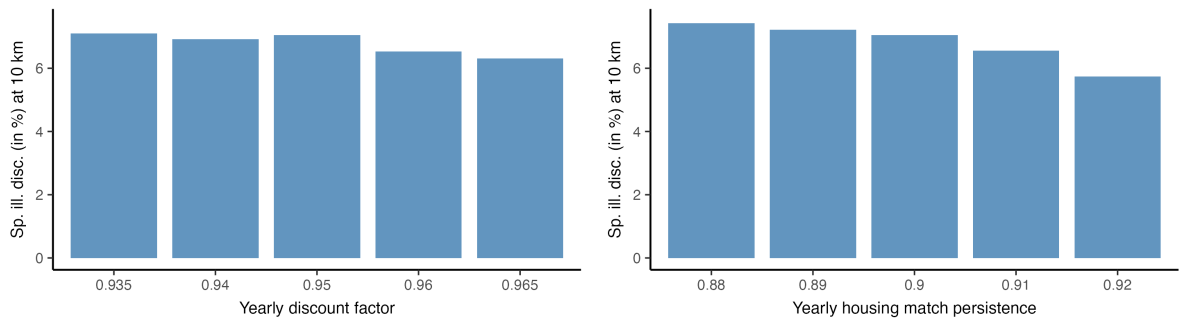
where $\Psi(d_1^{\Delta}) = 0$ by definition. The illiquidity discount measures the difference between the two spatial price curves in Figure 4(b) by distance to the city center. Figure 5 displays our illiquidity discount measurements. The model implies an illiquidity discount of around 7% in the outskirts. This price distortion due to frictional illiquidity falls into a range of related measures. First, it resembles the magnitude of real estate commission fees at 5% to 6% in the United States (Han and Strange, 2015). Such fees are market outcomes which, similarly to our illiquidity discount, quantify valuations for easing matching frictions between real estate

[22]For a discussion of level effects in a non-spatial setting, see Krainer and LeRoy (2002).

buyers and sellers. In Germany, real estate commission fees are similar to those in the United States, however, less plausibly market outcomes (Stoll, 2023). Second, Piazzesi, Schneider, and Stroebel (2020) quantifies price discounts due to search frictions in the housing market as ranging up to 6%.

Figure 6: *Illiquidity discount at 10km distance to the city center, all German cities pooled*

(a) *By* β^{yr}*, with* $\pi^{yr} = 0.90$ **(b)** *By* π^{yr}*, with* $\beta^{yr} = 0.95$



Notes: These figures show the illiquidity discount, as defined in (24)*, at 10km distance to the city center for different yearly discount factors and housing match persistence probabilities.*

Moreover, using the spatial price curves with and without search frictions and the spatial price data, we compare to what extent search frictions explain the empirical spatial price gradient. We regress log sales prices from the two model versions and the data on the distance to the city center, as we do in the empirical part of the paper. Then, we calculate the difference in the regression coefficients with and without search frictions and set this difference in relation to the data coefficient. The resulting fraction quantifies the share of the empirical price gradient explained by frictional illiquidity according to our model. We find that frictional illiquidity explains 19% of the empirical spatial price gradient.

Sensitivity analysis. In the calibration, we set the yearly discount factor to 0.95, a standard choice. 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 sample in January 1990. We also check if our illiquidity discount estimates change if we use different housing match persistence probabilities. In Figure 6, we plot the illiquidity discount at 10km distance to the city center, 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. Our illiquidity discount estimates are robust to changes in both parameters.

6 Conclusion

In this paper, we demonstrate that housing market liquidity decreases with distance to the city center, using novel spatial datasets for Germany and the United States. We rationalize our findings by building a spatial search model of a housing market in a monocentric city. We show analytically that as a result of an increasing cost of travel to the city center, liquidity and sales prices decrease with distance to the city center. Using our model, we structurally estimate a substantial price discount due to frictional illiquidity in the outskirts relative to the city center. We conclude that within-city spatial housing liquidity differences play an important role in the pricing of housing assets. Our findings can also inform research on other asset classes, especially if they have characteristics that are valued idiosyncratically. In particular, with a recent "great rotation" (Koijen, Shah, and Van Nieuwerburgh, 2025) towards infrequently traded and heterogeneous private and real assets, our results can help future research in determining systematic variation in the pricing of such assets.

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Appendix

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 of the German and the U.S. data.

A.1 Germany

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 7, we provide further information on the matched observations by city.

Table 7: *Summary statistics: matched dataset*

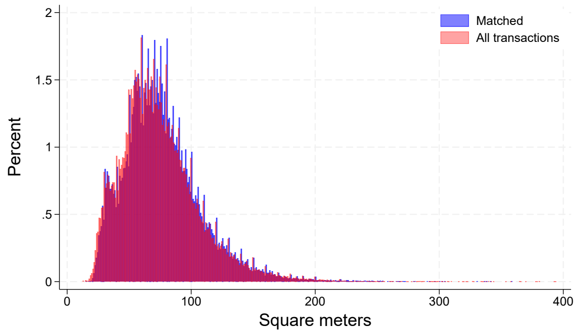
City	# Transactions	# Ads	# Matched	Avg. sales price (€)	Avg. asking price (€)
Hamburg	78845	70692	20303	392181	389802
Munich	56301	110207	26424	495367	493899
Cologne	35599	43034	14957	241388	257731
Frankfurt	34984	36015	15428	384459	446754
Duesseldorf	35578	32121	10390	305374	318527

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

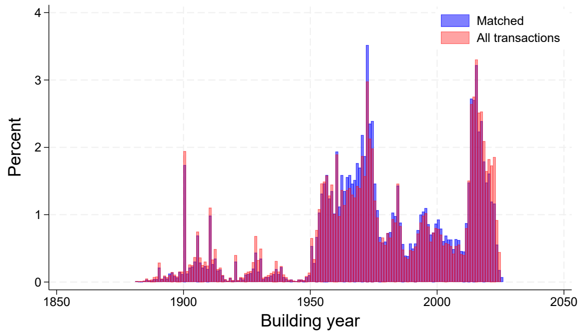
We show that the matched sample is not biased along several important characteristics of the transacted properties in Figure 7. We plot the distributions from the matched sample and the universe of transactions, with all cities pooled together, of the variables living area, building year, distance to 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 7: *Matched sample and universe of transactions, all German cities pooled*

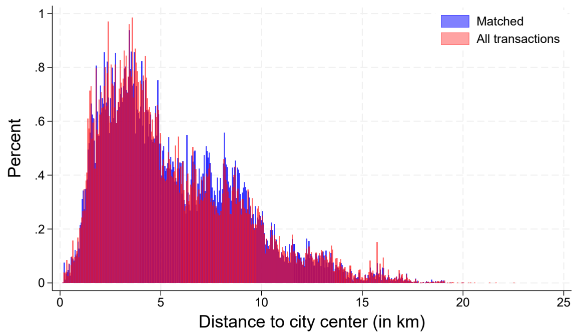
(a) *Living area in square meters*



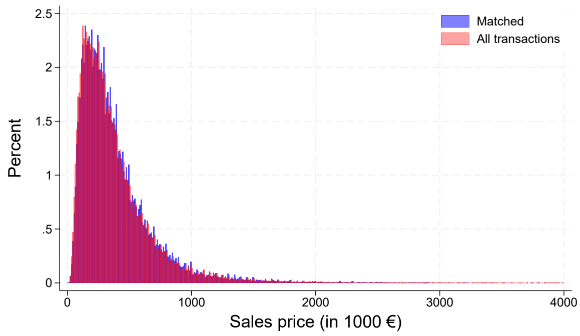
(b) *Building year*



(c) *Distance to the city center*



(d) *Sales price*



Notes: These figures 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.

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 and 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, 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 pump 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 United States

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 Zillow, 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 8, 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.

Table 8: *Time on the market and distance to the city center in the U.S. (2016–2023)*

	(1) Redfin	(2) Realtor.com	(3) Redfin	(4) Realtor.com
Distance to center (in km)	0.01***	0.02***	0.03***	0.04***
	(0.002)	(0.001)	(0.003)	(0.002)
Median income			-0.09	-0.39***
			(0.067)	(0.043)
MSA × Year-Month FE	✓	✓	✓	✓
Property characteristics			✓	✓
N	290703	290703	290703	290703
ZIP Codes	3727	3727	3727	3727
Adj. R^2	0.50	0.42	0.56	0.48
Mean(TOM)	6.04	6.96	6.04	6.96

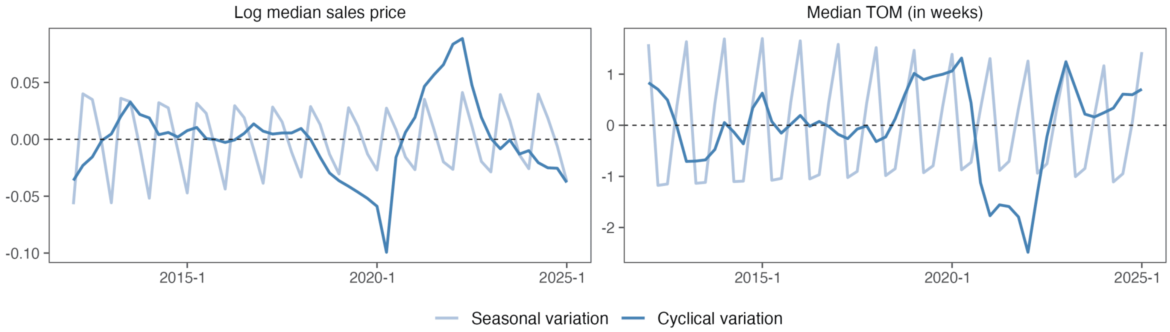
Notes: This table shows results for regressions of time on the market on the distance to the city center as specified in Regression (1). *Time on the market is measured in weeks. Standard errors (in parentheses) are clustered at the ZIP-Code level. Median income and property characteristics are control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

For the control variables on social mobility and neighborhood quality, we employ data from the Chetty et al. (2025) "Opportunity Atlas" (link). We calculate ZIP-Code-level averages of the Census-tract-level probability of reaching the top quintile of the 2014-2015 U.S. household income distribution when born between 1978 and 1983 (variable: *kfr_top20_pooled_pooled_mean*) and the fraction of children born between 1978 and 1983 who were incarcerated on April 1st, 2010 (variable: *jail_pooled_pooled_mean*). The primary data sources are the 2000 and 2010 Censuses, federal income tax returns from 1989, 1994, 1995, and 1998-2015, and the 2005–2015 American Community Surveys.

B Additional empirical results

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

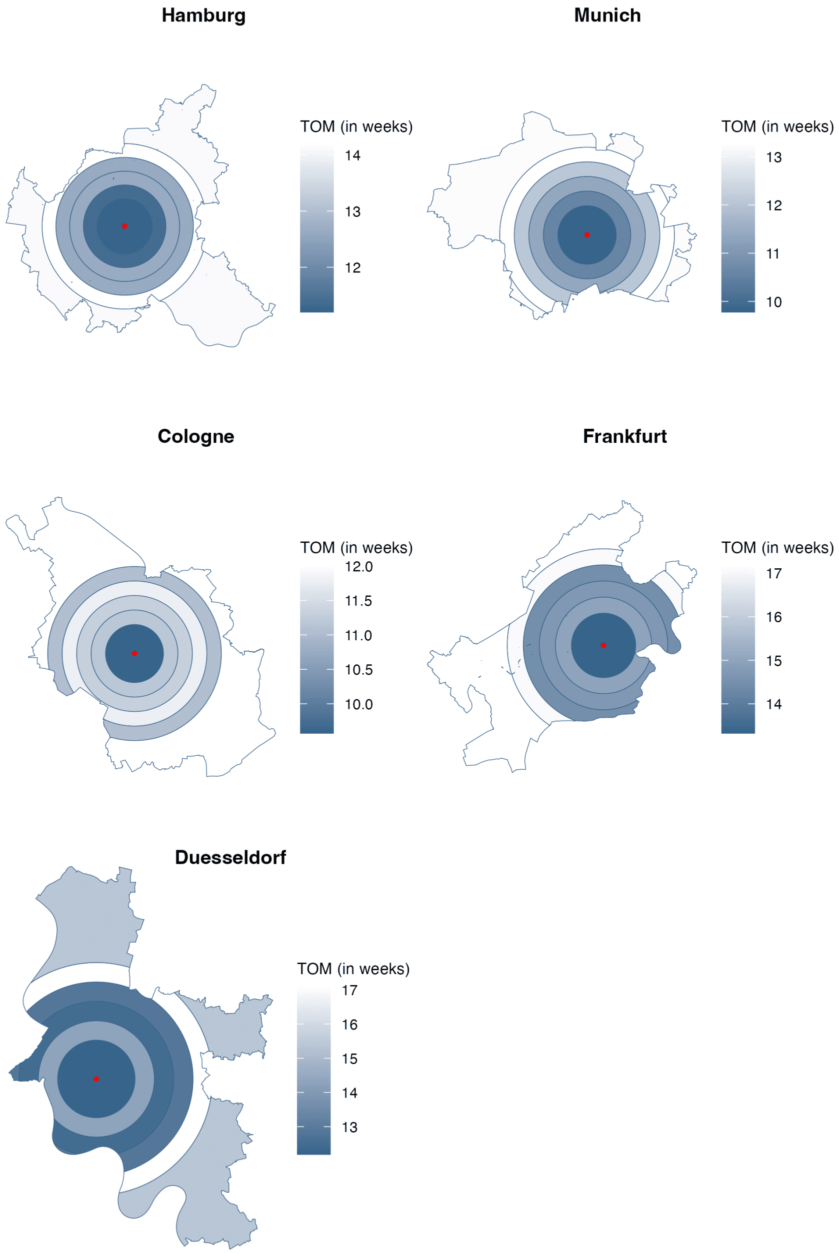
Figure 8: *Variation of U.S. housing market variables around long-run trends*



Notes: These figures display Redfin time series of U.S.-level quarterly median sales prices and time on the market (TOM), decomposed via a Hodrick–Prescott filter with standard penalty parameter $\lambda = 1600$*. The cyclical variation is obtained by isolating the cyclical component of a seasonally adjusted (provided by Redfin via X-13ARIMA-SEATS) time series 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.*

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

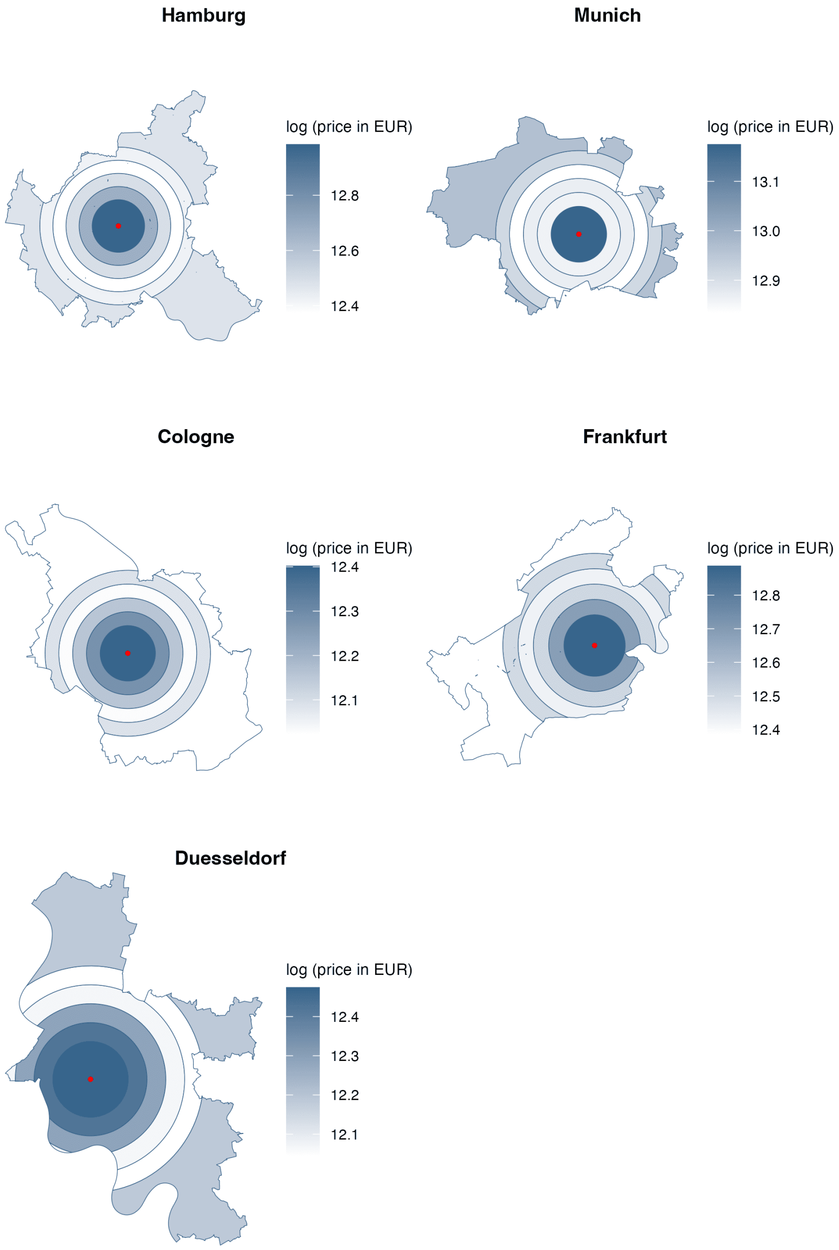
Figure 9: *Time on the market across space (German cities, 2012- 2024)*



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

B.3 Spatial distribution of sales prices in German cities

Figure 10: *Sales prices across space (2012- 2024)*



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

Table 9: *Log sales prices and distance to the city center, Germany (2012–2024)*

	(1) Price	(2) Price	(3) Price	(4) Price	(5) Price	(6) Price
Distance to center (in km)	-0.04***	-0.05***	-0.04***			
	(0.01)	(0.00)	(0.01)			
Travel time to center (in min)				-0.02***	-0.02***	-0.02***
				(0.00)	(0.00)	(0.00)
City × Year-quarter FE	✓	✓	✓	✓	✓	✓
Property characteristics		✓	✓		✓	✓
Borough FE			✓			✓
N	87499	87499	87499	86165	86165	86165
Adj. R^2	0.28	0.85	0.86	0.28	0.84	0.86
Mean(log(price))	12.62	12.62	12.62	12.61	12.61	12.61

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 borough ("Stadtbezirk") level. The property characteristics are control variables. See Appendix A.1 for a full list of these characteristics.* $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

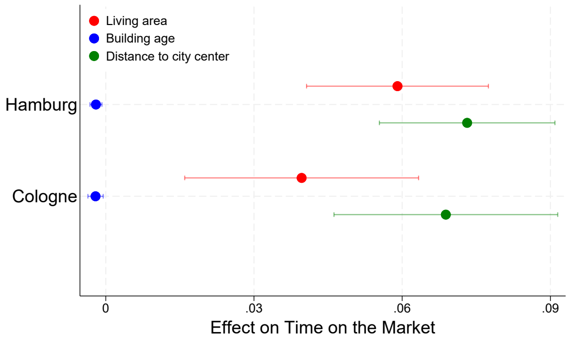
B.4 Additional determinants of housing liquidity in German cities

In our main analysis, we focus on how liquidity affects prices via location. Nevertheless, houses differ in other dimensions which might also impact their liquidity. In particular, the size and age of properties might be strong determinants of liquidity, as typically the market is also segmented along these dimensions. Although our focus in this paper is not on these additional dimensions, we also provide evidence that location has a stronger effect on liquidity than these other factors. In Figure 11, we plot the standardized coefficients for size as measured by living area in square meters, age of the building, and distance to the city center. The coefficients are derived from Regression 1. All coefficients are positive and significant, suggesting that these dimensions have a significant impact on liquidity as measured by time on the market. As is also evident from the graph, the distance to the city center has the largest impact on liquidity.

B.5 Asking price discount in German cities

In Figure 12, 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

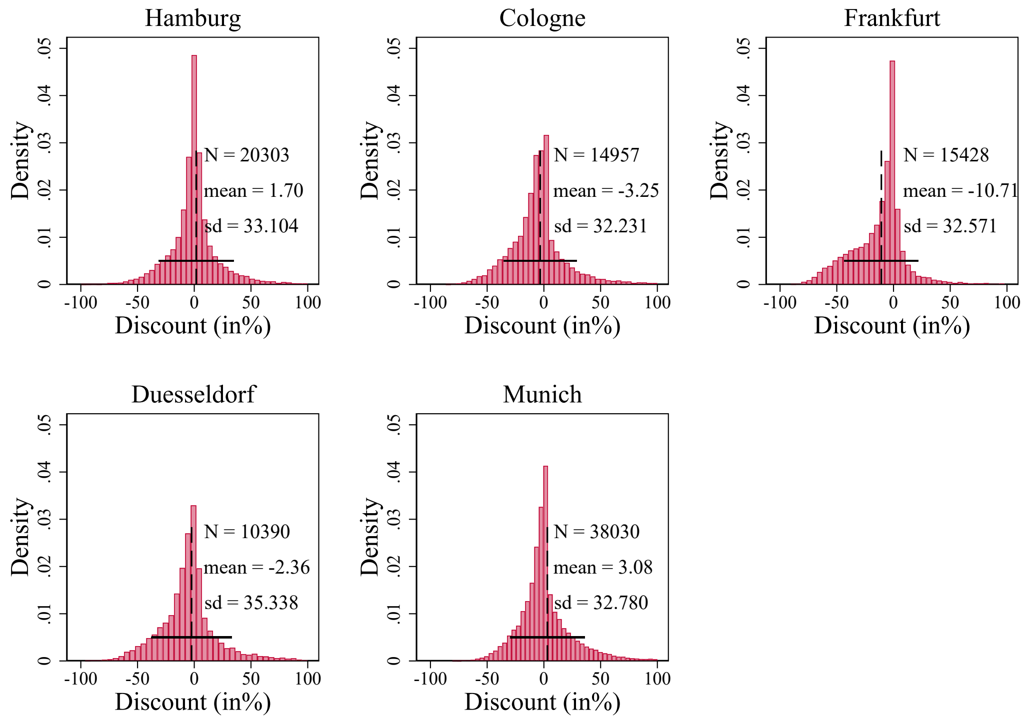
Figure 11: *Determinants of time on the market, (2012- 2024)*



Notes: This figure shows the OLS regression coefficients by city, as well as its respective 99% confidence intervals. See Appendix A.1 for a full list of these characteristics. Distance to the city center is measured as the kilometer distance. The coefficients are standardized across the displayed determinants using the respective sample standard deviation.

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 10, we present results for regressions of 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 12: *Histograms of asking price discount (2012- 2024)*



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

Table 10: *Asking price discount and distance to the city center, Germany (2012 – 2024)*

	(1) APD	(2) APD	(3) APD	(4) APD	(5) APD	(6) APD
Distance to center (in km)	-0.43***	-0.45***	-0.37**			
	(0.09)	(0.09)	(0.14)			
Travel time to center (in min)				-0.24***	-0.25***	-0.24***
				(0.04)	(0.04)	(0.07)
City × Year-quarter FE	✓	✓	✓	✓	✓	✓
Property characteristics		✓	✓		✓	✓
Borough FE			✓			✓
N	87497	87497	87497	86162	86162	86162
Adj. R^2	0.04	0.06	0.06	0.04	0.06	0.06
Mean(APD)	-1.65	-1.65	-1.65	-1.67	-1.67	-1.67

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 borough (Stadtbezirk) level. The property characteristics are control variables. See Appendix A.1 for a full list of these characteristics.* $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

B.6 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 *immobilienscout24.de*. 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 11. 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.

Table 11: *Contact clicks and distance to the city center, Germany (2012 – 2024)*

	(1) Clicks	(2) Clicks
Distance to center (in km)	-0.49***	-0.46***
	(0.10)	(0.10)
City × Year-quarter FE	✓	✓
Property characteristics		✓
N	192512	192512
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 to contact clicks per ad as defined in the text. Standard errors (in parentheses) are clustered at the ZIP Code (PLZ) level. The property characteristics are control variables. The data are from immobilienscout24.de. See text for a full list of these characteristics.* $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

C Summary statistics

C.1 German cities

Table 12: *Summary statistics: time on the market and prices in German cities (2012–2024)*

	Time on the market in weeks				Sales price in 1000€				
City	Mean	SD	P25	p75	Mean	SD	P25	P75	N
Hamburg	12.38	15.01	2.40	16.50	392	335	191	475	20303
Munich	11.59	15.29	2.00	15.30	495	324	278	615	26424
Cologne	11.01	14.88	1.90	14.00	241	159	130	308	14957
Frankfurt	14.80	18.01	2.50	19.90	384	262	200	495	15428
Duesseldorf	13.50	20.15	2.30	16.50	305	273	132	379	10390

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.

C.2 U.S. cities

Table 13: *Summary statistics: time on the market and prices in U.S. cities (2012–2023)*

	Time on the market in weeks				Sales price in 1000$					
MSA	Mean	SD	P25	p75	Mean	SD	P25	P75	Nr. ZIP Codes	N
Atlanta-Sandy Springs-Alpharetta, GA	6.70	5.06	3.72	8.59	274	188	150	348	190	26992
Austin-Round Rock-Georgetown, TX	5.93	4.75	2.93	7.71	413	263	238	502	73	10509
Baltimore-Columbia-Towson, MD	7.36	5.99	3.63	9.48	405	179	281	496	121	17477
Boston-Cambridge-Newton, MA-NH	7.49	6.46	3.21	11.20	577	345	359	673	247	24295
Charlotte-Concord-Gastonia, NC-SC	10.87	7.42	6.43	13.29	256	175	148	315	105	13508
Chicago-Naperville-Elgin, IL-IN-WI	8.30	5.27	5.12	10.25	288	215	159	348	342	25102
Cincinnati, OH-KY-IN	10.87	9.51	6.71	13.71	188	105	118	236	123	17681
Dallas-Fort Worth-Arlington, TX	5.83	3.75	3.42	7.08	285	193	166	351	245	18665
Denver-Aurora-Lakewood, CO	4.08	6.15	1.21	4.71	455	198	315	561	108	15480
Detroit-Warren-Dearborn, MI	5.04	4.24	2.47	6.49	210	121	121	275	201	16703
Houston-The Woodlands-Sugar Land, TX	6.17	4.42	3.14	8.00	266	201	156	302	204	29363
Las Vegas-Henderson-Paradise, NV	9.44	7.12	6.00	11.21	296	145	200	366	62	8858
Los Angeles-Long Beach-Anaheim, CA	5.97	4.78	3.96	7.09	933	735	512	1061	337	30265
Miami-Fort Lauderdale-Pompano Beach, FL	9.93	5.29	7.01	11.26	533	601	274	565	174	7709
Minneapolis-St. Paul-Bloomington, MN-WI	6.77	7.31	3.08	8.33	307	146	210	374	196	27638
New York-Newark-Jersey City, NY-NJ-PA	11.12	9.04	5.59	14.21	627	650	367	695	739	23776
Orlando-Kissimmee-Sanford, FL	7.81	7.95	3.15	10.57	279	142	179	349	85	11945
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	7.96	5.92	4.06	10.26	320	165	208	390	270	11026
Phoenix-Mesa-Chandler, AZ	7.01	3.55	4.87	8.13	338	241	200	409	142	20050
Pittsburgh, PA	13.62	7.18	8.57	16.57	176	111	102	221	149	21432
Portland-Vancouver-Hillsboro, OR-WA	4.95	5.23	1.59	6.32	426	184	294	522	110	15046
Riverside-San Bernardino-Ontario, CA	7.20	4.65	4.48	8.73	375	203	234	478	125	17533
Sacramento-Roseville-Folsom, CA	4.21	4.07	1.86	5.14	424	208	288	519	85	12198
San Antonio-New Braunfels, TX	8.11	5.58	4.79	9.86	238	125	151	304	93	13386
San Diego-Chula Vista-Carlsbad, CA	4.54	4.41	2.14	5.36	791	531	480	900	84	12239
San Francisco-Oakland-Berkeley, CA	2.77	1.56	1.81	3.16	1218	680	757	1523	130	8610
Seattle-Tacoma-Bellevue, WA	3.27	3.26	1.11	4.30	599	390	356	730	140	11693
St. Louis, MO-IL	11.85	27.78	5.29	12.86	182	137	94	230	213	25043
Tampa-St. Petersburg-Clearwater, FL	7.57	5.83	3.14	10.64	281	191	164	345	126	18144
Washington-Arlington-Alexandria, DC-VA-MD-WV	6.22	5.10	3.13	7.79	541	293	342	661	248	23122

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

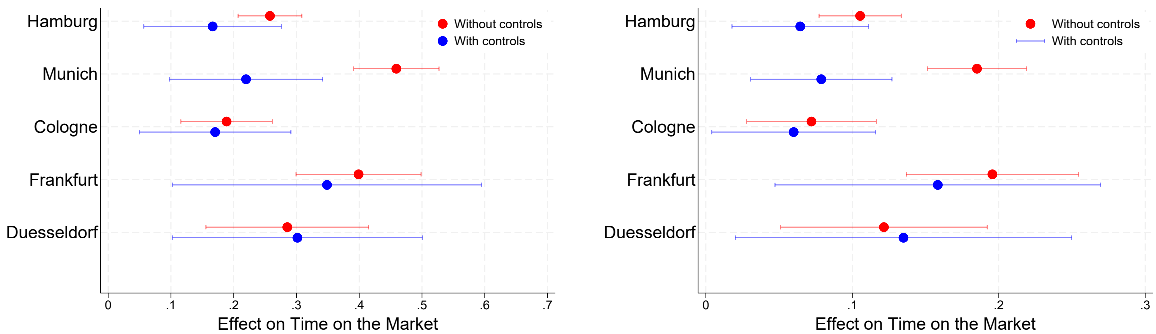
D Robustness analysis

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 13. 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 13: *Time on the market and distance to city center by city (2012–2024)*

(a) *Distance to city center (in km)* **(b)** *Travel time to city center (in min)*



Notes: These figures 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 borough (Stadtbezirk) level. All regressions include year-quarter fixed effects. See Appendix A.1 for a full list of property characteristics controls.*

United States. We 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 the exception of New York-Newark-Jersey City, NY-NJ-PA and San Francisco-Oakland-Berkeley, CA. For New York-Newark-Jersey City, NY-NJ-PA, the estimate is indistinguishable from zero, which stems from complex spatial patterns in the large housing market of New York City MSA. 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.

Table 14: *TOM and price gradient by MSA (Redfin data), 2012-2023*

MSA	TOM gradient	Price gradient	P-value TOM	P-value Price	N
Atlanta-Sandy Springs-Alpharetta, GA	0.066	-0.004	0.00	0.00	27278
Austin-Round Rock-Georgetown, TX	0.099	-0.014	0.00	0.00	10509
Baltimore-Columbia-Towson, MD	0.110	0.000	0.00	0.87	17413
Boston-Cambridge-Newton, MA-NH	0.054	-0.006	0.00	0.00	35411
Charlotte-Concord-Gastonia, NC-SC	0.103	-0.008	0.00	0.00	13508
Chicago-Naperville-Elgin, IL-IN-WI	0.028	-0.010	0.00	0.00	49128
Cincinnati, OH-KY-IN	0.056	0.001	0.01	0.70	17681
Dallas-Fort Worth-Arlington, TX	0.039	-0.005	0.00	0.00	34692
Denver-Aurora-Lakewood, CO	0.172	-0.002	0.00	0.24	15480
Detroit-Warren-Dearborn, MI	0.024	0.002	0.00	0.07	28146
Houston-The Woodlands-Sugar Land, TX	0.049	-0.004	0.00	0.00	29363
Las Vegas-Henderson-Paradise, NV	0.051	-0.002	0.00	0.07	8858
Los Angeles-Long Beach-Anaheim, CA	0.034	-0.002	0.00	0.23	48366
Miami-Fort Lauderdale-Pompano Beach, FL	0.015	-0.002	0.02	0.05	23083
Minneapolis-St. Paul-Bloomington, MN-WI	0.112	-0.005	0.00	0.00	28208
New York-Newark-Jersey City, NY-NJ-PA	-0.003	-0.002	0.72	0.04	86424
Orlando-Kissimmee-Sanford, FL	0.092	-0.006	0.02	0.01	12230
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	0.054	-0.000	0.00	0.98	38705
Phoenix-Mesa-Chandler, AZ	0.052	-0.004	0.00	0.01	20330
Pittsburgh, PA	0.075	-0.003	0.00	0.05	21432
Portland-Vancouver-Hillsboro, OR-WA	0.130	-0.007	0.00	0.00	15614
Riverside-San Bernardino-Ontario, CA	0.033	-0.005	0.00	0.00	17818
Sacramento-Roseville-Folsom, CA	0.065	0.003	0.00	0.08	12198
San Antonio-New Braunfels, TX	0.084	0.005	0.00	0.00	13386
San Diego-Chula Vista-Carlsbad, CA	0.084	0.001	0.00	0.45	12095
San Francisco-Oakland-Berkeley, CA	-0.019	-0.005	0.01	0.05	18716
Seattle-Tacoma-Bellevue, WA	0.058	-0.009	0.00	0.00	20158
St. Louis, MO-IL	0.266	-0.005	0.00	0.00	25043
Tampa-St. Petersburg-Clearwater, FL	0.113	-0.003	0.00	0.02	18144
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.059	-0.005	0.00	0.00	35537

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. Information on the data sources are in the text. N stands for the number of ZIP-Code-year-month observations.

D.2 COVID

Table 15: *TOM gradients before and after COVID, Germany (2012–2024)*

	(1) Full sample	(2) Pre-2020	(3) Post-2020
Distance to center (in km)	0.23***	0.24***	0.15***
	(0.03)	(0.04)	(0.03)
City × Year-quarter FE	✓	✓	✓
Property characteristics	✓	✓	✓
N	87497	61848	25645
R^2	0.12	0.14	0.30
Mean(TOM)	12.47	12.42	12.56

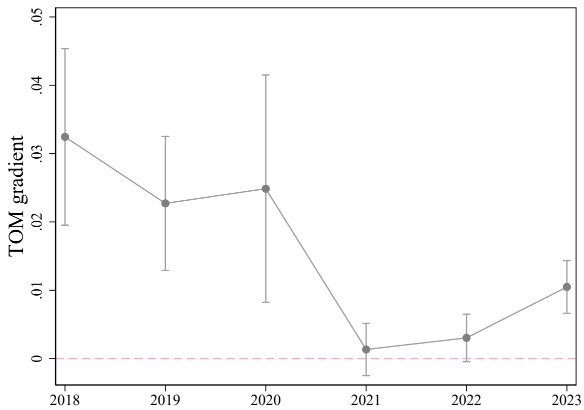
Notes: This table displays the output of Regression (1) *on time on the market (TOM). The list of property characteristics is available in Appendix A.1. Regressions are based on the matched sample for all cities covering the period between 2012 and 2024. Standard errors (in parentheses) are clustered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

Table 16: *TOM gradients before and after COVID, U.S. (2012–2023)*

	(1) Full sample	(2) Pre-2020	(3) Post-2020
Distance to center (in km)	0.04***	0.06***	0.01***
	(0.004)	(0.004)	(0.003)
Median income	-0.46***	-0.53***	-0.82***
	(0.054)	(0.076)	(0.054)
MSA × Year-month FE	✓	✓	✓
State FE	✓	✓	✓
Property characteristics	✓	✓	✓
Demographic controls	✓	✓	✓
N	754955	494468	260487
Zip-codes	5467	5457	5460
Adj. R^2	0.28	0.27	0.20
Mean(TOM)	7.63	8.87	5.28

Notes: This table displays the output of Regression (1) *on time on the market (TOM). 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 ZIP-Code level.* $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

Figure 14: *Variation over time of the TOM gradient, U.S. (2018–2023)*



Notes: This figure displays outputs of Regression (1) *on time on the market (TOM) by year. Regressions are based on data for the 30 largest MSAs. 95% Confidence bands are constructed using standard errors clustered at the ZIP-Code level.*

D.3 Different housing types

Table 17: *Time on the market and distance to city center, U.S.: all housing types (2012–2023)*

	(1) TOM	(2) TOM	(3) TOM	(4) TOM	(5) TOM	(6) TOM
Distance to center (in km)	0.02***	0.02***	0.03***			
	(0.002)	(0.002)	(0.003)			
Travel time to center (in min)				0.02***	0.02***	0.04***
				(0.003)	(0.003)	(0.004)
Median income		-0.53***	-0.44***		-0.53***	-0.40***
		(0.053)	(0.052)		(0.052)	(0.051)
MSA × Year-month FE	✓	✓	✓	✓	✓	✓
Property type FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Property characteristics			✓			✓
Demographic controls			✓			✓
N	1342681	1342681	1342681	1342681	1342681	1342681
ZIP Codes	5128	5128	5128	5128	5128	5128
Adj. R^2	0.26	0.26	0.27	0.26	0.26	0.27
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). 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 ZIP-Code level.* $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

Table 18: *Time on the market and distance to the city center by property type, U.S. (2012–2023)*

	(1) Single-family	(2) Condos	(3) Multi-family	(4) Townhouse
Distance to center (in km)	0.04***	0.02***	0.04***	0.03***
	(0.004)	(0.005)	(0.009)	(0.004)
Median income	-0.41***	-0.01	-0.80***	0.02
	(0.050)	(0.152)	(0.295)	(0.141)
MSA × Year-month FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Property characteristics	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
N	682641	321867	93061	244968
ZIP Codes	4955	2428	918	1840
Adj. R^2	0.30	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). 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 ZIP-Code level.* $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

Table 19: *Log sales prices and distance to the city center by property type, U.S. (2012–2023)*

	(1) Single-family	(2) Condos	(3) Multi-family	(4) Townhouse
Distance to center (in km)	-0.004***	-0.002***	-0.005***	-0.003***
	(0.000)	(0.001)	(0.001)	(0.001)
Median income	0.085***	0.176***	0.190***	0.236***
	(0.006)	(0.015)	(0.022)	(0.020)
MSA × Year-month FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Property characteristics	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
N	682641	321867	93061	244968
ZIP Codes	4955	2428	918	1840
Adj. R^2	0.78	0.71	0.84	0.75
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 ZIP-Code level.* $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

D.4 Alternative city definitions

Table 20: *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)	0.015***	-0.003***		
	(0.003)	(0.000)		
Distance to FUA center (in km)			0.013***	-0.005***
			(0.002)	(0.000)
Median income	0.156**	0.156***	0.155**	0.146***
	(0.061)	(0.008)	(0.062)	(0.008)
FUA × Year-month FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Property characteristics	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
N	656524	656524	656524	656524
ZIP Codes	4746	4746	4746	4746
Adj. R^2	0.44	0.79	0.44	0.80
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 (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 ZIP-Code level.* $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

D.5 Alternative city centers

Table 21: *Price and liquidity gradients using alternative city centers, Germany (2012–2024)*

	(1) TOM	(2) TOM	(3) TOM	(4) Price	(5) Price	(6) Price
Distance to center (in km)	0.28***	0.23***	0.15**	-0.05***	-0.05***	-0.04***
	(0.06)	(0.04)	(0.06)	(0.01)	(0.01)	(0.01)
City × Year-quarter FE	✓	✓	✓	✓	✓	✓
Property characteristics		✓	✓		✓	✓
Borough FE			✓			✓
N	61073	61073	61073	61073	61073	61073
Adj. R^2	0.05	0.12	0.12	0.21	0.81	0.82
Mean dep. variable	12.85	12.85	12.85	12.48	12.48	12.48

Notes: This table displays the output of Regression (1) *on time on the market (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 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 borough (Stadtbezirk) level.* $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

D.6 Properties that do not get sold

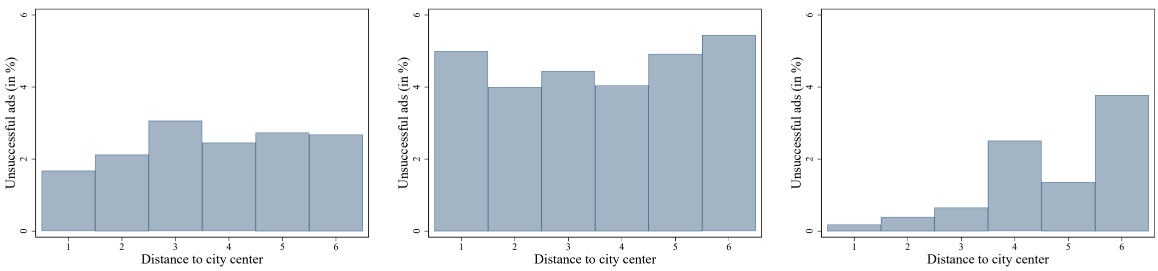
We identify listed properties that do not get sold via three steps. First, we match all ads with transactions that occurred within the same neighborhood (*Stadtteil*). Each ad is then associated with a set of potential transactions in the neighborhood. Out of these ads, we identify those as "unsuccessful" 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 do 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 15. 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 15: *Unsuccessful ads and distance to the city center, Germany (2012–2024)*

(a) *Munich* **(b)** *Hamburg* **(c)** *Cologne*



Notes: These figures 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:

$$h(TOM_{it}) = h_0(TOM) \times \exp\left[\gamma \times \text{distance}_i + \delta \times X_i + f_t + g_c + \varepsilon_{it}\right], \tag{25}$$

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 to that point in time and the distance to the city center, the property characteristics X_i, time fixed effects f_t, and city fixed effects g_c. We estimate the hazard rate using various error term distributions and present the results in Table 22. 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", that is, not ending up in a sale, in the outskirts than in the city center.

Table 22: *Expected time on the market and distance to city center, Germany (2012–2024)*

	Exponential	Weibull	Cox
main			
Distance to center (in km)	1.013***	1.012***	1.014***
	(0.0032)	(0.0037)	(0.0037)
City × Year FEs	✓	✓	✓
Property characteristics	✓	✓	✓
N	56279	56279	56279

Notes: This table displays the output of Regression (25) *for three different duration models of time on the market. The first row displays the estimated hazard ratio of predicted distance to city center. The regressions are based on data for apartments in Hamburg, Cologne and Munich. Standard errors are in parentheses.* $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

D.7 Focal ZIP Codes

Table 23: *Time on the market and distance to job centers, U.S. (2012–2023)*

	(1) TOM	(2) TOM	(3) TOM	(4) TOM
Distance to largest job center (in km)	0.02***	0.02***		
	(0.002)	(0.002)		
Distance to nearest job center (in km)			0.02***	0.02***
			(0.003)	(0.002)
Median income		0.11*		-0.15**
		(0.065)		(0.058)
MSA × Year-month FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Property characteristics		✓		✓
Demographic controls		✓		✓
N	595808	595808	595808	595808
ZIP codes	4312	4312	4312	4312
Adj. R^2	0.39	0.42	0.39	0.43
Mean(TOM)	7.27	7.27	7.27	7.27

Notes: This table displays the output of Regression (1) *on time on the market (in weeks) using the job access index instead of distance to the city center. 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 ZIP-Code level.* $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

E Maximum in the seller's optimization problem

The first-order condition of the seller's profit maximization problem is

$$\frac{\partial \Pi}{\partial p(d)|_d} = \gamma(d) + p(d)\frac{\partial \gamma}{\partial p(d)|_d} - \beta \Pi(d)\frac{\partial \gamma}{\partial p(d)|_d} = 0. \tag{26}$$

Hence, the second-order condition for a maximum is

$$\frac{\partial^2 \Pi}{\partial p^2(d)|_d} = 2\frac{\partial \gamma}{\partial p(d)|_d} + \frac{\partial^2 \gamma}{\partial p^2(d)|_d}\big(p(d) - \beta \Pi(d)\big) < 0. \tag{27}$$

Using (11), we know that

$$\frac{\partial \gamma}{\partial p(d)|_d} = -\frac{1-\pi\beta}{\beta} < 0. \tag{28}$$

Therefore,

$$\frac{\partial^2 \gamma}{\partial p^2(d)|_d} = 0, \tag{29}$$

and

$$\frac{\partial^2 \Pi}{\partial p^2(d)|_d} = -2\frac{1-\pi\beta}{\beta} < 0, \tag{30}$$

which provides the required maximum.

F 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 expectd 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 given by

$$\begin{aligned} \Pi(d) = \theta\Big(\gamma_n(d)p(d) + \big(1-\gamma_n(d)\big)\beta\Pi(d)\Big) \\ + \big(1-\theta\big)\Big(\gamma_c(d)\max\big[r(d),\beta\Pi(d)\big] + \big(1-\gamma_c(d)\big)\beta\Pi(d)\Big). \end{aligned} \tag{31}$$

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

$$W = E_{d,\varepsilon}\big[\theta V_n(d,\varepsilon) + \big(1-\theta\big)V_c(d,\varepsilon)\big]. \tag{32}$$

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

$$V_n(d,\varepsilon) = \max\left[V(d,\varepsilon) - p(d), \beta W\right]. \tag{33}$$

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

$$V_c(d,\varepsilon) = \max\left[\delta(d)\big(V(d,\varepsilon) - o(d)\big) + \big(1-\delta(d)\big)\big(\beta W\big), \beta W\right], \tag{34}$$

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.

F.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 (31) then simplifies to

$$\Pi(d) = \theta\gamma_n(d)p(d) + \big(1-\theta\gamma_n(d)\big)r(d). \tag{35}$$

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

$$p(d) = r(d) - \frac{\gamma_n(d)}{\partial\gamma_n/\partial p(d)|_d}, \tag{36}$$

and plugging the condition $r(d) = \beta\Pi(d)$ into (35) yields

$$r(d) = \frac{\beta\theta\gamma_n(d)p(d)}{1-\beta\big(1-\theta\gamma_n(d)\big)}. \tag{37}$$

The pair of the optimal asking price and reservation value for a given distance to the city center solves equations (36) and (37) simultaneously.

Buyer's optimization. Via the buyer value function in the no-counteroffer scenario (33), we define a reservation dividend $\varepsilon_n^*(d)$ such that a buyer is indifferent indifferent between buying a housing unit and continuing to search:

$$V(d,\varepsilon_n^*(d)) - p(d) = \beta W. \tag{38}$$

Analogously, via the buyer value function in the counteroffer scenario (34), we define a reservation dividend $\varepsilon_c^*(d)$ such that

$$V(d,\varepsilon_c^*(d)) - r(d) = \beta W. \tag{39}$$

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,

$$\gamma_n(d) = \tilde{\varepsilon} - \varepsilon_n^*(d), \tag{40}$$

and in the counteroffer scenario,

$$\gamma_c(d) = \tilde{\varepsilon} - \varepsilon_c^*(d). \tag{41}$$

Thus, for the derivative in the seller optimality condition (36) we have that

$$\frac{\partial \gamma_n}{\partial p(d)|_d} = -\frac{\partial \varepsilon_n^*}{\partial p(d)|_d}. \tag{42}$$

By proceeding as in the main text, we get

$$\varepsilon_n^*(d) = \frac{1-\pi\beta}{\beta} p(d) + \tau(d) - \big(1-\pi\big)\Pi(d) + \big(\pi - \pi\beta\big)W \tag{43}$$

and

$$\frac{\partial \gamma_n}{\partial p(d)|_d} = -\frac{1-\pi\beta}{\beta}. \tag{44}$$

Analogous relations hold for the counteroffer scenario.

F.2 Analytical results in the extended model

Again, we start with auxiliary derivations. First, Lemma 1 enables us to simplify expressions that contain reservation dividends and probabilites of sale.

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

Proof. Using the buyer indifference condition (39) and the linear expression of the buyer value function (9), we have that

$$\varepsilon_c^*(d) = \frac{1-\pi\beta}{\beta} r(d) + \tau(d) - \big(1-\pi\big)\big(\Pi(d) + W\big) + \big(1-\pi\beta\big)W \tag{45}$$

$$= \varepsilon_n^*(d) - \gamma_n(d), \tag{46}$$

where the second line follows from the seller optimality condition (36), the linear expression of the reservation value (43), and the value of the derivative $\partial\gamma_n/\partial p(d)|_d$ (44) . Therefore, we also have that $\varepsilon_c^*(d) = 2\varepsilon_n^*(d) - \tilde{\varepsilon}$, as well as $\gamma_c(d) = 2\gamma_n(d)$, via the equilibrium relations between reservation dividends and probabilities of sale (40) and (41). □

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 (43) that

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

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 (36) and (37) and get

$$p(d) = -\frac{\big(1-\beta\big)\gamma_n(d) + \beta\theta\gamma_n^2(d)}{\big(1-\beta\big)\big(\partial\gamma_n/\partial p(d)|_d\big)}. \tag{47}$$

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 (40) and (44), we have that

$$p(d) = \frac{\beta}{1-\pi\beta}\big(\tilde{\varepsilon} - \varepsilon_n^*(d)\big) + \frac{\beta^2\theta}{\big(1-\beta\big)\big(1-\pi\beta\big)}\big(\tilde{\varepsilon} - \varepsilon_n^*(d)\big)^2. \tag{48}$$

Next, using the seller's conditions (35) and (36), we get

$$\Pi(d) = p(d) + \frac{\gamma_n(d) - \theta\gamma_n^2(d)}{\partial\gamma_n/\partial p(d)|_d}, \tag{49}$$

which, using (48) and again expressing the probability of sale and the derivative in terms of the reservation dividend via (40) and (44), amounts to

$$\Pi(d) = \frac{\beta\theta}{\big(1-\pi\beta\big)\big(1-\beta\big)}\big(\tilde{\varepsilon} - \varepsilon_n^*(d)\big)^2. \tag{50}$$

Therefore, we can express the reservation dividend as

$$2\varepsilon_n^*(d) - 1 + \frac{\pi\beta\theta}{1-\pi\beta}\big(\tilde{\varepsilon} - \varepsilon_n^*(d)\big)^2 = \tau(d) + \big(\pi - \pi\beta\big)W. \tag{51}$$

We take the derivative with respect to the distance to the city center d on both sides and get

$$\frac{\partial \varepsilon_n^*}{\partial d} \underbrace{\left(2 - 2\frac{\pi\beta\theta}{1-\pi\beta}(\tilde{\varepsilon} - \varepsilon_n^*(d))\right)}_{>0} = \frac{\partial \tau}{\partial d} \tag{52}$$

and therefore $\partial \varepsilon_n^*/\partial d > 0$, given that $\partial \tau/\partial d > 0$. Via Lemma 1, also $\partial \varepsilon_c^*/\partial d > 0$. □

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

Proof. Using (50), we have that

$$\frac{\partial \Pi}{\partial d} = \frac{2\beta\theta}{\big(1-\pi\beta\big)\big(1-\beta\big)}\big(\tilde{\varepsilon} - \varepsilon_n^*(d)\big)\left(-\frac{\partial \varepsilon_n^*}{\partial d}\right) < 0, \tag{53}$$

where $\partial \varepsilon_n^*/\partial d > 0$ via Lemma 2. Next, using (48), we get

$$\frac{\partial p}{\partial d} = -\frac{\beta}{1-\pi\beta}\frac{\partial \varepsilon_n^*}{\partial d} + \frac{2\beta^2\theta}{\big(1-\pi\beta\big)\big(1-\beta\big)}\big(\tilde{\varepsilon} - \varepsilon_n^*(d)\big)\left(-\frac{\partial \varepsilon_n^*}{\partial d}\right) < 0. \tag{54}$$

We express the seller reservation value in terms of the reservation dividend via (48), the seller optimality condition (36), the equilibrium relation between the reservation dividend and probability of sale in the no-counteroffer scenario (40), and the derivative (44) of the probability of sale in the no-counteroffer scenario with respect to the asking price:

$$r(d) = p(d) - \frac{\beta}{1-\pi\beta}\big(\tilde{\varepsilon} - \varepsilon_n^*(d)\big). \tag{55}$$

Then,

$$\frac{\partial r}{\partial d} = \frac{2\beta^2\theta}{\big(1-\pi\beta\big)\big(1-\beta\big)}\big(\tilde{\varepsilon} - \varepsilon_n^*(d)\big)\left(-\frac{\partial \varepsilon_n^*}{\partial d}\right) < 0, \tag{56}$$

using (54). The expected sales price $\mathbb{E}\big[Sales\ price(d)\big] = \theta p(d) + \big(1-\theta\big) r(d)$ 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. □

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:

$$\gamma_{nc}(d) = \theta\gamma_n(d) + \big(1-\theta\big)\gamma_c(d). \tag{57}$$

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

$$\mathbb{E}\big[TOM(d)\big] = \frac{1}{\gamma_{nc}(d)}. \tag{58}$$

Proposition 1. *The expected time on the market* $\mathbb{E}\big[TOM(d)\big]$ *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 (40) and (41), we can express the expected time on the market in terms of the reservation dividend in the no-counteroffer scenario:

$$\mathbb{E}\big[TOM(d)\big] = \frac{1}{\big(2-\theta\big)\big(\tilde{\varepsilon} - \varepsilon_n^*(d)\big)}. \tag{59}$$

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

$$\frac{\partial \mathbb{E}\big[TOM\big]}{\partial d} = \underbrace{-\Big(\big(2-\theta\big)\big(\tilde{\varepsilon} - \varepsilon_n^*(d)\big)\Big)^{-2}}_{<0} \left(\underbrace{-\big(2-\theta\big)}_{<0} \underbrace{\frac{\partial \varepsilon_n^*}{\partial d}}_{>0} \right) > 0. \tag{60}$$

□

Intuition. See main text.

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

$$\mathbb{E}\big[APD(d)\big] = \theta \cdot APD_n(d) + \big(1-\theta\big) \cdot APD_c(d) = \big(1-\theta\big) \cdot APD_c(d), \tag{61}$$

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

$$APD_c(d) = \frac{r(d) - p(d)}{p(d)}. \tag{62}$$

Proposition 2. *Given that the probability of no counteroffer* $\theta \in (0,1)$*, the expected asking price discount* $\mathbb{E}\big[APD(d)\big] < 0$ *decreases 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 $\theta < 1$. Plugging in the optimal reservation value $r(d)$ of a seller from (37), we have that

$$APD_c(d) = -\frac{1-\beta}{1-\beta+\beta\theta\big(\tilde{\varepsilon}-\varepsilon_n^*(d)\big)} < 0, \tag{63}$$

using the equilibrium relation between the reservation dividend and the probability of sale (40). Hence, we also have that the expected asking price discount $\mathbb{E}\big[APD(d)\big] = \big(1-\theta\big)APD_c(d) < 0$. The derivative of the expected asking price discount with respect to the distance to the city center amounts to

$$\frac{\partial \mathbb{E}\big[APD\big]}{\partial d} = \underbrace{-\big(1-\theta\big)\big(\beta-1\big)\Big(1-\beta+\beta\theta\big(\tilde{\varepsilon}-\varepsilon_n^*(d)\big)\Big)^{-2}}_{>0}\Bigg(\underbrace{-\beta\theta}_{<0}\underbrace{-\frac{\partial \varepsilon_n^*}{\partial d}}_{>0}\Bigg) < 0, \tag{64}$$

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. The asking price and the seller reservation value both 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.[23] 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 asking price.[24]

Intuitively, we can express the expected profit in terms of the probability of sale and the

[23]Formally,

$$\frac{\partial \mathbb{E}\big[Discount\big]}{\partial d} = \big(1-\theta\big)\frac{\partial\left(\frac{r-p}{p}\right)}{\partial d} = \big(1-\theta\big)\left(\frac{\partial r}{\partial d}\frac{1}{p(d)} - \frac{\partial p}{\partial d}\frac{r}{\big(p(d)\big)^2}\right), \tag{65}$$

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

$$\underbrace{\frac{\partial r/\partial d}{r(d)}}_{<0} < \underbrace{\frac{\partial p/\partial d}{p(d)}}_{<0}, \tag{66}$$

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

[24]Formally,

$$\frac{\partial r/\partial d}{r(d)} = \frac{\partial\big(\beta\Pi\big)/\partial d}{\beta\Pi(d)} = \frac{\partial \Pi/\partial d}{\Pi(d)} < \frac{\partial p/\partial d}{p(d)}. \tag{67}$$

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. All of these variables decrease with distance to the city center because buyers want to be compensated for a higher travel cost with higher reservation dividends.

Proof: the expected profit decreases more steeply with distance to the city center than the asking price in relative terms.

Via (35), we can express the expected profit as

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

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

$$\Pi(d) = \frac{\theta\gamma_n(d)p(d)}{1 - \beta + \theta\beta\gamma_n(d)} \tag{68}$$

and

$$\frac{\partial\Pi}{\partial d} = \frac{\big(1 - \beta + \theta\beta\gamma_n(d)\big)\Big(\theta\frac{\partial\gamma_n}{\partial d}p(d) + \theta\gamma_n(d)\frac{\partial p}{\partial d}\Big) - \theta^2\beta\frac{\partial\gamma_n}{\partial d}\gamma_n(d)p(d)}{\big(1 - \beta + \theta\beta\gamma_n(d)\big)^2}. \tag{69}$$

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

$$\frac{\partial\Pi/\partial d}{\Pi(d)} = \underbrace{\frac{\partial\gamma_n/\partial d}{\gamma_n(d)}}_{<0} + \underbrace{\frac{\partial p/\partial d}{p(d)}}_{<0} - \underbrace{\frac{(\theta\beta)(\partial\gamma_n/\partial d)}{1 - \beta + \theta\beta\gamma_n(d)}}_{<0}. \tag{70}$$

Statement (67) says that

$$\frac{\partial\Pi/\partial d}{\Pi(d)} < \frac{\partial p/\partial d}{p(d)}, \tag{71}$$

for which to hold we need that

$$\frac{\partial\gamma_n/\partial d}{\gamma_n(d)} < \frac{(\theta\beta)(\partial\gamma_n/\partial d)}{1 - \beta + \theta\beta\gamma_n(d)}. \tag{72}$$

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

$$\frac{1}{\gamma_n(d)} > \frac{\theta\beta}{1 - \beta + \theta\beta\gamma_n(d)}, \tag{73}$$

or equivalently

$$1 - \beta > 0, \tag{74}$$

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. □

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 time on the market $\mathbb{E}\big[TOM(d)\big]$ and the expected asking price discount $\mathbb{E}\big[Discount(d)\big]$ is negative.*

Proof. We start by expressing the time on the market in terms of the asking price discount. Then, we evaluate the derivative of $\mathbb{E}\big[TOM(d)\big]$ with respect to $\mathbb{E}\big[APD(d)\big]$ at a given distance to the city center. First, from the proofs of Propositions 1 and 2 we have that

$$\mathbb{E}\big[TOM(d)\big] = \frac{\beta\theta}{2-\theta}\left(\frac{(\beta-1)(1-\theta)}{\mathbb{E}\big[Discount(d)\big]} - 1 + \beta\right)^{-1}. \tag{75}$$

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

$$\frac{\partial \mathbb{E}\big[TOM\big]}{\partial \mathbb{E}\big[Discount(d)\big]|_d} = \underbrace{-\frac{\beta\theta}{2-\theta}}_{<0}\underbrace{\left(\frac{(\beta-1)(1-\theta)}{\mathbb{E}\big[Discount(d)\big]} - 1 + \beta\right)^{-2}}_{>0}\underbrace{\left(-\frac{(\beta-1)(1-\theta)}{\left(\mathbb{E}\big[Discount(d)\big]\right)^2}\right)}_{>0} < 0, \tag{76}$$

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

G 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 $\theta = 1$.

G.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 (9), we can express the buyer's value in the extended model as

$$V(d,\varepsilon) = \frac{\beta}{1-\pi\beta}\Big(\varepsilon - \tau(d) + \big(1-\pi\big)\big(\Pi(d)+W\big)\Big). \tag{77}$$

Hence, $V(d,\varepsilon)$ is linear in ε and there exist reservation dividends as defined in the buyer indifference conditions (38) and (39). 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.

G.2 Equilibrium uniqueness

To show uniqueness of the model's solution, we follow Vanhapelto and Magnac (2024), showing that two possible ways of expressing the value of search allow for only one value of the idiosyncratic reservation dividend at every distance to the city center such that both of these expressions hold. The first expression decreases in the idiosyncratic reservation dividend, whereas the second expression increases in the idiosyncratic reservation dividend. 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 travel cost function, and the idiosyncratic reservation dividend.

Expression 1. We set up the first expression for the value of search in terms of the buyer's reservation dividends via the definitions (32), (33), and (34):

$$W = \mathbb{E}_{d,\varepsilon}\big[\theta \max\big[V(d,\varepsilon)-p(d),\beta W\big] + \big(1-\theta\big)\max\big[V(d,\varepsilon)-r(d),\beta W\big]\big], \tag{78}$$

and hence

$$W = \frac{1}{1-\beta}\mathbb{E}_{d,\varepsilon}\left[\theta \max\left[V(d,\varepsilon) - p(d) - \beta W, 0\right] + \left(1-\theta\right)\max\left[V(d,\varepsilon) - r(d) - \beta W, 0\right]\right]. \tag{79}$$

Next, we express the relations within the max operators in terms of the buyer's reservation dividends. Note that when the buyer indifference conditions (38) and (39) hold, we have that

$$\beta W = V(d, \varepsilon_n^*(d)) - p(d) = V(d, \varepsilon_c^*(d)) - r(d). \tag{80}$$

Inserting the linear buyer value (77), we get

$$\beta W = \frac{\beta}{1-\pi\beta}\Big(\varepsilon_n^*(d) - \tau(d) + \big(1-\pi\big)\big(\Pi(d) + W\big)\Big) - p(d) \tag{81}$$

and

$$\beta W = \frac{\beta}{1-\pi\beta}\Big(\varepsilon_c^*(d) - \tau(d) + \big(1-\pi\big)\big(\Pi(d) + W\big)\Big) - r(d). \tag{82}$$

Hence,

$$\frac{\beta}{1-\pi\beta}\varepsilon_n^*(d) = \frac{\beta}{1-\pi\beta}\tau(d) - \frac{\beta\left(1-\pi\right)}{1-\pi\beta}\Pi(d) + \frac{\pi\beta\left(1-\beta\right)}{1-\pi\beta}W + p(d) \tag{83}$$

and

$$\frac{\beta}{1-\pi\beta}\varepsilon_c^*(d) = \frac{\beta}{1-\pi\beta}\tau(d) - \frac{\beta\left(1-\pi\right)}{1-\pi\beta}\Pi(d) + \frac{\pi\beta\left(1-\beta\right)}{1-\pi\beta}W + r(d). \tag{84}$$

Again using (77), we can express the sum within the first max operator from (79) as

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

Then, via (83), we get

$$V(d,\varepsilon) - p(d) - \beta W = \frac{\beta}{1-\pi\beta}\varepsilon - \frac{\beta}{1-\pi\beta}\varepsilon_n^*(d) = \frac{\beta}{1-\pi\beta}\big(\varepsilon - \varepsilon_n^*(d)\big). \tag{85}$$

Analogously, using (84), we have that

$$V(d,\varepsilon) - r(d) - \beta W = \frac{\beta}{1-\pi\beta}\big(\varepsilon - \varepsilon_c^*(d)\big). \tag{86}$$

We can then express the value of search from (79) as

$$W = \frac{1}{1-\beta}\mathbb{E}_{d,\varepsilon}\left[\theta \max\left[\frac{\beta}{1-\pi\beta}\big(\varepsilon - \varepsilon_n^*(d)\big), 0\right] + \big(1-\theta\big)\max\left[\frac{\beta}{1-\pi\beta}\big(\varepsilon - \varepsilon_c^*(d)\big), 0\right]\right], \tag{87}$$

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

Expression 2. We set up the second expression via the buyer indifference conditions (38) and (39). Using (77), we can express the indifference condition for the no-counteroffer scenario (38) as

$$W = \frac{1}{\pi - \pi\beta}\Big(\varepsilon_n^*(d) - \tau(d) + \big(1-\pi\big)\Pi(d) - \frac{1-\pi\beta}{\beta}p(d)\Big). \tag{88}$$

Hence,

$$\frac{\partial W}{\partial \varepsilon_n^*(d)|_d} = \frac{2}{\pi - \pi\beta} + \frac{2\pi\beta\theta}{\big(\pi - \pi\beta\big)\big(1-\pi\beta\big)}\big(\tilde{\varepsilon} - \varepsilon_n^*(d)\big) > 0. \tag{89}$$

Using the buyer indifference condition from the counteroffer scenario (39) and going through the same steps yields

$$W = \frac{1}{\pi - \pi\beta}\Big(\varepsilon_c^*(d) - \tau(d) + \big(1-\pi\big)\Pi(d) - \frac{1-\pi\beta}{\beta}r(d)\Big). \tag{90}$$

Via (36), (44), (47), and the auxiliary expressions for the probabilities of sale, we get

$$r(d) = \frac{\beta^2\theta}{4\big(1-\pi\beta\big)\big(1-\beta\big)}\big(\tilde{\varepsilon} - \varepsilon_c^*(d)\big)^2 \tag{91}$$

and

$$\Pi(d) = \frac{\beta\theta}{4\big(1-\pi\beta\big)\big(1-\beta\big)}\big(\tilde{\varepsilon} - \varepsilon_c^*(d)\big)^2. \tag{92}$$

Then, via (90), the derivative of the search value with respect to the reservation dividend in the buyer's price scenario amounts to

$$\frac{\partial W}{\partial \varepsilon_c^*(d)|_d} = \frac{1}{\pi - \pi\beta} + \frac{\pi\beta\theta}{2\big(\pi - \pi\beta\big)\big(1-\pi\beta\big)}\big(\tilde{\varepsilon} - \varepsilon_c^*(d)\big) > 0. \tag{93}$$

Since the first expression for the value of search decreases in the reservation dividends and the second one increases in the reservation dividends, there can only be a single pair of reservation dividends at a given distance to the city center such that both of these conditions are fulfilled. With W being constant across space, this holds for all distances to the city center.

H Additional model results

H.1 Steepness of price vs. liquidity gradient

As mentioned in Section 4.3.2., the model predicts the price gradient to be steeper than the liquidity gradient. For this comparison, we express both gradients in absolute values and in relative terms to the respective variables. For the expected time on the market, this gradient is

$$\left|\frac{\partial E[TOM]/\partial d}{E[TOM(d)]}\right| = \left|\frac{\partial \gamma/\partial d}{\gamma(d)}\right|, \tag{94}$$

which follows from Equations (7), (16) and (17). 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 Equations (7), (13), and (18), the relative price gradient amounts to

$$\left|\frac{(\partial\gamma/\partial d)\Big(1+2\Big(\beta/(1-\beta)\Big)\gamma(d)\Big)}{\gamma(d)+\Big(\beta/(1-\beta)\Big)(\gamma(d))^2}\right| > \left|\frac{\partial \gamma/\partial d}{\gamma(d)}\right|. \tag{95}$$

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 value.

Table 24: *Standardized TOM and price gradients, Germany and U.S.*

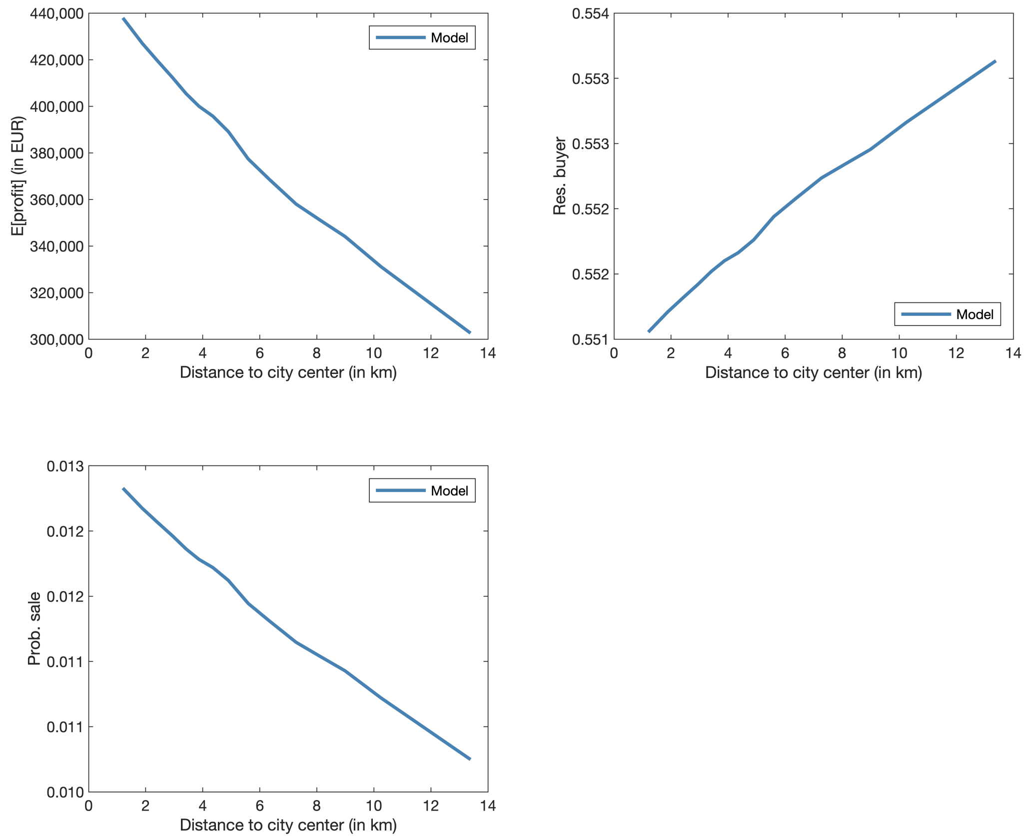
Country	Dataset	TOM gradient	Price gradient
Germany	Condos full sample	0.048	-0.202
U.S.	Single-family FUA (full sample)	0.029	-0.146
U.S.	Single-family MSA (50km radius)	0.048	-0.276
U.S.	Single-family MSA (full sample)	0.134	-0.074

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 24 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.

H.2 Spatial distributions of additional variables

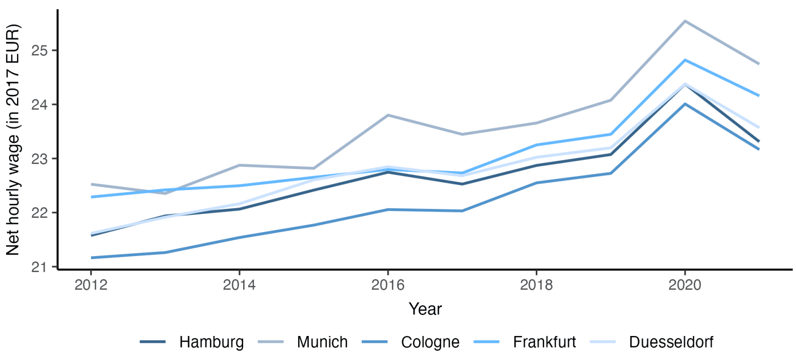
Figure 16: *Spatial distributions of additional variables, main model*



H.3 Alternative travel cost calibration

In the main model, we target a physical cost of car travel when estimating the parameter μ. This parameter 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 of this opportunity cost as translating travel time to the city center in minutes linearly into a monetary cost via the alternative conversion parameter μ^{alt}. Then, we must specify what a minute of travel time is worth to agents in the model. We do this using the population-weighted average hourly wage across our sampled cities. Via the regional portal of the German Statistics Office, we retrieve average gross hourly wages in Hamburg, Munich, Cologne, Frankfurt, and Duesseldorf between 2012 and 2021. Net hourly wages are not available. To get a rough measure of the net hourly wage, we multiply the gross hourly wage by the fraction of total city-level net household income over total city-level gross household income, retrieved via the same data source. Next, using the GENESIS database, we retrieve the German consumer price index between 2012 and 2021 to adjust wages for inflation (variable code: 61111-0001). We choose 2017 as the base year, as the travel cost measure in Andor et al. (2020) refers to this year. Figure 17 plots the resulting time series of real net wages for the 5 cities in our sample. The regional database of GENESIS gives us the yearly population levels (variable code: 12411-01-01-4). Averaging these values across cities and years with city-level population weights yields a net real hourly wage of 22.91 EUR.

Figure 17: *Average net hourly wage across cities*

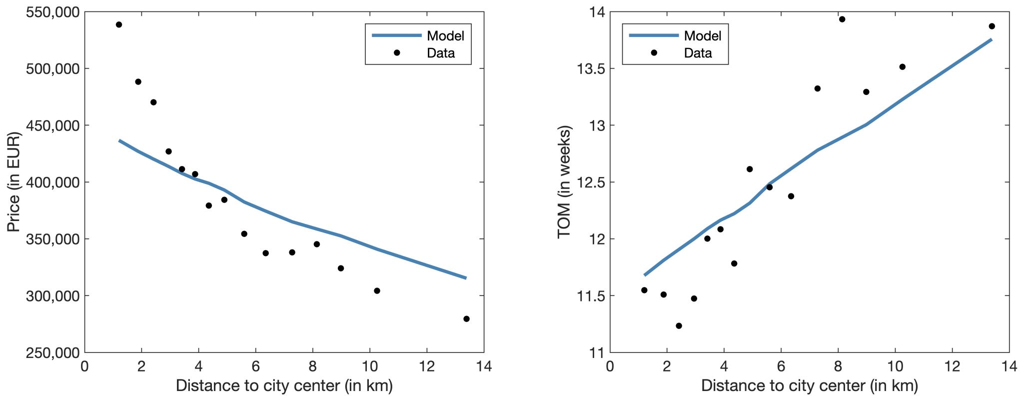


Then, we calculate the average travel time in our sample, multiplied by 2, to get a measure of daily travel time. In our model, agents travel to and from the city center for 33 minutes per day on average. Measured in terms of an opportunity cost, if we assume that the value of time lost can be expressed in terms of the net real average wage, they lose (33/60)$\times$22.91 EUR =12.63 EUR per day. Table 25 and Figure 18 present model results when using the alternative target for the model-implied travel cost of 12.63 EUR. The results are nearly identical to our main results. The price and liquidity gradients are slightly less steep.

Table 25: *Estimated parameters, all cities pooled, alternative travel cost calibration*

Parameter	Description	Value	Bootstr. 95% CI	Target statistic	Target (model) value
μ^{alt}	Travel time scaling	0.0045	$[0.0044, 0.0046]$	Avg. opportunity cost	12.63 (12.63) €
$\bar{\varepsilon}^{alt}$	Dividend dist. bound	0.55	$[0.54, 0.56]$	Avg. time on mkt.	12.47 (12.46) wk

Figure 18: *Spatial distributions of liquidity and prices, alternative travel cost calibration*



Notes: "TOM" refers to the (expected) time on the market. The data points are calculated using Regression (1) *with year-quarter fixed effects, city fixed effects, and apartment characteristics controls.*

H.4 Model results for individual cities

Table 26: *Calibrated parameters; individual cities*

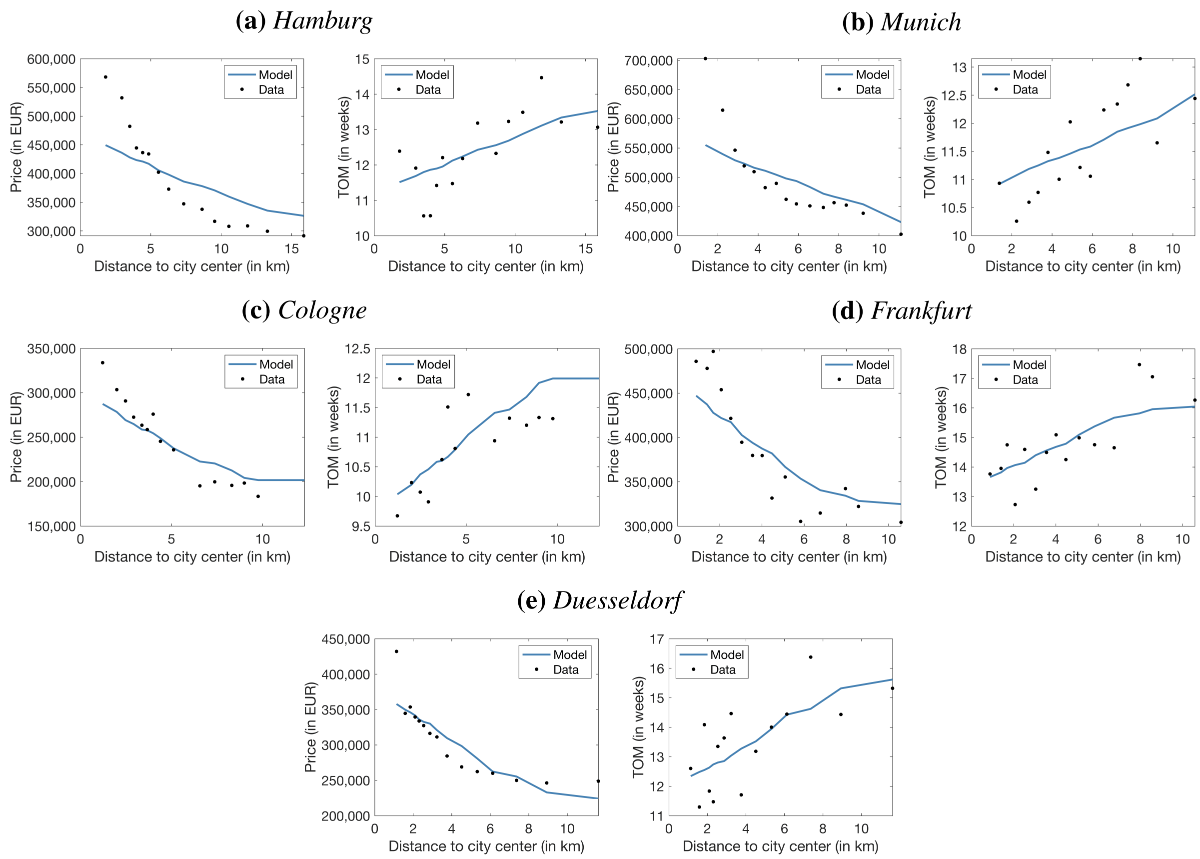
Parameter	Description	Value	Source
β	Discount factor	0.99986 (yearly: 0.95)	Standard parameter
π^{Hamburg}	Housing match persistence	0.9997 (yearly: 0.90)	Apartment holding periods
π^{Munich}	"	0.9997 (yearly: 0.91)	"
π^{Cologne}	"	0.9997 (yearly: 0.90)	"
$\pi^{\text{Frankfurt}}$	"	0.9997 (yearly: 0.90)	"
$\pi^{\text{Duesseldorf}}$	"	0.9997 (yearly: 0.90)	"

Notes: For Hamburg and Frankfurt we do not have (sufficient) data on apartment holding periods available and use the average holding period from the combined sample.

Table 27: *Estimated parameters, individual cities*

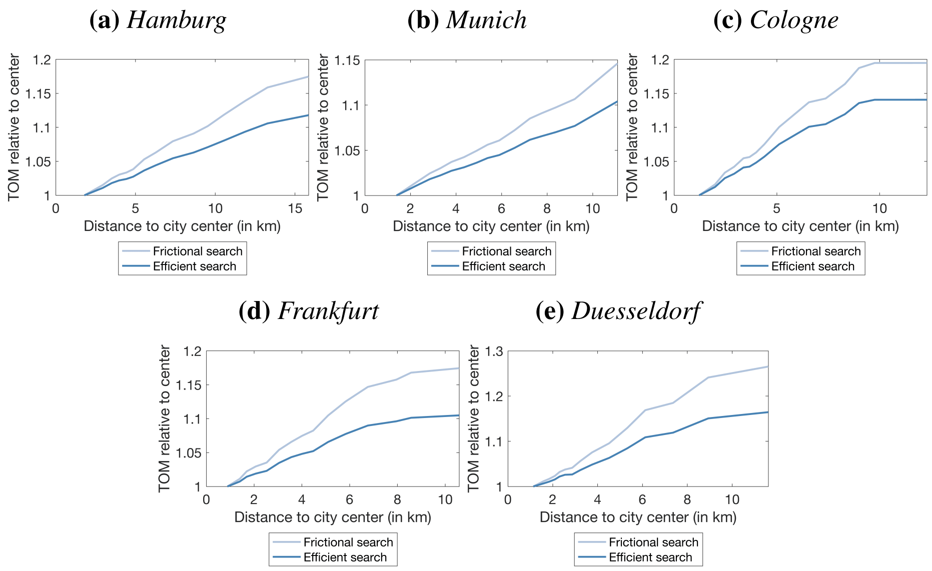
Parameter	Description	Value	Bootstr. 95% CI	Target statistic	Target (model) value
μ^{Hamburg}	Travel time scaling	0.0039	$[0.0037, 0.0041]$	Daily car op. cost	14.17 (14.17) €
μ^{Munich}	"	0.0047	$[0.0043, 0.0049]$	"	14.17 (14.16) €
μ^{Cologne}	"	0.0106	$[0.0100, 0.0112]$	"	14.17 (14.18) €
$\mu^{\text{Frankfurt}}$	"	0.0047	$[0.0045, 0.0050]$	"	14.17 (14.17) €
$\mu^{\text{Duesseldorf}}$	"	0.0074	$[0.0068, 0.0081]$	"	14.17 (14.16) €
$\tilde{\varepsilon}^{\text{Hamburg}}$	Dividend dist. bound	0.57	$[0.55, 0.59]$	Avg. time on mkt.	12.38 (12.37) wk
$\tilde{\varepsilon}^{\text{Munich}}$	"	0.62	$[0.59, 0.64]$	"	11.59 (11.59) wk
$\tilde{\varepsilon}^{\text{Cologne}}$	"	0.73	$[0.70, 0.77]$	"	11.02 (11.01) wk
$\tilde{\varepsilon}^{\text{Frankfurt}}$	"	0.44	$[0.43, 0.46]$	"	14.80 (14.81) wk
$\tilde{\varepsilon}^{\text{Duesseldorf}}$	"	0.53	$[0.50, 0.56]$	"	13.50 (13.50) wk

Figure 19: *Model results, individual cities*



Notes: "TOM" refers to (expected) time on the market. The data points are calculated using Regression (1) *with year-quarter fixed effects and property characteristics controls.*

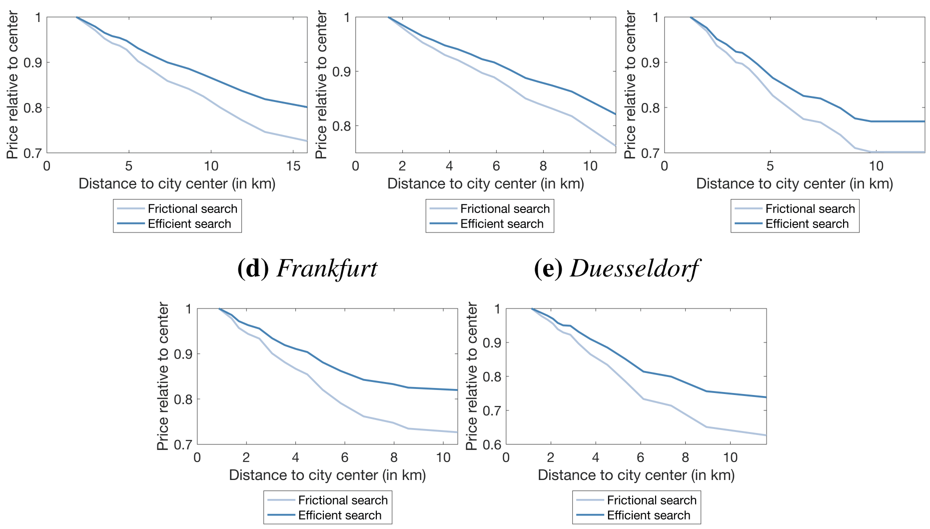
Figure 20: *Normalized spatial liquidity distributions, individual cities*



Notes: These figures show the equilibrium expected time on the market from our main model ("frictional search") and the expected time on the market from the efficient allocation ("efficient search") as implied by (23)*, normalized by the expected time on the market at the location closest to the city center.*

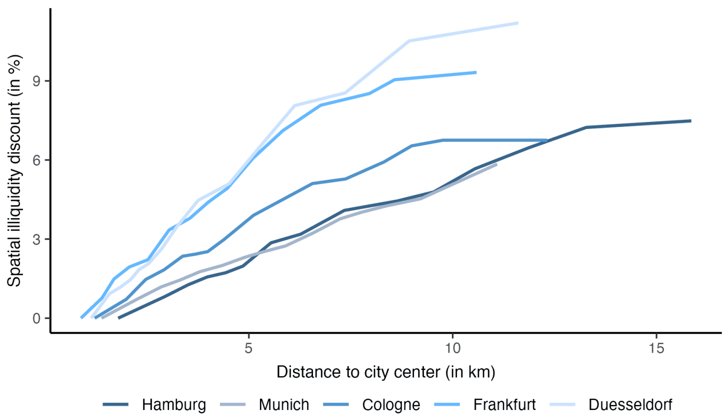
Figure 21: *Normalized spatial price distributions, individual cities*

(a) *Hamburg* **(b)** *Munich* **(c)** *Cologne* **(d)** *Frankfurt* **(e)** *Duesseldorf*



Notes: These figures show the equilibrium prices from our main model ("frictional search") and the prices from the efficient allocation ("efficient search") as specified in (13)*, normalized by the apartment price at the location closest to the city center.*

Figure 22: *Illiquidity discount, individual cities*

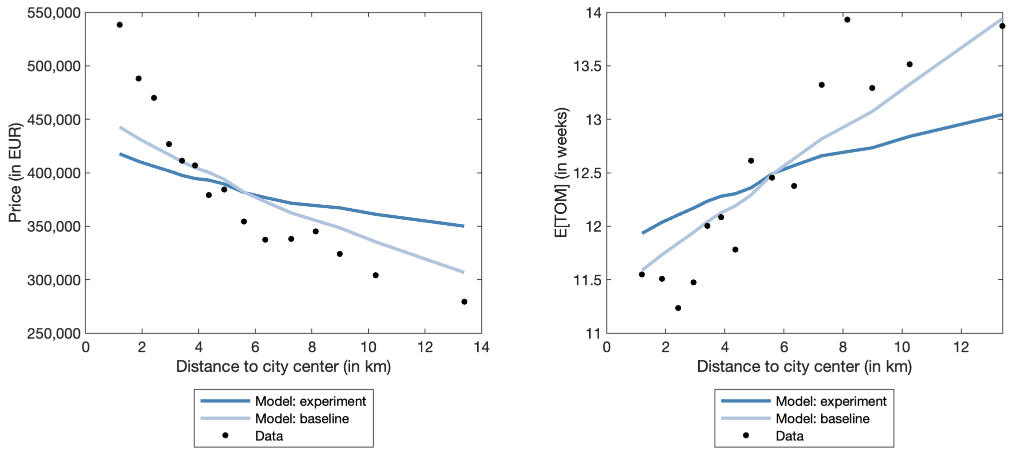


Notes: This figure shows the price discount due to frictional illiquidity relative to the city center as defined in (24)*.*

H.5 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 flattened liquidity gradient as we document in our empirical results. The COVID-19 pandemic induced a shift to working from home. We conduct this experiment with all estimated parameters of the baseline model unchanged. 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.

Figure 23: *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 year-quarter fixed effects and property characteristics controls.*

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 of 14.17€ per day 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 Appendix D.2, see Figure 23.

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