The price of productivity *

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Abstract

We construct a new micro-geographic commercial rent index for Germany to study the capitalization of agglomeration economies into floor space prices. In large local labor markets, commercial rents decline by -17% per kilometer from the central business district, compared to 13% for residential rents, reflecting stronger agglomeration benefits at the center. Commercial rents in central business districts increase with local labor market size at an elasticity of 15%, implying that wage responses capture only about half of the agglomeration effect on total factor productivity.

Key words: Floor space, rents, spatial equilibrium, total factor productivity

JEL: L2, R3

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1 Introduction

Agglomeration effects on wages have been studied extensively, showing that firms in denser areas pay higher wages to attract and retain workers. These firms also compete for floor space, particularly in dense city centers. With inelastic land supply, additional floor space can only be produced at increasing cost, making congestion inevitable. As a result, additional firms in the most productive areas can only be accommodated at higher rents, which they are only willing to pay if there is a compensating differential. The most prominent candidate channel discussed in the urban economics literature is higher total factor productivity (TFP) arising from external returns to scale—i.e., agglomeration benefits. Despite the central role of commercial rents in shaping firms' location choices and the spatial distribution of economic activity, this capitalization channel remains understudied, in part because commercial rent data are scarce and transactions far less frequent than in residential markets.

This paper quantifies the capitalization of agglomeration forces into commercial rents for floor space. We develop a new micro-geographic commercial rent index for Germany using a newly available dataset from the FDZ Ruhr on commercial real estate. Consistent with the standard land use model, commercial rents fall steeply with distance from the central business district (CBD), at -17% per kilometer in the largest cities, reflecting strong agglomeration forces within CBDs. Commercial rents in CBDs also rise steeply with city population, increasing at an elasticity of 15%. In a Roback (1982)-style spatial equilibrium model, where spatial differences in productivity capitalize into both wages and rents, this elasticity can be used to infer the effect of agglomeration on TFP rather than on wages alone. Interpreted through this lens, the capitalization of productivity into commercial rents implies a city-size elasticity of TFP of about 2%. Combining this rent-based capitalization channel with the 2–4% wage-based effects typically found in the literature yields an overall agglomeration elasticity of TFP of 4–6%.[1] This suggests that estimates based on wages alone miss an important component of the productivity premium of cities—particularly in large cities, where the capitalization of agglomeration forces into commercial rents is especially strong.

Constructing micro-geographic commercial rent indices is challenging because transactions are more sparse than residential data. Standard hedonic regressions augmented by fixed effects are ill-suited for such data environments. To address this challenge, we develop a variant of the locally weighted regression approach employed

[1] See Combes and Gobillon (2015) and Ahlfeldt and Pietrostefani (2019) for reviews.

by Ahlfeldt et al. (2023) that fits the particular needs of spatially scarce commercial rent data. Our algorithm uses observations within a local spatial window to predict a rent index for an arbitrary set of points, such as postcode centroids, giving higher weights to observations that are closer. The spatial window is endogenously chosen, depending on the density of observations, thereby maximizing precision in areas of greater commercial activity, such as CBDs. This approach yields a continuous price surface that provides imputed values for locations with few or no commercial transactions, making the index particularly suited for the quantification of urban models. Combining this index with the Ahlfeldt et al. (2023) residential rent index allows us to study where, when, and why different users outbid each other for locations. Our analysis draws on the newly available dataset on commercial real estate (RWI-GEO-REDC) by RWI (Breidenbach et al., 2025), which provides comprehensive coverage of commercial property listings across Germany. The resulting postcode-level panel of commercial rent indices spans 15 years and is made publicly available, representing a unique resource for research on local commercial real estate markets.[2]

The second challenge for a comprehensive evaluation of floor space rent gradients through the lens of a standard land use model is to define the CBD consistently across a large set of cities. For residential gradients, the precise definition of the CBD is arguably less consequential, as long as it is reasonably close to the economic center of the city. For commercial gradients, however, a precise delineation is crucial: the CBD marks the peak of the gradient and is needed to obtain sensible estimates of rents at the most productive locations as well as the rate of spatial decay. To delineate CBDs for all German cities, we employ the methodology developed by Ahlfeldt et al. (2025), which identifies hyper-dense clusters of economic activity—*prime locations*—based on densities that are highly unlikely to arise under spatial randomness.[3] We take advantage of the commercial rent data and use the *unit value*, defined as the product of price per sqm and unit size, as a theory-consistent proxy for economic activity that, unlike employment, incorporates the productivity of a location.

Our delineation of prime locations reveals that many LLMs in Germany are monocentric. 74% of LLMs have no more than one prime location. Among the others, there is a large degree of primacy: the largest prime location—our definition of the CBD—is on average more than twice as large as the second-largest. Reassuringly, the delineated CBDs stand out in terms of commercial floor space rents

[2]The data are available as part of the AHS2023 toolkit.

[3]We use the GitHub toolkit implementation of the methodology by Ahlfeldt et al. (2024).

in our index, especially in the cities conventionally viewed as the most important business centres. This not only lends credibility to our delineation of CBDs and our real estate index, but also reveals that the standard land use model remains a relevant framework for studying German LLMs.

With our novel commercial rent index and CBD definitions for German cities at hand, we begin the empirical analysis by documenting new stylized facts on the distribution of commercial rents within and between German LLMs. Consistent with the standard land use model, commercial rents are generally higher at the CBD than residential rents. Commercial and residential rents decline with distance from the CBD, in line with theory. However, the gradients do not always intersect, suggesting a role for zoning. In Berlin, for example, commercial rents exceed residential rents throughout the city, pointing to land use regulation that favors residential development at the expense of lower floor space supply. In Munich, the most expensive residential market, residential bid rents exceed commercial rents almost everywhere, suggesting that residential development could not keep up with city growth.

To generate accessible summary statistics of the spatial distribution of rents within and between LLMs, we follow Combes et al. (2019) and estimate LLM-year-specific bivariate gradient models. These provide a good fit to our micro-geographic rent data, especially for the large LLMs, where the R^2 exceeds 0.5 throughout the study period from 2008 to 2022. Appreciation of suburban locations post-COVID and the rise of work from home is a marked feature of our estimated rent gradients, echoing evidence from the US (Brueckner et al., 2023; Delventhal and Parkhomenko, 2026). Unlike in the US (Rosenthal et al., 2022), the impact on commercial rent gradients is weak at best. Overall, CBDs in German cities have remained remarkably strong. If anything, our results suggest that the spatial pull of CBDs has been increasing, especially in the large LLMs.

Turning to the question of how agglomeration-induced productivity advantages capitalize into commercial floor space prices, we investigate how CBD rents scale with city size, the commercial analogue to the analysis of the French residential market in Combes et al. (2019). For comparison, we also provide estimates of how residential rents measured at the city centre scale with city size in Germany. Using deep lags in population as instrumental variables to address endogeneity, we estimate an average city-size elasticity of rent of about 0.14 for both the commercial and residential markets. As in the case of the French residential market, we find that the elasticity increases with city size. While the average residential elasticity in Germany is lower than in France, the elasticity for large cities, at about 0.25–0.3, is comparable. The commercial elasticity we estimate for Germany is even greater for the largest cities.

Interpreting the estimated city-size elasticity of commercial rent through the lens of a standard spatial equilibrium model and assuming a floor space input share of 15%, the capitalization of productivity into commercial rents implies an agglomeration elasticity of TFP of about 2%. This reflects the contribution of the floor space margin to productivity differences across cities, alongside the 2–4% elasticity typically inferred from wage data (Combes and Gobillon, 2015). Because commercial rents respond more strongly to agglomeration than wages in the data, we would be underestimating the true agglomeration elasticity of TFP by 33% to 50% if we inferred it from wages alone—like much of the literature does.[4] Since the rent capitalization effect is especially pronounced in large cities, while the wage capitalization effect appears to be flat across city sizes (Ahlfeldt and Pietrostefani, 2019), wage-based estimates may understate the agglomeration benefits of the largest cities even more.

With these results, we contribute to a large literature on agglomeration economies. Seminal papers have documented density effects on labor productivity and wages (Ciccone and Hall, 1996; Combes et al., 2008). The wage agglomeration elasticity is typically estimated in the range of 2% to 4%, towards the lower end when accounting for worker fixed effects (Combes and Gobillon, 2015). As noted by Rosenthal and Strange (2004), most works in urban economics estimate the elasticity using wage data alone, with only a few studies covering rent capitalization effects. One exception is Dekle and Eaton (1999), who attempt to estimate the agglomeration effect on productivity using housing rents data as a proxy for commercial rents. Another notable exception is Ahlfeldt et al. (2015), who estimate an agglomeration elasticity of 7% for Berlin that also accounts for commercial rent capitalization effects. They, too, do not observe commercial rents, but they do observe land values in commercial zones, which depend on commercial rents. Our contribution to the literature is to exploit a new measure of commercial rent to estimate the degree to which agglomeration effects capitalize into commercial rents. Beyond evidence from a single city, we exploit micro-geographic datasets for a large country, offering rich variation in density within and between cities of vastly different sizes.

Additionally, our paper relates to the large literature on urban gradients. Following the neoclassical monocentric city model synthesized in Brueckner (1987), a vast body of empirical work has documented how residential land prices, rents, and

[4] In a production framework with multiple inputs, the agglomeration elasticity of TFP is a cost-share–weighted average of the agglomeration elasticities of input prices. Incorporating commercial floor space as an input only increases the TFP elasticity relative to wage-based estimates if the agglomeration elasticity of commercial rents exceeds that of wages, as we find empirically.

densities decline with distance from the CBD (e.g., Colwell and Munneke (1997); McMillen (1996); Combes et al. (2019)). Evidence on the commercial property market, however, remains relatively scarce, with a few exceptions such as Rosenthal et al. (2022); Helsley and Strange (1990); McDonald (1987); Wheaton (1974). By developing a comprehensive commercial rent index at a fine spatial scale and systematically comparing commercial and residential gradients across cities and years, our paper fills an important gap in this literature. We provide empirical evidence showing that commercial and residential price gradients behave in real-world cities as predicted by stylized land use models (Ahlfeldt and Barr, 2022).

In delineating the prime locations, our paper also links to the literature on spatial concentration, employment decentralization, and the emergence of subcenters. While urban employment has decentralized over the past decades (Glaeser and Kahn, 2001; Baum-Snow et al., 2017), a large share of economic activity remains concentrated in a few clusters of very high density, or "prime locations" (Ahlfeldt et al., 2025). Desmet and Fafchamps (2005) explain the seemingly contradicting trends with sectoral differences: while the non-service sector is more spread out, the service sector remains highly clustered. This dual pattern of decentralization alongside persistent concentration has motivated a rich literature on subcenters (McDonald, 1987; Giuliano and Small, 1991; Gordon and Richardson, 2001; McMillen, 2001), which documents the extent to which cities retain monocentric cores while developing polycentric structures. We contribute to this literature to this debate, showing that prime locations still account for a large share of commercial activity in Germany and documenting a sizeable rent premium for central locations even in decentralized urban structures.

Our work also relates to the literature on quantitative urban models, which provide flexible frameworks for analyzing cities that are more dispersed or decentralized and where the monocentric model offers a less accurate description of urban structure (Ahlfeldt et al., 2015; Redding, 2025).[5] In such settings, our commercial rent index offers a key input: it captures variation in rents both across and within cities at a granular spatial level and provides values even in locations with sparse transactions through its imputation strategy. This allows for the inversion of micro-geographic fundamentals in spatial models (e.g. productivity and amenities), accounting for the capitalization of these factors into commercial and residential rents. The availability of two distinct rent indices also allows future generations of spatial models not only to better account for agglomeration effects, but also to capture distortions in the

[5] Related urban models with varying assumptions or focuses include Monte et al. (2018); Heblich et al. (2020); Bryan et al. (2020), as well as more recent developments in dynamic urban models such as Greaney et al. (2025).

supply of floor space originating from land use regulation.

There has been growing academic interest in German real estate markets in recent years (Ahlfeldt et al., 2023; Tielkes, 2025; Groiss and Syrichas, 2025; Breidenbach et al., 2022). However, this literature continues to focus on residential markets. Our paper is the first to provide a comprehensive analysis of commercial real estate across and within German cities, introducing a micro-geographic commercial rent panel dataset that opens up a wide range of previously inaccessible questions on the spatial structure and functioning of commercial property markets.

The remainder of the paper is structured as follows. Section 2 describes the data sources, the construction of the commercial rent index, and the delineation of prime locations (CBDs), and presents descriptive statistics. Section 3 introduces a monocentric city model with productivity declining in distance from the CBD, documents stylized facts consistent with the model, and estimates the agglomeration elasticity of commercial rents with respect to city size. The final Section 4 concludes.

2 Data

This section introduces the data used to construct the micro-geographic commercial rent index and to delineate prime locations (CBDs) across German cities. We describe the underlying geographic units, the commercial real estate listings data, the index construction algorithm, and provide descriptive evidence on the resulting rent patterns.

2.1 Geography

We construct the commercial rent index at the postal code level and delineate CBDs for each LLM (or commuting zones, in German: Arbeitsmarktregion), both using the listing data on commercial real estate (RWI-GEO-REDC) by RWI (Breidenbach et al., 2025). We provide a brief discussion of the geographic units here and refer the interested reader to Supplement A.1 for more descriptive statistics.

There are 8,255 unique five-digit postcode regions in Germany. Each postcode region has approximately ten thousand residents. As a result, these regions vary in geographic size. Postcode regions are much smaller in denser areas such as major cities than in less densely populated regions. For instance, Berlin has 190 postcode regions and the Munich LLM has 230.

We follow the definition of local labour markets (LLMs) by (BBSR, n.d.) and delineate prime locations for each of these regions. These local labour markets contain multiple postcode regions and are defined such that at least 65% of workers commute within their own LLM and commute times do not exceed 45 minutes (one way). BBSR, n.d. identifies 258 local labour markets in Germany with varying area sizes and populations in the 2017 version. The average population of a local labour market in 2024 is approximately 300,000 people, and the average area size is 1,381 square kilometres.

In our commercial dataset introduced below, we observe on average 160 commercial units per postcode region and over 5,000 units per local labour market. However, the distribution is naturally skewed towards postcode regions in city centres, with many postcode regions containing only a handful of observations.

2.2 Commercial rents

Raw data. Our main data source is the newly available dataset on commercial real estate (RWI-GEO-REDC) by RWI (Breidenbach et al., 2025). It contains five million listings of commercial units across Germany that were advertised on *Immoscout24* between 2007 and 2024. Each listing advertises a commercial unit with geographic information at the 1 km × 1 km grid-cell level. These commercial units vary in size and industry type, with the great majority advertised as potential office spaces. Listings without information on rent and usable area were excluded from the analysis. It is important to note that the same unit may be advertised on the platform more than once if the landlord makes edits to the original listing (e.g., reduces the rent) or re-uploads the listing. We identify such duplicate listings by comparing location, unit size, and other attributes. Only the most recent observation within each duplicate group is kept for the analysis.

Algorithm. To build a micro-geography commercial rent index, we employ a variant of the algorithm developed by Ahlfeldt et al. (2023), tailored to account for the much lower liquidity of the commercial compared to the residential market. Just like Ahlfeldt et al. (2023), we generate a mix-adjusted rent index for an arbitrary set of *target* spatial units indexed by $j \in \mathcal{J}$ by running a locally weighted regression of the following type for each unit j:

$$\begin{aligned} \ln \mathcal{P}_{i,t} = \; & \alpha_t^j + \bar{S}_i b^j + e^j I(D_i^j > T^j)_i \\ & + f^j(X_i - X^j) + g^j(Y_i - Y^j) + h_t^j I(M_i \neq M^j) + \epsilon_{i,t}^j, \end{aligned} \tag{1}$$

where $\mathcal{P}_{i,t}$ is the rent of a unit $i \in \mathcal{I}$ transacted in year $t \in \mathcal{T}$. α_t^j captures j-specific time-fixed effects, $\bar{S}_i$ is a vector of covariates stripped off the national average (we subtract the national mean from the observed value of S_i), and b^j are the LWR-j-

specific hedonic implicit prices. $I(.)$ is an indicator function that returns a value of one if a condition is true and zero otherwise and T^j is a threshold distance. Hence, $e^j I(D_i^j > T^j)_i$ is a fixed effect for all transacted properties i that are outside the vicinity of the catchment area. Adding this control, ensures that cross-sectional component of j-specific fixed effects α_t^j captures local conditions in the vicinity of j. X_i and Y_i are the coordinates of transacted properties, X^j and Y^j are the coordinates of the target unit, and f^j and g^j are parameters to be estimated. M_i and M^j describe spatial sub-markets that can be defined arbitrarily by the user. Hence, the term $h_t^j I(M_i \neq M^j)$ allows for transactions i to be on a different time-trend if they fall into a different spatial sub-market than target unit j. $\epsilon_{i,t}^j$ is the residual term.

We differ from Ahlfeldt et al. (2023) in that we do not add the distance from a unit i to the target unit j, D_i^j, as a covariate in Eq. (1). The reasons is that with generally much fewer observations in the commercial market, the estimation of the distance gradient is less precise and the point prediction at zero distance is more noisy. Instead, we incorporate D_i^j into the spatial weight each observation i receives in LWR j:

$$W_i^j = \frac{w_i^j}{\sum_i w_i^j}$$

$$w_i^j = \exp\left(\frac{\ln a}{A} D_i^j\right) \times I(D_i^J \leq A^j),$$

where $\{a, A\}$ are parameters governing the spatial decay of the spatial weight. Intuitively, each observation i receives a weight that is inversely related to its distance from the target unit j. Specifically, the spatial weight falls to a fraction of a of its value at zero distance after A units of distance, beyond which it drops to zero. We choose the distance threshold A^j for each target unit j as the minimum distance required to include at least N^A observations:[6]

$$A^j = \min\left\{d \in \mathbb{R}_+ : \left|\left\{i : D_i^j \leq d\right\}\right| \geq N^A\right\}$$

Similarly, we choose the threshold distance T^j for the spatial fixed effect such that there are at least N^T observations within distance D_i^j:

$$T^j = \min\left\{d \in \mathbb{R}_+ : \left|\left\{i : D_i^j \leq d\right\}\right| \geq N^T\right\}$$

The recovery of the rent index from the LWR-j-specific estimates is as in Ahlfeldt

[6] Hansen (2024) in his `R` implementation of the residential Ahlfeldt et al. (2023) algorithm, takes a similar approach.

et al. (2023). The time-fixed effects correspond to the locally weighted conditional expectation

$$\hat{\alpha}_t^j = \mathbb{E}_W \left(\ln P_t^j | S = \bar{S}, X = X^j, Y = Y^j, M = M^j \right),$$

which is the locally weighted expected log rent at location j at time t for a unit with the average national characteristics ($\mathbb{E}_W$ denotes an expectation under the spatial weights W_i^j). We convert this conditional expectation into a rent index measured in the same units as $P_{i,t}$ (here, €$/m^2$) as follows:

$$\hat{\mathcal{P}}_t^j = \exp(\hat{\alpha}_t^j) \times \mathcal{C}^j = \mathbb{E}_W \left(P_t^j | S = \bar{S}, X = X^j, Y = Y^j, M = M^j \right),$$

where $\mathcal{C}^j = \exp\left(\frac{1}{2}(\hat{\sigma}_\epsilon^2)^j\right)$ is an adjustment factor that depends on the variance of the error $(\sigma_\epsilon^2)^j$ of LWR j.[7] This adjustment is necessary to correct for the bias that would otherwise arise when reversing the log transformation (Duan, 1983). This way, we ensure that our index can be interpreted as the expected rent of a unit with average characteristics.

Intuitively, the rent index for a target unit is a year-specific local conditional mean that is adjusted for unit characteristics (deviations from the national average), location (time-varying distance from j effects, and time-invariant spatial trends in X and Y coordinates), and a spatial fixed effect. Since $\{A^j, T^j\}$ are endogenously chosen by the algorithm, the precision of the index automatically increases as the density of observations increases.

Parameterization. We choose the centroids of German postcodes as target units j. We set $a = 1$, which implies that the spatial weight falls to 1% of its value at zero distance at the distance threshold A^j. We choose $\{N^A, N^T\}$ to ensure that we have at least 2,500 observations with positive spatial weights (within distance A^j) and at least 500 observations in the vicinity of the target point (within distance T^j). We control for the following covariates: time on the market, floor area, and building age.[8] Since in this project, we are not interested in boundary discontinuities, we refrain from the definition of submarkets.

Descriptives. Figure 1 shows the distribution of rents across postcodes in levels and changes by different LLM sizes. Consistent with the standard land use model, commercial rents are generally higher than residential rents, especially in the large

[7] We use the square of the Root Mean Square Error (RMSE) as an estimate of the error variance.

[8] We measure age as the years since construction or the last modernization, whichever is shorter. We impute missing values in floor and age with the respective means and control for dummies denoting imputed values.

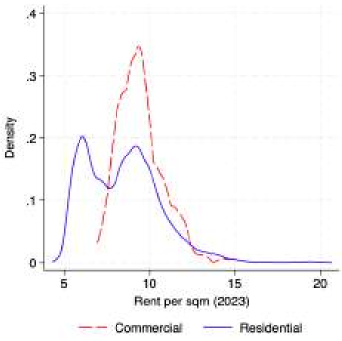
LLM (Panel c). On average, commercial rents are also higher in the other LLMs. There is a handful of postcodes in small and mid-sized LLMs with very high residential rents, which are typically located in upscale touristic areas by the sea or in the Alps (Ahlfeldt et al., 2023). In mid-sized cities, the relatively similar distributions of commercial and residential rents are consistent with mixed land use. In many smaller German cities, land use is less functionally segregated, reflecting planning objectives that promote vibrant city centres used throughout the week and into the evening. These centres combine employment, retail, and leisure activities and are sustained by a resident population. Across all types of LLMs, residential rents tend to appreciate faster than commercial rents. This pattern is consistent with a relative increase in demand for residential floor space, for example due to telecommuting, as well as the presence of binding land-use regulations.

Figure 2a maps our new postcode-level commercial rent index for 2023. As expected, rents are higher in postcode areas close to the centres of the largest LLMs and lower in suburban or more rural areas. Zooming into Berlin, this spatial pattern is even more pronounced. Postcode areas in and around the CBD (circled in red) have the highest commercial rents, which gradually decline with distance from the CBD. The rent index also captures the East–West division of Berlin, with postcode areas in the West having notably higher average commercial rents in 2023. However, Panel (b) shows that East Berlin has been catching up, with rent indices increasing more in the East than in the West between 2007 and 2023. It also shows that areas with the highest rates of appreciation are not located in the city centre but rather in the surrounding ring, reflecting an expansion of commercial activity beyond the traditional core, for example in the rapidly developing *Mediaspree* area. Similar expected gradients are also visible in the next largest 12 cities, for which we present comparable maps in Section S.1 of the Online Supplement.

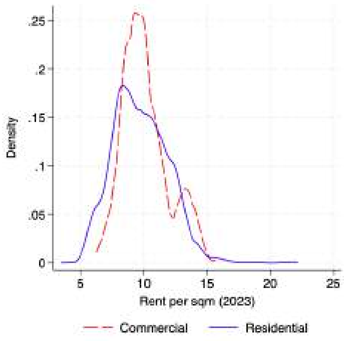
2.3 Prime locations

Raw data. To delineate CBDs, we require micro-geographic information on economic activity. While GDP is not observable at a sufficiently fine spatial scale, we can rely on the RWI-GEO-REDC data to construct a theory-consistent proxy. Under a canonical Cobb–Douglas production function, total payments to floor space are a constant share of output. Therefore, we calculate the *unit value* as the product of rent per sqm and usable area for all units in the RWI-GEO-REDC. This measure can be interpreted as proportional to unit-level output. Since the RWI data reference establishments only at the 1 km $\times$ 1 km grid-cell level, we randomly assign establishments to locations drawn from a uniform distribution within their respec-

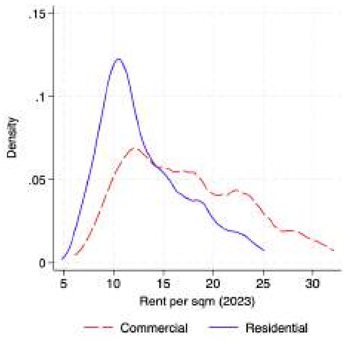
Figure 1: Rents in levels and changes



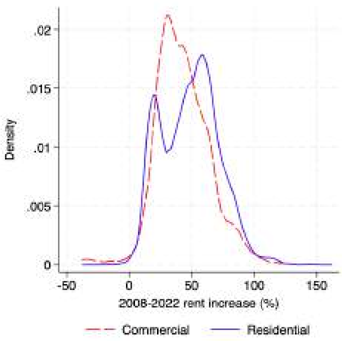
(a) Small LLMs



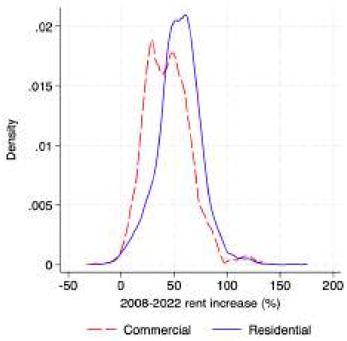
(b) Medium LLMs



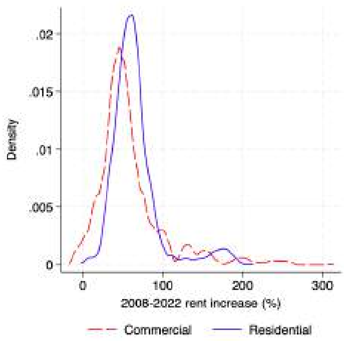
(c) Large LLMs



(d) Small LLMs



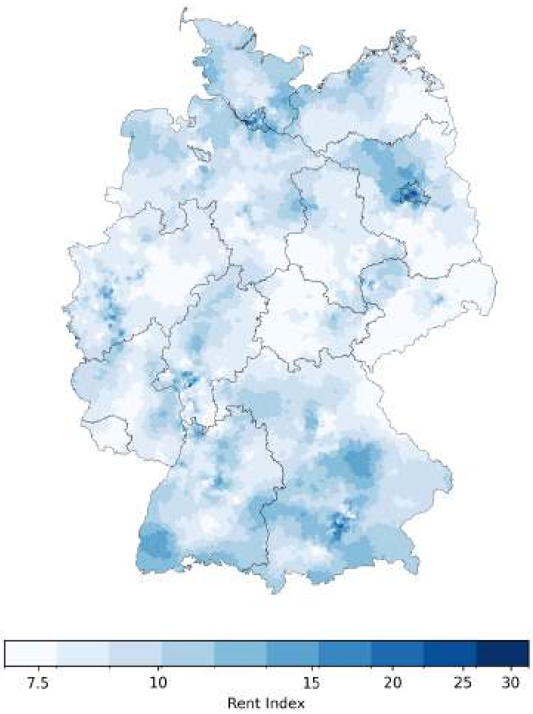
(e) Medium LLMs



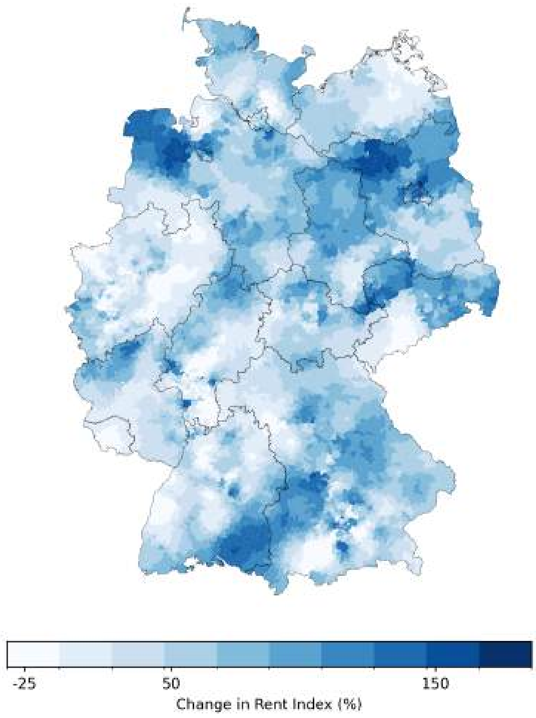
(f) Large LLMs

Note: Red dashed lines are commercial gradients. Blue solid lines are residential gradients. Locally weighted polynomial regressions. The rent indices are weighted by the floor space available in each postcode regions. Small, medium, large refer to LLMs with up 250k, 250-750k and more than 750k population.

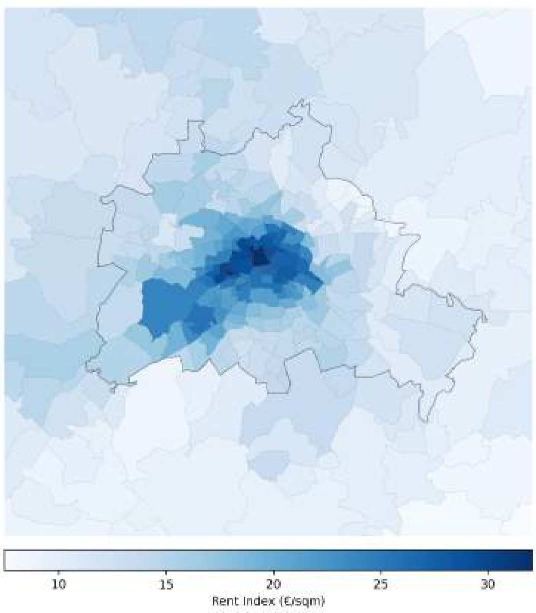
Figure 2: Commercial rents by postcode



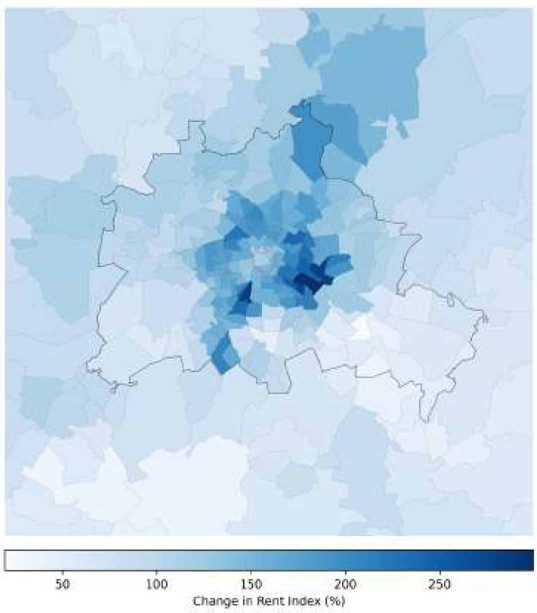
(a) Germany: 2023 rent (€/sqm)



(b) Germany: % change 2007–2023



(c) Berlin: 2023 rent (€/sqm)



(d) Berlin: % change 2007–2023

Note: For panel (a) and (b), the black lines are German state borders. For panel (c) and (d), the grey lines are the postcode region boundaries and the black lines are the local labor market boundaries. Prime locations are circled in red.

tive grid cells when computing establishment coordinates to generate a fine-grained spatial distribution.

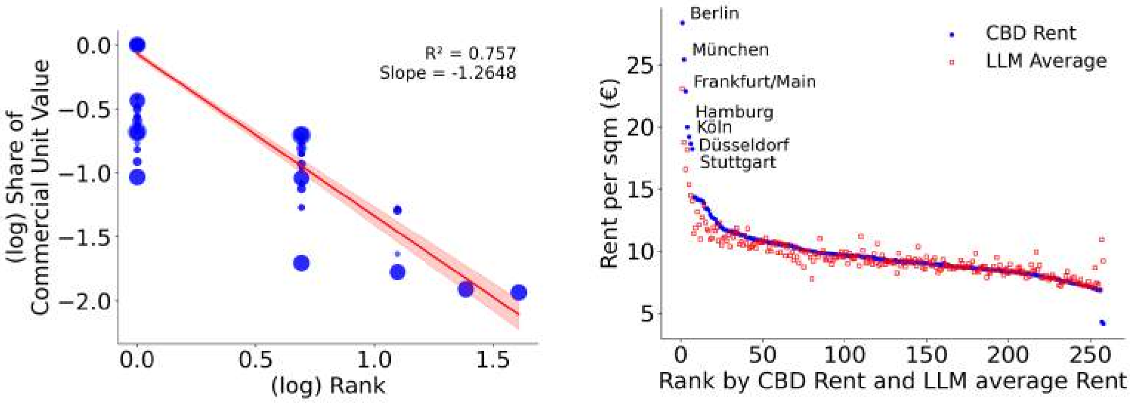
Algorithm. We identify prime locations as clusters of grid cells with abnormally high densities of economic activity, following the procedure detailed in Ahlfeldt et al. (2025). To this end, we apply the Ahlfeldt et al. (2024) toolkit to the establishment-level measures of unit value, looping over all 258 LLMs in Germany.

Intuitively, we proceed as follows: First, we draw 100k random points within the commercial areas of an LLM and compute the density within a disk of radius 750 meters around each point. To identify commercial areas, we overlay a 250 meter × 250 meter grid and keep only grid cells with at least one commercial unit in our data. Once the draws are completed, we obtain the 99.5th percentile cutoff of the density distribution for this LLM. We then compute the density within a disk of radius 750 meters around all commercial units and flag those points with densities above the cutoff as cluster points. Finally, we join grid cells with at least one cluster point into a single cluster and assign the same cluster ID if they are connected. For cells that contain cluster points but are not connected to the first cluster, a new cluster is assigned until the new cluster accounts for less than 5% of the mass of the largest cluster in the LLM. Clusters with centroid distances shorter than 2.5 km or border distances of less than 1 km are also merged. This approach does not impose any restrictions on the location, size, or number of prime locations allowed in each LLM and identifies areas of very high density by detecting cells that contain points with abnormally high unit values—levels that are highly unlikely to arise from spatial randomness within the LLM.

Descriptive statistics. For the 258 local labour markets in Germany, we identify 242 prime locations. 74% LLMs have no more than one prime location. For the remaining LLM, we rank all prime locations within by their share of unit value. Figure 3a shows the rank-size distribution of all prime locations. The steep downward slope indicates that the largest prime locations dominate the smaller ones. With a coefficient of -1.26, the second-largest prime location has only about 41.62% of the mass of the largest prime location. While many German LLMs are polycentric, the pronounced degree of primacy implies that a monocentric framework provides a useful and parsimonious summary of the internal structure of German LLMs, with the largest prime location serving as the CBD.

Figure 3b shows that the seven largest CBDs—Berlin, Munich, Frankfurt, Hamburg, Cologne, Düsseldorf, and Stuttgart—exhibit commercial rents that are substantially higher than those in the rest of Germany, whereas CBD rents are relatively

Figure 3: Rank-size distributions for German prime locations



(a) Prime location value share by rank

(b) CBD rent per sqm by rank

Note: Panel (a) shows the share of commercial unit value for all prime locations and their rank (within the LLM, in log) across all cities. The red line shows the OLS fit. Panel (b) shows average commercial rent in the CBD (calculated as the weighted average of commercial rent indices of all postcode regions that are partially within the delineated prime locations, using intersected area size as weights) and their rank within Germany. For LLMs without a prime location, we impute the CBD rent using the commercial rent index of the grid cell with the highest value.

similar across all other LLMs. For these cities, CBD rents also stand out relative to commercial rents elsewhere in the city, indicating strong agglomeration economies that make their CBDs exceptionally attractive locations for commercial activity. Readers are referred to Supplement A.1 for a detailed table of commercial rents and changes over time for all 258 LLMs. Notably, the seven outliers with the highest CBD rents coincide with conventional rankings of cities by business opportunities, such as *Best Cities in Germany for Work* (Studying in Germany, 2024). This is reassuring, as it confirms that the combination of algorithms employed to generate the commercial rent index and to delineate CBDs successfully uncovers the leading business centres in Germany that we would expect to observe, lending credibility to both algorithms at the same time.

3 Empirical analysis

3.1 Intuition

The analysis so far suggests that German cities can be reasonably approximated as monocentric, as LLMs are strongly dominated by a single largest prime location, the CBD. However, the classical neoclassical monocentric city model synthesized by

Brueckner (1987) is not well suited to guide our analysis. In these models, the CBD is reduced to a single point with no spatial extent, and the commercial real estate market and commercial rent gradients are typically absent. We therefore employ a land use framework in which the CBD has positive mass and its spatial extent is endogenously determined by the interaction between commercial and residential bid rents, as in Duranton and Puga (2015). Specifically, we follow the functional forms and basic notation of the monocentric general-equilibrium land use model in Ahlfeldt and Barr (2022), though we use this framework primarily to guide a partial-equilibrium analysis.[9] We extend the framework and the notations to a multi-city setting.

Workers. Consider n linear, symmetric, and open cities. There are N_i identical individuals in city i, for $i = 1, \ldots, n$. Individuals are mobile within cities. They earn a city-specific wage y_i and live at location x. The centre of the CBD is located at $x = 0$, so that distance from the CBD is $d = |x|$. We further assume that cities are symmetric, so that locations within a city can be summarized by x. Worker income is fully spent on residential floor space, $f_i^R(d)$, and a tradable good g, with the price of the latter normalized to one. Individuals maximize the following utility function:

$$U_i(d) = A_i^{R(d)} \left(\frac{g}{\alpha^R}\right)^{\alpha^R} \left(\frac{f_i^{R_i(d)}}{1-\alpha^R}\right)^{1-\alpha^R},$$

where A^R is the residential amenity and α^R is the expenditure share on tradable goods, with $0 < \alpha^R < 1$. The residential amenity, $A^R(d) = \bar{a}^R e^{\tau_i^R d}$, is assumed to decrease with distance from the CBD, where $\bar{a}^R$ is the residential amenity at the city centre and $\tau_i^R < 0$ is a parameter governing the rate of decay. $\tau_i^R(N_i)$ is a function of city size since larger cities may have better transport infrastructure and be more congested. This formulation is consistent with individuals visiting the central point once per day and transport being inconvenient but free, arguably a reasonable approximation for German cities with strong CBDs and well-developed public transit and cycling infrastructure. $p_i^R(d)$ denotes the unit price of residential floor space at distance d in city i. Individuals, therefore optimize their location choice subject to the budget constraint $y_i = p_i^R(d) f_i^R(d) + g$.

Since workers are mobile within cities, the utility levels within all cities are equal. We denote city utility levels by $\bar{U}_i$ and solve for the residential bid rent as a function

[9] We also abstract from within-building differences in productivity.

of distance d as follows:

$$\ln p_i^R(d) = \frac{1}{1-\alpha^R}\left(\ln \bar{a}_i^R - \ln \bar{U}_i + \tau_i^R d + \ln y_i\right). \tag{2}$$

Firms. We assume perfect competition and a Cobb-Douglas production function with two input factors, labor, l, and floor space, $f_i^C(d)$, whose price is a function of distance from the CBD. α^C is the fixed factor share of labor. The production function of a firm in city i is:

$$g_i(d) = A_i^C(d, N_i)\left(\frac{l_i}{\alpha^C}\right)^{\alpha^C}\left(\frac{f_i^C(d)}{1-\alpha^C}\right)^{1-\alpha^C}, \quad 0 < \alpha^C < 1. \tag{3}$$

For each city, productivity is assumed to be highest at the CBD and to decline with distance. Let β_i denote the city-specific agglomeration effect. The location-specific productivity shifter in city i at distance d from the CBD is:

$$A_i^C(d, N_i) = \bar{a}_i^C N_i^{\beta_i} e^{\tau_i^C d}, \tag{4}$$

where $\bar{a}$ denotes fundamental productivity at the CBD ($d = 0$) and $\tau_i^C(N_i) < 0$ is the city-specific decay parameter of productivity. τ_i^C is assumed to be a function of city size, allowing for different rates of productivity decay, as larger cities may offer better transport infrastructure or be more congested. The term $A_i^C(d, N_i)$ summarizes the agglomeration effects on productivity at each location in city i. Duranton and Puga (2004) discuss several micro-foundations of agglomeration effects, including sharing, matching, and learning. $\beta_i(N_i)$ denotes the agglomeration elasticity of productivity, which determines how the agglomeration effect increases with city size and may itself vary with city size, as cities of different sizes differ in industry and skill composition, generating different urbanization and localization economies.

The zero-profit condition yields the commercial bid rent as a function of distance from the CBD, city size, and wages:

$$\ln p_i^C(d, N_i) = \frac{1}{1-\alpha^C}(\ln \bar{a}_i^C + \beta_i \ln N_i + \tau_i^C d) + \frac{\alpha^C}{\alpha^C - 1}\ln y_i. \tag{5}$$

The CBD rent at $d = 0$, is $\ln p_i^C(0, N_i) = \frac{1}{1-\alpha^C}\left(\ln \bar{a}_i^C + \beta_i \ln N_i\right) + \frac{\alpha^C}{\alpha^C-1}\ln y_i$, which we can use to express the endogenous productivity (including agglomeration benefits) at the CBD as follows:

$$\ln A_i^C(d = 0, N_i) = (1 - \alpha^C)\ln p_i^C(0, N_i) + \alpha^C \ln y_i. \tag{6}$$

Equation (6) guides our empirical analysis of the capitalization of agglomeration economies into commercial rents. We do so by estimating how commercial CBD rents scale with city size. Combined with the agglomeration elasticity of wages, this allows us to recover the total agglomeration effect capitalized through both wages and commercial rents. Formally,

$$\frac{\partial \ln A_i^C(d=0,N_i)}{\partial \ln N_i} = \beta_i = (1-\alpha^C)\underbrace{\frac{\partial \ln p_i^C(d=0,N_i)}{\partial \ln N_i}}_{\substack{\text{city-size elasticity}\\ \text{of CBD rent}}} + \alpha^C \underbrace{\frac{\partial \ln y_i}{\partial \ln N_i}}_{\substack{\text{city-size elasticity}\\ \text{of wage}}} . \tag{7}$$

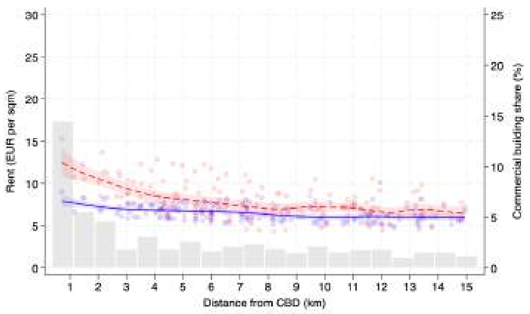
3.2 Rent gradients

The granularity of our commercial rent index permits the analysis of changes over time for areas as small as postcode regions. We begin by showing gradients for the two cities with the highest commercial rents, Berlin and Munich, over a 15-year period in Figure 4. Munich has traditionally been the most expensive city, while Berlin is the city that has appreciated the fastest. Distance is calculated between the centroids of the CBD and all postcode regions within the LLM.

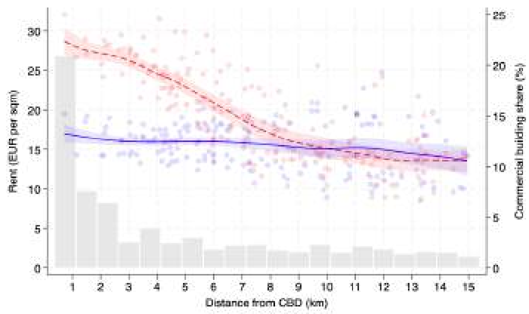
As predicted by Eq. (5), commercial rent gradients decline with distance from the CBD, reflecting falling productivity. Similarly, residential rent gradients fall as predicted by Eq. (2), reflecting the increasing inconvenience of commuting. Standard urban land use models (Duranton and Puga, 2015) also predict that commercial and residential rent gradients intersect close to the CBD, a pattern that is clearly visible for Munich in 2008. Within the CBD, commercial rents exceed residential rents, which is consistent with a higher share of commercial buildings. Because residential rent gradients are less steep than commercial rent gradients, residential use dominates beyond the point where the two gradients intersect.

By 2022, however, this intersection has shifted very close to the CBD in Munich, owing to residential rents outpacing commercial rents. As a result, residential rents are higher than commercial rents at almost all distances from the CBD. One explanation for this pattern is that residential development may not have kept pace with the rapid growth in housing demand, potentially due to land use regulations that favor commercial development. Indeed, we observe a sizeable increase in the share of commercial buildings between 2008 and 2022, particularly in the urban outskirts. Moreover, there is a pronounced increase in the share of commercial buildings at around 10 km from the CBD, accompanied by a modest rise in both commercial and residential rents, although neither reaches the levels observed in the CBD. This pattern is indicative of emerging subcenters and a more polycentric urban struc-

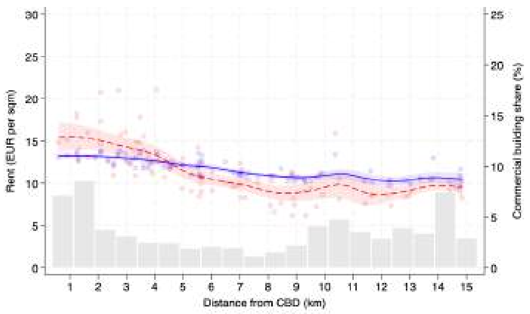
Figure 4: Rents Gradient for Berlin and Munich



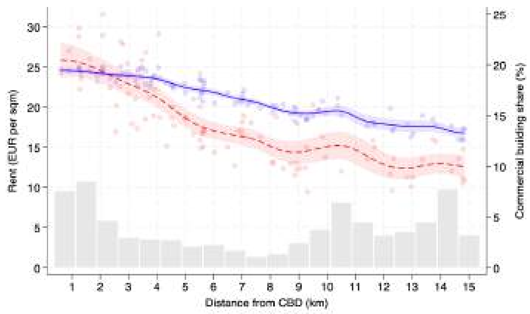
(a) Berlin, 2008



(b) Berlin, 2023



(c) Munich, 2008



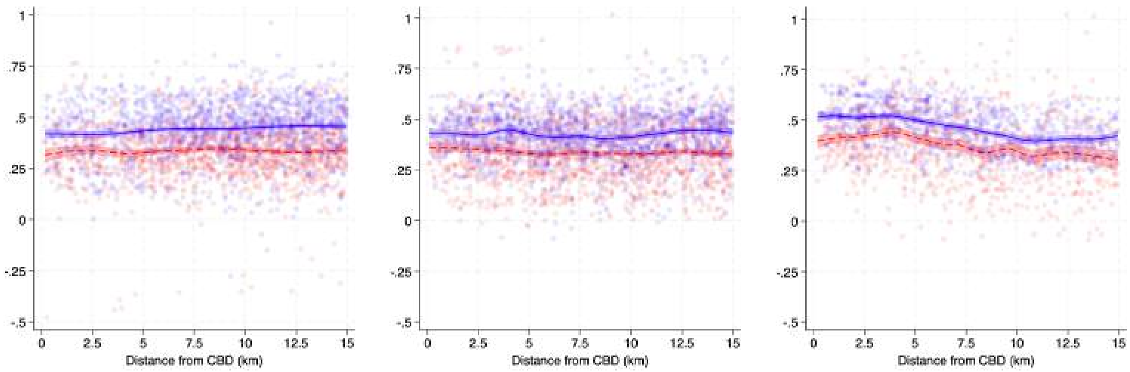
(d) Munich, 2023

Note: Point estimates and confidence intervals are from locally weighted polynomial regressions using Gaussian kernels at the postcode level (each dot represents on postcode). Red dashed lines are commercial gradients. Blue solid lines are residential gradients.

ture in Munich. Of course, the marked increase in residential rents could also be explained by increased quality of life (Roback, 1982).

In contrast, commercial rents exceed residential rents at all locations in Berlin, a pattern consistent with zoning regulations that favor residential use over commercial development. Such regulations constrain the supply of commercial floor space and can lead to a rapid appreciation of commercial rents. Consistent with this interpretation, we observe a sharp increase in the share of commercial buildings close to the CBD over time, while the commercial share remains largely unchanged at greater distances. The absence of a comparable expansion of commercial floor space outside the city centre suggests that the commercial market has remained tightly constrained. This helps explain why Berlin has overtaken Munich in terms of CBD commercial rents, while remaining comparatively more affordable for residents. Overall, Berlin's rent gradients potentially reflect the effects of restrictive zoning policies on the spatial allocation of commercial floor space. Of course, the lower residential rent level compared to Munich could also be explained by a lower quality of life (Roback, 1982).

Figure 5: Rent appreciation



(a) Small LLMs (b) Medium LLMs (c) Large LLMs

Note: Red dashed lines are commercial gradients. Blue solid lines are residential gradients. Locally weighted polynomial regressions. Small, medium, large refer to LLMs with up 250k, 250-750k and more than 750k population, excluding Berlin, which is a positive outlier as shown in Figure 4.

To provide a more general picture of rent appreciation over the study period, Figure 5 compares changes in commercial and residential rents across local labour markets (LLMs) of different sizes. For small and medium LLMs (with populations below 750,000), appreciation rates are largely insensitive to distance from the CBD, while residential rents increase more strongly than commercial rents. In larger LLMs, rent gradients have become steeper over time, consistent with the resurgence of downtown areas in consumer cities (Glaeser et al., 2001). More generally, the fact that residential rent growth exceeds commercial rent growth in most cities outside

Berlin is consistent with a shift in demand—potentially related to increased working from home—interacting with land use constraints. Table A3 provides additional summary statistics on rent appreciation by LLM size.

To further explore heterogeneity over space and time, we estimate reduced-form versions of Eqs. (2) and (5) for each LLM i and year t:

$$\ln \text{rent}_{b,i,t} = a_{c,t} + b_{i,t} d_{b,i,t} + \epsilon_{b,i,t} \tag{8}$$

where b indexes a 1-km distance from CBD bin in LLM c in year t and $\text{rent}_{b,i,t}$ is the mean rent within a city-distance-year-bin, and $\epsilon_{b,i,t}$ is an error term. Estimating the gradient model at the level of bins instead of postcodes (or units) avoids over-weighting remote locations in circular cities where area within distance rings naturally increases in distance (Gonzalez-Navarro and Turner, 2018). The estimated intercepts, $\hat{a}_{c,t}$, represent theory-consistent measures of CBD rent, whereas the estimates of the slope parameters capture the decay in amenity and productivity weighted by the shares of floor space in consumption and production, $\hat{b} = \frac{\tau^U}{1-\alpha^U}$, where $U = \{C, R\}$.

Figure 6 summarizes the estimates from Eq. (8) and provides a comprehensive overview of commercial rent gradients across German cities over time. Consistent with standard land use theory, rent gradients are negative throughout. In large LLMs, commercial rent gradients are substantially steeper than in small and medium LLMs. In the latter, gradients remain negative but are considerably flatter. This pattern is consistent with Figure 3 and highlights that strong spatial concentration of commercial activity is primarily a feature of large cities. The pronounced differences in gradients across city sizes underscore the importance of modelling the productivity decay parameter, τ_i, as a function of city size; failing to do so would not only obscure important heterogeneity but also attenuate the estimated CBD rent premium in large cities.

Over time, CBD rents in large cities have continued to increase, with little evidence of COVID-induced negative shocks. If anything, CBDs in large cities appear stronger than ever. Commercial rent gradients have become steeper, mirroring the pattern in Figure 5a, where appreciation rates decline with distance from the CBD. Residential rent gradients also remain negative throughout, but have flattened since COVID, indicating a relative increase in the attractiveness of suburban residential locations. This flattening is visible not only in large LLMs but also in smaller cities, suggesting a broad-based shift in residential demand consistent with increased working from home.

Figures 6e and 6f report the R^2 values from simple OLS regressions of rents on distance to the CBD. Despite using distance as the sole regressor, the model explains around 67% of the variation in commercial rents and 66% in residential rents in large LLMs, with explanatory power remaining high—and even increasing—over time. These results demonstrate that, despite its parsimonious structure, the monocentric land use model continues to provide a highly relevant and informative framework for understanding rent patterns in German cities.

3.3 Agglomeration effects

It is well-documented that residential rents at the CBD—i.e. rents adjusted for commuting costs—increase with city size, reflecting a sizeable costs of agglomeration (Combes et al., 2019). The effect of city size on commercial rents is equally interesting, as commercial floor space is a key input in firms' production functions alongside labor. Yet, this channel has received little attention, most likely because comprehensive data on commercial rents is less accessible. Understanding how agglomeration effects capitalize into commercial rents is important, as productivity advantages are priced into rents in a standard spatial equilibrium framework (Roback, 1982). Focusing exclusively on wages to infer agglomeration effects may therefore mask part of the productivity gains associated with agglomeration that are instead capitalized into the cost of commercial floor space.

Figure 7 reports a positive correlation between LLM population and the CBD rent estimated using Eq. (8). The relationship holds for both residential and commercial rents and both years, suggesting that agglomeration effects on productivity are indeed priced into the commercial rents. The relationship is mildly convex, pointing to agglomeration-induced productivity effects that are particularly pronounced for large cities.

For a parametric estimate of the city-size elasticity of CBD rent in Eq. (7), we regress the log of the CBD rent against the log of the 2022 population. Thus, we estimate the second-stage equation

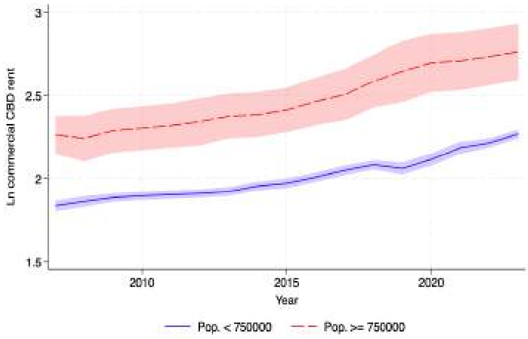
$$\ln(\text{CBD rent}_i) = \gamma_0 + \gamma_1 \ln \widehat{\text{pop}}_i^{2022} + \gamma_2 \ln \text{area}_i + \varepsilon_i \tag{9}$$

with the corresponding first stage

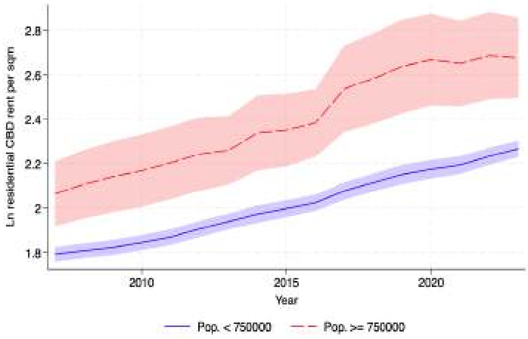
$$\ln \text{pop}_i = \delta_0 + \delta_1 \ln \text{pop}_i^{1871} + \delta_2 \ln \text{area}_i + \nu_i \tag{10}$$

using 2SLS. As implied by Eq. (7), inferring the agglomeration elasticity β from the reduced-form elasticity estimates reported in Table 1 requires values for both the

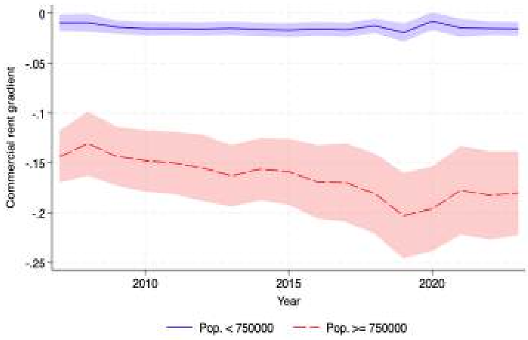
Figure 6: Parametric rent gradients



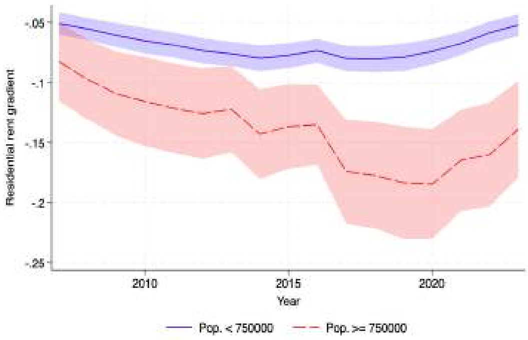
(a) CBD Rent, commercial



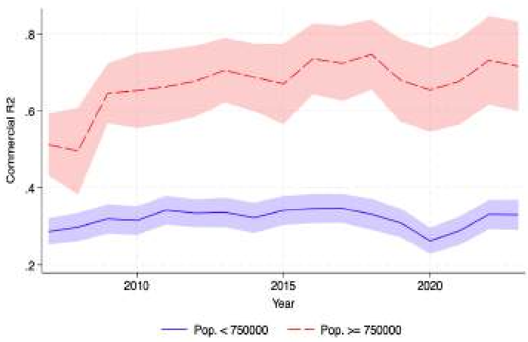
(b) CBD Rent, residential



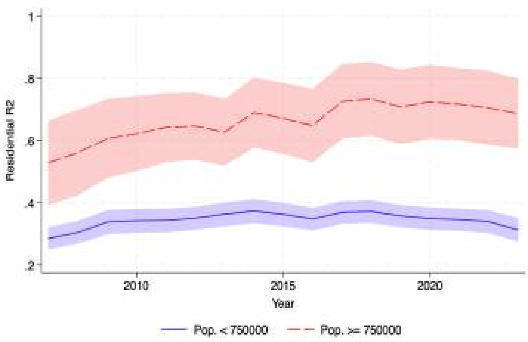
(c) Rent Gradient, commercial



(d) Rent Gradient, residential



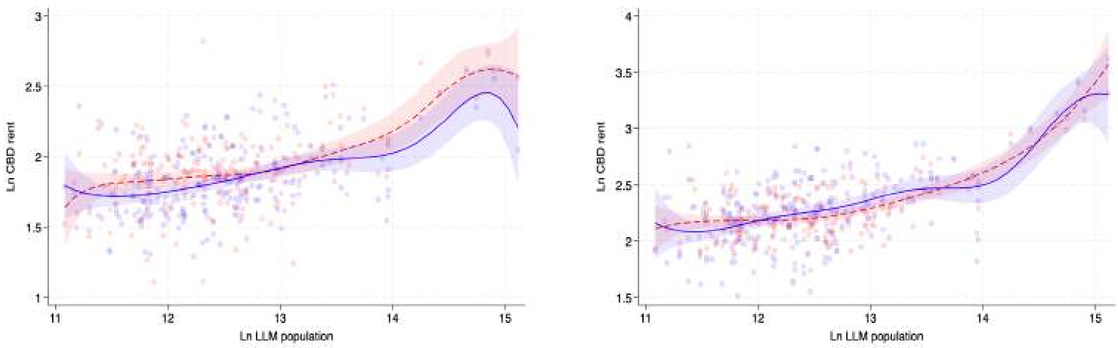
(e) R^2, commercial



(f) R^2, residential

Note: This figure shows the estimated central business district (CBD) rent levels, rent gradients, and model fit statistics for both commercial and residential units. Panels (a), (c), and (e) correspond to commercial data; panels (b), (d), and (f) show the respective residential estimates. Graphs summarize CBD rent (a) coefficients and the gradient coefficients (b) along with the R^2 from 258 (LLM) x 13 (years) regressions of Eq. (8). The shaded areas are 95% confidence intervals resulting from taking the mean across LLMs within years.

Figure 7: Parametric rent gradients



(a) 2008

(b) 2022

Note: This figure shows the estimated central business district (CBD) rent levels against LLM population using local polynomial regressions of degree three with Gaussian kernel (optimal bandwidth). The Shaded areas are 95% confidence intervals resulting from taking the mean across LLMs within years.

city-size elasticity of wages and the input factor share α^C. Estimates of the wage agglomeration elasticity typically fall into the range of 0.02 and 0.04 (Ahlfeldt and Pietrostefani, 2019). For the input share, we use a canonical value of $\alpha^C = 0.85$ (Lucas and Rossi–Hansberg, 2002). Based on the 2022 estimate in Column (2), the implied agglomeration elasticity is then between $\beta = 0.15 \cdot 0.145 + 0.85 \cdot 0.02 = 0.038$ and $\beta = 0.15 \cdot 0.145 + 0.85 \cdot 0.04 = 0.056$. By implication, ignoring the capitalization effect into rents leads to an underestimation of the agglomeration elasticity of about one-third to one-half.[10]

A comparison of Columns (1) and (2) reveals an increase in the rent capitalization effect of agglomeration over time, adding to the rise in the urban wage premium that has already been documented for Germany (Dauth et al., 2022). Hence, the urban productivity premium is not only larger than previously assumed, it is also increasing more strongly over time.

Column (3) confirms the impression from Figure 7 that commercial rents increase with city size at an increasing rate, as the squared population term is positive and statistically significant. Because log population is rescaled to have zero mean, the coefficient on the linear term captures the marginal effect at the LLM with mean log population. At this level, the capitalization effect is close to zero, implying that the average effect is driven entirely by larger LLMs, for which we estimate substantially higher elasticities. For example, for Augsburg—a city with a population of 690k and approximately one log unit above the mean—the implied elasticity is as large as

[10]First stage results and OLS estimates without historical population as IV are reported in A5 and A4.

0.408 (2×0.204), corresponding to an agglomeration elasticity in the range of 7% to 9%. Hence, the underestimation of agglomeration elasticities resulting from ignoring rent capitalization is primarily a concern for large cities. This finding is consistent with Ahlfeldt et al. (2015), who account for the capitalization of productivity into both wages and rents and estimate an agglomeration elasticity of 7% based on a within-city analysis of Berlin.

For comparison, we also estimate the elasticity of residential rents with respect to city size. On average, its magnitude is similar to that of commercial rents, it increases over time at a comparable rate, and the relationship is convex, albeit less strongly than for commercial rents. The residential rent elasticity in Germany is smaller than that estimated for France, where it is around 0.25 (Combes et al., 2019). However, for larger cities, our estimates fall within a similar range. For Augsburg, for example, the implied elasticity is approximately $2 \cdot 0.144 = 0.288$, which is close to the values of about 0.3 reported for large French cities.

Taken together, the results in Table 1 imply that higher floor space rents in larger cities are as relevant for firms as they are for residents. Residents benefit from urban productivity premia through higher wages, which allow them to afford more expensive housing in dense cities. Firms, in turn, pay higher wages to attract workers but also compete directly with residents for scarce floor space. While the cost of agglomeration for workers reflects productivity advantages indirectly—through higher wages that bid up residential rents—the capitalization of productivity into commercial rents captures the agglomeration effect more directly. In both cases, productivity advantages in large, dense cities come at a price: firms ultimately pay for access to these advantages through premia on both wages and rents. In this sense, our results provide a unified perspective on the price of productivity in urban environments.

4 Conclusion

This paper highlights a limitation of standard empirical approaches to measuring agglomeration economies. When commercial floor space is an essential and inelastically supplied input—as is typical for tradable services in dense urban cores—productivity advantages are capitalized not only into wages but also into commercial rents. Because data on commercial rents are rarely observed, the literature has largely inferred agglomeration effects from spatial variation in wages alone, thereby missing an important capitalization channel. By observing commercial rents directly, we show that this omission leads to an understatement of agglomeration gains, especially in

Table 1: Agglomeration Elasticities: 2SLS Estimates

	Commercial			Residential		
	(1)	(2)	(3)	(4)	(5)	(6)
Year	2008	2022	2022	2008	2022	2022
Ln population	0.113***	0.148***	-0.019	0.082**	0.106**	-0.027
	(0.035)	(0.052)	(0.050)	(0.033)	(0.050)	(0.051)
Ln area	-0.030	-0.005	0.015	0.016	0.052	0.068**
	(0.022)	(0.028)	(0.023)	(0.021)	(0.032)	(0.027)
Ln population qs.			0.208***			0.166***
			(0.040)			(0.036)
Constant	2.519***	2.368***	1.838***	1.487***	1.182*	0.758
	(0.465)	(0.591)	(0.491)	(0.438)	(0.667)	(0.575)
Year	2008	2022	2022	2008	2022	2022
R^2	0.200	0.309	0.361	0.173	0.226	0.191

Notes: The dependent variable is the log commercial or residential rent in the central business district (CBD) of a local labour market (LLM). Each observation corresponds to one LLM. Population is measured in 2022. ln population is rescaled to have a zero mean, so that the coefficient on the linear term in the quadratic models (3) and (6) gives the marginal effect for the LLM with the mean log population. Historic population (the instrumental variable) is from 1871. Area controls capture the total land area of the LLM. Estimation is by two-stage least squares (2SLS). Robust standard errors are reported in parentheses. Historical population data for 1871 are drawn from Roesel (2022). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

large cities and prime locations where competition for space is most intense. Importantly, productivity is not capitalized into rents instead of wages; rather, wage-based measures capture only part of the price system through which productivity differences are reflected, so accounting for commercial rents changes both the level and the spatial distribution of estimated agglomeration elasticities.

Our results also have implications for quantitative modeling. A key contribution of the paper is the development of a methodology to construct comprehensive microgeographic commercial rent indices in sparse data environments, and the resulting rent index for Germany. These indices make it possible to incorporate spatial variation in the prices of both production factors into quantitative urban models, allowing researchers to recover fine-grained variation in total factor productivity rather than inferring productivity differences from wages alone. The agglomeration elasticity inferred from a quantitative urban model will be larger than that obtained from models that rely solely on labor-market outcomes, yielding improved structural estimates and more realistic counterfactual analyses.

A larger total agglomeration elasticity has important policy implications. If the total productivity advantages from spatial concentration exceed those captured by wage-based estimates, then constraints that limit firms' access to dense, high-productivity locations—most notably tight land-use regulation in superstar cities—

imply larger efficiency losses than previously measured (Hsieh and Moretti, 2019). Conversely, policies and investments that facilitate agglomeration, such as transport infrastructure that improves access to central business districts or expands the effective supply of commercial floor space, may generate higher productivity gains and social returns than conventional evaluations suggest. More broadly, the strong capitalization of productivity into commercial rents helps explain the persistence of spatial concentration in large cities, where firms continue to locate in central areas even as the cost of commercial floor space rises steeply.

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A Appendix

This appendix contains detailed summary statistics of the two main spatial units: local labour market and postcode regions.

A.1 Descriptive statistics

Table A3 reports the various appreciation rates of commercial or residential rents of the postcode regions, grouped by the LLM sizes and distance from the prime location.

Table A1: Summary Statistics: Local Labour Market (LLM)

	Value
Coverage	
Number of LLMs	258
Geographic/Demographic characteristics	
Mean population	321,212
Mean area (km^2)	1,382
Std. dev. area (km^2)	936
Postal code zones (PLZ)	
Mean per LLM	32.0
Std. dev. per LLM	28.7
Range	[5, 230]
Commercial unit listings	
Mean per LLM	5,123
Std. dev. per LLM	30,793

Notes: Statistics describe the 258 local labor markets (LLM) used in the analysis, following the delineation of BBSR (n.d.). Population and area figures reflect averages across all LLMs.

A.2 Estimates

This section complements Section 3.

Table A2: Summary Statistics: Postal Code Zones (PLZ)

	Value
Coverage	
Number of PLZs	8255
Demographic characteristics	
Mean population	10,073
Std. dev. population	9,524
Geographic characteristics	
Mean area (km^2)	43.2
Std. dev. area (km^2)	53.9
Commercial unit listings	
Mean per PLZ	160
Std. dev. per PLZ	1,514

Notes: Statistics describe the 8255 postal code zones (Postleitzahl, PLZ) used in the analysis. PLZs are nested within local labour markets. We construct the rent index at the PLZ-level.

Table A3: Appreciation rates by city sizes and distance to prime location

Distance Category	Commercial			Residential		
	Small	Medium	Large	Small	Medium	Large
Distance $\leq$ 5 km	51.70%	53.00%	63.37%	56.33%	57.24%	67.50%
5 km $<$ Distance $\leq$ 10 km	52.19%	51.64%	61.28%	57.84%	55.84%	63.89%
10 km $<$ Distance $\leq$ 20 km	51.59%	51.41%	54.41%	58.62%	57.40%	57.42%
Distance $>$ 20 km	52.08%	52.25%	50.37%	56.57%	56.78%	56.47%

Notes: Average appreciation rates are calculated as the percentage change in commercial or residential rent from 2008 to 2022 for each bin of postcode area. Small, medium, and large refer to local labour markets (LLMs) in which the postcode areas are located. Small LLMs have less than 250 thousand people, medium refers to LLMs between 250 and 750 thousand people, and large refers to LLMs with more than 750 thousand people. Distance from PL is calculated as the distance between the postcode centroid to the biggest prime location centroid within the LLM.

Table A4: Agglomeration Elasticities: OLS Estimates

	Commercial			Residential		
	(1)	(2)	(3)	(4)	(5)	(6)
Year	2008	2022	2022	2008	2022	2022
Ln population	0.181***	0.214***	0.124***	0.171***	0.234***	0.180***
	(0.024)	(0.032)	(0.025)	(0.026)	(0.031)	(0.033)
Ln area	-0.057***	-0.031	-0.022	-0.018	0.002	0.007
	(0.021)	(0.023)	(0.019)	(0.021)	(0.029)	(0.027)
Ln population qs.			0.119***			0.072***
			(0.017)			(0.020)
Constant	3.080***	2.911***	2.650***	2.216***	2.230***	2.072***
	(0.426)	(0.476)	(0.395)	(0.437)	(0.615)	(0.568)
Year	2008	2022	2022	2008	2022	2022
R^2	0.233	0.340	0.481	0.232	0.306	0.341

Notes: This table report results of the OLS estimation. The dependent variable is the log commercial or residential rent in the central business district (CBD) of a local labour market (LLM). Each observation corresponds to one LLM. Population is measured in 2022. ln population is rescaled to have a zero mean, so that the coefficient on the linear term in the quadratic models (3) and (6) gives the marginal effect for the LLM with the mean log population. Area controls capture the total land area of the LLM. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Agglomeration Elasticities: First Stage Results

	Commercial			Residential		
	(1)	(2)	(3)	(4)	(5)	(6)
Year	2008	2022	2022	2008	2022	2022
Ln population in 1871	0.948***	0.948***	-3.480***	0.948***	0.948***	-3.480***
	(0.068)	(0.068)	(0.885)	(0.068)	(0.068)	(0.885)
Ln area	-0.105*	-0.105*	-0.078	-0.105*	-0.105*	-0.078
	(0.057)	(0.057)	(0.050)	(0.057)	(0.057)	(0.050)
Ln population qs.			0.190***			0.190***
			(0.039)			(0.039)
Constant	-8.708***	-8.708***	16.385***	-8.708***	-8.708***	16.385***
	(1.141)	(1.141)	(5.006)	(1.141)	(1.141)	(5.006)
Year	2008	2022	2022	2008	2022	2022
R^2	0.599	0.599	0.630	0.599	0.599	0.630
Observations	214	214	214	214	214	214

Notes: This table reports the first stage results of the 2SLS estimation. The dependent variable is the log population in 2022 of a local labour market (LLM). Each observation corresponds to one LLM. ln population is rescaled to have a zero mean. Historic population (the instrumental variable) is from 1871. Area controls capture the total land area of the LLM. Robust standard errors are reported in parentheses. Historical population data for 1871 are drawn from Roesel (2022). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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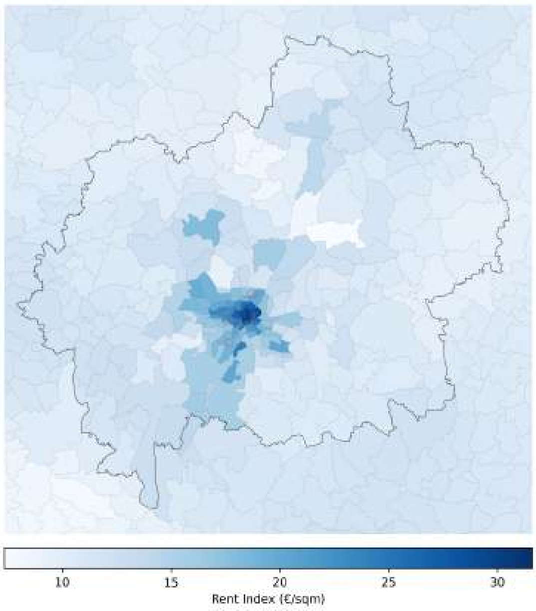
S Online Supplemental Appendix

This supplement contains maps of commercial rent levels in 2023 and changes between 2007 and 2023 for the 12 largest cities (after Berlin) in Germany. We also provide a complete table of all LLMs ranked by the commercial rent in CBD in 2024.

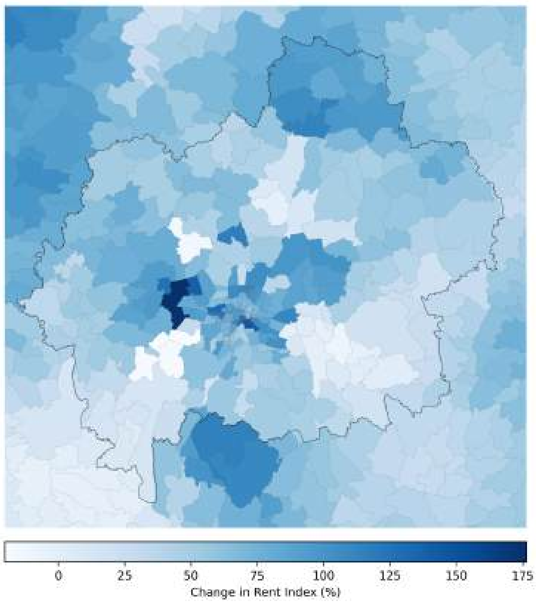
S.1 City maps

This section complements Section 2.2.

Figure S1: Commercial Rent in Munich



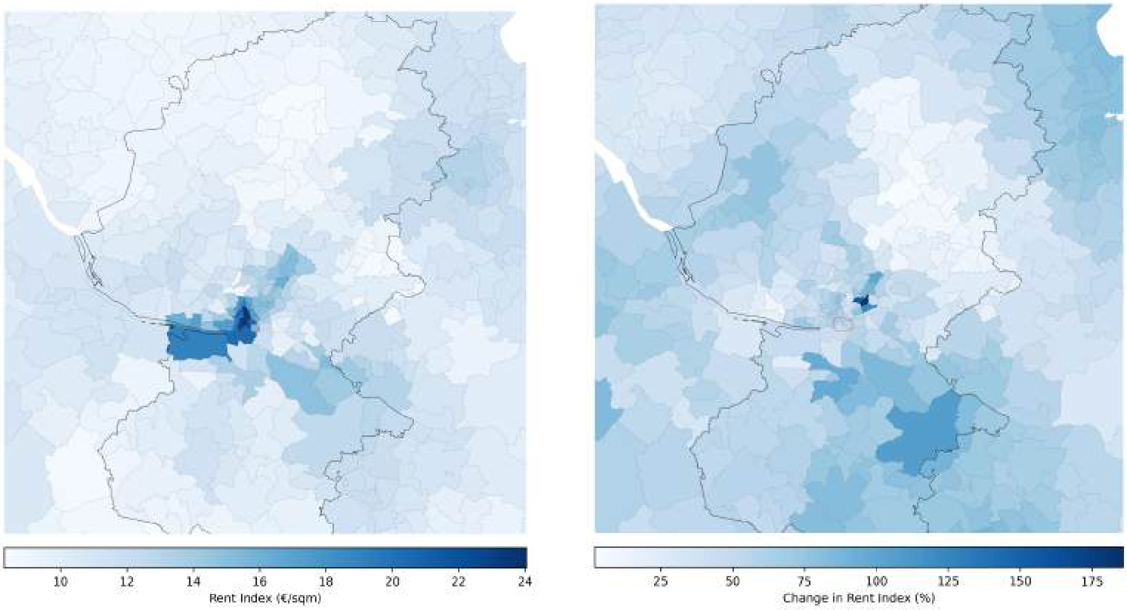
(a) Munich: 2023 rent (€/sqm)



(b) Munich: % change 2007–2023

Note: Grey lines denote postcode region boundaries; black lines denote local labor market boundaries. Prime locations are circled in red.

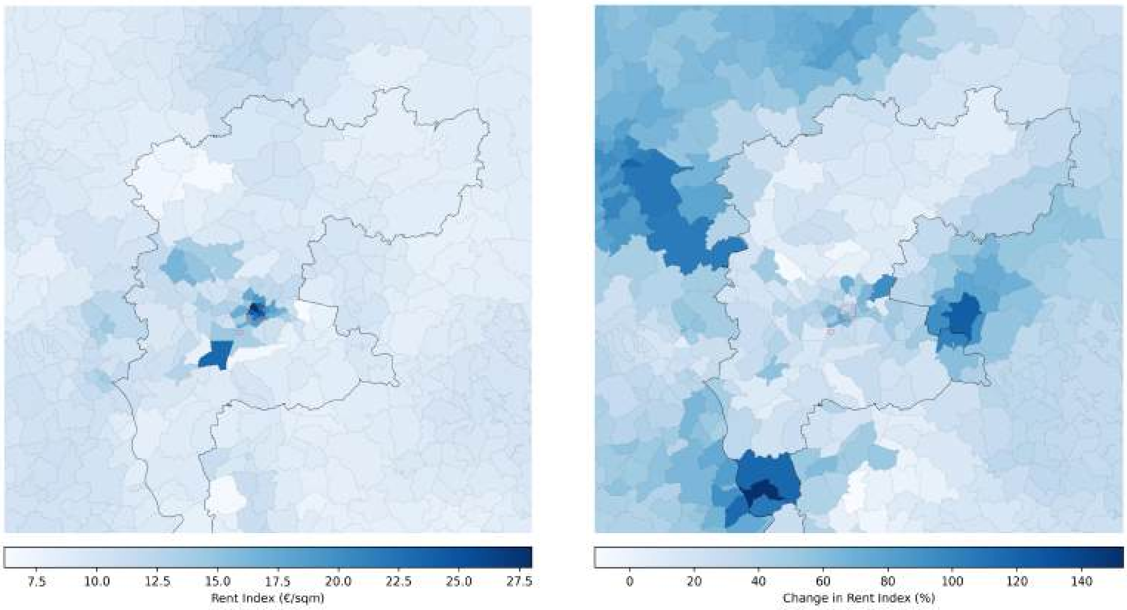
Figure S2: Commercial Rent in Hamburg



(a) Hamburg: 2023 rent (€/sqm) (b) Hamburg: % change 2007–2023

Note: Grey lines denote postcode region boundaries; black lines denote local labor market boundaries. Prime locations are circled in red.

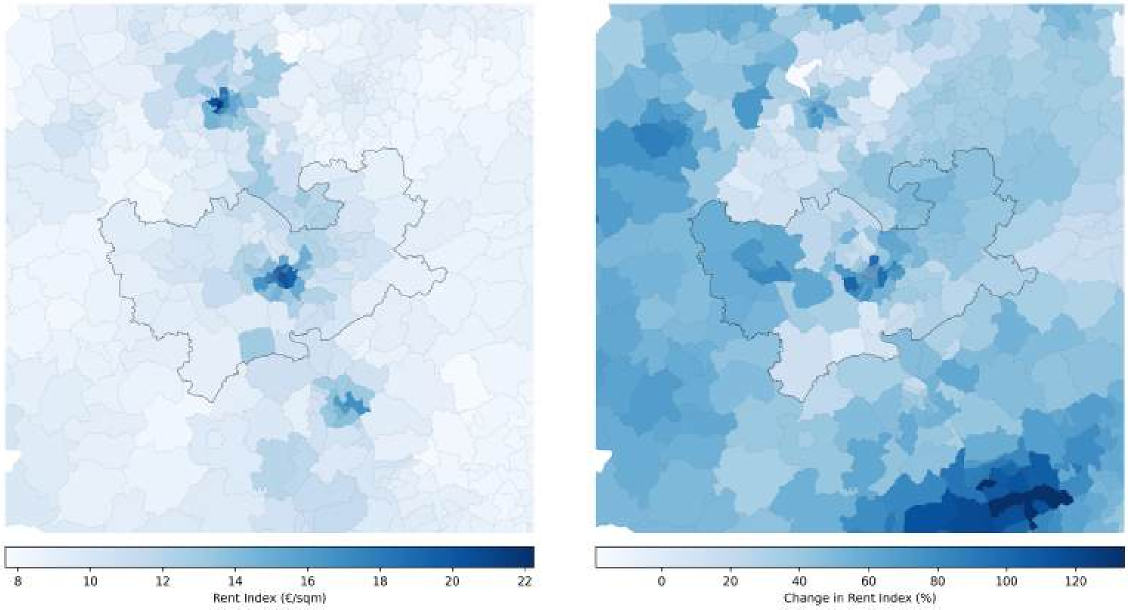
Figure S3: Commercial Rent in Frankfurt



(a) Frankfurt: 2023 rent (€/sqm) (b) Frankfurt: % change 2007–2023

Note: Grey lines denote postcode region boundaries; black lines denote local labor market boundaries. Prime locations are circled in red.

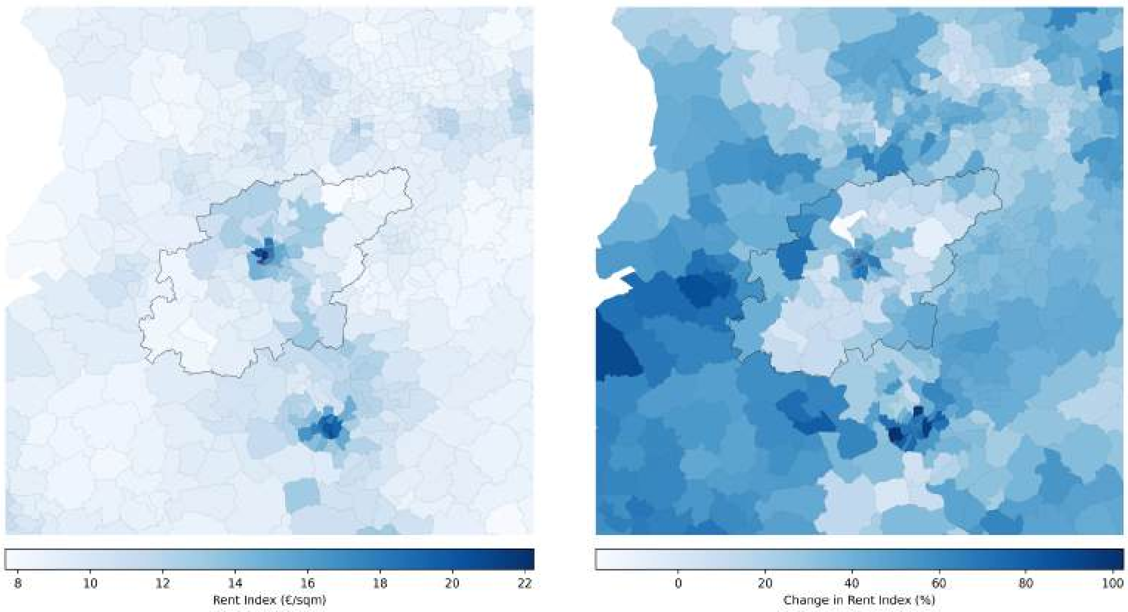
Figure S4: Commercial Rent in Cologne



(a) Cologne: 2023 rent (€/sqm) (b) Cologne: % change 2007–2023

Note: Grey lines denote postcode region boundaries; black lines denote local labor market boundaries. Prime locations are circled in red.

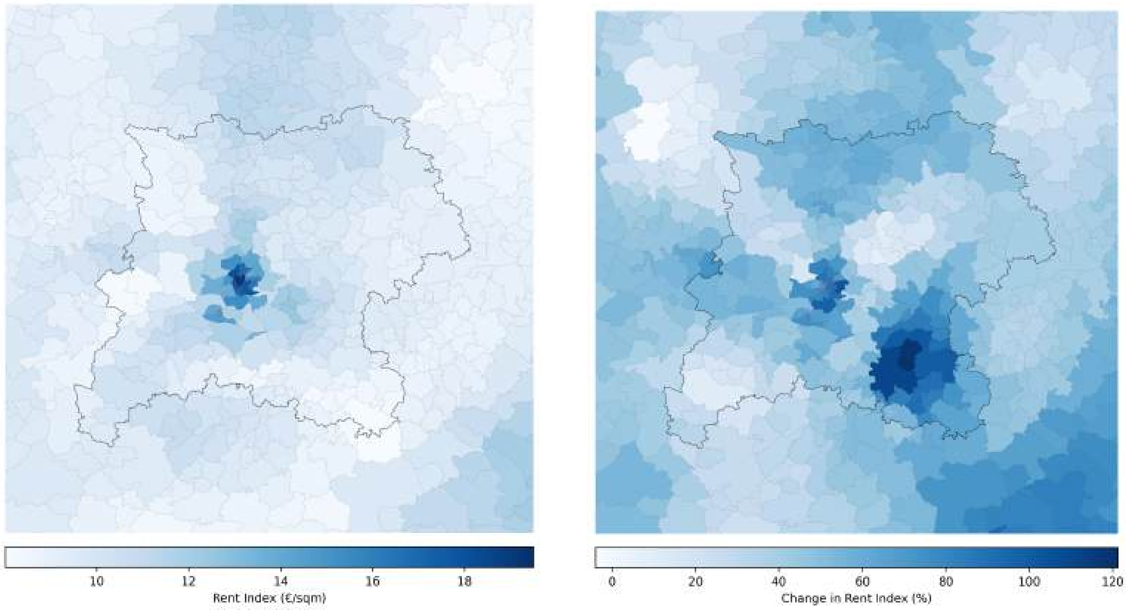
Figure S5: Commercial Rent in Düsseldorf



(a) Düsseldorf: 2023 rent (€/sqm) (b) Düsseldorf: % change 2007–2023

Note: Grey lines denote postcode region boundaries; black lines denote local labor market boundaries. Prime locations are circled in red.

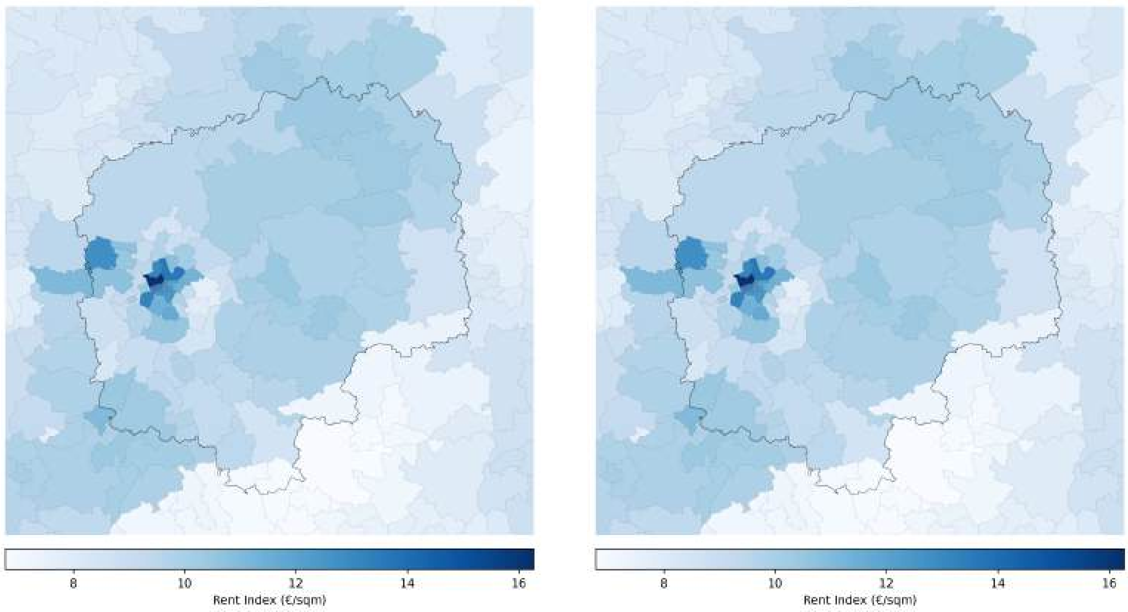
Figure S6: Commercial Rent in Stuttgart



(a) Stuttgart: 2023 rent (€/sqm) (b) Stuttgart: % change 2007–2023

Note: Grey lines denote postcode region boundaries; black lines denote local labor market boundaries. Prime locations are circled in red.

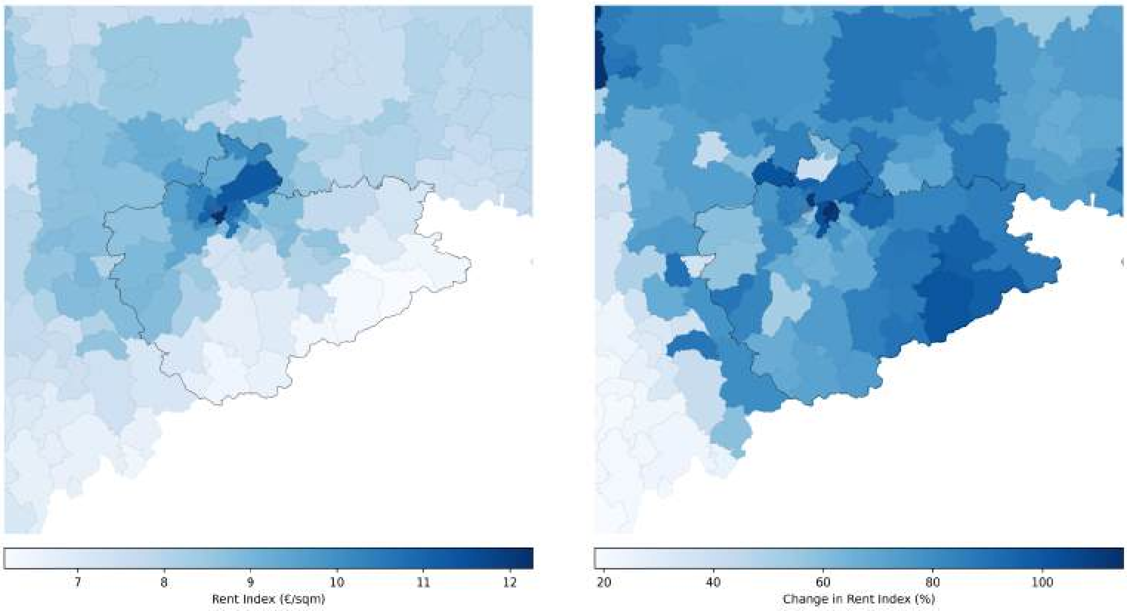
Figure S7: Commercial Rent in Leipzig



(a) Leipzig: 2023 rent (€/sqm) (b) Leipzig: % change 2007–2023

Note: Grey lines denote postcode region boundaries; black lines denote local labor market boundaries. Prime locations are circled in red.

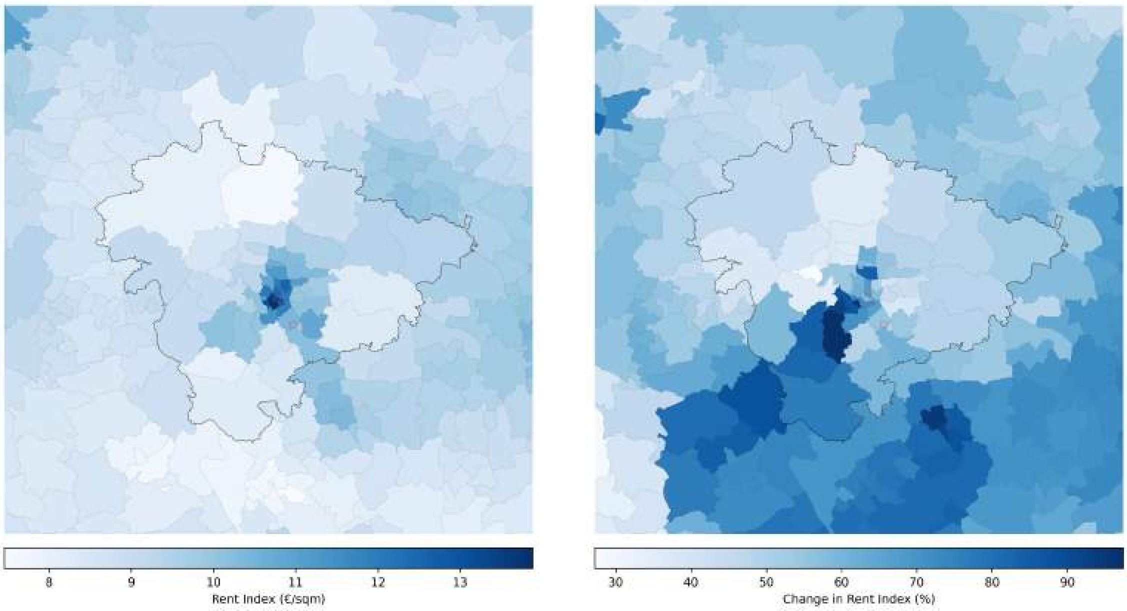
Figure S8: Commercial Rent in Dresden



(a) Dresden: 2023 rent (€/sqm) (b) Dresden: % change 2007–2023

Note: Grey lines denote postcode region boundaries; black lines denote local labor market boundaries. Prime locations are circled in red.

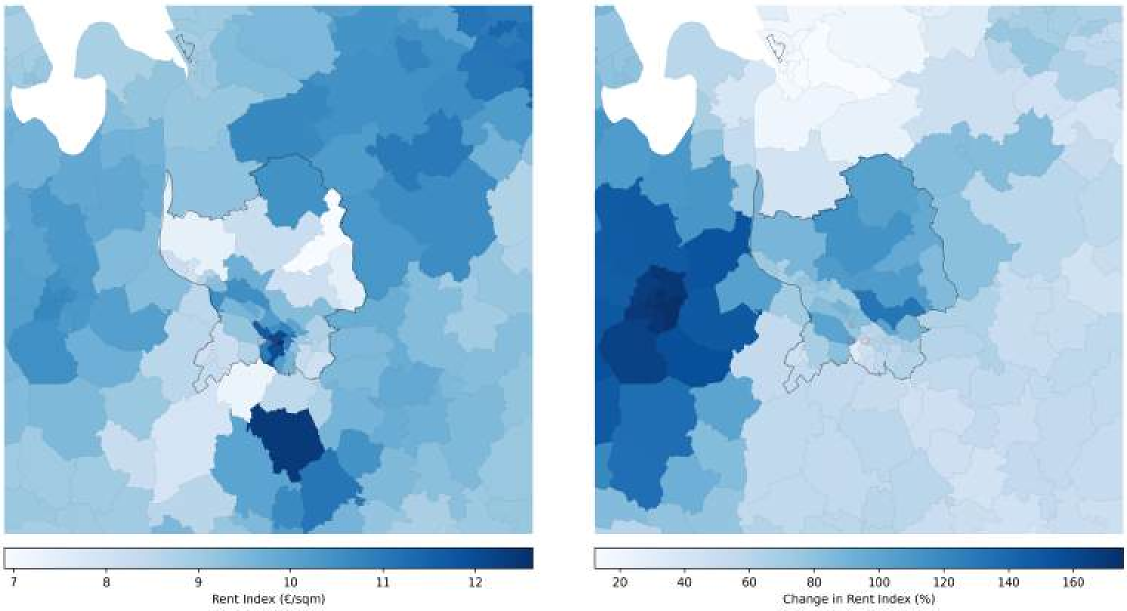
Figure S9: Commercial Rent in Hanover



(a) Hanover: 2023 rent (€/sqm) (b) Hanover: % change 2007–2023

Note: Grey lines denote postcode region boundaries; black lines denote local labor market boundaries. Prime locations are circled in red.

Figure S10: Commercial Rent in Bremen

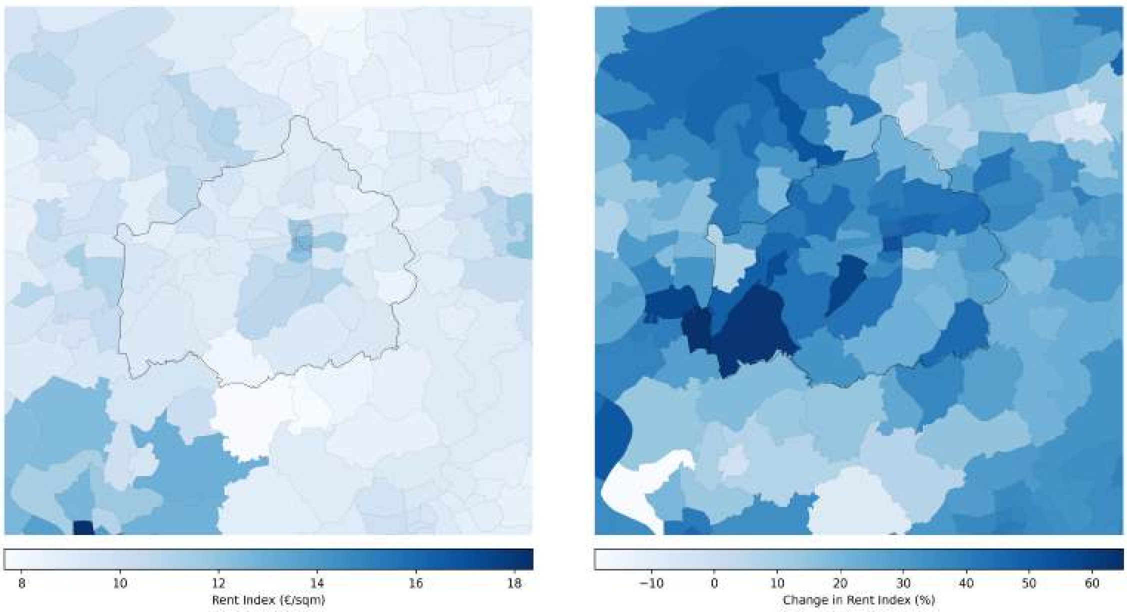


(a) Bremen: 2023 rent (€/sqm)

(b) Bremen: % change 2007–2023

Note: Grey lines denote postcode region boundaries; black lines denote local labor market boundaries. Prime locations are circled in red.

Figure S11: Commercial Rent in Essen

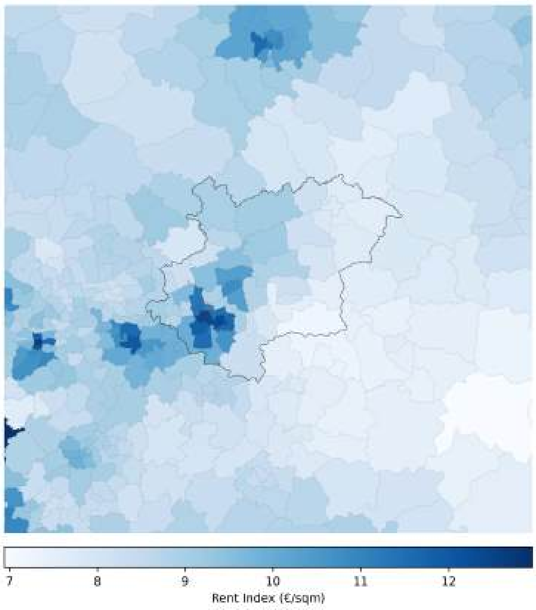


(a) Essen: 2023 rent (€/sqm)

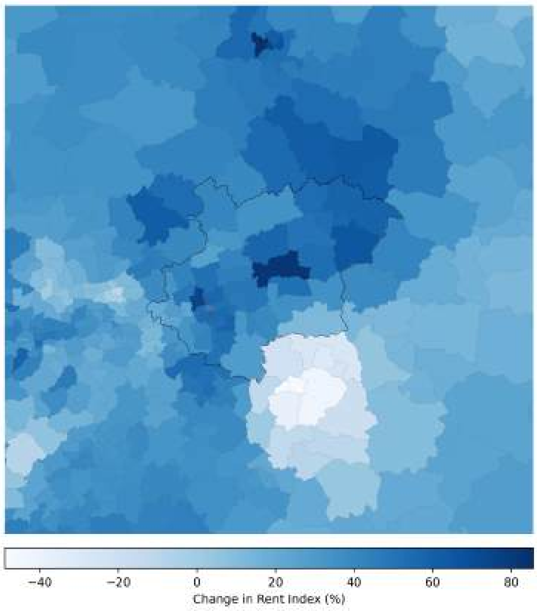
(b) Essen: % change 2007–2023

Note: Grey lines denote postcode region boundaries; black lines denote local labor market boundaries. Prime locations are circled in red.

Figure S12: Commercial Rent in Dortmund



(a) Dortmund: 2023 rent (€/sqm)



(b) Dortmund: % change 2007–2023

Note: Grey lines denote postcode region boundaries; black lines denote local labor market boundaries. Prime locations are circled in red.

S.2 Commercial rents for all LLM

We report both the rents in the CBD (prime location) in 2007 and 2024. The LLMs are ranked using rent index in 2024. We also report the average commercial rent index for all LLMs in 2024 by weighting the rent indices of all postcode regions with commercial floor space, which is a time invariant weight, calculated as the average floor space across all years between 2007 and 2024. For LLMs without prime location, we take define the grid cell with the highest commercial rent as CBD.

Table S1: Average Commercial Rent per sqm by LLM and Percentage Change

Rank	LLM Name	2024	2007	Change (%)	LLM Avg. 2024
1	Berlin	28.38	12.95	119.14	23.06
2	München	25.43	13.39	90.00	18.76
3	Frankfurt/Main	22.86	15.85	44.20	16.58
4	Hamburg	19.98	12.89	54.96	18.16
5	Köln	19.21	11.27	70.52	15.35
6	Düsseldorf	18.67	11.85	57.60	14.48
7	Stuttgart	18.22	9.84	85.17	14.03
8	Karlsruhe	14.33	8.45	69.59	11.42
9	Mainz	14.32	10.07	42.17	11.86
10	Freiburg	14.15	9.71	45.69	13.16
11	Heidelberg	14.11	7.82	80.43	12.10
12	Husum	14.09	6.53	115.75	10.96
13	Leipzig	14.05	6.99	100.91	12.72
14	Regensburg	13.87	7.62	82.02	13.70
15	Kelheim-Mainburg	13.45	7.52	78.69	12.29
16	Wiesbaden	13.44	9.06	48.40	11.76
17	Luckenwalde	13.30	8.94	48.85	11.62
18	Mannheim	12.96	9.21	40.74	10.94
19	Hannover	12.72	8.07	57.50	11.04
20	Leverkusen	12.66	8.96	41.32	11.91
21	Augsburg	12.58	6.58	91.33	11.61
22	Lübeck	12.26	7.16	71.18	11.86
23	Essen	12.18	8.13	49.82	10.84

Continued on next page

Table S1: Average Commercial Rent per sqm by LLM and Percentage Change

Rank	LLM Name	2024	2007	Change (%)	LLM Avg. 2024
24	Potsdam-Brandenburg	11.96	6.29	90.08	12.25
25	Ratzeburg	11.89	7.64	55.69	10.48
26	Nürnberg	11.78	7.35	60.14	11.01
27	Garmisch-Partenkirchen	11.71	7.40	58.23	11.13
28	Wolfsburg	11.69	7.00	66.91	10.83
29	Heide	11.60	6.97	66.25	11.30
30	Eberswalde	11.59	4.60	152.20	10.36
31	Lörrach	11.54	7.52	53.47	11.59
32	Ulm	11.50	6.94	65.74	11.10
33	Friedrichshafen	11.49	5.17	122.27	11.39
34	Bonn	11.49	8.72	31.76	11.86
35	Konstanz	11.39	6.11	86.45	11.37
36	Dortmund	11.30	7.57	49.28	10.58
37	Rostock	11.30	7.25	55.94	10.77
38	Dresden	11.28	6.46	74.62	10.47
39	Erlangen	11.25	4.82	133.33	11.27
40	Helmstedt	11.11	6.92	60.59	10.63
41	Bad Tölz	11.08	6.25	77.21	11.79
42	Ahrweiler	11.08	5.31	108.55	10.24
43	Jena	11.01	6.79	62.17	10.34
44	Neuruppin	11.00	4.08	169.69	10.51
45	Kiel	10.99	6.64	65.60	10.63
46	Duisburg	10.94	8.80	24.26	10.24
47	Würzburg	10.92	8.43	29.50	10.84
48	Heilbronn	10.89	7.95	36.88	10.70
49	Kitzingen	10.88	8.74	24.42	10.68
50	Ingolstadt	10.85	5.93	83.17	10.71
51	Germersheim	10.79	7.48	44.17	10.76
52	Rosenheim	10.76	8.40	28.10	11.07
53	Sigmaringen	10.74	4.79	124.33	9.94

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Table S1: Average Commercial Rent per sqm by LLM and Percentage Change

Rank	LLM Name	2024	2007	Change (%)	LLM Avg. 2024
54	Oldenburg	10.72	3.88	176.12	10.35
55	Reutlingen/Tübingen	10.67	6.46	65.25	9.96
56	Landshut	10.64	7.52	41.50	10.69
57	Landsberg	10.63	7.77	36.91	10.76
58	Ravensburg	10.62	5.51	92.81	10.52
59	Bochum	10.62	7.96	33.45	9.86
60	Bad Reichenhall	10.57	7.44	41.98	10.70
61	Emden	10.54	4.88	115.80	9.89
62	Gießen	10.50	7.64	37.40	10.59
63	Günzburg	10.49	5.95	76.19	10.51
64	Magdeburg	10.49	5.69	84.16	9.59
65	Lüneburg	10.46	6.52	60.37	10.30
66	Traunstein	10.46	7.60	37.64	10.53
67	Montabaur	10.44	6.19	68.69	9.61
68	Braunschweig	10.43	6.18	68.96	9.90
69	Donauwörth-Nördlingen	10.31	4.96	107.92	9.25
70	Offenburg	10.28	9.97	3.10	10.37
71	Münster	10.28	6.55	56.99	9.52
72	Hanau	10.25	5.43	88.81	9.05
73	Straubing	10.17	6.12	66.26	10.14
74	Regen-Zwiesel	10.12	6.13	65.17	9.99
75	Erfurt	10.08	6.64	51.82	8.71
76	Deggendorf	10.05	6.01	67.09	9.83
77	Westerstede	10.03	4.11	144.28	10.02
78	Leer	10.02	5.55	80.62	10.03
79	Bielefeld	10.02	7.95	25.99	9.48
80	Weimar	10.01	5.99	67.01	7.76
81	Celle	9.97	6.58	51.45	9.18
82	Zeven	9.96	7.06	40.96	9.75
83	Neustadt/Aisch	9.91	5.97	66.07	9.78
84	Freudenstadt	9.87	7.05	40.07	9.53

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Table S1: Average Commercial Rent per sqm by LLM and Percentage Change

Rank	LLM Name	2024	2007	Change (%)	LLM Avg. 2024
85	Oranienburg	9.85	6.96	41.61	11.00
86	Verden	9.85	5.96	65.21	9.80
87	Biberach	9.83	4.87	101.78	10.01
88	Cochem	9.83	5.90	66.65	9.32
89	Wittenberg	9.78	5.87	66.72	9.29
90	Tauberbischofsheim	9.78	7.52	30.06	9.59
91	Darmstadt	9.77	7.65	27.76	9.29
92	Meißen	9.76	4.80	103.40	8.91
93	Wetzlar	9.75	6.12	59.29	9.27
94	Marburg	9.75	7.00	39.29	9.45
95	Fulda	9.72	6.12	58.67	9.45
96	Bamberg	9.70	5.73	69.37	9.66
97	Kaiserslautern	9.69	7.12	36.22	9.52
98	Krefeld	9.68	6.90	40.24	9.93
99	Koblenz	9.68	6.38	51.58	9.52
100	Cham	9.66	5.71	69.04	9.48
101	Lohr am Main	9.66	7.12	35.67	9.96
102	Wuppertal	9.63	6.91	39.30	8.98
103	Dillingen	9.61	5.12	87.71	9.84
104	Landau	9.61	5.85	64.23	9.47
105	Bayreuth	9.61	5.86	63.92	9.37
106	Stade	9.61	7.00	37.28	9.37
107	Mühldorf	9.60	6.43	49.38	9.58
108	Dingolfing	9.59	6.03	58.99	9.63
109	Aschaffenburg	9.59	7.15	34.10	8.81
110	Waldshut	9.55	5.87	62.50	11.19
111	Schwandorf	9.54	5.15	85.49	10.05
112	Freyung	9.53	6.26	52.29	9.48
113	Burgenlandkreis	9.53	6.54	45.77	9.07
114	Cloppenburg	9.53	4.31	121.09	9.06
115	Burghausen	9.49	6.39	48.49	9.37
116	Osnabrück	9.46	7.58	24.84	9.23

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Table S1: Average Commercial Rent per sqm by LLM and Percentage Change

Rank	LLM Name	2024	2007	Change (%)	LLM Avg. 2024
117	Neuwied	9.44	6.30	49.92	8.92
118	Schweinfurt	9.42	6.76	39.42	9.77
119	Bad Kreuznach	9.37	6.64	41.05	9.04
120	Ludwigshafen	9.35	5.97	56.78	10.60
121	Salzlandkreis	9.34	4.79	94.93	8.83
122	Amberg	9.33	5.75	62.41	8.94
123	Flensburg	9.31	5.98	55.88	9.64
124	Mönchengladbach	9.30	5.95	56.48	9.35
125	Mosbach	9.28	7.12	30.42	8.91
126	Nordenham	9.26	6.63	39.66	9.13
127	Soltau	9.23	5.35	72.61	9.20
128	Uelzen	9.22	5.49	67.86	9.08
129	Neumarkt	9.22	4.59	101.04	9.08
130	Lingen	9.20	5.42	69.64	9.00
131	Villingen-Schwenningen	9.20	6.03	52.58	9.24
132	Korbach	9.16	6.00	52.74	8.22
133	Memmingen	9.16	4.90	86.71	9.82
134	Kleve	9.15	8.56	7.01	8.85
135	Bremerhaven	9.14	7.41	23.45	9.27
136	Göttingen	9.13	5.83	56.76	9.04
137	Minden	9.13	6.07	50.35	8.74
138	Haßfurt	9.12	6.17	47.96	9.19
139	Kempten	9.12	5.81	56.88	9.45
140	Kulmbach	9.11	6.00	52.00	9.06
141	Daun	9.11	5.11	78.42	9.21
142	Ansbach	9.10	7.65	18.92	9.02
143	Kassel	9.09	5.20	74.88	9.32
144	Lauterbach	9.08	7.27	24.88	8.77
145	Aachen	9.06	5.48	65.38	10.37
146	Heidenheim	9.05	5.45	65.98	9.28
147	Bitburg	9.04	6.50	39.10	9.13

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Table S1: Average Commercial Rent per sqm by LLM and Percentage Change

Rank	LLM Name	2024	2007	Change (%)	LLM Avg. 2024
148	Einbeck	9.04	5.77	56.76	8.64
149	Simmern	9.04	6.26	44.37	8.53
150	Alzey-Worms	9.03	6.04	49.60	9.52
151	Salzwedel	9.00	5.15	74.85	8.97
152	Bad Kissingen	8.95	6.32	41.53	9.10
153	Salzgitter	8.94	5.39	65.88	8.83
154	Pößneck	8.93	6.14	45.40	9.21
155	Schwerin	8.93	5.62	59.02	9.43
156	Tuttlingen	8.93	5.72	56.03	8.70
157	Südvorpommern	8.92	7.28	22.62	8.26
158	Viersen	8.91	6.22	43.11	8.48
159	Limburg	8.90	4.92	80.78	8.51
160	Calw	8.89	6.47	37.29	9.31
161	Heinsberg	8.87	5.67	56.36	8.95
162	Gütersloh	8.84	7.23	22.15	8.77
163	Pirmasens	8.84	6.47	36.49	8.88
164	Düren	8.79	5.50	59.77	8.58
165	Itzehoe	8.78	7.40	18.76	8.74
166	Gera	8.78	5.23	67.77	8.72
167	Stendal	8.74	4.94	77.15	8.57
168	Trier	8.74	6.49	34.61	8.69
169	Kronach	8.74	5.93	47.45	8.75
170	Euskirchen	8.72	7.38	18.28	8.71
171	Hildesheim	8.72	4.73	84.40	9.25
172	Kaufbeuren	8.72	6.33	37.71	9.00
173	Hersfeld	8.70	6.52	33.41	8.63
174	Nordhorn	8.70	5.76	50.97	8.74
175	Lichtenfels	8.68	6.00	44.57	8.66
176	Eggenfelden/Pfarrkirchen	8.67	6.19	40.17	8.98
177	Wilhelmshaven	8.66	5.01	72.87	8.74
178	Pforzheim	8.66	6.02	43.90	9.16
179	Saalfeld	8.62	5.44	58.44	8.30

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Table S1: Average Commercial Rent per sqm by LLM and Percentage Change

Rank	LLM Name	2024	2007	Change (%)	LLM Avg. 2024
180	Bremen	8.60	4.57	88.31	9.80
181	Aalen	8.59	5.46	57.31	8.45
182	Göppingen	8.59	6.86	25.15	8.31
183	Passau	8.58	6.27	36.87	8.71
184	Weißenburg-Gunzenhausen	8.57	6.09	40.73	8.65
185	Gelsenkirchen	8.56	7.17	19.36	8.78
186	Vechta	8.55	4.66	83.31	8.75
187	Lüdenscheid	8.53	6.57	29.80	7.88
188	Cottbus	8.52	5.41	57.63	8.38
189	Altenkirchen	8.50	6.67	27.44	8.25
190	Coburg	8.50	5.56	52.95	8.47
191	Nienburg	8.49	5.73	48.02	8.73
192	Dessau-Roßlau	8.47	5.68	49.23	8.47
193	Baden-Baden	8.47	7.24	16.92	9.47
194	Hagen	8.46	5.86	44.42	8.48
195	Weilheim	8.44	8.35	1.03	8.86
196	Merzig	8.43	6.70	25.77	8.37
197	Schwäbisch Hall	8.43	6.70	25.86	8.05
198	Hof	8.38	6.37	31.47	8.49
199	Steinfurt	8.36	6.66	25.47	8.59
200	Remscheid	8.34	6.13	35.91	8.23
201	Schwalm-Eder	8.33	5.77	44.32	8.93
202	Sonneberg	8.33	5.08	64.05	8.39
203	Saarbrücken	8.32	6.86	21.33	8.37
204	Hameln	8.30	4.50	84.50	8.32
205	Halle	8.28	6.28	31.82	8.28
206	Rottweil	8.28	5.59	48.04	8.64
207	Stadthagen	8.27	5.76	43.67	8.71
208	Weiden	8.27	4.73	74.78	8.21
209	Detmold	8.25	7.38	11.88	8.37
210	Marktredwitz	8.24	5.69	44.81	8.18

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Table S1: Average Commercial Rent per sqm by LLM and Percentage Change

Rank	LLM Name	2024	2007	Change (%)	LLM Avg. 2024
211	Anhalt-Bitterfeld	8.23	5.21	58.04	7.85
212	Bad Neustadt/Saale	8.20	5.64	45.42	8.22
213	Höxter	8.17	5.32	53.56	7.96
214	Schwelm	8.12	7.32	11.01	8.89
215	Holzminden	8.11	5.01	61.92	8.41
216	Bernkastel-Wittlich	8.10	6.15	31.70	8.47
217	Nordvorpommern	8.09	6.77	19.48	9.90
218	Perleberg	8.04	4.76	68.81	8.51
219	Borken	8.02	7.36	8.99	8.85
220	Gotha	8.01	6.27	27.81	7.88
221	St. Wendel	8.01	6.32	26.64	7.84
222	Siegen	7.91	6.33	25.02	7.89
223	Gummersbach	7.90	7.05	12.06	8.07
224	Soest	7.90	6.88	14.86	7.88
225	Chemnitz	7.90	7.12	10.83	7.68
226	Paderborn	7.87	6.60	19.24	7.83
227	Balingen	7.85	6.09	29.03	8.10
228	Eichsfeld	7.85	6.03	30.26	7.87
229	Arnstadt	7.74	5.90	31.17	7.77
230	Olpe	7.74	6.64	16.45	7.76
231	Mittelsachsen	7.73	5.25	47.25	7.25
232	Eisenach	7.63	5.82	30.98	7.17
233	Görlitz	7.60	3.82	98.99	7.47
234	Vogtlandkreis	7.58	5.87	29.08	7.58
235	Prenzlau	7.57	4.35	73.87	8.01
236	Homburg/Saar	7.56	6.07	24.65	8.35
237	Finsterwalde	7.52	4.21	78.35	7.61
238	Goslar	7.47	5.18	44.39	7.63

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Table S1: Average Commercial Rent per sqm by LLM and Percentage Change

Rank	LLM Name	2024	2007	Change (%)	LLM Avg. 2024
239	Mecklenburgische Seenplatte	7.41	5.44	36.38	7.85
240	Altenburg	7.38	4.94	49.47	7.89
241	Osterode	7.36	6.13	20.09	7.40
242	Bautzen	7.32	4.69	56.26	7.51
243	Harz	7.31	5.07	44.11	7.38
244	Erbach	7.31	5.89	24.04	7.73
245	Sondershausen	7.30	4.04	80.74	7.25
246	Mühlhausen	7.25	4.74	53.05	7.19
247	Eschwege	7.23	5.31	36.29	7.26
248	Nordhausen	7.18	4.84	48.21	7.18
249	Meschede	7.11	5.58	27.33	7.56
250	Zwickau	7.11	6.02	18.12	7.13
251	Idar-Oberstein	7.05	5.58	26.37	7.25
252	Erzgebirgskreis	7.03	6.07	15.80	6.98
253	Sulingen	7.01	4.67	49.97	8.66
254	Meiningen	6.86	4.82	42.31	7.45
255	Mansfeld-Südharz	6.85	4.18	63.70	7.33
256	Suhl	6.81	4.79	42.04	6.88
257	Lindau	4.29	2.25	90.71	10.93
258	Frankfurt/Oder	4.14	2.36	75.25	9.20

References