

Revaluing Proximity: Working from Home and the Spatial Distribution of Urban Housing Prices

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Abstract

We study the impact of working from home (WFH) on the spatial distribution of urban housing prices. Using data on over 20 million geocoded property listings across 50 German metropolitan areas from 2014 to 2024, we exploit postcode-level variation in WFH potential through a difference-in-differences design. WFH led to a sustained compression of the urban price gradient, but crucially the WFH effect on prices persists even after controlling for distance from city centers: conditional on distance, postcodes with higher WFH potential lost value systematically relative to areas with lower WFH potential. We then examine whether local amenities drive this within-distance heterogeneity. We find that amenities explain large shares of that effect, with good transport connections being the most important. These findings are consistent with WFH eroding the capitalized value of amenities and point to a broader revaluation of urban location fundamentals, rather than a simple center-to-suburb reallocation.

Keywords: Working from Home, Urban Housing Prices, Real Estate, Cities, Amenities

JEL Codes: D1, J2, R1, R2, R3

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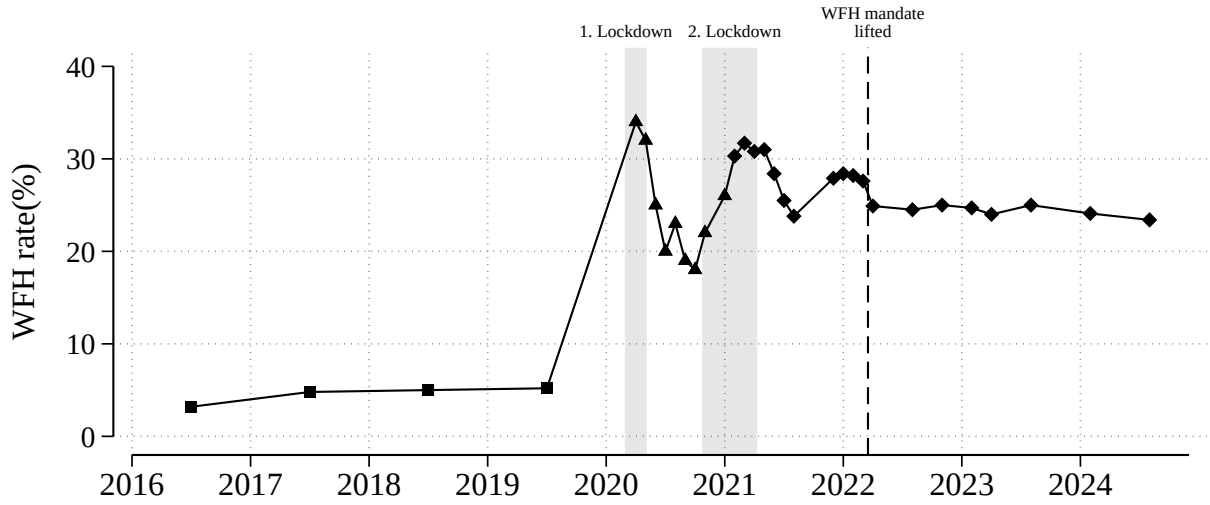
1 Introduction

The sudden rise in working from home (WFH) in 2020 marks an unprecedented shock to work arrangements around the world (Aksoy et al., 2025; Barrero et al., 2023; Hansen et al., 2023). Positive experiences and investments in enabling technologies have made this shift enduring, with many employees favoring a hybrid work model that blends office and remote work (Barrero et al., 2026). Mirroring the global trend, Figure 1 shows that the share of German employees regularly working from home has stabilized at around 25 percent, up from 5 percent in 2019.

WFH is concentrated in cities, where workers in teleworkable occupations sorted into central, transit-accessible neighborhoods close to their offices before the pandemic (Dingel and Neiman, 2020; Alipour et al., 2023). Dense, amenity-rich urban centers traditionally attract high-skilled workers and productive firms driving innovation and economic growth (Glaeser et al., 1992). However, the Covid-19 pandemic disrupted these dynamics, with population losses and declining housing prices in city centers (Ramani et al., 2024; Gupta et al., 2022; Brueckner et al., 2023; Althoff et al., 2022; Delventhal et al., 2022; Delventhal and Parkhomenko, 2026). While many of these studies attribute urban housing price shifts to WFH, most rely on city-level variation or coarse center-periphery comparisons (Mondragon and Wieland, 2022). This limitation matters: if WFH changes which amenities workers value, its price effect should vary systematically within the city, and not only by distance to the center. Identifying the amenity channels through which it operates, has remained out of reach for lack of fine-grained spatial data on housing prices and local amenity profiles. This paper closes this gap.

We provide causal evidence on how WFH reshapes the spatial distribution of housing prices *within* metropolitan areas (MAs). We draw on over 20 million residential property offerings, geocoded at the postcode level, across Germany’s 50 metropolitan areas from 2014 to 2024. Identification exploits variation in postcodes’ *WFH potential* – the share of employed residents in teleworkable occupations – as a measure of exposure to the Covid-induced WFH shock. We adopt a difference-in-differences (DiD) design to compare postcodes with higher and lower WFH potential *within* the same metropolitan area over time. We estimate the WFH price effect unconditionally and conditional on distance from the city center, separating the within-distance WFH effect from the broader gradient shift. We then trace this within-distance effect back to specific amenities, interacting local amenity profiles with WFH potential and decomposing their contributions to that effect.

Figure 1: Persistent Increase in WFH Share of German Workforce 2012–2024



Notes: WFH data for Germany are from Eurostat (2012–2019), infas360 (2020–2021) and ifo Business Survey (2021–2024). Shaded areas highlight “lockdown” periods.

Our analysis reveals four key findings. First, we document parallel price trends from 2014 to 2019, followed by a sharp and persistent drop in prices in central relative to peripheral neighborhoods within metro areas. This flattening of Germany’s urban housing price gradient since 2020 confirms for a European context a pattern prior work has highlighted for the U.S. (Gupta et al., 2022; Ramani et al., 2024). The magnitude is somewhat smaller than in the U.S., consistent with European cities retaining relatively strong amenity appeal. Consistent with that, we show that WFH drives this shift. Prices fell in high-WFH-potential, mostly central areas, while peripheral and low-WFH-potential areas saw relative gains: a one percentage point higher WFH potential is associated with a 0.3–0.4 percent decline in sale and rent prices.

Second, we find that WFH potential reduces housing prices even after controlling for distance from the city center. One to two thirds of the total WFH price effect remains even once distance is accounted for: postcodes with higher WFH potential lost value relative to equally distant postcodes. The result holds for different parametric and nonparametric approaches that control for distance. Thus, WFH explains relative price changes within a metro area beyond a simple gradient story.

Third, we show that revaluation of classical local amenities accounts for a substantial share of this within-distance WFH effect. Controlling for pre-pandemic amenity profiles attenuates the within-distance effect by approximately 50 percent for sale prices and 40 percent for rents. Decomposing the contribution of individual amenity categories, transportation quality emerges as the dominant channel. As WFH reduces the need for daily commuting, a good transportation infrastructure loses much of its

capitalized price premium, and neighborhoods that derived their relative advantage from transit access see the largest price declines. Services and consumer goods form a second channel of only slightly smaller weight. As the working day shifts from office to home, restaurants and leisure facilities are used more intensively where people live, and neighborhoods that offer them are revalued accordingly. Green space and broadband coverage, by contrast, account for only a small share of the attenuation.

Finally, we confirm that the gradient shift operates through demand rather than supply, consistent with WFH as a demand-side shock. High-WFH-potential urban cores experienced net population losses as remote workers gained the flexibility to live farther from the office. Interestingly, the net population loss is driven by strongly reduced in-migration, and not by an urban exodus, which was observed in the U.S. (Ramani et al., 2024). The resulting fall in housing demand lowered prices in high-WFH-potential urban cores relative to peripheral areas, consistent with evidence that WFH primarily increases commuting distances via job transitions rather than relocations (Coskun et al., 2026; Akan et al., 2025; Boeri and Rigo, 2024). We find no differential trends in the number of property listings after 2020, suggesting limited effects on housing supply.

Our central contribution is to show that the WFH affects housing prices beyond flattening the price gradient: we identify the revaluation of local amenities as a channel through which WFH reshapes urban housing prices. As remote work loosens the connection between home and workplace, workers revalue neighborhoods for the amenities they offer relative to the access to jobs they provide. We thereby expand the literature on the consequences of the “Big Shift” to remote work for cities, which documents changes in commuting and migration (Coskun et al., 2026; Akan et al., 2025; Boeri and Rigo, 2024), local spending and service employment (Alipour et al., 2026; De Fraja et al., 2021; Althoff et al., 2022), neighborhood choice (Ferreira and Wong, 2022), crime (Matheson et al., 2024), and the location of economic activity (Liu and Su, 2025). Our results corroborate the narrative that cities shift from access to production toward access to consumption (Glaeser and Ratti, 2023; Glaeser et al., 2001; Leonardi and Moretti, 2023).

Prior work studying WFH’s impact on real estate markets documents flatter urban price gradients and a “donut effect” in U.S. cities (Gupta et al., 2022; Ramani et al., 2024; Monte et al., 2026; Liu and Su, 2021), in line with predictions of spatial models that WFH reduces the value of proximity to jobs (Brueckner, 2025; Brueckner et al., 2023; Gokan et al., 2022; Davis et al., 2024a; Kyriakopoulou and Picard, 2023). Empirical studies have mainly studied city-level impacts. Our key novelty is that we leverage

the intra-city variation in WFH potential, which allows us to study how WFH interacts with changing amenity values at similar distances from the urban center. As German cities are more monocentric, denser, and public transit-oriented than in the U.S., our results differ from U.S. evidence. We find a smaller effect magnitude in the urban price gradient shift and a reduction of spatial disparities in housing prices. Our finding that WFH effects persist in both large and small cities contrasts with theoretical work by [Monte et al. \(2026\)](#), who predict a return to pre-pandemic conditions in smaller cities. Complementary research shows that demand for office space and urban commercial real estate has fallen as a consequence of the WFH shock ([Gupta et al., 2026](#); [Bergeaud et al., 2023](#); [Rosenthal et al., 2022](#)), which has prompted proposals to convert excess office space to residential use ([Gupta et al., 2023](#)).

The paper proceeds as follows. [Section 2](#) describes the data. [Section 3](#) documents the flattening of the urban housing price gradient since 2020. [Section 4](#) lays out the empirical framework and estimates the causal WFH effect on housing prices. [Section 5](#) shows that local amenity revaluation explains a substantial share of the within-distance effect. [Section 6](#) examines mechanisms behind the broader gradient shift of housing prices, and [Section 7](#) concludes.

2 Postcode-Level Data on the Housing Market and WFH in Germany

Sample. Our sample includes 4,543 postcodes in Germany’s 50 metropolitan areas (MAs), covering about two-thirds of the population (56 million people). Our study period spans from 2014 to 2024.¹ [Figure 2](#) illustrates our sample of 50 MAs on a map of Germany. The metro areas, similar to U.S. commuting zones, are defined by the [German Federal Office for Building and Regional Planning \(BBSR\)](#) as *Großstadtregionen* – comprising all municipalities in which at least 25 percent of employed residents commute to the central city. In general, German cities tend to be more monocentric, denser, and public transit-oriented than U.S. cities, which are more sprawling, polycentric, car-dependent, and economically segregated ([Ahlfeldt et al., 2015](#); [Roback, 1982](#); [Lucas and Rossi-Hansberg, 2002](#); [Glaeser et al., 1992](#); [Heblich et al., 2020](#)). Within the 50 German MAs, we use the administrative classification of postcodes into four catchment areas: urban core, suburban area, close commuting belt, and wider commuting belt.² For each postcode, we observe monthly real estate prices, WFH po-

¹In Germany, there were two lockdown periods during the Covid-19 pandemic, with a WFH mandate from January to June 2021 and from November 2021 to March 2022. Pandemic restrictions were lifted in April 2022.

²Appendix [Figure A.1](#) illustrates the catchment areas for the Berlin-Potsdam metro region, representative of others.

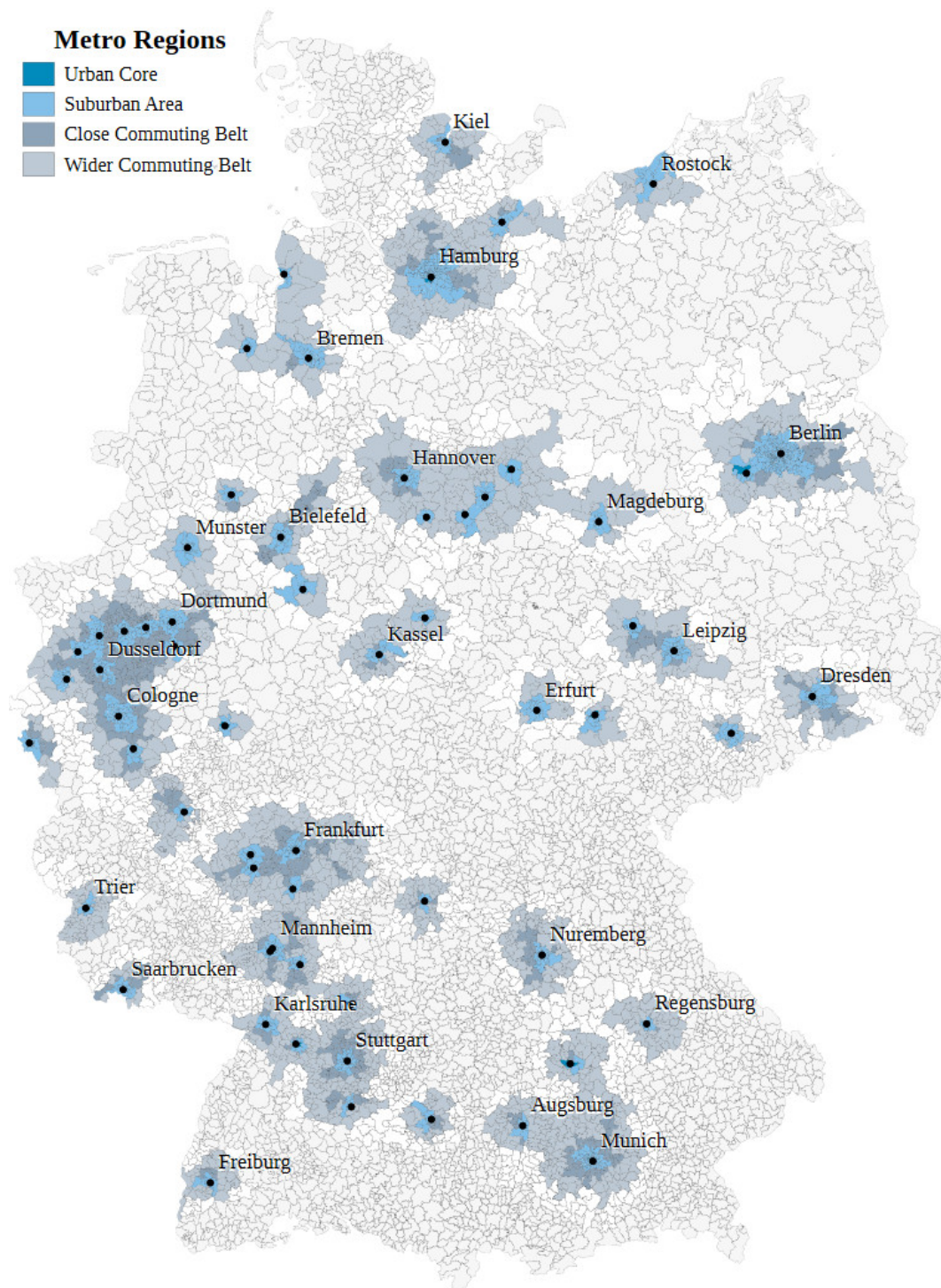
tential, the Euclidean distance from the nearest MA center, and local characteristics. We define the city center of each MA as the postcode containing the townhall (*Rathaus*) of its central municipality.³ We validate this definition using postcode-level payment card transaction data from *Mastercard*: in around 80 percent of MAs, the townhall postcode has the highest spending density in the metro area, and in 97 percent it ranks among the top three — confirming that townhalls reliably mark the economic hub of the city (Appendix Table B.2).

Real Estate Data. We use comprehensive data on the German housing market from the real estate consulting firm *F+B IGES*. The data include nearly all property listings for sale and rent in Germany between 2014 and 2024, covering over 20 million listings in total. Listings are consolidated from over 140 sources (e.g., online platforms, newspapers, property agencies) and purged of duplicate entries. Listings are geocoded at the postcode level and record property characteristics, including the segment, type, asking price, listing date, size, age, and features. To address manual entry errors, we remove the top and bottom one percent of property prices and floor space as extreme outliers. We compute the average final asking price per square meter at the postcode-month level. Appendix Figure A.2 shows the distribution of log sale prices and rents per square meter. To validate the use of offering prices as a proxy for actual market transactions, Appendix Figure B.3 compares our listing price data to transaction prices recorded by municipal property valuation committees in major German cities. The close alignment supports the validity of the data for measuring price dynamics.

WFH Survey Data. We complement our real estate data with postcode-level WFH potential from *infas360*, a micro-geographic survey provider. We included WFH-related questions in the spring 2022 wave of the *infas360 CASA Monitor*, a recurring and representative online survey of roughly 11,000 German adults. Respondents reported whether their primary job could be done remotely at least one day per week, as well as their current and pre-pandemic WFH status. Applying established methods from the U.S. and U.K. (Dingel and Neiman, 2020; Matheson et al., 2024), *infas360* estimates postcode-level WFH rates by first calculating WFH prevalence by occupation and then extrapolating to postcodes based on local occupational composition. We define a postcode’s *WFH potential* as the share of employed residents whose jobs allow at least partial remote work, which includes both hybrid and fully remote work arrangements. Appendix Figure B.4 shows that county-level aggregates of our measure align

³Six of the 50 MAs are polycentric, containing multiple city centers (resulting in 62 city centers total); for postcodes in these areas, distance is measured to the nearest center. Results are robust to restricting the sample to the 44 monocentric MAs (Appendix Table D.6 and Table E.10).

Figure 2: Sample Illustration of 50 German Metro Regions



Notes: This figure displays the sample comprised of the 50 largest metro regions in Germany with the corresponding urban core (dark blue), the suburban area (blue), as well as the close and wider commuting belt (dark gray/ light gray). The administrative classification of the metro areas and the catchment areas within the metros is provided by the German Federal Office for Building and Regional Planning (BBSR).

closely with the spatial pattern of WFH potential calculated by [Alipour et al. \(2023\)](#) for Germany.

Cellphone Mobility Data. We use novel cellphone “ping” data provided by *T-Systems by Deutsche Telekom*, Germany’s largest telecommunications company, as first introduced by [Alipour et al. \(2026\)](#). Telekom leverages a proprietary algorithm that tracks users’ movements based on mobile phone pings to cell towers. The data allow us to track monthly population changes at the postcode level based on the count of initial morning cellphone pings within each area.

Local and Administrative Data. We also include a broad range of information on socioeconomic, population, and area characteristics at the postcode level compiled from surveys and administrative sources. In particular, we use administrative data on migration flows and employment statistics at the county level ([German Federal Employment Agency, 2024](#); [Destatis, 2023](#)).

Summary statistics are reported in [Table A.1](#) of the Appendix. The mean postcode size in our sample is 12,950 inhabitants.

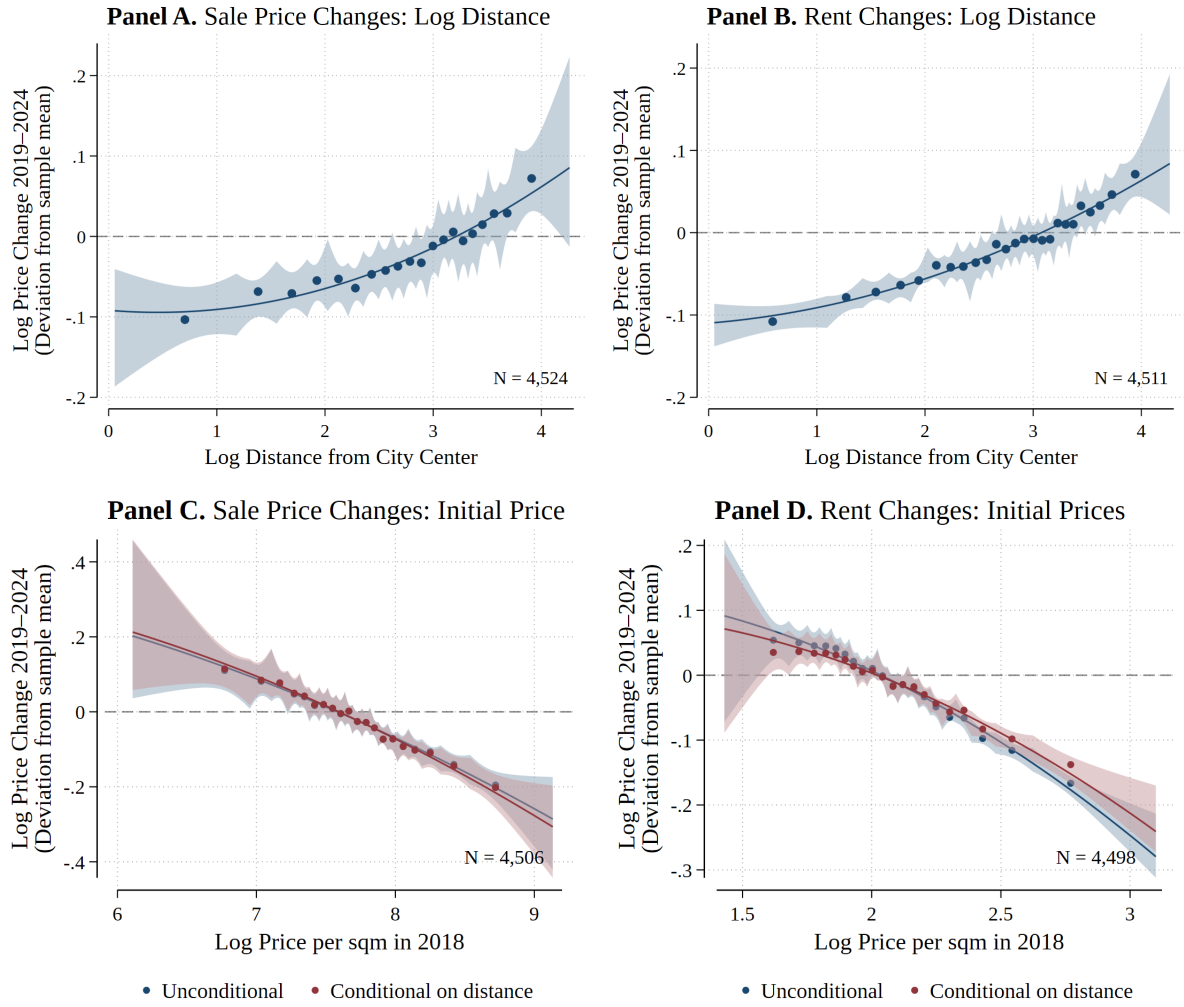
3 Motivating Evidence: Flattening of the Urban Price Gradient

The urban housing price gradient is traditionally characterized by higher prices and rents in city centers due to agglomeration effects, proximity to jobs, access to amenities, and limited land supply. Since the Covid-19 pandemic, the gradient has significantly flattened: properties farther from city centers gained in relative value, creating a “donut effect” similar to patterns documented in major U.S. cities ([Gupta et al., 2022](#); [Ramani et al., 2024](#)), though with a smaller magnitude in Germany. We document this pattern below; [Section 4](#) then establishes that local differences in WFH potential are a key driver of the observed spatial price dynamics.

[Figure 3](#) presents binned scatter plots of deviations from the average housing price changes between 2019 and 2024 against log distance from the city center (Panels A and B) and pre-pandemic log price levels (Panels C and D). Panels A and B show that price growth is stronger the farther the distance from the urban core, with the relationship appearing non-linear and steepening toward the periphery. Panels C and D plot the 2018 price level against the subsequent 2019–2024 price change⁴. Areas

⁴To avoid a mechanical regression-to-the-mean bias – whereby sampling noise in the base year enters both the initial price level and the subsequent price change with opposite signs, inducing a spurious negative slope – we use 2018 prices as the baseline measure.

Figure 3: Flattening of the Urban Housing Price Gradient



Notes: This figure displays binned scatter plots following the methodology proposed by [Cattaneo et al. \(2024\)](#). Panels A and B show the postcode-level relationship between log distance from the city center and the change in log sale and rent prices from 2019 to 2024. Panels C and D overlay two series: the unconditional relationship between pre-pandemic prices and the 2019–2024 price change (blue), and the relationship conditional on distance (red). To avoid regression-to-the-mean bias, Panels C and D use 2018 log prices as the baseline measure. The shaded areas show 95% confidence bands of the conditional mean functions. Metro-area fixed effects are absorbed in all panels. Log price changes are expressed as deviations from the sample mean.

that were more expensive before the pandemic grew less: unconditionally (blue), but also when comparing postcodes at similar distances from the city center (red). This indicates a reduction in spatial housing price inequality that goes beyond the spatial gradient: even within similar distances from the center, initially cheaper areas and initially more expensive ones converged.

These patterns are similar when using normalized distance (see Appendix [Figure C.5](#)), and hold when only analyzing monocentric areas (Appendix [Figure C.7](#)), as well as

under an alternative urban delineation based on the 223 BBSR *Arbeitsmarktregionen* (Appendix Figure C.8). We further confirm the significant gradient flattening as well as flat pre-trends, using a dynamic DiD approach that interacts log distance from the city center with monthly time dummies, shown in Figure C.9. On average, a 10 percent increase in distance from the city center is associated with a 0.5 percent rise in sale prices and rents by 2024 — a notably smaller magnitude than documented for the U.S. (Gupta et al., 2022).

Overall, our descriptive findings show that the pandemic has permanently changed the micro-geography of urban housing markets. The housing price gradient has flattened. In the following sections, we analyze the role of WFH potential.

4 WFH Impact on Urban Housing Prices

4.1 Conceptual Framework

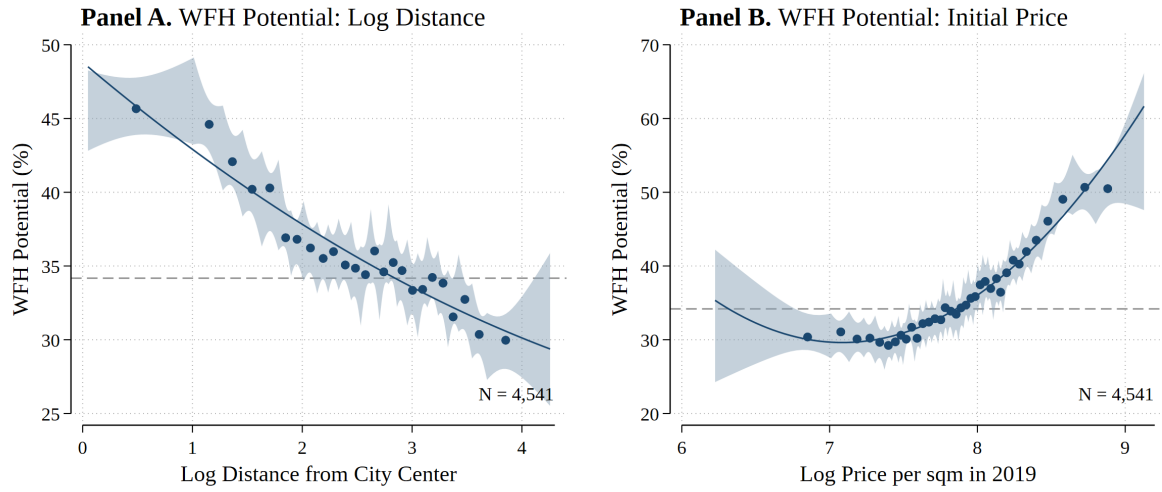
The impact of WFH on urban housing markets can be analyzed through the Rosen–Roback urban spatial equilibrium model (Rosen, 1974; Roback, 1982), where workers choose locations by balancing wages, housing costs, and local amenities to equalize utility across space. Figure 4 documents this pre-pandemic equilibrium: WFH potential – the share of residents in teleworkable jobs – decreases monotonically with distance from the city center (Panel A), consistent with office workers sorting centrally to reduce commuting costs, and high-WFH areas commanded higher pre-pandemic housing prices (Panel B), reflecting the income premium of office workers embedded in the equilibrium (Dingel and Neiman, 2020; Delventhal and Parkhomenko, 2026; Ahlfeldt et al., 2015).

WFH disrupts this equilibrium by partially decoupling workplace and residence: the widespread adoption of hybrid work (Barrero et al., 2023; Bloom et al., 2024) reduces commuting frequency, enabling households to tolerate greater distances to city centers in exchange for lower housing costs or more living space, with residential adjustments occurring primarily *within* rather than across metro areas (Ramani et al., 2024; Althoff et al., 2022; Gupta et al., 2022; Brueckner et al., 2023).⁵

WFH affects urban housing demand through two channels: first, households in high-WFH-potential areas may relocate to peripheral neighborhoods, directly reducing demand and prices in urban cores; second, even without relocating, the weakened link

⁵According to the German micro-census, a quarter of the workforce worked at least partly remotely in 2023 (Office, 2024); among them, 74 percent followed a hybrid model, making full decoupling of residence and workplace unreasonable.

Figure 4: Pre-Pandemic Sorting: WFH Potential, Distance from City Center, and Housing Prices



Notes: This figure displays binned scatter plots following [Cattaneo et al. \(2024\)](#) on the postcode-level relationship of WFH potential at the place of residence with log distance from the city center (Panel A) and with pre-pandemic log housing prices in 2019 (Panel B). The shaded areas highlight 95% confidence bands. WFH potential is measured as the share of employed residents who can work from home at least one day per week. The dashed line marks the average WFH potential of 34.18%. Metro-area fixed effects are absorbed in all panels.

between job location and residence lowers expected future in-migration to central areas ([Monras, 2020](#)), depressing property values as owners and landlords revise their expectations downward. In contrast, housing supply adjustments are expected to play a minor role, as housing is inelastically supplied, especially in the short run ([Baum-Snow and Han, 2024](#)).

These mechanisms generate two testable predictions. First, WFH *contributes to flattening* the urban housing price gradient as demand shifts from center to periphery. Second, the effect is not reducible to distance: WFH potential varies substantially among postcodes located at similar distances from the city center, so prices may fall in high-WFH-potential neighborhoods relative to equally distant neighborhoods within the same metro area. The size of these adjustments is likely moderated by local amenities that make peripheral locations closer substitutes for central ones.

4.2 Identification Strategy

Building on these predictions, our empirical strategy exploits pre-determined, cross-sectional variation in postcode-level WFH potential to identify its causal effect on local housing price changes, using two complementary difference-in-differences (DiD) specifications: a dynamic DiD that captures the temporal evolution of the WFH ef-

fect and tests for parallel pre-trends, and a long DiD that quantifies persistent price changes between 2019 and 2024.

Dynamic DiD. We estimate dynamic treatment effects of the Covid-induced WFH shock by comparing postcodes with high and low WFH potential *within* MAs. The dynamic DiD regression is:

$$\text{Log_Price}_{ct} = \sum_{k \neq \text{Dec}_{2019}} [\beta^k \mathbb{1}(k = t) \times \text{WFH_Potential}_c] + \gamma_c + \delta_{m(c)t} + \lambda_{d(c)t} + \varepsilon_{ct}, \quad (1)$$

where Log_Price_{ct} is the log average sale price or rent in postcode c and month t , WFH_Potential_c is the share of employed residents with WFH-feasible jobs, and γ_c and $\delta_{m(c)t}$ are postcode and metro-area-by-month-year fixed effects. The terms $\lambda_{d(c)t}$ are distance-decile-by-month-year fixed effects, where $d(c)$ is the decile of postcode c in the within-metro distribution of distance from the city center — the same ten distance bands used in the long DiD specification below. They enter Panels C and D of [Figure 5](#) only, absorbing monthly price dynamics common to a distance band, so that β^k is identified from variation in WFH potential among postcodes at comparable distances from their city center. We use December 2019 as the reference period⁶, weight by postcode-level employment, and cluster standard errors at the postcode level.

Long DiD. We employ a long DiD approach from 2019 to 2024 to examine the long-run effects of WFH potential on the spatial distribution of urban housing prices. Formally, we estimate the following regression:

$$\Delta_{2019-2024} \text{Log_Price}_c = \beta_1 \times \text{WFH_Potential}_c + \delta_{m(c) \times d(c)} + \varepsilon_c, \quad (2)$$

where $\Delta_{2019-2024} \text{Log_Price}_c$ is the change in log sale prices or rents in postcode c from 2019 to 2024, WFH_Potential_c is the share of employed residents with WFH-feasible jobs, and $\delta_{m(c) \times d(c)}$ are metro-area-by-distance-band fixed effects. Thus, we non-parametrically absorb any distance-price relationship without functional form

⁶We choose December 2019 to anchor the dynamic estimates to the same pre-pandemic baseline as the long DiD in [Equation 2](#). Estimates do not change when using January, February, or March 2020 instead.

assumptions.⁷ We weight by postcode-level employment and cluster standard errors at the postcode level.

The coefficient β_1 captures the effect of WFH potential on housing price changes among postcodes at similar distances from the city center within the same metro area. As shown in [Figure 4](#), WFH potential varies substantially among equidistant postcodes, so β_1 is identified from this within-distance-band variation.

Identification. The validity of the DiD design rests on the strong parallel trends (SPT) assumption that, absent the Covid-induced WFH shock, postcodes would have exhibited similar housing price dynamics regardless of their WFH potential. Since the pandemic constituted an unanticipated aggregate shock, the SPT assumption is unlikely to be violated by selection on expected housing price returns. A more relevant concern is that WFH potential proxies for the educational and income composition of local residents: if housing prices evolved differentially across these groups for reasons unrelated to WFH adoption, our DiD estimates may reflect a preexisting trend rather than the causal effect of WFH. Checking for pre-trends in the dynamic DiD offers a diagnostic for such confounding; we note, however, that flat pre-trends are necessary but not sufficient for the SPT assumption to hold post-treatment. Following [Callaway et al. \(2024\)](#), estimates are best interpreted as *average causal responses* (ACR): the average price change associated with a marginal increase in WFH potential across the dose distribution.

4.3 Dynamic DiD Results

The dynamic effect of WFH potential on urban housing prices is shown with monthly DiD coefficients in [Figure 5](#). Panels A and B report estimates for log sale prices and rents conditional on postcode and metro-area-by-month fixed effects. Panels C and D add distance-decile-by-month fixed effects, so that the estimates are identified from variation in WFH potential among postcodes at comparable distances from their city center. Pre-pandemic coefficients are centered around zero and insignificant, confirming parallel trends across groups before the pandemic shock. The DiD results indicate that postcodes with higher WFH potential experienced gradual price declines following the pandemic, stabilizing by 2023. On average, a one percentage point increase in WFH potential is associated with a 0.4 percent decrease in sale prices and a 0.3 percent decrease in rents. Conditioning on distance attenuates these effects but leaves them clearly negative and statistically significant, at roughly 0.2 percent for sale prices and

⁷Appendix [Table D.4](#) also shows the results parametrically controlling for distance.

0.1 percent for rents. Distance from the city center thus accounts for part, but not all, of the WFH effect: postcodes with higher WFH potential lost value relative to equally distant postcodes in the same metro area. This mirrors the within-distance price convergence documented in [Figure 3](#). The DiD results suggest that WFH has contributed to the flattening of the urban housing price gradient. Since WFH data were collected in early 2022, after some WFH-related adjustments had already occurred, our estimates likely represent a lower bound of the true effect of WFH on urban housing markets. Inference is robust to spatial correlation: re-estimating with wild cluster bootstrap standard errors yields the same conclusions ([Appendix Table D.3](#)).

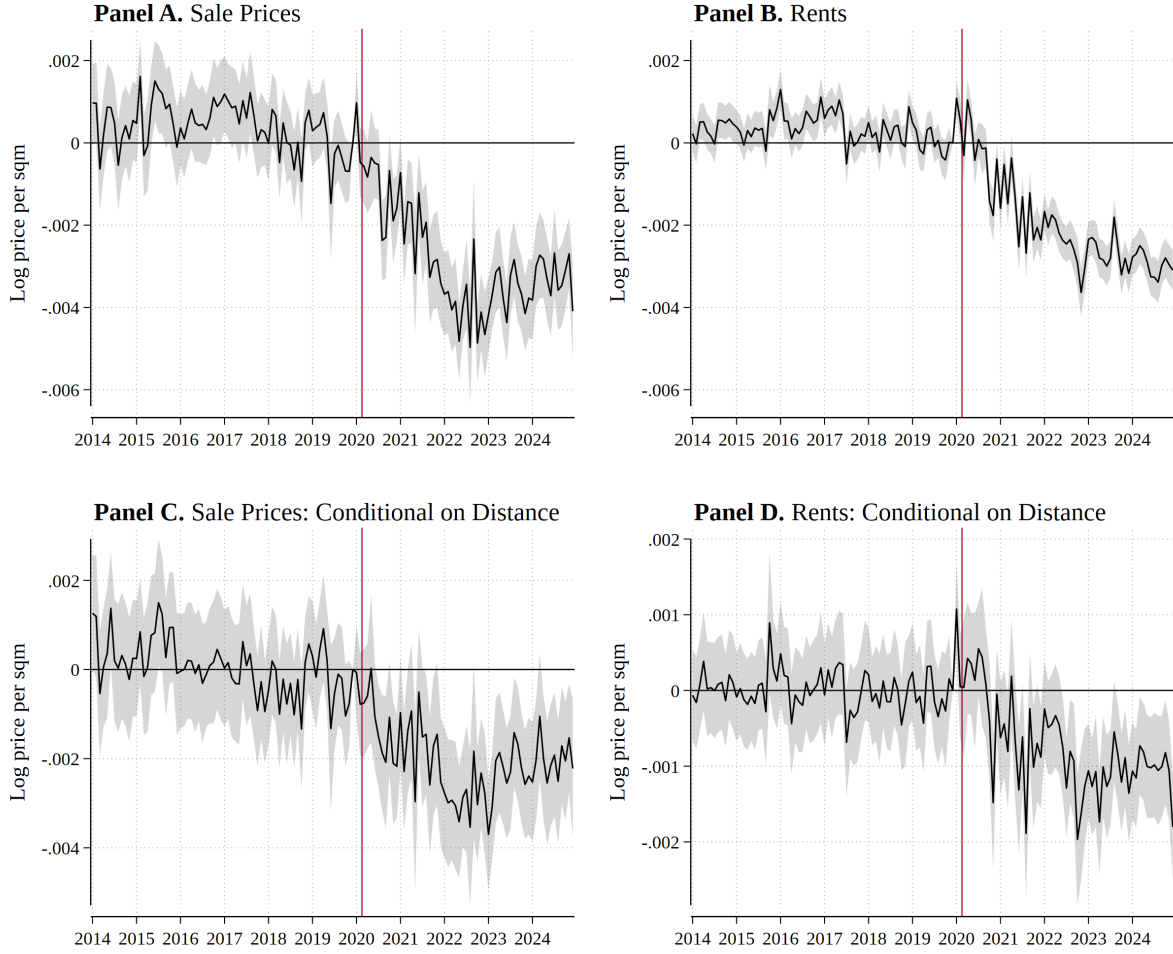
The results are heterogeneous within and across MAs, as shown in [Appendix Figure D.10](#). Within metros, the most pronounced effects of WFH potential are observed in the urban core and suburbs. Across metros, the strongest effects are seen in the largest 10 MAs, but the effects remain significant across all MAs. Our evidence therefore contrasts with findings by [Monte et al. \(2026\)](#) from the U.S., where the WFH impact is concentrated in large cities.

4.4 Long DiD Results

The long DiD analysis from 2019 to 2024 examines the persistent effect of WFH, providing novel evidence that WFH significantly affects the spatial distribution of housing prices in MAs beyond flattening the urban gradient.

The results in [Table 1](#) show that WFH explains spatial differences in housing price changes, even after controlling non-parametrically for distance from city centers. Panel A presents results for sale prices and Panel B for rents. Column (1) establishes the baseline: postcodes with higher WFH potential experienced significantly larger price declines between 2019 and 2024, with a coefficient of approximately -0.003 for both sale prices and rents. Columns (2)–(4) introduce non-parametric distance controls via metro-area-by-distance-band fixed effects, isolating the within-distance-band WFH effect. The coefficient on WFH potential remains negative and highly significant across all distance control specifications, though it decreases in magnitude — from -0.003 to approximately -0.001 to -0.002 — indicating that part of the total WFH effect operates through the urban price gradient, while a substantial within-distance component remains. The standard deviation of WFH potential is 9.22 overall and 6.70 conditional on distance. A one-standard-deviation increase in WFH potential is thus associated with a price decline of approximately 2.8% without distance controls (Column 1) and 0.7–1.3% within distance bands (Columns 2–4). This within-distance effect is our key finding: even among postcodes at similar distances from the city center, those with

Figure 5: DiD Results on the Impact of WFH Potential on Urban Housing Prices



Notes: This figure presents DiD estimates $\hat{\beta}_k$ from Equation 1, interacting monthly dummies with postcode-level WFH potential, measured as the share of employed residents who can work from home at least one day per week. The dependent variable is the average log sale price per m^2 (Panels A and C) and the average log rent per m^2 (Panels B and D). All panels absorb postcode and metro-area-by-month fixed effects; Panels C and D additionally absorb distance-decile-by-month fixed effects, with deciles constructed within metro areas. Shaded areas show 95% confidence intervals with standard errors clustered at the postcode level. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020.

higher WFH potential experienced larger price declines, implying that WFH reduces spatial disparities in housing costs beyond flattening the urban gradient.

Robustness. Results are consistent across the three non-parametric specifications (deciles, quintiles, and catchment-area-by-distance-terciles fixed effects), confirming robustness to the choice of distance binning. Results are also robust to controlling parametrically for distance, as shown in Appendix Table D.4. The findings are further robust to shortening the time horizon: restricting the long difference to 2019–2021

Table 1: Long DiD Results: Effect of WFH Potential on Urban Housing Price Changes 2019–2024

	(1)	(2)	(3)	(4)
<i>Panel A Dependent Variable: 2019–2024 Change in Log Property Sale Prices</i>				
WFH Potential	-0.0031*** (0.0003)	-0.0019*** (0.0004)	-0.0019*** (0.0003)	-0.0021*** (0.0004)
R^2	0.23	0.38	0.33	0.35
Number Postcodes	4,522	4,504	4,522	4,487
<i>Panel B Dependent Variable: 2019–2024 Change in Log Property Rents</i>				
WFH Potential	-0.0030*** (0.0001)	-0.0010*** (0.0002)	-0.0013*** (0.0002)	-0.0013*** (0.0002)
R^2	0.31	0.54	0.49	0.53
Number Postcodes	4,509	4,492	4,509	4,474
Metro Area FE	✓			
Metro × 10 Distance Decile FE		✓		
Metro × 5 Distance Quintile FE			✓	
Metro × Catchment × 3 Distance Tercile FE				✓

Notes: This table reports long DiD estimates of the effect of WFH potential on postcode-level changes in log housing prices from 2019 to 2024, based on [Equation 2](#). Panel A presents results for sale prices and Panel B for rents. Column (1) reports the baseline estimate conditional on metro area fixed effects only, corresponding to the total WFH effect without distance control. Columns (2)–(4) introduce non-parametric distance controls: column (2) absorbs distance via metro-area-by-distance-decile fixed effects (10 bins), column (3) uses distance quintile fixed effects (5 bins), and column (4) uses metro-area-by-catchment-area-by-distance-tercile fixed effects (3 bands within each of the 4 catchment areas per metro). All specifications weight observations by postcode-level employment. Standard errors are clustered at the postcode level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

and 2019–2022 yields negative and highly significant coefficients throughout ([Appendix Table D.7](#)).

[Appendix Table D.5](#) shows that the within-distance effect is not confined to the largest metro areas: estimates are negative and statistically significant for the top 10, mid 20, and bottom 20 metro groups alike, with no systematic gradient by metro size.

The within-distance WFH effect is also robust to the definition of the city center and the delineation of market boundaries. [Appendix Table D.6](#) reports estimates from the preferred Metro × 10 Distance Decile FE specification under four setups: the baseline using townhall postcodes as city centers and the 50 BBSR *Großstadtregionen* as market boundaries (Column 1), restricting to the 44 monocentric metro areas (Column 2), replacing the townhall postcode with the postcode of highest Mastercard spending density as the city center (Column 3), and using the 223 BBSR *Arbeitsmarktregionen* as market boundaries (Column 4). The results are robust and the key result, that WFH

potential reduces housing prices even among equidistant postcodes, does not hinge on how city centers are defined or how metro boundaries are drawn.

5 Local Amenities and the Within-Distance WFH Effect

The within-distance WFH effect established in [Section 4.4](#) raises a natural question: among postcodes at similar distances from the city center, why do those with higher WFH potential experience larger housing price declines? One potential explanation is that high-WFH-potential locations at a given distance have systematically different local amenity profiles, and that the WFH shock revalued these amenities. Before 2020, commuting-enabling amenities were valued largely because they reduced the effective cost of accessing city-center employment. As WFH permanently lowers the value of commuting, the premium embedded in transit-accessible locations should partially unwind, and this unwind should be steepest where WFH potential is highest. On the other hand, amenities such as leisure facilities or green space may gain in relevance for high-WFH-potential areas as workers spend more time at home. This section therefore examines the role of amenities in explaining this effect.

5.1 Descriptive Evidence – Amenity Profiles at Equal Distance

[Glaeser et al. \(2001\)](#) identify four critical urban amenities, three of which map onto groups we observe. Their notion of *(transport) speed*—ease of movement within the city—corresponds to **(i) Transport**, which we measure by public transit quality and car transit time to the city center. Their *rich variety of services and consumer goods* corresponds to **(ii) Services and consumer goods**, measured by restaurants, leisure, health, and education points of interest per capita. Their *aesthetics and physical setting* is captured by **(iii) Green space** (share of green area), the only measure of this dimension available to us; weather, which they also place in this category, is irrelevant here because all comparisons are made within a metro area. Their fourth category, *good public services*, has no counterpart in our data: they define it as good schools and low crime, and neither is observable at the postcode level in Germany. There is no established measure of school quality, and crime statistics are published at the county level at best—too coarse for comparisons within a distance band of a metro area⁸. We add one group with no counterpart in a taxonomy written two decades before remote work: **(iv) Broadband**, measured by fiber-optic coverage.

⁸Health and education points of interest are counts of local establishments rather than measures of service quality, and therefore belong to the density of local service provision rather than to the quality-based notion of public services.

Each group corresponds to a distinct channel through which the WFH shock may have revalued locations. **Transport** proxies commuting ease—the dimension the commuting premium hypothesis predicts should lose value as WFH rises. **Services and consumer goods** capture the neighborhood service and consumption environment that workers and families use more intensively once the workday shifts from office to home. **Green space** similarly gains value as residential neighborhoods become work environments. **Broadband** is a prerequisite for remote work rather than a consumption amenity, and should matter where connectivity would otherwise constrain it. Amenities, where time-dependent, are measured at end-2019 to reflect pre-shock conditions.

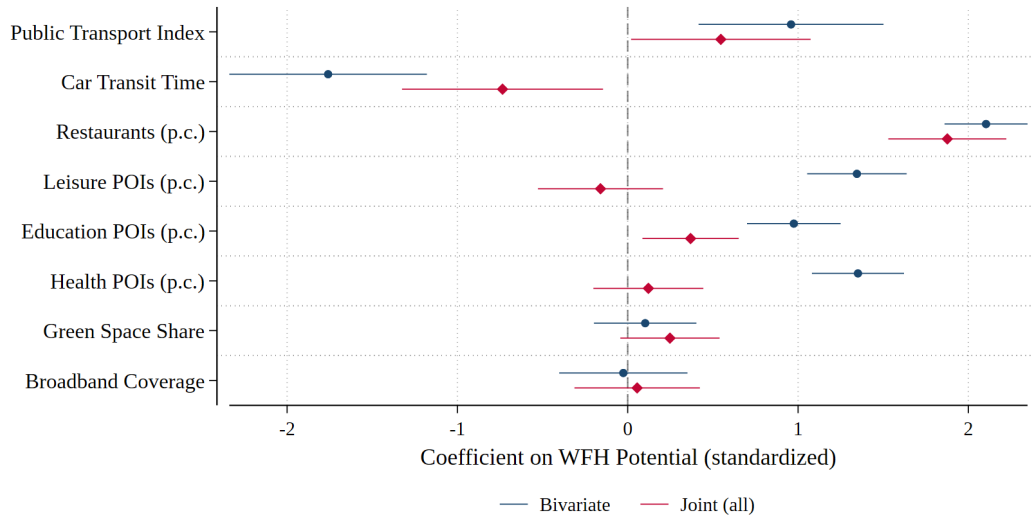
Figure 6 documents which of these amenities are systematically associated with WFH potential, conditional on metro area and distance. Among postcodes at comparable distances from the city center, high-WFH-potential areas have substantially better public transport access and lower car transit times to the city center. They also have more restaurants, health, leisure, and education facilities per capita, though except for restaurants, these associations become insignificant when estimated jointly. Green space share and fiber broadband coverage do not differ significantly between high- and low-WFH-potential areas.

The correlations in Figure 6 point to two distinct mechanisms through which amenities could explain the within-distance WFH effect on prices. The first is the *depreciation of commuting-enabling amenities*. High-WFH-potential postcodes systematically have better transit access, meaning their pre-shock prices embedded a commuting premium. As WFH reduces the value of that premium, prices should decline where WFH potential and transit quality are jointly high—predicting a negative $\text{WFH} \times \text{transit}$ interaction in price changes. The second mechanism is the *differential revaluation of amenities that were previously irrelevant for both groups*. Broadband coverage, green space access, and neighborhood service density show little or no correlation with WFH potential—because before 2020, office workers spent little time in their home neighborhoods and these amenities were similarly (un)important for everyone. Post-WFH, however, they gain value specifically for remote workers who now spend the working day at home, which may translate into relative price gains in these neighborhoods.

5.2 Amenities and Attenuation of the WFH Effect

The two mechanisms identified above share a testable implication: if the within-distance WFH coefficient partly reflects spatial sorting of WFH potential onto amenities whose relative value changed after the WFH shock, then including amenity $\times$

Figure 6: Amenity Correlates of WFH Potential Within Distance Bands

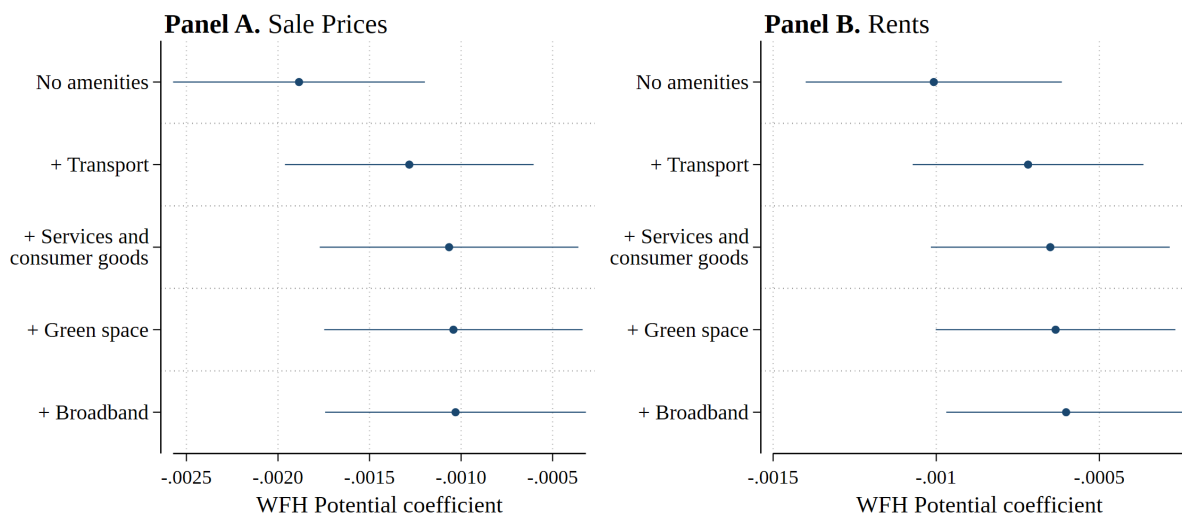


Notes: This figure presents bivariate and joint OLS estimates of the association between standardized local amenity variables and postcode-level WFH potential, conditional on Metro $\times$ Distance Decile fixed effects and weighted by postcode-level employment. Blue circles report bivariate estimates (one regression per amenity); red diamonds report joint estimates with all amenities simultaneously. All amenity variables are standardized to zero mean and unit variance. Standard errors are clustered at the postcode level; 95-percent confidence intervals are shown.

WFH interaction terms should absorb part of the main coefficient. A large attenuation would indicate that the WFH gradient in price changes is substantially a gradient in the revaluation of specific local amenities. To quantify this attenuation, we augment the baseline long DiD regression in [Equation 2](#) with amenity controls. Each amenity group enters both in levels and as interactions with WFH potential, retaining Metro $\times$ Distance Decile fixed effects throughout. Full regression results appear in [Appendix Table E.8](#) (sale prices) and [Table E.9](#) (rents). [Figure 7](#) summarizes the evolution of the main WFH coefficient as amenity groups are added sequentially.

For sale prices (Panel A), the results confirm that the depreciation of commuting-enabling amenities and the revaluation of the neighborhood service environment are the two leading channels. The baseline within-distance WFH coefficient of -0.0019 falls by one third to -0.0013 once transport controls enter, driven by a negative interaction between WFH potential and public transit quality and a positive one with car transit time: sale price declines occurred precisely in postcodes where both WFH potential and transit access are highest, the locations that most likely embedded a commuting premium before 2020. Adding leisure and services controls provides further evidence of the second mechanism: health, education and leisure density further attenuate the WFH coefficient to -0.0011 , indicating that part of the WFH effect reflects the revaluation of service amenities by remote workers. Nature and broadband

Figure 7: Attenuation of the Within-Distance WFH Coefficient as Amenity Controls are Added



Notes: This figure shows how the estimated WFH potential coefficient from the long DiD regression in Equation 2 evolves as local amenity controls are added sequentially. Panel A presents results for sale prices and Panel B for rents. All specifications include Metro $\times$ Distance Decile fixed effects and weight by postcode-level employment. Amenity groups are added in the following sequence: transport, services and consumer goods, green space, and broadband. Each group enters in levels and as interactions with WFH potential; the plotted coefficient refers to the main WFH potential effect. Standard errors are clustered at the postcode level; 95-percent confidence intervals are shown.

controls contribute an additional increment, bringing the fully saturated coefficient to -0.0010 and total attenuation to approximately 50 percent.

For rents (Panel B), both the magnitude and character of attenuation differ, consistent with rents reflecting current service flows rather than capitalizing on the long-run revaluation of the amenity stock. The coefficient falls from -0.0010 to -0.0006 across the five specifications—a total attenuation of 40 percent, compared to 50 percent for sale prices. The gap reflects an asset-pricing logic: buyers form long-run expectations about which locations will gain or lose value as WFH permanently reshapes commuting patterns, embedding the full revaluation of the amenity stock into sale prices; renters, renegotiating on shorter horizons, respond primarily to current residential utility and are therefore less sensitive to permanent shifts in the commuting premium. That 40 percent of the rent effect can nonetheless be attributed to the observable amenity stock indicates that amenity revaluation is not confined to ownership markets but also shapes the rental gradient.

The attenuation pattern is robust to how city centers are defined and how metro markets are delineated. Appendix Table E.10 reports WFH coefficients without and with the full amenity bundle across the same four alternative specifications used in Ap-

pendix [Table D.6](#). In every case the baseline coefficient is negative and significant at the one percent level, and adding amenity controls attenuates it toward zero. As the relationship between outcome and covariates may be sensitive to the order of covariate addition ([Gelbach, 2016](#)), we apply an order-invariant Shapley decomposition of the covariates, following [Shorrocks \(2013\)](#). The decomposition confirms that the channel ranking is robust to sequential entry order: transport quality and the neighborhood service environment each account for a substantial and roughly comparable share of the total attenuation, with transport contributing somewhat more ([Appendix Figure E.11](#)).

Together, the results establish that the within-distance WFH effect is substantially explained by local amenity revaluation, with transport quality and the neighborhood service environment as the two leading channels. Beyond this within-distance dimension, WFH also contributed to the broader flattening of the urban housing price gradient documented in [Section 3](#) and [Section 4](#). The next section examines the mechanisms behind this overall effect.

6 Mechanisms Driving the WFH Effect

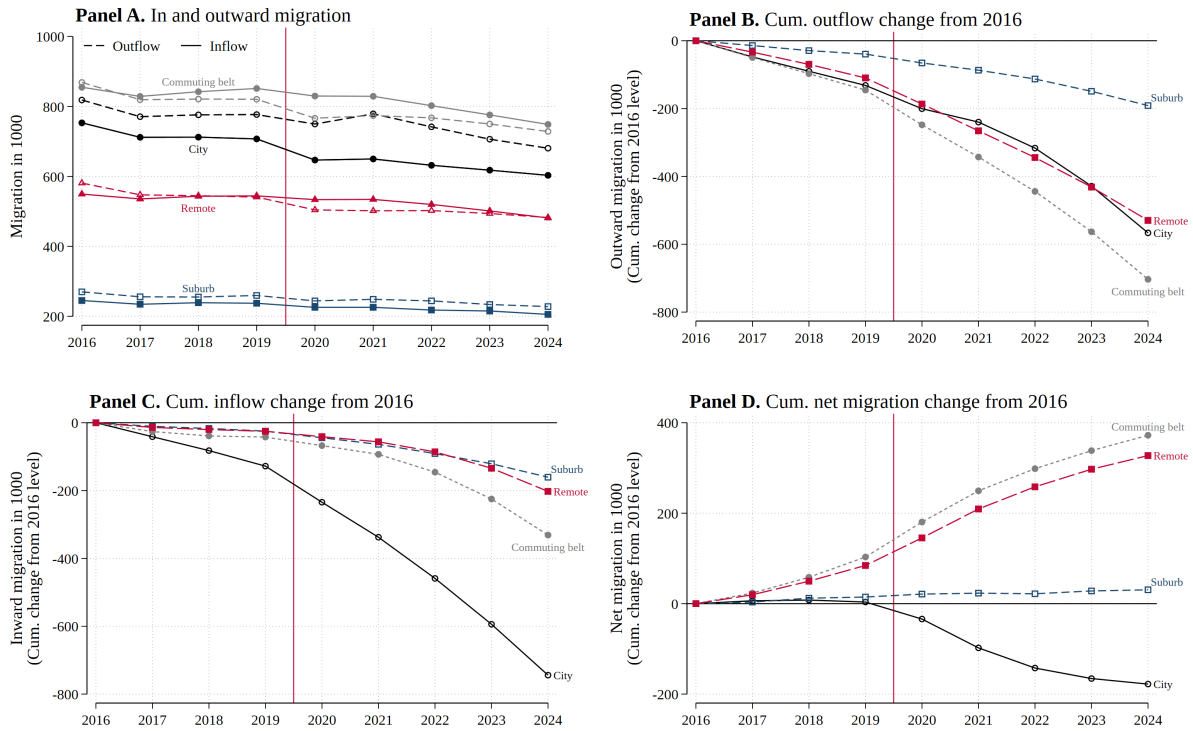
Having established that the Covid-induced WFH shock lowered housing prices in areas with high WFH potential, we now ask what changed on the ground to produce this price response. Prices can change because households relocate and migration patterns change, because employment shifts elsewhere, because the housing supply responds, or because expectations about future demand adjust. This section examines each of these channels, drawing on administrative migration statistics, administrative employment records, and cellphone-based mobility data.

6.1 Changes in Migration Flows Within Metros

We examine migration patterns as the first demand-side mechanism. Using administrative data from 2016 to 2024, we analyze net domestic migration flows both within and across MAs. As discussed in [Section 4](#), WFH influences migration in two main ways: Firstly, hybrid workers relocate to more affordable or spacious areas, reducing demand in urban cores. Secondly, workers can now accept urban jobs without relocating, lowering long-run expectations of urban living demand. Both mechanisms affect prices via the net present value of expected rents from housing demand.

[Figure 8](#) shows a clear post-pandemic slowdown in both urban inflows and outflows, with a sharper decline in inflows to cities (Panels B and C). This shift led to rising net outmigration, especially toward commuting belts and remote areas. Contrary to

Figure 8: Changes in Urban Net Migration Flows (Germans)



Notes: This figure displays domestic migration flows for German citizens across county borders, broken down by urban catchment area (city, suburb, commuting belt, remote area), based on annual origin-destination data from 2016 to 2024. Panel A shows annual inflows and outflows for each catchment area. Panels B and C show the cumulative change in outflows and inflows since 2016, where 2016 serves as the reference level. Panel D shows the cumulative change in net migration since 2016. Administrative data on migration statistics are provided by the German Federal Statistical Office.

the “urban exodus” narrative, the population decline in German cities stems more from reduced inflows than increased outflows. These altered migration patterns imply shifts in residential preferences and reduced proximity needs, as WFH allows workers to accept jobs in cities without relocating. These findings align with recent studies (Coskun et al., 2026; Akan et al., 2024; Boeri and Rigo, 2024) showing that WFH increases job-home distance mainly for job switchers. Our results are also consistent with models of households’ reactions to local economic shocks that do not expect substantial migration responses (Monras, 2020). Results are robust to restricting the sample to the 30–49 age group, for which tertiary education-related migration movements that were disrupted during 2020–2021 do not apply (Appendix Figure F.13).

Origin-destination migration data confirm that most population shifts occurred within MAs, primarily from cores to nearby peripheries (see Appendix Figure F.12). However, the overall scale was modest: Excess net migration from more to less central counties between 2020 and 2024 totaled around 400 thousand people, also keeping

in mind that even before the WFH shock, there was a slight outward-migration trend, though smaller. Thus, the net-outward migration due to the WFH shock was less than 400 thousand. This represents only a small fraction of the six million workers who transitioned to WFH since 2019.

To validate these results at finer spatial scales, we use Deutsche Telekom cellphone data to track home locations via first-morning pings. The results in [Figure 9](#) show that mobility declined during the pandemic but post-Covid patterns show no lasting shifts in residential locations relative to WFH potential. Reassuringly, these granular spatial data confirm that population shifts within cities relative to WFH have been minimal.

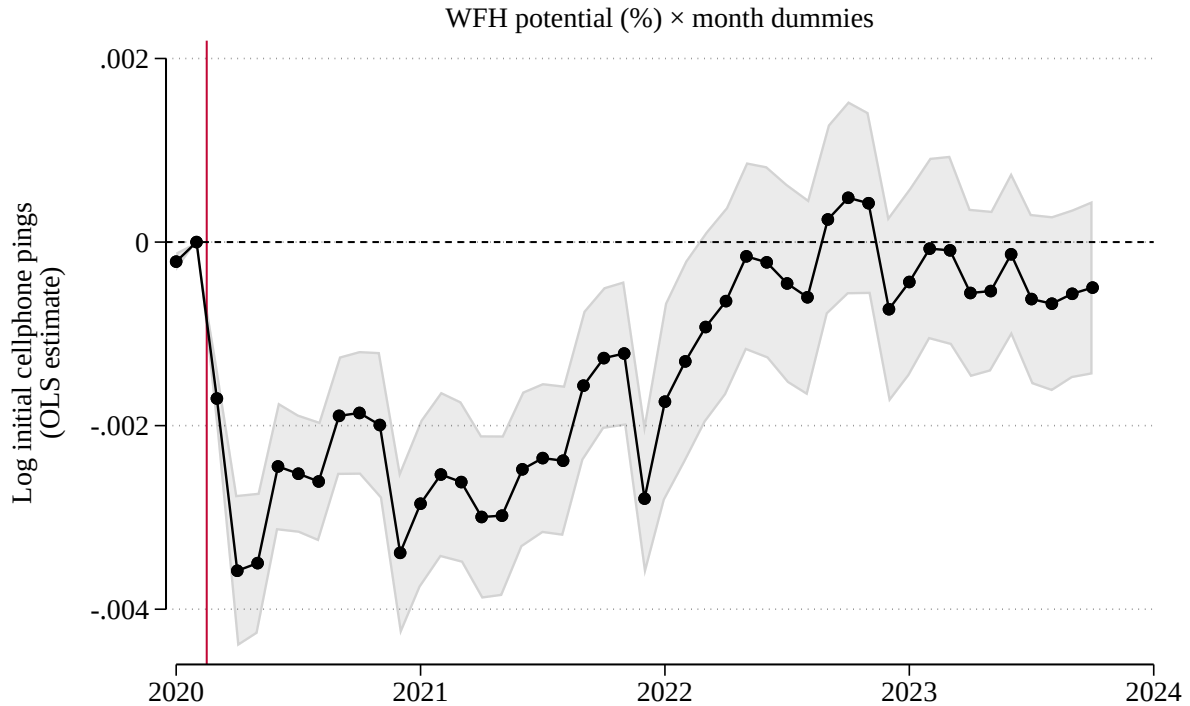
Overall, WFH affected housing demand in urban cores more through altered expectations than large-scale population moves. While physical migration remained limited, the sharp decline in inflows – especially of potential new residents – has likely shifted expectations about long-term urban housing demand. As a result, housing demand has declined in urban cores and risen in suburban and peripheral areas. Since the migration channel operates largely through expectations, its direct contribution to the impact of WFH on housing prices is difficult to quantify. However, WFH-induced shifts in migration patterns have revalued future demand and rental cash flows, flattening the urban price gradient and reducing spatial inequality in housing prices.

6.2 Broken Urbanization Trend in Employment Growth

We next examine spatial shifts in employment as a second demand-side mechanism. Consistent with recent studies ([Duguid et al., 2023](#); [Alipour et al., 2026](#); [Rosenthal et al., 2022](#); [Althoff et al., 2022](#)), WFH is associated with a relocation of economic activity toward suburban and peripheral areas, likely driven by shifting consumption and service demand.

[Figure 10](#) tracks how the spatial distribution of employment within German MAs evolved from 2016 to 2024, using 2016 as the reference year. Panel A documents a clear urbanization trend of employment in the pre-pandemic period: relative to 2016, employment became progressively more concentrated in city centers through 2019, with the coefficient on log distance declining steadily. This trend stops after 2020: peripheral areas kept or even slightly gained their relative employment share and the pre-pandemic urbanization of employment stalled. Panel B reveals a complementary pattern for WFH potential: high-WFH-potential areas, which are predominantly centrally located, saw their employment share grow steadily from 2016 to 2019, consistent with urban sorting of office workers. This upward trend stops after 2020, with the coefficient stabilizing and declining slightly toward 2024.

Figure 9: DiD Estimates of Changes in Cellphone Pings Relative to WFH Potential



Note: This figure reports monthly DiD estimates of the changes in cellphone users' first-morning pings within their home zones relative to WFH potential at the postcode level. The estimates use postcode and metro-area-by-month fixed effects. Standard errors are clustered at the postcode level. The cellphone-mobility data represent users' first-morning pings within their home zones, provided by T-Systems by Deutsche Telekom.

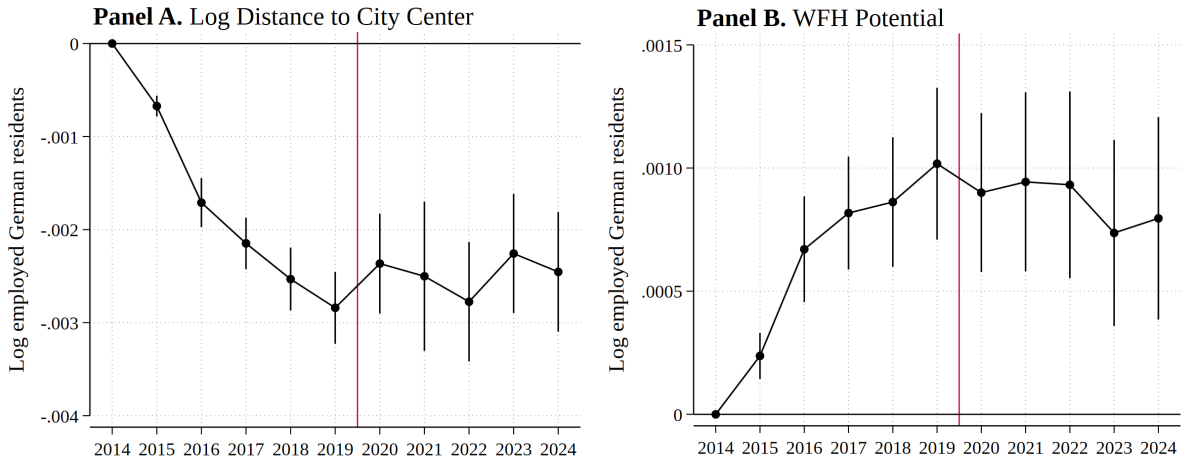
Together with the migration results, these findings reinforce the conclusion that WFH has weakened the traditional spatial linkage between residence and employment. Workers increasingly live farther from jobs without relocating their residences, contributing to the decentralization of both population and employment. This interpretation is consistent with evidence from Germany (Coskun et al., 2026), showing that WFH increases the distance between home and workplace primarily for job transitions.

6.3 Absence of Supply-Side Mechanisms

Finally, we investigate potential supply-side mechanisms in the context of the WFH impact on urban housing prices. Following Gupta et al. (2022), we focus on spatial changes in housing quantity and liquidity, measured as the number of property offerings per postcode and their average time on the market. We employ another dynamic DiD approach to test whether WFH potential has a differential effect on these outcomes over the period from 2014 to 2023.

We do not find evidence that housing quantity or liquidity change meaningfully after the Covid shock with respect to WFH potential. Detailed results for housing quan-

Figure 10: Spatial Employment Trends in Metro Areas



Notes: This figure depicts spatial employment trends across MAs from 2014 to 2024, based on the employment of Germans at their place of residence, with 2014 as reference year. The panels report estimates from regressions of the log number of employed German residents on the interaction between year dummies and log distance from the city center (Panel A) or WFH potential (Panel B). Confidence intervals are drawn at the 95 percent level using standard errors clustered by municipality. Administrative employment data are provided by the Federal Employment Agency (*Bundesagentur für Arbeit*).

tity and liquidity are provided in Appendix [Figure F.14](#) and [Figure F.15](#), respectively. These results suggest low supply elasticity, which is consistent with previous findings of an inelastic housing supply in the short run ([Baum-Snow and Han, 2024](#)).

7 Discussion and Conclusion

This paper provides causal evidence on how WFH reshaped the spatial distribution of housing prices within German metropolitan areas. Our central finding goes beyond the well-documented flattening of the urban price gradient: WFH reduces housing prices even among postcodes at *similar distances* from the city center. Exploiting postcode-level variation in WFH potential across Germany’s 50 metropolitan areas, we show that among equidistant postcodes, those with higher WFH potential experienced systematically larger price declines between 2019 and 2024. To our knowledge, this is the first study to causally identify such a within-distance WFH effect, pointing to a revaluation of urban location fundamentals that goes beyond a simple center-to-suburb demand reallocation.

We then show that this within-distance effect is to a large extent explained by the revaluation of local amenities. Before 2020, high-WFH-potential locations at a given distance commanded higher prices partly because they offered better public transit access and richer service environments—amenities valued for reducing the cost of

commuting to city-center employment. As WFH permanently lowered the value of commuting, the premium embedded in these transit-accessible, service-dense locations partially unwound. Controlling for local amenities and their interactions with WFH potential attenuates the within-distance WFH coefficient by approximately 47 percent for sale prices and 40 percent for rents, with transport quality and the neighborhood service environment as the two leading channels. The larger attenuation for sale prices than for rents is consistent with an asset-pricing logic: buyers capitalize the full long-run revaluation of the amenity stock, while renters respond primarily to current service flows.

These findings are set against the background of a broader gradient flattening. A 10 percent greater distance from the city center is associated with a 0.5 percent increase in housing prices by 2024, while a one percentage point higher WFH potential lowers them by 0.3–0.4 percent unconditional on distance. These effects document a “donut effect” in Germany that mirrors U.S. evidence ([Gupta et al., 2022](#); [Ramani et al., 2024](#)), though at a smaller magnitude—consistent with European city centers retaining higher amenity value even as part of the commuting premium erodes.

The spatial price changes reflect demand-side mechanisms. WFH partially decoupled residential location from workplace proximity: urban cores experienced a slowdown in population inflows rather than an urban exodus, consistent with WFH enabling workers to accept city-center employment without relocating. Employment growth, which had urbanized steadily through 2019, stalled after 2020. Housing prices adjusted not only to actual relocations but also to revised expectations about future urban demand. Supply-side responses remain limited throughout.

Our findings nuance prior work on the welfare implications of WFH. While [Davis et al. \(2024b\)](#) and [Richard \(2024\)](#) argue that WFH reduces welfare for non-WFH workers by raising overall housing prices, and [Delventhal et al. \(2022\)](#) finds welfare gains through falling prices, our results reveal a more spatially differentiated picture: WFH improves affordability in central, high-WFH-potential areas but raises prices in suburban and peripheral locations, with an overall compression of spatial housing cost inequality.

Two policy implications follow directly from our findings. First, the case for transit-oriented investments has weakened. Good public and car transit access has traditionally been capitalized into urban property values, providing – among many other reasons – a fiscal rationale for transit spending. Our results show that WFH has substantially eroded this commuting premium: transit quality is the single largest channel through which high-WFH-potential locations lost value. Second, the erosion of

the commuting premium points to a structural shift in what cities need to offer. Our amenity analysis suggests that, as WFH reduces the value of workplace proximity, the consumption dimension of cities—restaurants, cultural facilities, leisure amenities—gains relative importance over their role as employment hubs. This transition toward a “consumer city” ([Glaeser et al., 2001](#)) implies that investing in residential and leisure amenities may sustain urban demand more effectively than continuing to prioritize commuting infrastructure.

Future research could examine how WFH-driven amenity revaluation feeds back into labor mobility, firm location, and urban wage premia, as well as whether the compression of spatial housing costs persists or partially reverses as cities adapt their amenity provision to the hybrid work equilibrium.

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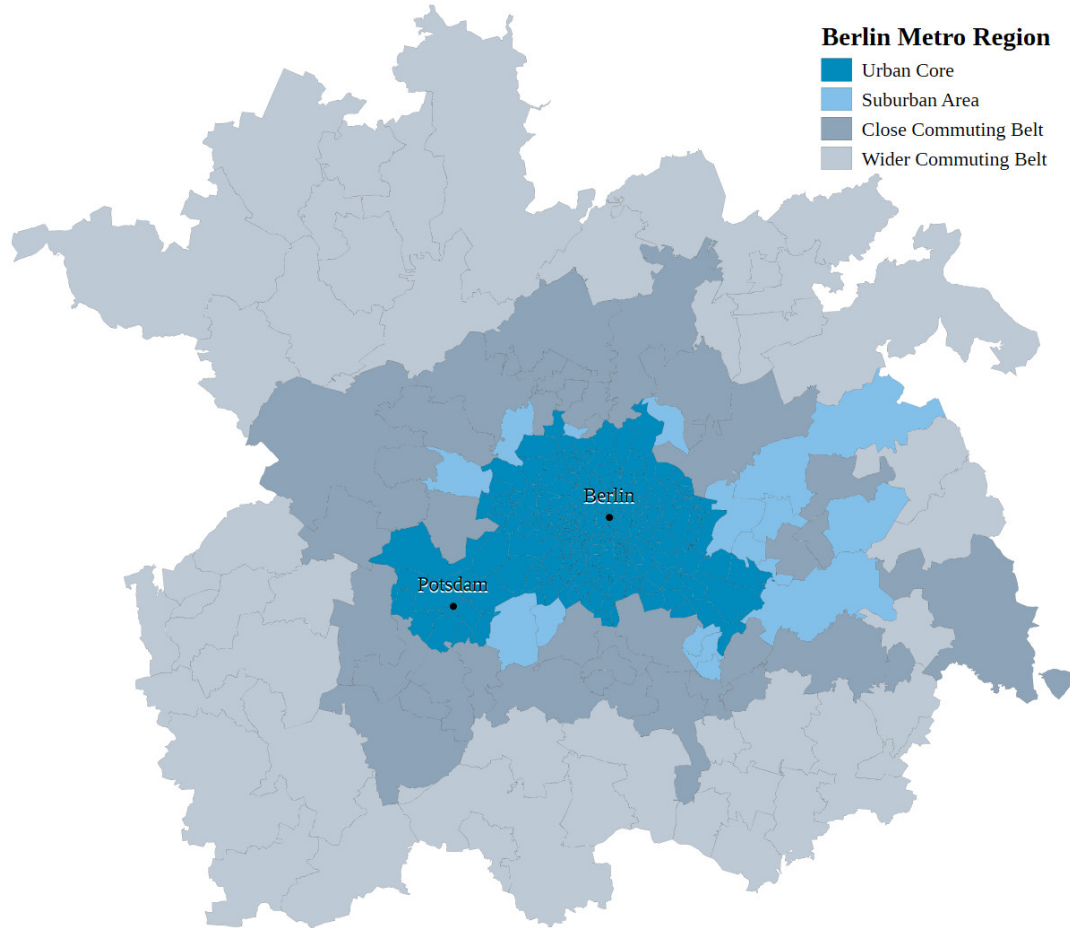
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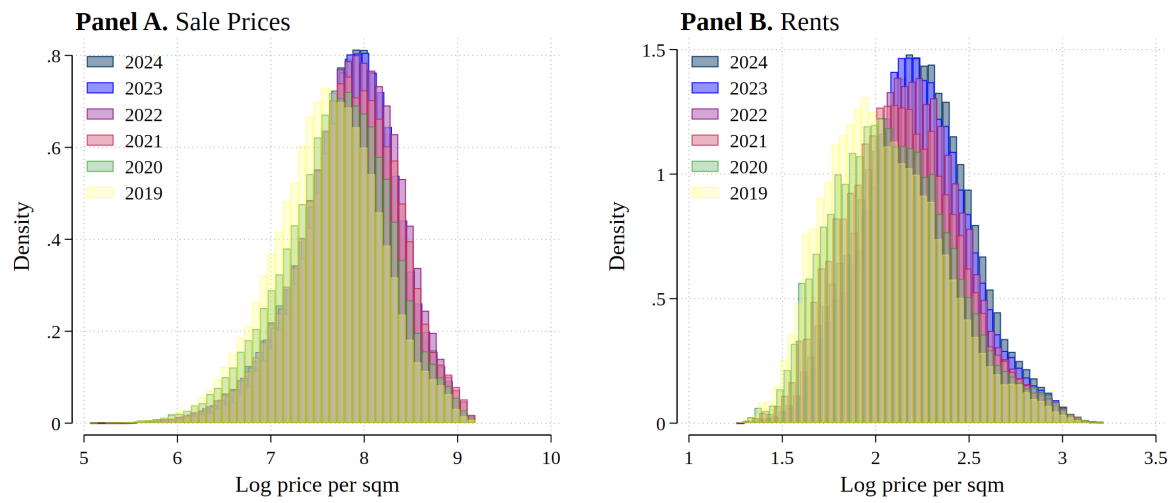
Appendix A Sample and Summary Statistics

Figure A.1: Illustration of Catchment Areas Within Berlin Metro Region



Notes: This figure displays the catchment areas defined by the BBSR for the metro region Berlin with the urban core, the suburban area, as well as the close and wider commuting belt.

Figure A.2: Histogram of Log Sale Prices and Rents 2019-2024 in Sample



Notes: This figure displays the distribution of log sale prices/rents in the years 2019 to 2024. The two panels plot the annual distributions of log prices/rents for residential sale prices and residential rents.

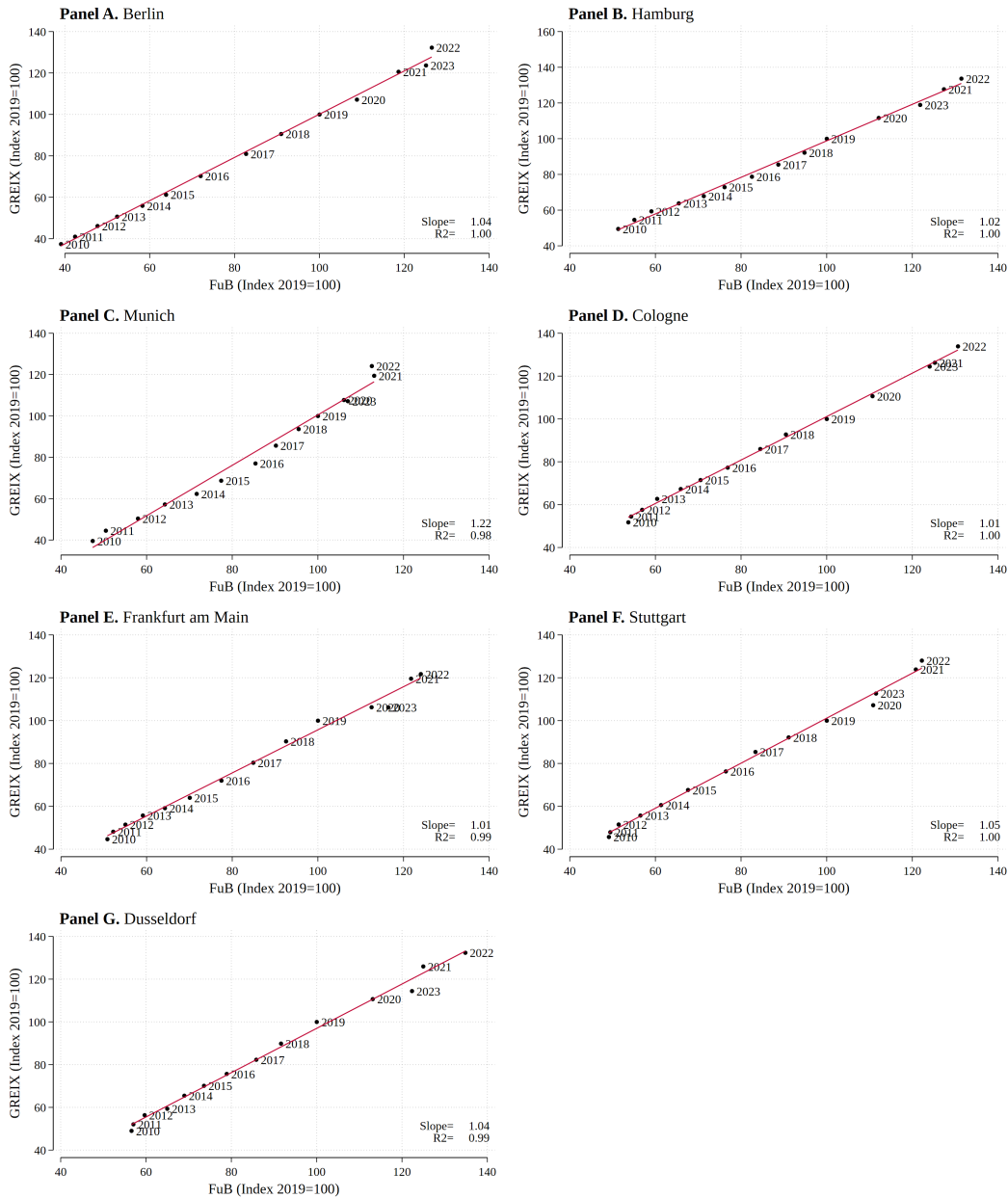
Table A.1: Summary Statistics: Real Estate and Postcode Characteristics

	Mean	SD	Min	Max
Panel A. Residential Real Estate Sale Prices				
Average Property Price per Square Meter	2520.18	1409.32	158.31	9811.32
Median Property Price per Square Meter	2485.55	1444.52	158.31	9811.32
Sum of Property Offers per Postcode and Month	16.36	18.22	1.00	562.00
Average Space in Square Meters	139.18	48.36	28.00	1416.00
Average Number of Rooms	4.54	1.60	0.00	84.00
Share New Buildings	0.20	0.23	0.00	1.00
Panel B. Residential Real Estate Rents				
Average Property Price per Square Meter	8.52	3.04	3.48	25.00
Median Property Price per Square Meter	8.36	3.05	3.48	25.00
Sum of Property Offers per Postcode and Month	19.90	27.91	1.00	1472.00
Average Space in Square Meters	82.66	21.74	23.00	300.00
Average Number of Rooms	2.83	0.77	0.00	18.00
Share New Buildings	0.12	0.19	0.00	1.00
Panel C. Working From Home				
WFH Potential Residence (Percent)	35.58	9.23	0.00	77.56
WFH Potential Workplace (Percent)	42.00	7.55	12.23	92.49
WFH Prior to Covid (Percent)	14.23	7.40	0.00	52.66
WFH Untapped Potential (Percent)	60.98	15.20	10.58	100.00
WFH During Covid (Percent)	21.12	8.69	0.00	54.68
WFH Growth	0.71	0.95	-0.66	22.74
WFH Employee Desires After Covid (Percent)	29.02	9.06	0.00	64.09
WFH Employer Plans After Covid (Percent)	14.83	7.82	0.00	62.78
Panel D. Postcode Structure				
Population per Postcode	13273.89	9284.35	0.00	58826.00
Area per Postcode (sqkm)	35.35	45.87	0.00	567.73
Population Density (Inhabitants per sqkm)	3191.98	4692.61	15.09	29715.43
Distance to City Center (km)	17.96	12.61	0.00	71.66
Share Married Inhabitants	0.43	0.08	0.12	0.67
Share Foreigners	0.12	0.08	0.00	0.60
Share Low Income Households (Net Income Below 1,500 €)	0.24	0.16	0.00	1.00
Share Inhabitants Below Age 15	0.14	0.02	0.00	0.27
Share Inhabitants Aged 15-29	0.16	0.03	0.05	0.33
Share Inhabitants Age 65 and Above	0.21	0.04	0.04	0.65
Firm Density (Firms per sqkm)	0.00	0.00	0.00	0.04
Panel E. Postcode Firm Structure				
Share of Sector: Trade and Maintenance and Repair of Vehicles	0.15	0.03	0.00	1.00
Share of Sector: Hospitality	0.04	0.02	0.00	0.28
Share of Sector: Art, Entertainment and Recreation	0.03	0.01	0.00	0.31
Share of Sector: Freelancing, Scientific and Technical Services	0.12	0.04	0.00	0.32
Share of Sector: Construction	0.08	0.03	0.00	0.28
Share of Sector: Education and Teaching	0.02	0.01	0.00	0.17
Share of Sector: Other Services	0.20	0.04	0.00	0.80

Notes: The table reports summary statistics for 4,543 postcodes of the 50 German metropolitan areas included in our sample. Real estate data are from F+B (Panels A and B). WFH data (Panel C), sociodemographic structure (Panel D) and industry composition (Panel E) are collected and provided by infas360 based on survey and administrative data.

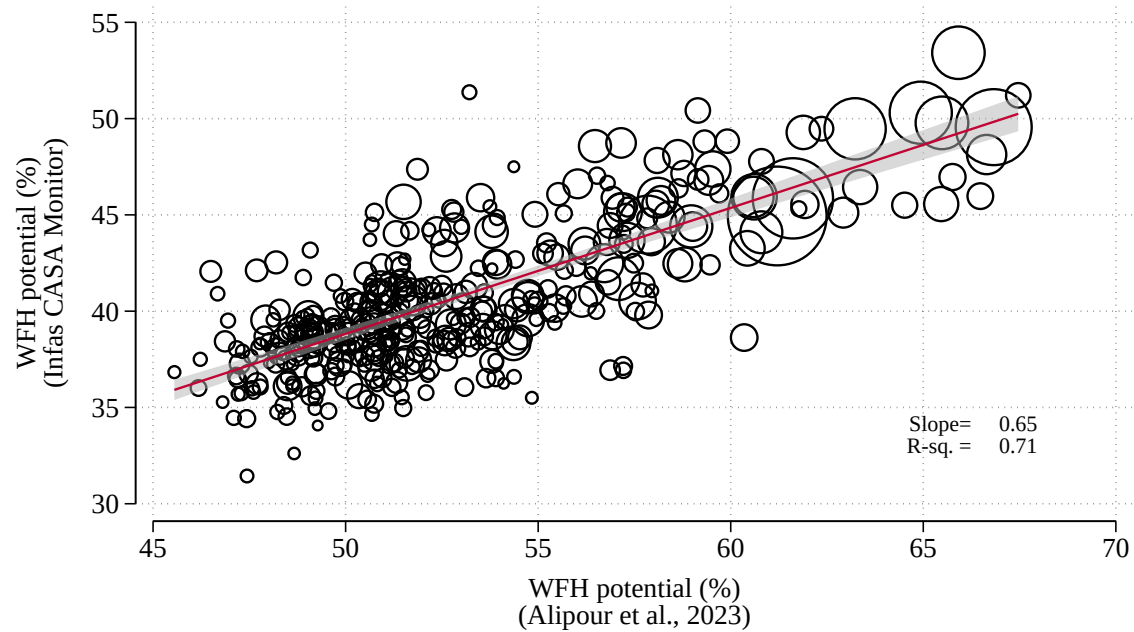
Appendix B Data Validation

Figure B.3: Data Validation of Property Offering Prices: Correlation of F+B Property Offerings Price Index and German Real Estate Index (GREIX)



Notes: This figure shows correlations of real estate prices in Germany's seven largest cities (Berlin, Hamburg, Munich, Cologne, Frankfurt, Stuttgart, and Dusseldorf) from 2010 to 2023. The x-axis displays the F+B property offering price indices, which are used in the analyses of this paper. The y-axis depicts the GREIX, an administratively compiled index based on actual transaction prices reported by municipal property valuation committees (Gutachterausschüsse). Both indices track prices of residential apartment sales and are normalized to an index value of 100 in 2019. Source: [Amaral et al. \(2023\)](#).

Figure B.4: Validation of WFH Data: Correlation of infas Postcode-Level Survey Data and County-Level Admin Data from Alipour et al. (2023)



Notes: This figure displays the correlation of the WFH potential measure based on survey data from infas360 used in this study (vertical axis) with the WFH capacity measure based on administrative occupational data from [Alipour et al. \(2023\)](#) (horizontal axis). Since the occupational data is at the county-level, we aggregate our postcode-level WFH measure accordingly.

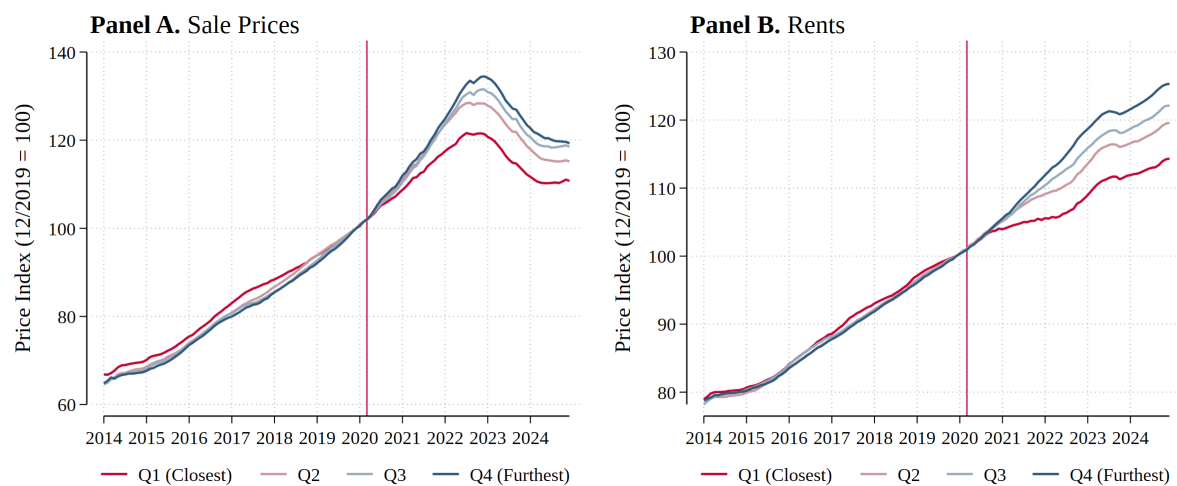
Table B.2: Validation of City-Center Definition: Rank of Townhall Postcode by Mastercard Spending Density Within Metro Area

<i>Rank</i>	Median Spending/km²		Mean Spending/km²	
	<i>Freq.</i>	<i>Cum. %</i>	<i>Freq.</i>	<i>Cum. %</i>
1st	49	79.0	49	79.0
2nd	8	91.9	7	90.3
3rd	3	96.8	4	96.8
4th+	2	100.0	2	100.0
<i>N</i>	62		62	

Notes: The table reports how the townhall postcode — the city-center proxy used in the baseline analysis — ranks within its metro area when all postcodes are ordered by Mastercard spending density (transaction volume per km²). It covers the 62 city centers of the 50 metro areas (six of these metro areas are polycentric and therefore have more than one city center). Ranks are computed separately by median and mean spending density across all postcodes. Ranks 4 and above are grouped as “4th+”.

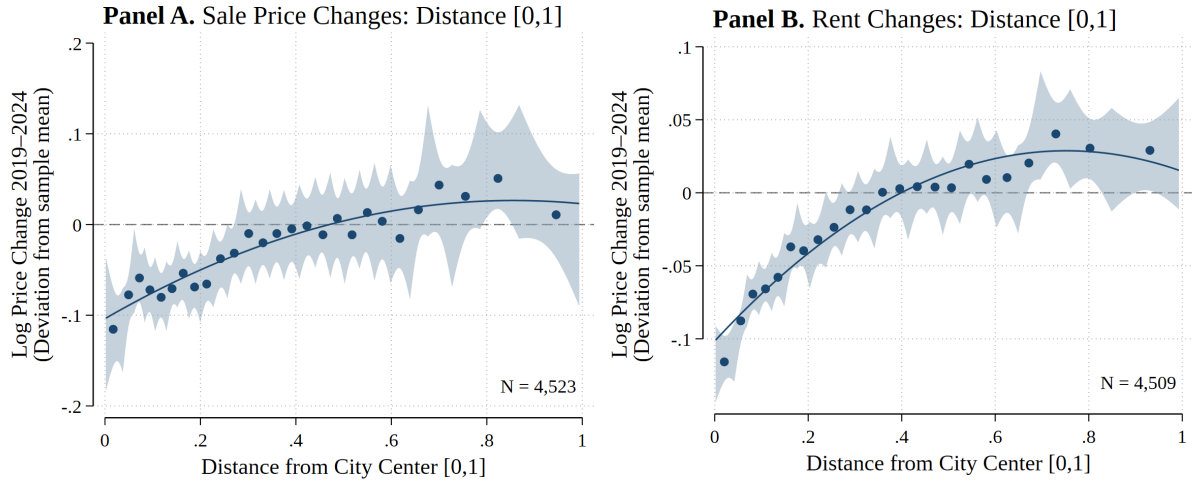
Appendix C Descriptive Evidence

Figure C.5: Donut Effect of Urban Housing Prices



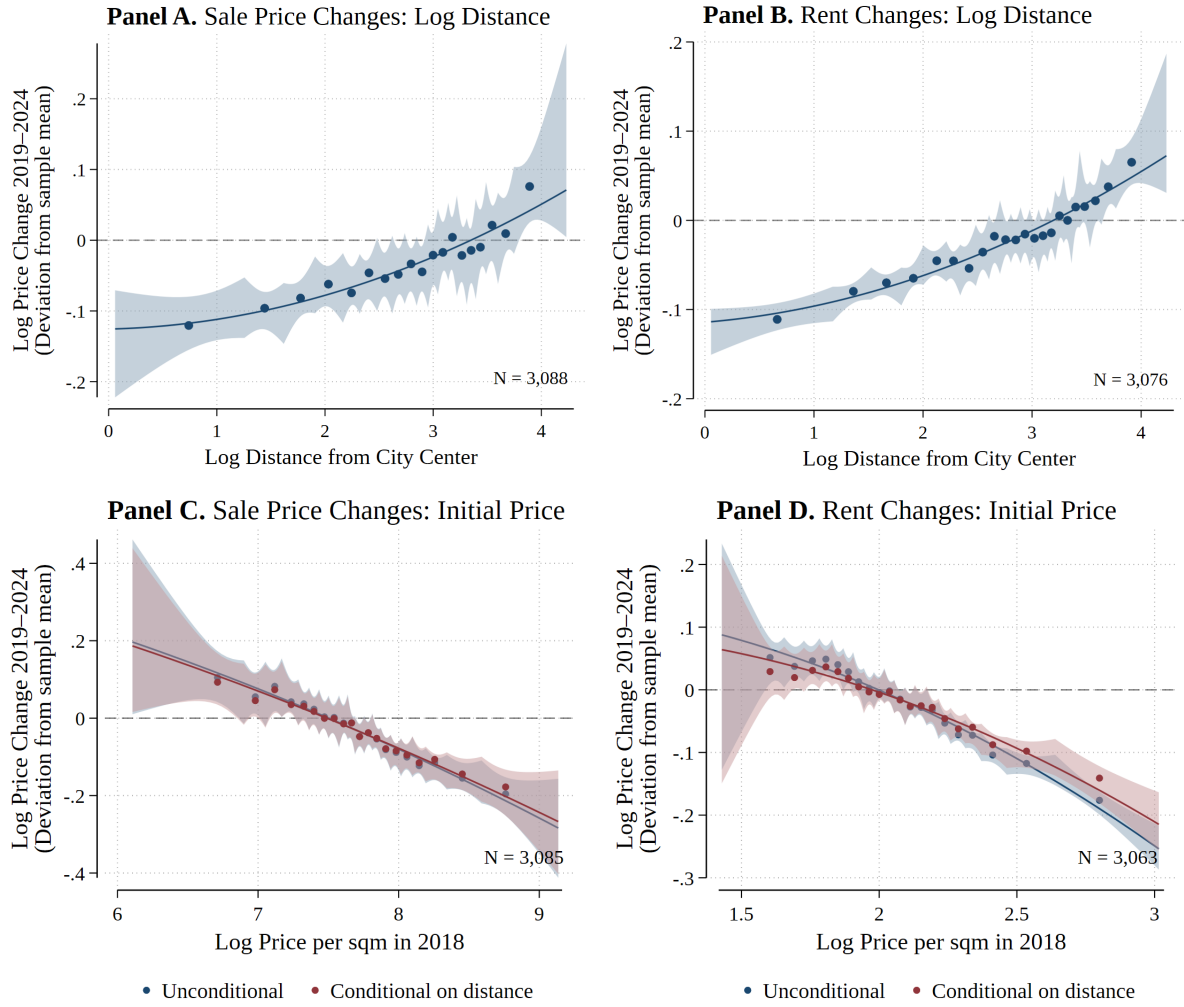
Notes: This figure displays the development of nominal real estate prices in German metropolitan areas between 2014 and 2024. The two panels plot the evolution of sale prices and rents. Postcodes are grouped into four quartiles by Euclidean distance from city center (Q1 = closest quarter, Q4 = furthest quarter). Average monthly nominal asking prices per square meter are transformed into an index that takes the value of 100 in December 2019. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020.

Figure C.6: Flattening of Urban Housing Price Gradient: Normalized Distance [0,1]



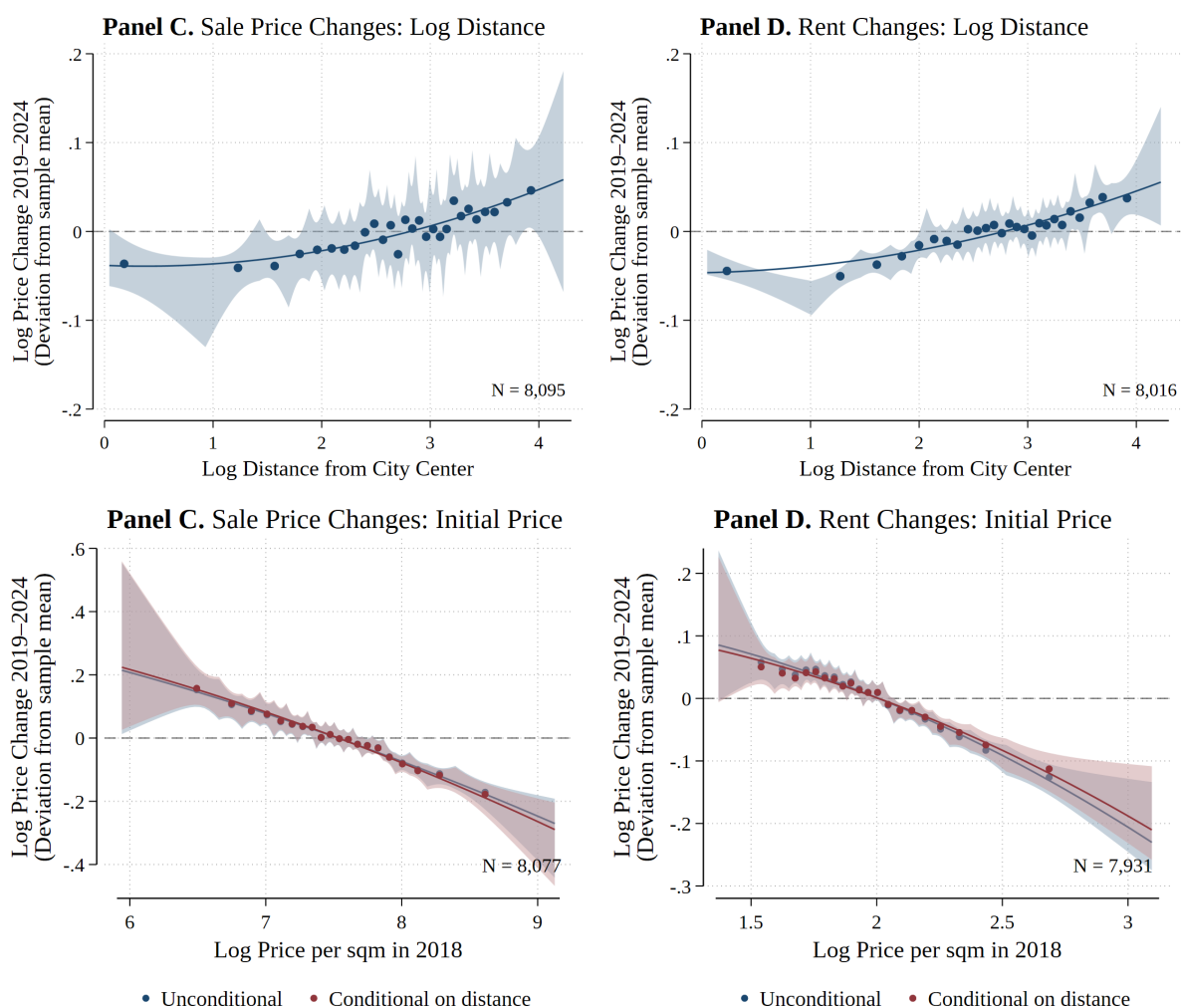
Notes: This figure displays binned scatter plots following the methodology proposed by [Cattaneo et al. \(2024\)](#) on the postcode-level relationship between the normalized distance from the city center [0,1] and the change in log sale prices (Panel A) and rents (Panel B) from 2019 to 2024. The shaded areas highlight 95% confidence bands. Metro-area fixed effects are absorbed in all panels. Log price changes are expressed as deviations from the sample mean.

Figure C.7: Flattening of Urban Housing Price Gradient: Only Monocentric Areas



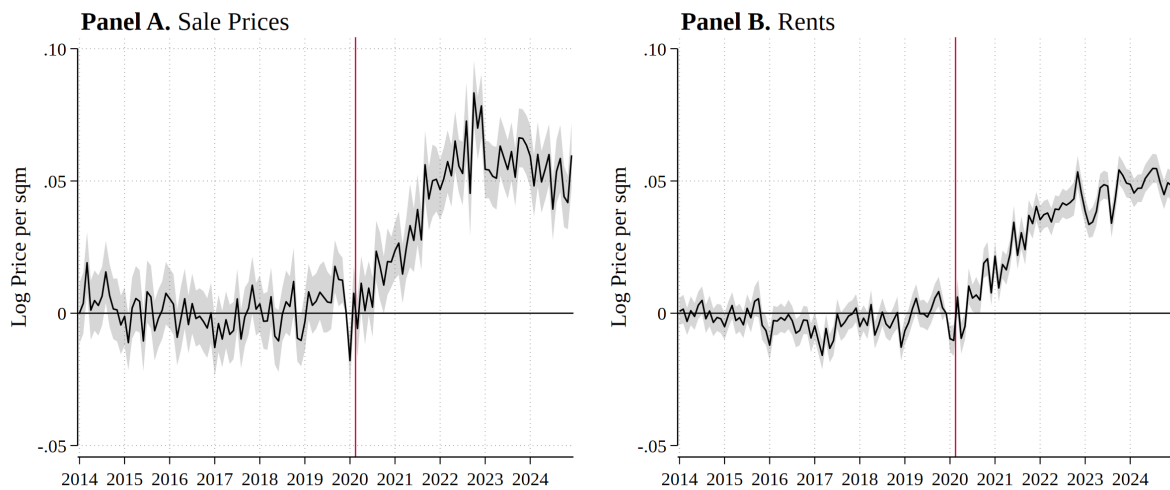
Notes: This figure replicates [Figure 3](#) using only the 44 (out of the 50) metro areas that are monocentric. Panels A and B plot the change in log sale prices and log rents from 2019 to 2024 against log distance from the city center; Panels C and D plot the same changes against the 2018 log price level, unconditionally (blue) and conditional on within-metro distance deciles (red). The shaded areas highlight 95% confidence bands. Metro-area fixed effects are absorbed in all panels. Log price changes are expressed as deviations from the sample mean.

Figure C.8: Flattening of Urban Housing Price Gradient: BBSR Arbeitsmarktreionen



Notes: This figure replicates [Figure 3](#) using an alternative urban delineation. Instead of the 50 BBSR *Großstadtreionen* used in the main analysis, metro areas are defined as the 223 BBSR *Arbeitsmarktreionen* (labor market regions), with city centers identified as the townhall of the most populous municipality within each region. Panels A and B plot the change in log sale prices and log rents from 2019 to 2024 against log distance from the city center; Panels C and D plot the same changes against the 2018 log price level, unconditionally (blue) and conditional on within-region distance deciles (red). The shaded areas highlight 95% confidence bands. Metro-area fixed effects are absorbed in all panels. Log price changes are expressed as deviations from the sample mean.

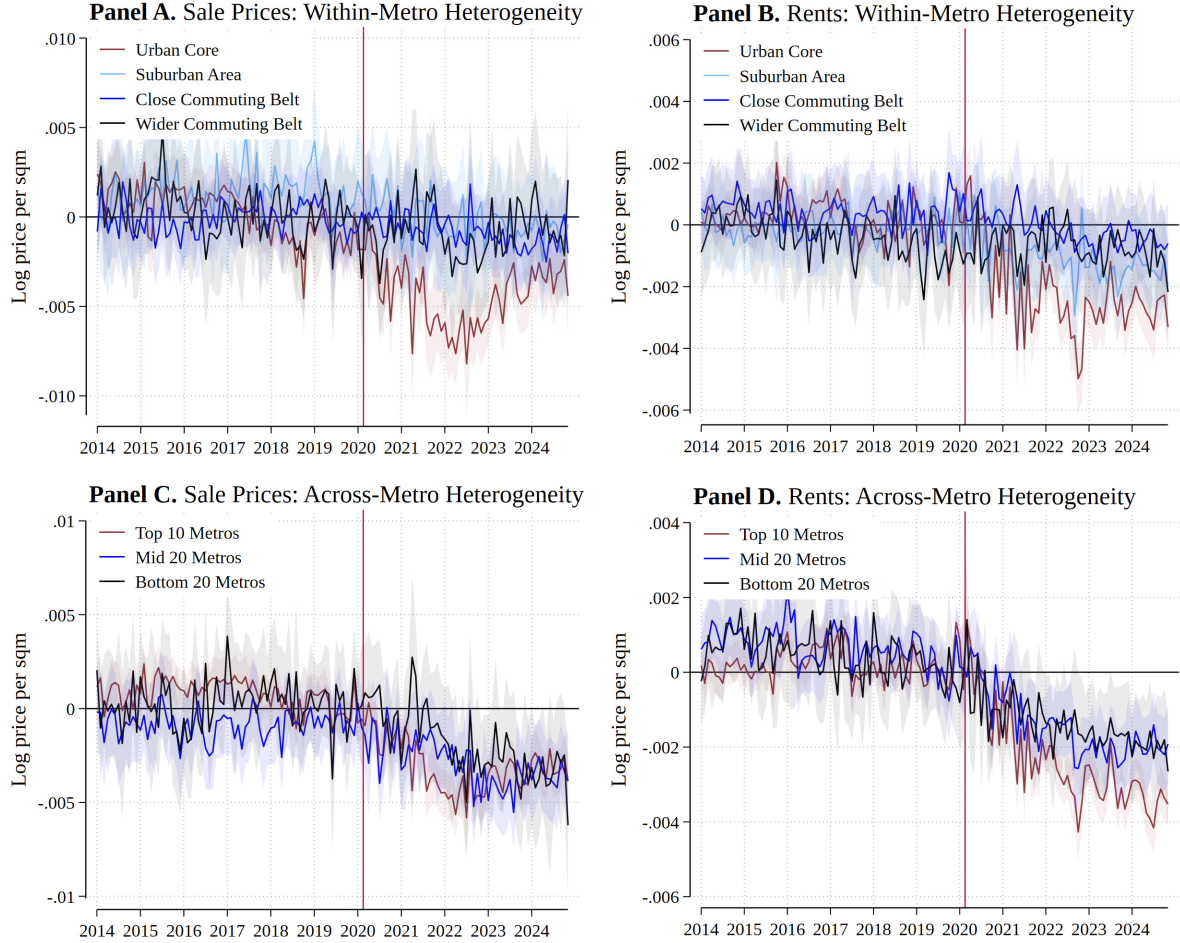
Figure C.9: DiD Results on Housing Price Changes Relative to Distance from Centers



Notes: This figure presents dynamic DiD estimates, in which the interaction terms are between monthly dummies from January 2014 until December 2024 and log distance from the city center. The dependent variable is the postcode-level average log sale price (per m^2) in Panel A and average log rent (per m^2) in Panel B. 95-percent confidence intervals are drawn with standard errors clustered at postcode level. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020.

Appendix D WFH Impact on Urban Housing Prices

Figure D.10: Heterogeneity of DiD Results on WFH Effect Within and Across Metro Areas



Notes: This figure presents DiD estimates $\hat{\beta}_k$ from separate regressions of Equation 1, in which the interaction terms are between monthly dummies from January 2014 until December 2024 and postcode-level WFH potential of residents by catch areas within metro regions in Panels A and B and by size of the metro region in Panels C and D. The WFH potential at the place of residence is measured by the percentage of local employees who can work from home at least one day per week. The dependent variable is the postcode-level average log sale price per square meter in Panels A and C and the average log rent per square meter in Panels B and D. 95-percent confidence intervals are drawn with standard errors clustered at the postcode level. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020.

Table D.3: Spatial Robustness of Dynamic DiD Results

	(1)	(2)	(3)
Panel A Dependent Variable: Log Sale Prices			
Residential WFH Potential			
× April - December 2020	-0.0016*** (0.0002)	-0.0018** (0.0007)	-0.0018** (0.0007)
× Year 2021	-0.0026*** (0.0003)	-0.0029*** (0.0008)	-0.0029*** (0.0008)
× Year 2022	-0.0044*** (0.0003)	-0.0051*** (0.0011)	-0.0051*** (0.0011)
× Year 2023	-0.0040*** (0.0002)	-0.0041*** (0.0008)	-0.0041*** (0.0008)
× Year 2024	-0.0036*** (0.0003)	-0.0039*** (0.0008)	-0.0039*** (0.0008)
R^2	0.89	0.84	0.84
N	548,285	548,285	548,285
Panel B Dependent Variable: Log Rents			
Residential WFH Potential			
× April - December 2020	-0.0006*** (0.0001)	-0.0006** (0.0003)	-0.0006** (0.0003)
× Year 2021	-0.0020*** (0.0001)	-0.0017*** (0.0004)	-0.0017*** (0.0004)
× Year 2022	-0.0027*** (0.0001)	-0.0025*** (0.0004)	-0.0025*** (0.0004)
× Year 2023	-0.0030*** (0.0001)	-0.0027*** (0.0004)	-0.0027*** (0.0004)
× Year 2024	-0.0033*** (0.0002)	-0.0029*** (0.0005)	-0.0029*** (0.0005)
R^2	0.92	0.88	0.88
N	527,088	527,088	527,088
Postcode FE	✓	✓	✓
Metro Area × Month FE	✓		
Clustered SE by Postcode	✓		
Clustered SE by MA		✓	
Wild Cluster Bootstrap SE by MA			✓

Notes: The table reports DiD estimates $\hat{\beta}^k$ of WFH potential on residential real estate prices based on Equation 1. Time dummies are grouped into bins: the pre-Covid period (reference period) and annual post-Covid period since April 2020. The dependent variable is log average real estate prices per postcode and month. The results for residential sale prices are reported in Panel A and the estimates for residential rents are shown in Panel B. Baseline estimates conditional on metropolitan area and month-year fixed effects are displayed in column (1) with standard errors clustered at the postcode level. Column (2) leaves out the metro-area-by-month fixed effects and clusters standard errors at the metro area level. Column (3) computes wild cluster bootstrap standard errors at the metro area level. *p<0.1; **p<0.05; ***p<0.01.

Table D.4: Long DiD Results on Effect of WFH Potential and Log Distance on Urban Housing Price Changes 2019–2024 – Parametric Distance Control

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A Dependent Variable: 2019–2024 Change in Log Property Sale Prices</i>						
WFH Potential Residence	-0.0031*** (0.0003)	-0.0015*** (0.0003)	-0.0007 (0.0007)	-0.0030*** (0.0009)	-0.0027*** (0.0007)	-0.0049*** (0.0009)
Log Distance from Center		0.0324*** (0.0030)	0.0460*** (0.0100)	-0.0175 (0.0140)	-0.0662*** (0.0194)	-0.1110*** (0.0231)
WFH Potential × Log Distance			-0.0004 (0.0003)	0.0006** (0.0003)	0.0005* (0.0003)	0.0014*** (0.0003)
Log Distance Squared					0.0179*** (0.0026)	0.0163*** (0.0031)
Number Postcodes	4,522	4,522	4,522	4,517	4,522	4,517
<i>Panel B Dependent Variable: 2019–2024 Change in Log Property Rents</i>						
WFH Potential Residence	-0.0030*** (0.0001)	-0.0010*** (0.0002)	-0.0010*** (0.0003)	-0.0025*** (0.0004)	-0.0021*** (0.0003)	-0.0031*** (0.0004)
Log Distance from Center		0.0400*** (0.0015)	0.0403*** (0.0048)	-0.0008 (0.0064)	-0.0224*** (0.0085)	-0.0315*** (0.0101)
WFH Potential × Log Distance			-0.0000 (0.0001)	0.0007*** (0.0001)	0.0004*** (0.0001)	0.0009*** (0.0001)
Log Distance Squared					0.0100*** (0.0012)	0.0054*** (0.0014)
Number Postcodes	4,509	4,509	4,509	4,504	4,509	4,504
Metro Area FE	✓	✓	✓		✓	
Metro × Catchment Area FE				✓		✓

Notes: This table reports DiD estimates of WFH potential and log distance from the city center on log property sale prices and rents based on Equation 2. Panel A displays the results for the 2019–2024 postcode-level changes in log sale prices and Panel B the changes in log rents. Column (1) reports baseline estimates for the effect of WFH potential at the place of residence conditional on metropolitan area fixed effects, which correspond to the main results of Equation 1 portrayed in Figure 5. Column (2) adds the log distance from the city center. Columns (3) and (4) additionally include an interaction term of WFH potential and distance from the urban center, conditional on metro area fixed effects in column (3) and conditional on metro area times catchment area fixed effects in column (4). Columns (5) and (6) introduce a quadratic term of distance from the urban center, reflecting the quadratic relationship between distance and price changes shown in Figure 3. In column (5), the estimates are conditional on metro area fixed effects, while in column (6) the results are conditional on metro area times catchment area fixed effects. Standard errors are clustered at the postcode-level. *p<0.1; **p<0.05; ***p<0.01.

Table D.5: Heterogeneity Across Metro Regions of Long DiD Results on Impact of WFH Potential

	Top 10 Metros		Mid 20 Metros		Bottom 20 Metros	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A Dependent Variable: 2019–2024 Change in Log Property Sale Prices</i>						
WFH Potential	-0.0019*** (0.0004)	-0.0023*** (0.0005)	-0.0014* (0.0007)	-0.0012* (0.0007)	-0.0024* (0.0012)	-0.0032*** (0.0012)
R^2	0.40	0.39	0.32	0.27	0.40	0.34
Number Postcodes	2,247	2,240	1,391	1,380	866	867
<i>Panel B Dependent Variable: 2019–2024 Change in Log Property Rents</i>						
WFH Potential	-0.0009*** (0.0003)	-0.0013*** (0.0002)	-0.0009*** (0.0003)	-0.0009*** (0.0003)	-0.0018*** (0.0006)	-0.0022*** (0.0005)
R^2	0.55	0.56	0.46	0.43	0.52	0.49
Number Postcodes	2,246	2,239	1,382	1,371	864	864
Metro $\times$ 10 Distance Decile FE	✓		✓		✓	
Metro $\times$ Catchment $\times$ 3 Distance Tercile FE		✓		✓		✓

Notes: This table reports long DiD estimates of WFH potential on postcode-level changes in log property prices between 2019 and 2024, estimated separately for metro area subsamples. Panel A displays results for sale prices and Panel B for rents. Columns (1)–(2) restrict the sample to the top 10 metro regions, columns (3)–(4) to the mid 20, and columns (5)–(6) to the bottom 20. Within each metro group, odd columns control for metro-area-by-distance-decile fixed effects (10 bins per metro area) and even columns for metro-area-by-catchment-area-by-distance-tercile fixed effects (3 bins per catchment area within each metro area). Both sets of fixed effects non-parametrically absorb any distance-price relationship within the respective metro subsample. Standard errors are clustered at the postcode level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table D.6: Robustness of Long DiD Results to Alternative City-Center Definitions and Market Delineations

	(1) <i>Main</i>	(2) <i>Monocentric Only</i>	(3) <i>Mastercard Spending Center</i>	(4) <i>BBSR Regions</i>
Panel A Dependent Variable: Log Sale Prices				
WFH Potential	−0.0019*** (0.0004)	−0.0013*** (0.0004)	−0.0016*** (0.0003)	−0.0015*** (0.0004)
R^2	0.38	0.43	0.39	0.46
N	4,504	3,070	4,126	7,682
Panel B Dependent Variable: Log Rents				
WFH Potential	−0.0010*** (0.0002)	−0.0008*** (0.0002)	−0.0018*** (0.0002)	−0.0010*** (0.0002)
R^2	0.54	0.59	0.51	0.55
N	4,492	3,058	4,124	7,597
Metro × 10 Distance Decile FE	✓	✓	✓	
BBSR × 10 Distance Decile FE				✓

Notes: This table reports long DiD estimates of WFH potential on postcode-level changes in log property prices between 2019 and 2024, using the preferred within-distance specification (Region × 10 Distance Decile FE) across alternative definitions of the city center and market boundary. Panel A shows results for sale prices, Panel B for rents. Column (1) is the baseline from [Table 1](#), using the townhall PLZ as city center and BBSR Großstadtregionen (≈50 metros) as market boundaries. Column (2) restricts the sample to monocentric metro areas, excluding the six polycentric regions. Column (3) redefines the city center as the postcode with the highest median Mastercard spending per km² within each metro area. Column (4) uses BBSR Arbeitsmarktregionen (223 labor market regions) as the market boundary, with city centers defined as the largest municipality by population. Standard errors are clustered at the postcode level. *p<0.1; **p<0.05; ***p<0.01.

Table D.7: Long DiD Robustness: Alternative End Years 2021 and 2022*Panel I: End Year 2021 (Pre-Interest-Rate-Rise)*

	(1)	(2)	(3)	(4)
Panel A Dependent Variable: 2019–2021 Change in Log Property Sale Prices				
WFH Potential	-0.0022*** (0.0003)	-0.0015*** (0.0004)	-0.0016*** (0.0003)	-0.0020*** (0.0004)
R^2	0.09	0.24	0.18	0.21
Number Postcodes	4,503	4,486	4,503	4,466
Panel B Dependent Variable: 2019–2021 Change in Log Property Rents				
WFH Potential	-0.0017*** (0.0001)	-0.0006*** (0.0002)	-0.0007*** (0.0002)	-0.0008*** (0.0002)
R^2	0.11	0.29	0.24	0.28
Number Postcodes	4,487	4,470	4,487	4,450
Metro Area FE	✓			
Metro × 10 Distance Decile FE		✓		
Metro × 5 Distance Quintile FE			✓	
Metro × Catchment × 3 Distance Tercile FE				✓

Panel II: End Year 2022 (Initial Rate-Rise Period)

	(1)	(2)	(3)	(4)
Panel A Dependent Variable: 2019–2022 Change in Log Property Sale Prices				
WFH Potential	-0.0040*** (0.0003)	-0.0028*** (0.0004)	-0.0029*** (0.0004)	-0.0035*** (0.0004)
R^2	0.26	0.40	0.36	0.38
Number Postcodes	4,520	4,503	4,520	4,485
Panel B Dependent Variable: 2019–2022 Change in Log Property Rents				
WFH Potential	-0.0024*** (0.0001)	-0.0007*** (0.0002)	-0.0009*** (0.0002)	-0.0012*** (0.0002)
R^2	0.22	0.44	0.40	0.43
Number Postcodes	4,497	4,480	4,497	4,460
Metro Area FE	✓			
Metro × 10 Distance Decile FE		✓		
Metro × 5 Distance Quintile FE			✓	
Metro × Catchment × 3 Distance Tercile FE				✓

Notes: This table reports long DiD estimates of WFH potential on postcode-level changes in log property prices for alternative end years. Panel I uses the 2019–2021 price change as the dependent variable, covering the period before the ECB interest rate increases began. Panel II uses 2019–2022. Within each panel, Sub-Panel A shows results for sale prices and Sub-Panel B for rents. Column (1) controls for metro-area fixed effects. Columns (2)–(4) introduce metro-area-by-distance-band fixed effects using 10 deciles, 5 quintiles, and catchment-area-by-distance-tercile bins, respectively. Standard errors are clustered at the postcode level. *p<0.1; **p<0.05; ***p<0.01.

Appendix E Local Amenities and the Within-Distance WFH Effect

Table E.8: Amenity Controls and the Within-Distance WFH Effect: Sale Prices

	(1)	(2)	(3)	(4)	(5)
WFH Potential	-0.0019*** (0.0004)	-0.0013*** (0.0003)	-0.0011*** (0.0004)	-0.0010*** (0.0004)	-0.0010*** (0.0004)
WFH × Pub. Transport Index		-0.0009*** (0.0003)	-0.0006* (0.0004)	-0.0007* (0.0004)	-0.0007** (0.0004)
WFH × Car Transit Time		0.0006* (0.0003)	0.0001 (0.0004)	0.0001 (0.0004)	0.0001 (0.0004)
WFH × Restaurants p.c.			0.0000 (0.0003)	0.0000 (0.0003)	0.0000 (0.0003)
WFH × Leisure POIs p.c.			-0.0006* (0.0004)	-0.0006* (0.0004)	-0.0006* (0.0004)
WFH × Education POIs p.c.			-0.0001 (0.0003)	-0.0000 (0.0003)	-0.0000 (0.0003)
WFH × Health POIs p.c.			-0.0006* (0.0003)	-0.0006* (0.0003)	-0.0006* (0.0003)
WFH × Green Space Share				-0.0001 (0.0003)	-0.0001 (0.0003)
WFH × Broadband Coverage					-0.0000 (0.0002)
R^2	0.38	0.39	0.39	0.39	0.39
N	4,496	4,496	4,496	4,496	4,496
Metro × Distance Decile FE	✓	✓	✓	✓	✓
Transport Controls		✓	✓	✓	✓
Services & Consumer Goods Controls			✓	✓	✓
Green Space Control				✓	✓
Broadband Control					✓

Notes: This table reports long DiD estimates of the effect of WFH potential on postcode-level changes in log sale prices from 2019 to 2024. All specifications include Metro × Distance Decile fixed effects and weight by postcode-level employment. Column (1) is the baseline within-distance specification without amenity controls, replicating column (2) of [Table 1](#). Columns (2)–(5) add transport (public transport index, car transit time), services and consumer goods (restaurants, leisure, education, and health POIs per capita), green space (share of green space), and broadband (fiber coverage) controls, each entering in levels and as interactions with WFH potential. WFH potential is centered at its sample mean. All amenity variables are standardized to zero mean and unit variance. Standard errors are clustered at the postcode level. *p<0.1; **p<0.05; ***p<0.01.

Table E.9: Amenity Controls and the Within-Distance WFH Effect: Rents

	(1)	(2)	(3)	(4)	(5)
WFH Potential	-0.0010*** (0.0002)	-0.0007*** (0.0002)	-0.0007*** (0.0002)	-0.0006*** (0.0002)	-0.0006*** (0.0002)
WFH × Pub. Transport Index		-0.0001 (0.0002)	0.0001 (0.0002)	0.0000 (0.0002)	0.0000 (0.0002)
WFH × Car Transit Time		0.0004*** (0.0002)	0.0002 (0.0002)	0.0002 (0.0002)	0.0001 (0.0002)
WFH × Restaurants p.c.			-0.0002 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)
WFH × Leisure POIs p.c.			-0.0001 (0.0002)	-0.0001 (0.0002)	-0.0001 (0.0002)
WFH × Education POIs p.c.			-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)
WFH × Health POIs p.c.			-0.0002 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)
WFH × Green Space Share				-0.0000 (0.0001)	-0.0000 (0.0001)
WFH × Broadband Coverage					-0.0001 (0.0001)
R^2	0.54	0.55	0.56	0.56	0.56
N	4,487	4,487	4,487	4,487	4,487
Metro × Distance Decile FE	✓	✓	✓	✓	✓
Transport Controls		✓	✓	✓	✓
Services & Consumer Goods Controls			✓	✓	✓
Green Space Control				✓	✓
Broadband Control					✓

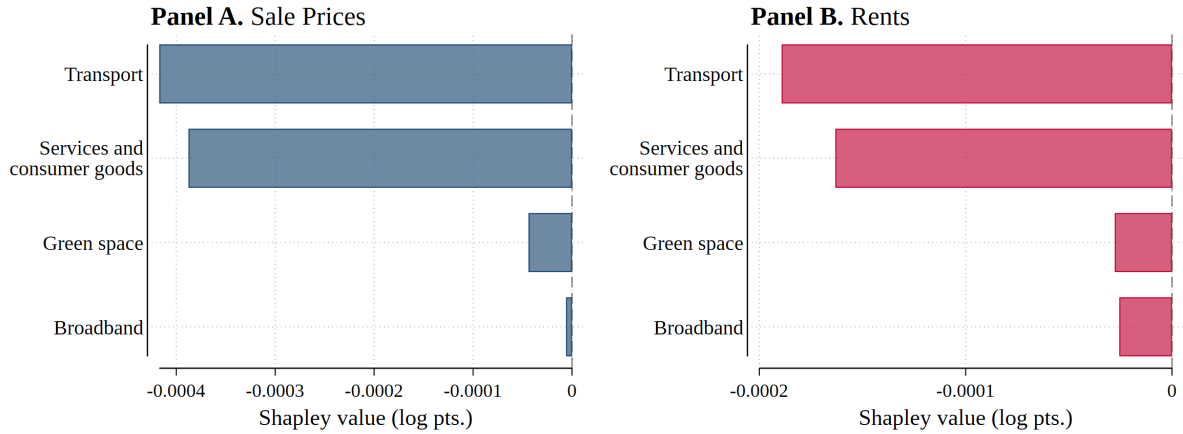
Notes: This table reports long DiD estimates of the effect of WFH potential on postcode-level changes in log rents from 2019 to 2024. All specifications include Metro × Distance Decile fixed effects and weight by postcode-level employment. Column (1) is the baseline within-distance specification without amenity controls. Columns (2)–(5) add transport, services and consumer goods, green space, and broadband controls, each entering in levels and as interactions with WFH potential. WFH potential is centered at its sample mean. All amenity variables are standardized to zero mean and unit variance. Standard errors are clustered at the postcode level. *p<0.1; **p<0.05; ***p<0.01.

Table E.10: Robustness of Amenity Attenuation Across City-Center Definitions and Market Delineations

	(1) <i>Main</i>	(2) <i>Monocentric Only</i>	(3) <i>Mastercard Spending Center</i>	(4) <i>BBSR Regions</i>
Panel A Dependent Variable: Log Sale Prices				
<i>Without amenity controls</i>				
WFH Potential	−0.0019*** (0.0004)	−0.0014*** (0.0004)	−0.0016*** (0.0003)	−0.0017*** (0.0004)
<i>With all amenity controls</i>				
WFH Potential	−0.0010*** (0.0004)	−0.0011** (0.0005)	−0.0008** (0.0004)	−0.0008* (0.0004)
<i>N</i>	4,496	3,063	4,125	4,040
Panel B Dependent Variable: Log Rents				
<i>Without amenity controls</i>				
WFH Potential	−0.0010*** (0.0002)	−0.0008*** (0.0002)	−0.0018*** (0.0002)	−0.0011*** (0.0002)
<i>With all amenity controls</i>				
WFH Potential	−0.0006*** (0.0002)	−0.0005** (0.0002)	−0.0007*** (0.0002)	−0.0005** (0.0002)
<i>N</i>	4,487	3,054	4,123	4,030
Metro × 10 Distance Decile FE	✓	✓	✓	
BBSR × 10 Distance Decile FE				✓

Notes: This table reports long DiD estimates of WFH potential on postcode-level changes in log property prices between 2019 and 2024, showing how the coefficient attenuates when all amenity controls are added. Panel A shows results for sale prices, Panel B for rents. Each column corresponds to a different city-center definition or market delineation: (1) baseline using the townhall PLZ as city center and BBSR Großstadtregionen (≈ 50 metros); (2) monocentric metro areas only, excluding the six polycentric regions; (3) Mastercard-spending city center (postcode with highest median spending per km^2 within each metro area); (4) BBSR Arbeitsmarktregionen (223 labor market regions). All specifications include Region × 10 Distance Decile FE's. Standard errors are clustered at the postcode level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

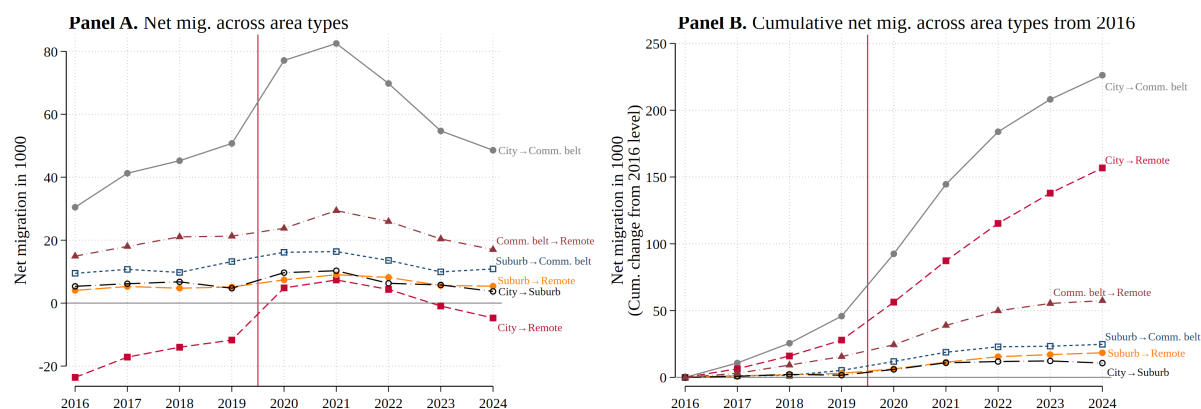
Figure E.11: Order-Invariant Shapley Decomposition of the Amenity Attenuation



Notes: This figure decomposes the total attenuation of the within-distance WFH coefficient into contributions from four amenity groups using order-invariant Shapley values. For each of the $2^4 = 16$ possible subsets, the long DiD regression is estimated with the corresponding amenity controls (levels and WFH interactions); the Shapley value for group k is then the weighted average marginal contribution across all $K! = 24$ entry orderings, with weights $|S|!(K-1-|S|)!/K!$ for subsets S not containing k . By construction, Shapley values sum to the total attenuation. The four groups follow [Figure 7](#): transport, services and consumer goods, green space, and broadband. Left panel: sale prices; right panel: rents. All specifications include $\text{Metro} \times \text{Distance Decile}$ fixed effects and weight by postcode employment.

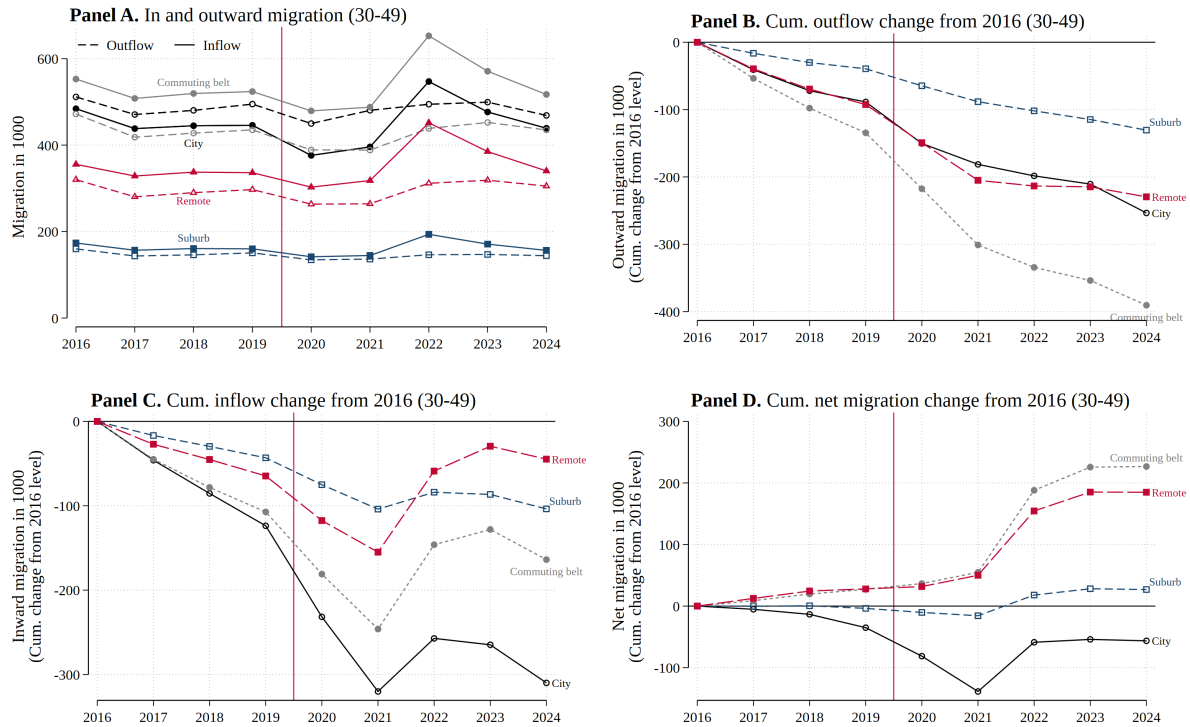
Appendix F Mechanisms

Figure F.12: Pairwise Net Migration Flows Across Urban Catchment Areas (Germans)



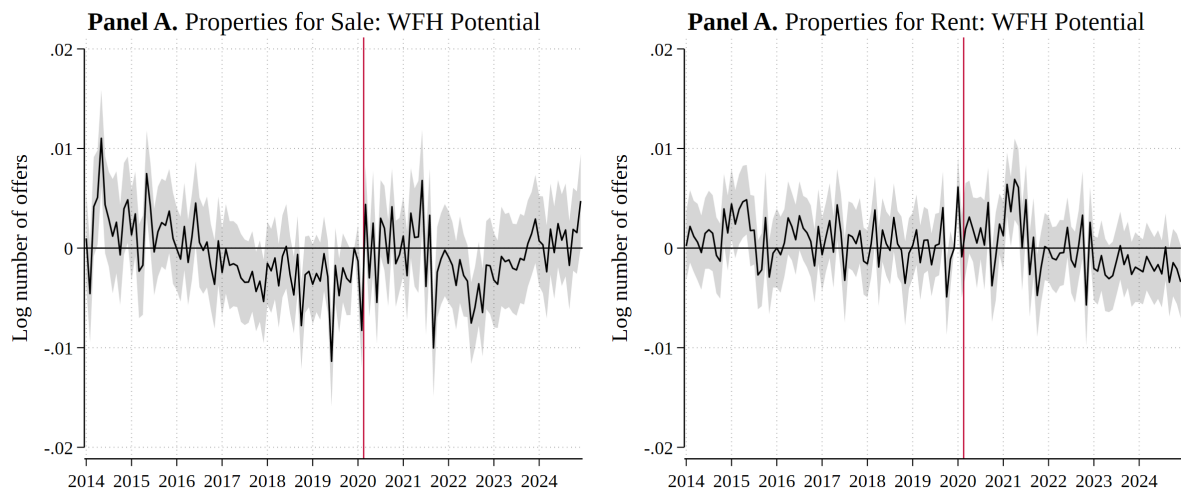
Notes: This figure displays pairwise net domestic migration flows of German citizens across county borders based on origin-destination matrices from 2016 to 2024. Panel A shows annual net migration between the six pairs of urban catchment area types (city, suburb, commuting belt, remote area). Positive values indicate net population gains for the destination area type relative to the origin. Panel B shows the cumulative change in pairwise net migration since 2016, where 2016 serves as the reference level (= 0) for each flow. Administrative data on migration statistics are provided by the German Federal Statistical Office.

Figure E.13: Changes in Urban Net Migration Flows – Age 30-49



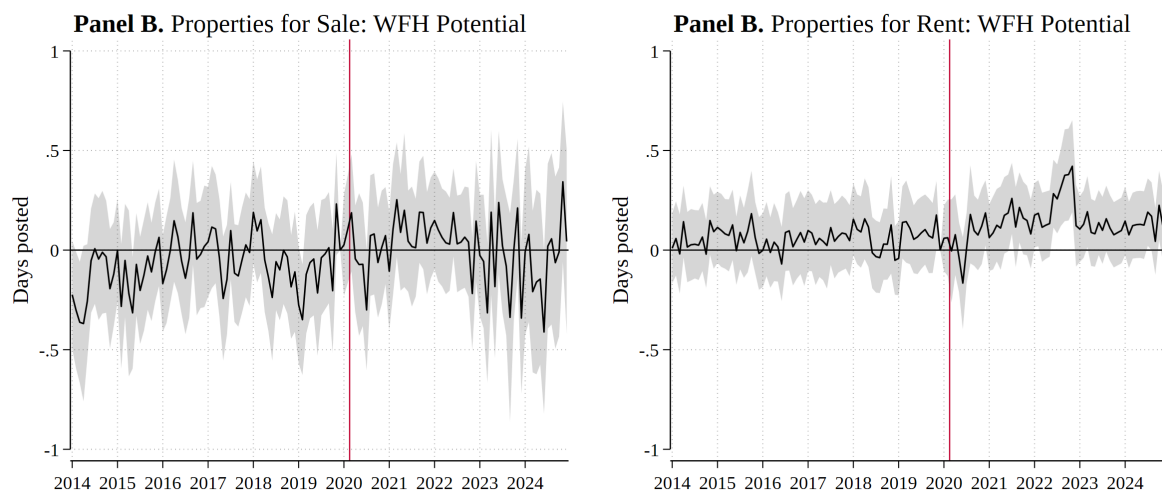
Notes: This figure displays domestic migration flows across county borders for all people aged 30 to 49, broken down by urban catchment area (city, suburb, commuting belt, remote area), based on annual origin-destination data from 2016 to 2024. Panel A shows annual inflows and outflows for each catchment area. Panels B and C show the cumulative change in outflows and inflows since 2016, where 2016 serves as the reference level. Panel D shows the cumulative change in net migration since 2016. Administrative data on migration statistics are provided by the German Federal Statistical Office.

Figure F.14: Supply-Side Mechanism Housing Quantity: Changes in Log Number of Property Offers Relative to WFH Potential



Notes: This figure presents DiD estimates $\hat{\beta}_k$ from separate regressions in the form of [Equation 1](#), in which the interaction terms are between monthly dummies from January 2014 until December 2024 and postcode-level WFH potential conditional on distance bands. The dependent variable is the postcode-level log number of offers of properties for sale in Panel A and for rent in Panel B. 95-percent confidence intervals are drawn with standard errors clustered at the postcode level. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020.

Figure F.15: Supply-Side Mechanism Housing Liquidity: Changes in Days-on-the-Market Relative to WFH Potential



Notes: This figure presents DiD estimates $\hat{\beta}_k$ from separate regressions in the form of [Equation 1](#), in which the interaction terms are between monthly dummies from January 2014 until December 2024 and postcode-level WFH potential conditional on distance bands. The dependent variable is the postcode-level average number of days a property is posted for sale in Panel A and for rent in Panel B. 95-percent confidence intervals are drawn with standard errors clustered at the postcode level. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020.