# Digitalization and the New Geography of Work: The Impact of Broadband and Remote Work on Real Estate and Consumer Spending

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# Digitalization and the New Geography of Work: The Impact of Broadband and Remote Work on Real Estate and Consumer Spending

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# Preface

Technological change has long shaped economic geography, from the growth of cities during the Industrial Revolution to the evolving spatial distribution of economic activity in the digital economy. Each wave of technological innovation has altered where and how people work, live, and consume. The digital transformation represents the latest shift, as advances in information and communication technologies (ICT) expand information access, reduce coordination frictions, lower the costs of data storage and processing, and enable remote collaboration (Goldfarb and Tucker, 2019). These changes have expanded market access, boosted productivity, and fueled economic growth (Bloom et al., 2012; Draca et al., 2009; Jorgenson and Stiroh, 1999), while also reshaping economic activity across space (Kalyani et al., 2025). Cairncross (1997) famously predicted the "death of distance," arguing that digital technologies would diminish the importance of geographic proximity in knowledge-intensive industries. Yet, despite these expectations, economic activity has remained highly concentrated. The recent economic literature emphasizes the persistent spatial clustering of innovation in knowledge hubs (Atkin et al., 2022; Carlino and Kerr, 2015) and the enduring strength of urban agglomeration forces (Glaeser and Ponzetto, 2010). However, the expansion of high-speed broadband Internet and the widespread adoption of remote work since the Covid-19 pandemic have begun to impact urban and regional economic outcomes in unprecedented ways.

As a key driver of the digital transformation, high-speed broadband Internet has become essential for firms and households to access digital tools and engage in economic activity. Broadband infrastructure underpins the knowledge economy, facilitating the diffusion of digital technologies that shape labor markets, consumer behavior, and firm decisions, while more broadly driving the shift toward a service-oriented economy (Ahlfeldt et al., 2017; Akerman et al., 2015; Zuo, 2021). Importantly, broadband expansion provided the technological foundation for remote work (Barrero et al., 2021a). The Covid-19 pandemic accelerated the adoption of working from home (WFH) worldwide, driving one of the most substantial and lasting labor market shifts in recent years (Aksoy et al., 2022; Barrero et al., 2021b, 2023). This shift has given rise to a new geography of work, where economic activity is less constrained by proximity to employment hubs and city centers (Althoff et al., 2022). As WFH changes commuting patterns, residential preferences, and office space needs, it reshapes urban structures and alters location choices for households and firms (Delventhal et al., 2022; Gupta et al., 2022a; Monte et al., 2023; Ramani et al., 2024; Rosenthal et al., 2022). These changes raise fundamental questions about how digitalization reorganizes economic activity across space.

This dissertation studies how two major technology shocks – broadband Internet and remote work – reshape the spatial distribution of economic activity. In four self-contained chapters, I empirically analyze the effects of the new geography of work on urban and regional economic outcomes in Germany. Using innovative, large-scale data and state-of-the-art microeconometric methods, I provide causal evidence on four key effects. The *first essay* shows that high-speed broadband Internet availability significantly increases rural real estate prices, reflecting its economic value to households. However, we find that broadband subsidies aimed at closing the rural-urban divide are often fiscally ineffective. Shifting from broadband to remote work, the next three essays explore its spatial effects on cities. The *second essay* finds that higher WFH adoption among residents leads to reduced mobility but increased local consumer spending, indicating shifts in economic activity. The *third essay* examines urban housing markets, showing that WFH decreases both the price premium for central locations and spatial inequality in housing costs within cities. Finally, the *fourth essay* studies office real estate, finding that WFH-intensive industries downsize office space, move toward higher-quality buildings, and relocate closer to city centers. These findings highlight distinct spatial patterns: While remote work decentralizes housing demand and consumer spending, it induces a centralization effect in office real estate. This dissertation extends prior U.S.-focused research with evidence from Germany, where denser cities, stronger public transit networks, and different land-use policies create different spatial dynamics. By examining how digitalization reshapes labor markets, real estate, and economic geography, my dissertation adds to the urban and regional economics literature. The results offer insights for navigating the future of cities and labor markets in the digital age.

As one of the foundational and most widely used ICTs, broadband Internet can be considered a "general purpose technology" (GPT) of the digital age (Breshanan and Trajtenberg, 1995). Similar to past GPTs, such as electricity or the steam engine, broadband has driven productivity growth, reshaped economic geography, altered firm dynamics, and impacted labor markets (Akerman et al., 2015; Czernich et al., 2011; Forman et al., 2018). With the Internet's growing importance , fast broadband access at home is important for households to enable remote work, virtual education, e-commerce, and online information and entertainment consumption. However, broadband access remains unevenly distributed, with a connectivity divide between urban and rural areas. In response, governments have invested heavily in broadband expansion to reduce spatial inequalities, but the economic returns and fiscal effectiveness of these subsidies remain uncertain. This motivates the first research question of this dissertation: How much economic value does high-speed broadband generate for households, and how efficiently do subsidies for broadband expansion close the rural-urban connectivity gap?

To answer this question, the *first chapter*, co-authored with Thomas Fackler and Oliver Falck, examines the causal effect of high-speed Internet access on real estate prices and the fiscal effectiveness of broadband expansion policies in rural areas. To quantify households' economic benefits from fast Internet, we leverage local variation in broadband availability and property prices. Using a capitalization approach, we model housing as a composite good, where property values reflect features, local amenities, and digital infrastructure such as broadband access. To identify causal effects, we employ a spatial regression discontinuity design that exploits policy-driven variation in broadband availability at German state borders across more than 4,000 rural municipalities and 1.1 million property listings between 2010 and 2019. We find that high-speed Internet availability (16 Mbit/s) increases rents by 3.8 percent (€17/month) and sale prices by eight percent (€14,700) compared to slower access at the discontinuity. For higher broadband speeds, we find still significantly positive but diminishing returns. These effects are demand-driven, as indicated by increased broadband subscriptions, migration, and remote work adoption, while housing supply remains unchanged. A cost-benefit analysis within the marginal-value-of-public-funds framework shows that for 90 percent of households, the benefits of broadband access exceed deployment costs. This suggests that universal broadband access could be achieved more cost-effectively with better-targeted subsidies. The findings from this chapter confirm broadband as a valued local amenity, impacting housing markets and enabling remote work.

The Covid-19 pandemic triggered a technology shock on the labor market, accelerating the adoption of remote work (Aksoy et al., 2022; Barrero et al., 2021b, 2023; Hansen et al., 2023). Although workers had long valued the option to work from home, with studies estimating that they were willing to forgo eight percent of their salary for this flexibility (Mas and Pallais, 2017), it remained the exception rather than the norm before the pandemic. Positive experiences during the acute phase of Covid-19 and investments in digital collaboration tools have proved the viability of WFH and made this shift enduring (Barrero et al., 2021b, 2023; Bloom et al., 2024). In this transition, high-quality broadband access has been a critical enabler of remote work, with universal availability linked to higher labor productivity and economic resilience (Barrero et al., 2021a). Today, hybrid work is the predominant WFH model, where employees alternate between office and remote work (Bloom et al., 2024; Destatis, 2024). In the U.S., around 27 percent of paid workdays are remote, while in Germany, about 25 percent of employees work from home at least part-time – a fivefold increase compared to 2019 (Barrero et al., 2021b; Destatis, 2024).

This shift has raised critical questions about productivity and the role of physical proximity in knowledge work. While remote collaboration is feasible in some settings and can even enhance productivity (Bloom et al., 2015; Choudhury et al., 2021), research shows that face-to-face interaction remains vital for innovation, complex problem-solving, and mentoring (Atkin et al., 2022; Gibbs et al., 2023; Yang et al., 2022). There is growing evidence that hybrid work offers the "best of both worlds," since it maintains productivity and increases retention and job satisfaction (Bloom et al., 2024; Choudhury et al., 2024). The persistence of remote work marks a structural shift in the organization of work, with far-reaching implications for firms, workers, and the spatial distribution of economic activity.

WFH is especially prevalent in knowledge-intensive occupations concentrated in large cities, where its effects on firms, labor markets, and real estate are most pronounced (Alipour et al., 2023; Dingel and Neiman, 2020). Urban growth has historically been driven by agglomeration forces: the clustering of high-skilled workers and firms, where physical proximity fosters knowledge spillovers, innovation, and productivity gains (Glaeser et al., 1992; Krugman, 1991; Lucas and Rossi-Hansberg, 2002). WFH challenges these forces by weakening the traditional link between workplace and residence. This development has fueled a scholarly debate about the future of cities (Duranton and Handbury, 2023; Florida et al., 2021; Glaeser and Cutler, 2021): Will remote work lead to decentralization, or will cities adapt and reinforce their role as centers of economic activity? Empirical evidence from the U.S. suggests a "donut effect," describing the outward shift in consumer spending and housing demand from city centers to suburbs, alongside urban population losses during the pandemic (Duguid et al., 2023; Gupta et al., 2022a; Ramani et al., 2024). However, face-to-face collaboration remains critical also with increased WFH, potentially reinforcing agglomeration. While much of the existing research focuses on the U.S., little is known about how these dynamics play out in other urban geographies. This dissertation examines German cities, which differ from their U.S. counterparts in three key ways: a higher share of residents in central business districts, stricter land-use regulations, and stronger public transit networks. The next three chapters analyze the impact of WFH on German cities, examining consumer spending, housing markets, and office real estate.

The *second chapter*, co-authored with Victor Alipour, Oliver Falck, Carla Krolage, and Sebastian Wichert, investigates the impact of WFH on urban consumer spending. We analyze novel, large-scale data on daily cellphone mobility as well as debit and credit card transactions across 50 German metropolitan areas at the postcode-level from 2019 to 2023. Using a difference-in-differences approach, we exploit local variation in residents' WFH potential, defined as the fraction of employed residents with a teleworkable job, applying an established method in calculating regional WFH measures (Alipour et al., 2023; Dingel and Neiman, 2020; Matheson et al., 2024). Our main finding is that postcodes with a higher residential WFH potential experience persistent declines in morning mobility and increases in consumer spending between 2019 and 2023. Instrumenting cellphone mobility changes (2019-2023) by WFH potential, we estimate an elasticity of spending of -3.7 percent with respect to a WFH-induced decline in morning mobility by one percent. The effects are driven by larger metro areas and spending in food services and grocery stores. Smaller metropolitan areas show no significant mobility changes, consistent with theoretical models predicting that small cities revert to pre-pandemic commuting patterns (Monte et al., 2023). We find no evidence that WFH-induced migration, firm turnover, or shifts to online spending explain these effects. Unlike in the U.S., where remote work spurred urban exodus and firm growth in peripheral areas (Coven et al., 2023; Duguid et al., 2023), Germany has seen no comparable shifts in population or firm dynamics. Instead, our results show that the effects stem entirely from changing consumer demand among remote workers. Workplace-dense urban centers exhibit persistent spending losses, indicating a redistribution of economic activity toward residential and peripheral areas. Overall, these findings confirm a "donut effect" in consumer spending in Germany, where urban demand declines while suburban retail benefits.

In the *third chapter*, Victor Alipour and I study the impact of working from home (WFH) on the spatial distribution of urban housing prices. Using geocoded data on over 20 million residential property listings across 50 German metropolitan areas from 2014 to 2023, we exploit postcode-level variation in the exposure to the WFH shock caused by the Covid-19 pandemic. While urban centers tend to have the highest share of residents with teleworkable jobs, WFH potential is unevenly distributed across postcodes. We use a difference-in-differences approach to compare house price changes across postcodes within the same metropolitan area but with different WFH potential. We find that WFH has significantly reduced the price premium associated with proximity to urban centers, contributing to a flattening of the urban housing price gradient. Importantly, WFH explains housing price changes even after controlling for distance from city centers, indicating a broader reduction in spatial inequality within cities. The effect is demand-driven, as WFH shifts preferences toward larger homes and suburban areas, while housing supply remains unaffected. Urban price declines reflect dampened expectations about future demand for city-center housing. The pre-pandemic trend of rising net in-migration to central, high-WFH-potential areas abruptly halted, lowering expected future rental cash flows. These shifts suggest location-specific welfare implications, improving affordability in urban cores but increasing housing costs in suburban and peripheral areas. Our findings underscore the need for urban resilience policies, including adaptive zoning, infrastructure investment, and increased housing supply.

Finally, in the *fourth chapter*, I examine the impact of WFH on urban office real estate, focusing on firm-level office space and within-city location decisions in Germany's seven largest metropolitan areas. Using a difference-in-differences approach and a novel dataset of 35,000 office leases and WFH survey data, I exploit industry-level variation in WFH adoption to estimate its effect on office leasing from 2019 to 2023. I find that a one percentage point increase in the industry-level WFH rate reduces total newly leased office space by two percent and average office size by one percent in 2023 relative to pre-pandemic levels. The impact is heterogeneous: newer, high-quality offices remain unaffected from the negative WFH impact, while older, lower-quality buildings experience the largest declines. Firms increasingly prioritize quality over quantity, which suggests a shift in the role of the office in hybrid work, where it evolves from the daily work environment to a collaboration hub. Spatially, WFH leads to a centralization effect, with increased demand for centrally located offices. The urban rent gradient remains stable, suggesting that firms continue to value central locations for their agglomeration benefits, accessibility, and amenities. At the same time, office vacancies rise particularly in suburban and peripheral areas. These shifts are driven by firm-level demand rather than supply-side adjustments or employment changes, as WFH-intensive firms downsize space and prioritize location quality. These findings suggest a reallocation of office demand rather than a uniform decline due to WFH. The centralization in office real estate contrasts with the suburbanization trend observed in housing markets and consumer spending. This has important implications for urban planning, real estate markets, and firm location choice.

Across the four chapters, my results underscore how broadband expansion and remote work reshape economic activity across space, impacting real estate markets and consumer spending. Another unifying feature of my dissertation is its use of innovative, large-scale data and microeconometric methods to causally estimate these effects. The analyses draw on granular, geocoded datasets covering property listings, office leases, consumer spending, and cellphone mobility, combined with survey-based WFH adoption measures and administrative statistics. Big data from firms play an increasingly important role in urban economics research, since they enable high-resolution and near real-time analyses of economic behavior. In this dissertation, I use data from *Mastercard*, *Deutsche Telekom*, and *Colliers*. Leveraging these rich data sources, I apply difference-in-differences, spatial regression discontinuity, and instrumental variable approaches. By employing big data and advanced microeconometric methods, my work contributes to the growing field of data-driven urban and regional economics.

The findings of my dissertation have important implications for the future of cities, labor markets, and public policy. As digitalization advances and WFH becomes a lasting feature of the labor market, households, firms, and policy-makers must manage these transformations effectively. Many organizations have moved from fully flexible WFH to structured hybrid models, coordinating office days to retain the benefits of in-person collaboration. This shift creates uneven urban dynamics, with city centers bustling on office days but emptier on remote days.

Urban resilience policies are needed to redefine cities as vibrant spaces for leisure and culture rather than primarily as workplaces and shopping hubs. As WFH shifts economic activity and consumer spending from urban centers to residential areas, local governments that depend on business taxes and per-resident federal funding face fiscal challenges. In the housing market, rising suburban demand calls for expanded public transport, increased housing supply, and zoning reforms to maintain affordability. This is especially important for on-site workers, who face welfare losses due to rising housing costs without gaining from remote flexibility (Davis et al., 2024b). Meanwhile, rising office vacancies, especially in suburban areas, highlight the need for conversion policies to support residential or mixed-use redevelopment. To support these shifts, policymakers must ensure equitable digital infrastructure across locations, not only to support economic and social participation but also to ease pressure on housing markets. However, broadband subsidies should be better targeted, prioritizing regions with low willingness or ability to pay. Successfully navigating these transitions will be critical to ensuring that cities and regions remain livable, inclusive, and economically dynamic.

The structural shifts from digitalization and the new geography of work raise fundamental long-term questions for cities, labor markets, and firms. How will future technological advances, such as AI-driven collaboration tools and virtual reality, further alter the need for physical proximity in knowledge work? Will hybrid work remain the dominant WFH model, will more organizations return to the office, or will entirely new ways of work emerge? While my nuanced findings suggest that cities are not facing an existential crisis, they must adapt to the spatial reallocation of economic activity and shifting demand for commercial and residential real estate. Policymakers will need to navigate these transitions carefully, ensuring that cities remain centers of innovation, productivity, and economic opportunity. As digitalization and remote work continue to evolve, their long-term implications for cities, labor markets, and firms remain uncertain, making them an important area of future research.

# Contents

# List of Figures

# List of Tables

# 1

# The Value of Connectivity: High-Speed Broadband Internet and Real Estate Prices

### Abstract

Governments worldwide subsidize rural broadband expansion to address the urban-rural connectivity divide, but the economic benefits and costs remain unclear. This paper examines the causal effect of high-speed Internet on real estate prices and evaluates the fiscal effectiveness of rural broadband subsidies. Using a spatial regression discontinuity design and comprehensive micro-data, our identification strategy exploits variation at state borders from German states' broadband expansion policies. We find that high-speed Internet availability (16 Mbit/s) increases rents by 3.8 percent (€17/month) and sale prices by 8 percent (€14,700) compared to slower access at the discontinuity, with diminishing returns at higher speeds. The capitalization effects are demand-driven, as evidenced by increased broadband uptake, migration, and remote work adoption, while property supply remains unaffected. A cost-benefit analysis within the marginal-value-of-public-funds framework shows the economic surplus exceeds deployment costs for 90 percent of households, while property owners benefit from subsidies through higher property prices. [1]



*Keywords*: High-Speed Broadband Internet, Real Estate Prices, Capitalization Effect, Policy Evaluation, Spatial RDD, MVPF

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## 1.1 Introduction

The digital transformation of the economy and society reshapes various aspects of our daily lives with a large and expanding impact. The increasing adoption of remote work, virtual education, e-commerce, and growing consumption of online information and entertainment during the Covid-19 pandemic further accelerated digitization. Given the growing importance of the Internet, fast broadband access at home has become essential for households to capture the benefits of the digital transformation. However, around the world, broadband access remains uneven, with a connectivity divide between rural areas lagging behind and urban regions with advanced broadband infrastructure. To address this divide, governments in advanced and emerging economies have introduced ambitious broadband policies, committing substantial public funds to expand high-speed Internet access in underserved rural areas.[2] Despite these policy efforts and an expanding body of literature on the subject, a comprehensive understanding of the economic benefits and costs of high-speed broadband in rural regions remains elusive. While fast Internet access may be particularly valuable to households in underserved rural areas, the high cost of expanding infrastructure raises questions about the optimal design of subsidies aimed at reducing spatial inequalities.[3]

This paper examines the causal effect of high-speed Internet access on real estate prices and evaluates the fiscal effectiveness of broadband expansion policies in rural areas. To quantify households' economic benefits from fast Internet, we leverage local variation in broadband availability and property prices. Adopting a capitalization approach, we model each house as a composite good, where its value reflects property features, local amenities, and public infrastructure such as wireline broadband access, making this method particularly suited for capturing broadband's economic value.[4] Our analysis exploits a quasi-experiment arising from variation in broadband expansion policies across German states between 2010 and 2019.

[2] For example, the United States has passed the "National Broadband Plan" (Federal Communications Commission, 2010), the European Union has prioritized fast broadband expansion in its "Digital Agenda 2020" (European Commission, 2021), and China has enacted a national "Broadband Strategy" (Liu, 2017).

[3] For the literature on optimal spatial policies and geographic redistribution, see Fajgelbaum and Gaubert (2020) and Gaubert (2021).

[4] Building on the foundational models of Oates (1969); Roback (1982); Rosen (1974); Sheppard (1999), Ahlfeldt et al. (2017) pioneered the hedonic property price approach to examine the capitalization effects of first-generation broadband expansion in England, finding positive impacts on property values. Unlike their study, we focus on the economic benefits and costs of faster broadband Internet in underserved rural areas.

These policies, differing in scope, funding, and governance, targeted rural areas where private broadband deployment is often unprofitable, creating spatial discontinuities in availability along state boundaries. We use a spatial regression discontinuity design (RDD) and a dataset of broadband availability and over 1.1 million real estate listings from more than 4,000 rural municipalities near state borders to estimate the property price effect of fast Internet access. Integrating administrative and micro-census data on Internet usage at home and migration, we uncover the mechanisms behind the property price effects. Importantly, we are the first to evaluate the fiscal effectiveness of rural broadband subsidies using detailed information on total investment costs and subsidies from a major German broadband expansion program in 2016 and 2017. We conduct a cost-benefit analysis within the Marginal Value of Public Funds (MVPF) framework of the local public finance literature (Finkelstein and Hendren, 2020; Hendren and Sprung-Keyser, 2020, 2022).

We identify the causal effect of high-speed Internet access on real estate prices in a spatial RDD by comparing similar properties in rural municipalities located on either side of the broadband discontinuity at state borders – those in policy-induced "high" broadband states (treatment) and those in "low" broadband states (control). The spatial RDD leverages variation from German states' expansion policies and uses a hedonic property price model to isolate the intent-to-treat effect of broadband access on property prices.[5] The identifying assumption is that municipalities on either side of state boundaries are valid comparison groups conditional on RD polynomials (distance to boundary as well as longitude and latitude) and boundary-segment-by-year fixed effects to account for spatial and temporal variation. We further control for differential municipality- and state-level characteristics within boundary segments (e.g., tax rates, income, and school quality) and individual property attributes (e.g., property type, size and condition) to isolate the impact of broadband access. Our empirical strategy addresses two key endogeneity concerns: the non-random spatial distribution of broadband access, which may correlate with housing prices, and the challenge of isolating broadband's effect from other property or locational attributes. By controlling for these factors, we ensure that the estimated property price effects are plausibly attributed to differences in local broadband availability. We validate our approach by demonstrating a strong discontinuity in municipal broadband availability at "high" and "low" broadband state bor-

[5] For seminal studies using spatial RDDs, see Black (1999), Dell (2010), Gibbons et al. (2013), Keele and Titiunik (2015), Becker et al. (2016), Calonico et al. (2019), Cantoni (2020), and Gonzalez (2021).

ders, while the covariates, such as local, state, and property characteristics, are balanced with minimal discontinuities.

Our main finding is that fast Internet access increases rural real estate prices by about 3.8 percent for rents and 8 percent for sale prices. These estimates translate to a monthly rent increase of approximately €17 and a property sale price increase of €14,700. This capitalization effect of 16 Mbit/s broadband represents the most relevant Internet speed upgrade, compared to the previously available 1 to 6 Mbit/s in rural areas. The surplus from high-speed broadband access at home may be a combination of consumption value from activities such as streaming, information value derived from Internet access as a complement to local amenities, and labor market value through activities like working from home. Notably, the effects differ between property sales and rentals. We interpret the smaller rental price effect (3.8 percent) as the immediate utility of high-speed Internet access, while the larger sale price increase (8 percent) captures both immediate benefits and buyers' expectations of future rental income premiums until full coverage is achieved in low-broadband states. This difference reflects buyers' stronger internalization of long-term benefits due to their greater commitment to properties, whereas more flexible renters focus on short-term utility. Overall, the capitalization effects reflect households' high willingness to pay and underscore the economic value of fast Internet access in rural areas. Our estimates are consistent and slightly higher than in the previous literature, which investigates the universal delivery of slower first-generation broadband Internet (Ahlfeldt et al., 2017). The magnitude of our estimated effect of fast Internet access is higher than the impact of introducing air pollution regulations (Chay and Greenstone, 2005) and the removal of nearby toxic waste sites (Greenstone and Gallagher, 2008), but lower than the opening of a new metro line (Diao et al., 2017; Gupta et al., 2022c).

In the subsequent analysis, we examine the heterogeneity and robustness of our results. First, we find positive but diminishing capitalization effects at higher broadband speeds (30 and 50 Mbit/s) compared to 16 Mbit/s, indicating a decreasing marginal willingness to pay for higher bandwidths. Second, an analysis of temporal heterogeneity shows that capitalization effects for the same broadband speed increase over time. Since we find this effect particularly for higher speeds, we interpret this as a growing demand for bandwidth-intensive applications in more recent years. Third, our results reveal stronger capitalization effects in rural areas with higher population densities, suggesting a positive relationship between broadband's economic value and population density. Fourth, we find that broadband availability has a greater impact on sale prices and rents for houses than for apartments. Fifth, our results are robust to varying bandwidths. Finally, a placebo check finds no discontinuities in property prices along state boundaries in 2019, after the differences in rural broadband availability had disappeared.

Moreover, we uncover the mechanisms behind the capitalization effects of high-speed Internet on property prices, identifying demand rather than supply as the primary driver. Using micro-census data, we find an increased uptake of high-speed broadband subscriptions in "high" broadband states, suggesting that expansion addressed pre-existing demand. This interpretation is consistent with the estimated effects on property rents, while the stronger effects for sale prices likely also incorporate anticipated future demand. The findings of higher net domestic migration to border regions in "high" compared to "low" broadband states and a higher share of remote work adoption (for which fast Internet access at home is plausibly a precondition) in these areas corroborate this interpretation. Conversely, we find no evidence of discontinuities in the number of property listings at state borders, suggesting that the effects are not driven by supply.[6]

Our evaluation of a major public broadband expansion program in rural German regions reveals that the economic benefits of high-speed Internet access exceed total deployment costs and public subsidies for the majority of rural households. In a cost-benefit analysis of subsidized broadband deployment projects from 2016 and 2017, we find that the broadband premium exceeds connection costs for nearly 90 percent of households. Using the MVPF approach, we incorporate potential increases in tax revenues from property transactions, which does not substantially change the results. Our findings imply that a lower subsidy level could have achieved the German government's objective of universal broadband access. However, public subsidies may have resolved a potential coordination problem among property owners and renters who, despite their willingness to pay, could not collectively finance broadband deployment. Notably, while both residents and property owners benefit from fast Internet access, property owners capture additional gains through higher property values and rents. This suggests that the subsidies, which aimed at improving households' access to fast Internet, redistributed much of the benefits to property owners.

[6] Our interpretation is further supported by evidence of low housing elasticity in the short-run (Baum-Snow and Han, 2024).

Our paper contributes to three strands of the literature. Firstly, it adds to research on the economic value of high-speed broadband by assessing the causal impact of rural broadband expansion and evaluating a major public subsidy program. While prior studies focus on slower, first-generation broadband, our results highlight the substantial economic value of more recent, faster broadband access in rural regions. Our work closely follows Ahlfeldt et al. (2017), who studied early broadband adoption in the UK between 1995 and 2010, finding that basic broadband speeds of 8 Mbit/s increase property values by 2.8 percent, with an additional 1 percent increase for speed upgrades to 24 Mbit/s. Similar results have been documented in the US (Deller and Whitacre, 2019; Molnar et al., 2019). Bourreau et al. (2023) study the fiscal effects of state-aid for broadband expansion in France, showing that subsidies induced more broadband expansion while a sizable fraction of them were inefficient. Regarding state aid for broadband infrastructure expansion in two German states between 2011 and 2013, Duso et al. (2021) find that subsidies increase both coverage and competition, leading to lower prices. Other studies find positive price effects from fiber broadband deployment (Klein, 2022; Koutroumpis et al., 2023; Wolf and Irwin, 2024). Unlike these studies, which focus on one broadband technology, we adopt a broader approach, incorporating all wireline broadband technologies.

Secondly, we expand on the literature examining the capitalization effects of local public goods and externalities. Studies show positive effects on property values from high-quality public goods such as schools (Collins and Kaplan, 2017; Figlio and Lucas, 2004; Gibbons et al., 2013). Similarly, other papers find positive housing price premiums of urban infrastructure, such as railway access (Gibbons and Machin, 2005), new metro lines (Diao et al., 2017; Gupta et al., 2022c), and urban green spaces (Conway et al., 2010). Further studies analyze the impact of negative externalities on property prices, including air pollution (Chay and Greenstone, 2005), hazardous waste (Greenstone and Gallagher, 2008), power plants (Davis, 2011), shale gas extraction (Muehlenbachs et al., 2015), cancer clusters (Davis, 2004), and neighborhood crime (Linden and Rockoff, 2008). Another set of papers examines the capitalization effects of property taxes (Dolls et al., 2025; Oates, 1969; Palmon and Smith, 1998). Finally, other studies investigate the premium of certain property amenities, such as energy efficiency (Aydin et al., 2020; Kahn and Kok, 2014).

Finally, our paper contributes to the growing literature on the effects of broadband Internet on economic, political, and social outcomes. For first-generation broadband, Czernich et al.

(2011) find that a 10 percentage-point increase in broadband usage is liked to higher GDP per capita growth by 0.9 to 1.5 percentage points. At the firm level, broadband improves performance, particularly in specific sectors and locations (Canzian et al., 2019; DeStefano et al., 2018, 2023). In labor markets, broadband has small but positive effects on employment, benefiting skilled workers while disadvantaging unskilled workers (Akerman et al., 2015; Falck et al., 2021; Zuo, 2021). For households, estimates place the average consumer surplus from broadband adoption in the US between USD 98 and USD 165 per month (Greenstein and McDevitt, 2011; Nevo et al., 2016).[7] The political impacts of broadband Internet have been studied in contexts like social capital (Geraci et al., 2022), protests (Enikolopov et al., 2020), ideological polarization (Gentzkow and Shapiro, 2011), and fake news (Allcott and Gentzkow, 2017). Variation in broadband infrastructure has also been linked to election outcomes in Germany (Falck et al., 2014), Italy (Campante et al., 2018), and the UK (Gavazza et al., 2019).

The remainder of this paper is structured as follows. Section 1.2 provides an overview of the institutional context, describes the quasi-experiment, and details the novel micro-dataset. The spatial RDD, sample and summary statistics are presented in section 1.3. Section 1.4 presents our principal empirical findings, discusses the results, investigates heterogeneities, and conducts robustness checks. We investigate the mechanisms underlying our main results in section 1.5. Section 1.6 conducts cost-benefit and MVPF analyses to evaluate broadband subsidies. The final section 1.7 concludes.

## 1.2 Institutional Background and Data

### 1.2.1 High-Speed Broadband Internet

This paper focuses on the provision of fast broadband Internet to households through wireline connections, such as extended bandwidth asymmetric digital subscriber line 2 (ADSL2+), very-high-speed digital subscriber lines (VDSL), cable TV networks (CATV), or fiber-to-the-building/fiber-to-the-home (FTTB/FTTH). This differs from first-generation Internet delivered through dial-up or early DSL (which are not high-speed) or mobile data plans (which

[7] Allcott et al. (2020) caution that valuations of Internet services, such as Facebook, may be overstated due to potential addiction or harm. Our valuation approach, based on overall Internet utility, is less susceptible to these concerns.

are not wireline).[8] "High-speed" Internet is classified as broadband connections with at least 16 Mbit/s downstream capacity since this is the minimum bandwidth to enable applications such as video streaming/conferencing, fast synchronization of large files, and thus working from home. We define Internet availability as the location-specific share of households who have access to high-speed broadband.

The provision of high-speed Internet access required the technological upgrading of the pre-existing broadband infrastructure through the deployment of next-generation access (NGA) networks. Specifically, at least the main distribution frames had to be upgraded.[9] Broadband networks are typically deployed by private telecommunication carriers. These carriers prioritize urban areas because of lower deployment costs per connection, creating an urban-rural connectivity divide. Policy-makers seek to close this divide by subsidizing rural broadband expansion.

### 1.2.2 Quasi-Experiment of German States' Broadband Policies

Our study leverages a quasi-experiment of German states' broadband expansion programs in rural areas that induced spatial discontinuities in Internet access at state boundaries. The different German states held distinct political and economic preferences regarding rural broadband expansion. This led them to enact expansion programs for rural municipalities between 2010 and 2019 with significant differences in scope, funding, regulations, and governance. In section A.1 we provide a detailed overview of all German states' broadband expansion policies. Previously, rural broadband speeds in many municipalities were limited to between 1 and 6 Mbit/s, making the subsequent expansion to 16 Mbit/s a significant technological upgrade. Appendix Figure A.1 shows that the number and the speed of broadband subscriptions in Germany increased substantially from 2010 until 2019, making this decade the relevant time period to investigate broadband expansion. The states' broadband policies took effect in the absence of federal funding, and we show that they were only weakly related to

[8]We additionally include information on mobile Internet availability (3G, 4G/LTE, and 5G), since households with poor broadband coverage may use it as an imperfect substitute for broadband Internet. Mobile Internet is typically slower than wireline connections and not used at home.

[9]Previous dial-up and DSL Internet was based on the pre-existing telephone network, which relied on copper wires to connect houses with nearby main distribution frames. Beginning with initial speeds of 384 kbit/s downstream and 128 kbit/s upstream, several technological standards (ADSL, ADSL2) were implemented over the 2000s. First-generation broadband reached its technological limit at 6 Mbit/s Internet speed and had to be upgraded, since it was unable to meet the demand for higher speeds.

other state-level policies, such as education, domestic security, and local taxes.[10] The different broadband policies led to spatial discontinuities in broadband availability at state boundaries, which were plausibly external to residents on both sides of the borders. These spatial discontinuities enable us to categorize German states into two groups – those with policy-induced "high" and those with "low" broadband availability – based on whether they achieve the national goal of covering at least 75 percent of households with fast Internet.[11] In the empirical analysis, we validate this approach by demonstrating a strong discontinuity in local broadband availability in municipalities at state borders between "high" and "low" broadband states. Furthermore, we conduct robustness checks to ensure that the results are robust to variations in the coverage threshold level, underscoring the significance of the discontinuity itself.

### 1.2.3 Data

**Administrative Data on Broadband Internet** The first component of our dataset consists of administrative data on broadband availability across Germany's 16 states and approximately 11,000 municipalities from 2010 to 2019. This information is sourced from the "broadband atlas," published by the German Ministry of Transport and Digital Infrastructure (Bundesministerium für Verkehr und digitale Infrastruktur, 2010).[12] The dataset reports the share of households covered by broadband infrastructure at both state and municipality levels.

The data differentiate broadband availability by technology and speed. We focus on all fixed-line broadband technologies (ADSL2+, VDSL, CATV, and FTTB), while mobile Internet is included as a control variable. The dataset covers total fixed-line connections with Internet speeds of 16, 30 and 50 Mbit/s. Appendix Figure A.1 shows that these speeds constitute the relevant broadband expansions from 2010 to 2019. State-level data are available for the entire period (2010–2019) across all speeds, while municipality-level data are available for 16 Mbit/s from 2011 to 2016, for 30 Mbit/s from 2013 to 2018, and for 50 Mbit/s from 2011 to 2018.

[10] A federal broadband expansion scheme was formally enacted in 2015 and revised in 2018, but took effect only several years later.

[11] This policy objective was defined in the German broadband expansion agenda (Bundesministerium für Verkehr und digitale Infrastruktur, 2015, 2018).

[12] The "broadband atlas" was compiled by *TÜV Rheinland Consulting GmbH* from 2010 to 2018 and by *atene KOM GmbH* since 2018.

This dataset provides regional variation in broadband availability across rural municipalities at the borders of "high" and "low" broadband states, enabling us to exploit these discontinuities to estimate the causal effect of broadband access on property prices.

For the cost-benefit and MVPF analyses, we use deployment costs from subsidized projects under the federal program (ifo et al., 2021), since individual project deployment costs under the subsidized state programs are unavailable. These applications were filed in 2016 and 2017, but implemented in subsequent years.

**Large Micro-Dataset on the German Real Estate Market** We use a comprehensive micro-dataset on the German real estate market, compiled by the real estate consulting firm *F+B IGES*. It includes property advertisements from approximately 140 sources, spanning online platforms, newspapers, and property agencies. Covering the period from 2010 to 2019, the dataset comprises over 12 million properties for sale and 13 million for rent with individual property-level information. The observations are evenly distributed over time (approximately 1 million observations per year each for sale and for rent) and geographically across the German states and municipalities.

For each property, the dataset includes detailed attributes (e.g., location, type, amenities) and the final offering price for sales and rentals. Although we do not observe transaction prices of sales and rents, the offering prices closely approximate them.[13] We use logarithmized square meter (sqm) prices to ensure comparability across properties. Property-level control variables comprise property characteristics (e.g., type, size, construction year), amenities (e.g., garden, balcony, parking), and neighborhood attributes (e.g., quiet location, public housing). Location data include municipality, postal code, and state. Data cleaning ensures each property is listed only once, although some were offered concurrently on multiple channels. Finally, we winsorize the bottom and top one percent of observations to remove outliers due to false data entries.

**Local Socioeconomic and Micro-Census Data** The third component of our dataset includes supplementary socioeconomic data at the municipality level, drawn from the Federal Institute for Research on Building, Urban Affairs and Spatial Development (Bundesinsti-

[13] For the evolution of property prices in Germany over time and the construction of local property price indices, see Ahlfeldt et al. (2023).

tut für Bau-Stadt-und Raumforschung, 2021), the Regional Statistical Agencies (Statistische Ämter des Bundes und der Länder, 2021), and GIS data from the Federal Agency for Cartography and Geodesy (Bundesamt für Kartographie und Geodäsie, 2019). These data comprise municipality characteristics, including population size (in deciles), growth or shrinkage trends, and housing market regions. Geographic data include the longitude and latitude of each municipality's centroid and its proximity to state borders. We also include municipal business tax and property tax rates. Furthermore, we control for state-level differences in real estate transfer taxes, which affect property prices (Dolls et al., 2025). Additionally, we incorporate micro-census data from 2018 at the municipality level (FDZ der Statistischen Ämter des Bundes und der Länder, 2018). The administrative information on broadband uptake (subscriptions), migration, and remote work adoption allows us to examine the mechanisms through which broadband availability impacts property prices.

## 1.3 Empirical Framework

### 1.3.1 Spatial RDD at State Borders

We estimate the causal effect of high-speed Internet access on real estate prices using a spatial regression discontinuity design (RDD). This section outlines the empirical framework and identification strategy, followed by the sample construction and descriptives.

The spatial RDD exploits geographic discontinuities in rural broadband availability at the borders of "high" and "low" broadband states, induced by the quasi-experiment in broadband expansion policies across German states. This approach compares similar properties in rural municipalities located on either side of state borders, where broadband availability differs due to state expansion policies. Properties in "high" broadband states are the treatment group, while those in "low" broadband states serve as the control group. The spatial RDD integrates a hedonic property price model to disentangle the effect of rural broadband access from other factors impacting property prices. By leveraging the discontinuity in broadband availability over time and across state boundaries as well as by controlling for municipal, state, and property characteristics, we isolate the intent-to-treat effect of high-speed broadband access on property prices. In particular, our identification benefits from variation in boundary regions that contain municipalities from more than two neighboring states. Our empirical strategy builds on seminal studies that have employed spatial RDDs and hedonic pricing models to infer the value of local public goods (Ahlfeldt et al., 2017; Becker et al., 2016; Black, 1999; Calonico et al., 2019; Cantoni, 2020; Dell, 2010; Gibbons et al., 2013; Gonzalez, 2021; Keele and Titiunik, 2015).

The identifying assumption of the spatial RDD is that municipalities on either side of state borders are valid comparison groups after accounting for observable differences, with broadband availability being the only discontinuous variable. To control for spatial characteristics, we use several RD specifications with polynomials either in distance to the boundary or in longitude and latitude. Boundary-segment-by-year fixed effects capture temporal and local variation at the borders, capturing differential shocks over time at a small spatial level. Within the boundary segments, we control for municipality- and state-level variation, including local tax rates, income, and school quality. We further add individual property-level controls, such as property type, size, and condition, to capture differences in property attributes. These controls ensure that the observed variation in property prices at the boundary is plausibly attributable to differences in broadband availability, which we argue is exogenous to residents in small boundary segments.

We employ the hedonic property pricing model to disentangle the effect of broadband availability from other determinants of property values. This approach assumes that property prices reflect the implicit value of their attributes, including internal characteristics and locational features such as access to local public goods like broadband – although unlike classic public goods, broadband requires households to pay an additional subscription fee to the telecommunications provider. In a spatial equilibrium with free mobility, the hedonic model captures the capitalization effect, i.e., how locational advantages and disadvantages are reflected in property prices. By estimating the relationship between property values and these attributes, we quantify the market premium households are willing to pay for high-speed Internet access. Building on a long tradition of research (Oates, 1969; Roback, 1982; Rosen, 1974), the framework has been widely applied to value local public goods while controlling for confounding factors.

Our empirical strategy addresses two endogeneity concerns. First, broadband access is often correlated with locational characteristics, such as population density or economic activity, which may independently influence housing prices. To mitigate this bias, we leverage variation in broadband availability at state borders and control for municipality- and state-level differences. Second, housing prices represent a bundle of property and locational attributes, making it challenging to isolate the broadband effect. By incorporating RD polynomials, boundary-segment-by-year fixed effects as well as comprehensive controls for property characteristics and local conditions, we ensure that the remaining variation in housing prices is plausibly attributable to differences in broadband access.

Many RDDs assume no selective sorting around the threshold – in this case migration across state borders in response to differences in broadband availability. While this assumption could be violated if households systematically relocate, we treat migration patterns as a potential channel of the treatment effect rather than a source of bias. Using micro-census data, we examine net migration flows to assess their role as a demand-side driver of the observed capitalization effects.

We estimate the spatial RDD for three main outcomes: municipal broadband availability, real estate sale prices, and rents. Our primary analysis focuses on broadband speeds of 16 Mbit/s, capturing the main effects of interest, while the broadband speeds 30 and 50 Mbit/s are used for heterogeneity analyses. First, we validate our empirical strategy by demonstrating a clear discontinuity in municipal broadband availability at borders between "high" and "low" broadband states, while the covariates (local, state, and property characteristics) are balanced with minimal discontinuities. We then estimate the local causal effect of "high" broadband states on sale prices and rents, i.e., the capitalization effect of broadband access on property values.

We estimate the spatial RDD using two sets of specifications. The first employs one-dimensional (linear, quadratic, linear interacted) polynomials in distance to the state border, which is most intuitive. The second specification uses multi-dimensional polynomials in longitude and latitude (linear up to quartic), which leverage more detailed geographic information for greater accuracy but are subject to econometric issues (Gelman and Imbens, 2019). This model identifies the causal effect of broadband access by separating its treatment effects from other continuous effects of geographic location. We primarily use a bandwidth of 25 km around state borders, which has favorable characteristics with regard to the bias-variance tradeoff in RDDs (Calonico et al., 2019). For robustness checks, we use smaller and larger bandwidths (15–50 km) and employ a "donut hole" approach that excludes observations directly at boundaries.

Formally, we estimate multiple specifications of the spatial RDD (Equation 1.1):

$$
\begin{aligned}
y_{imt} = & \beta highbroadbandstate_{mt} + f(geographic\ location)_{b(m)} \\
& + X_{imt}\gamma + \delta_{b(m)} \times \delta_t + \varepsilon_{imt}
\end{aligned} \tag{1.1}
$$

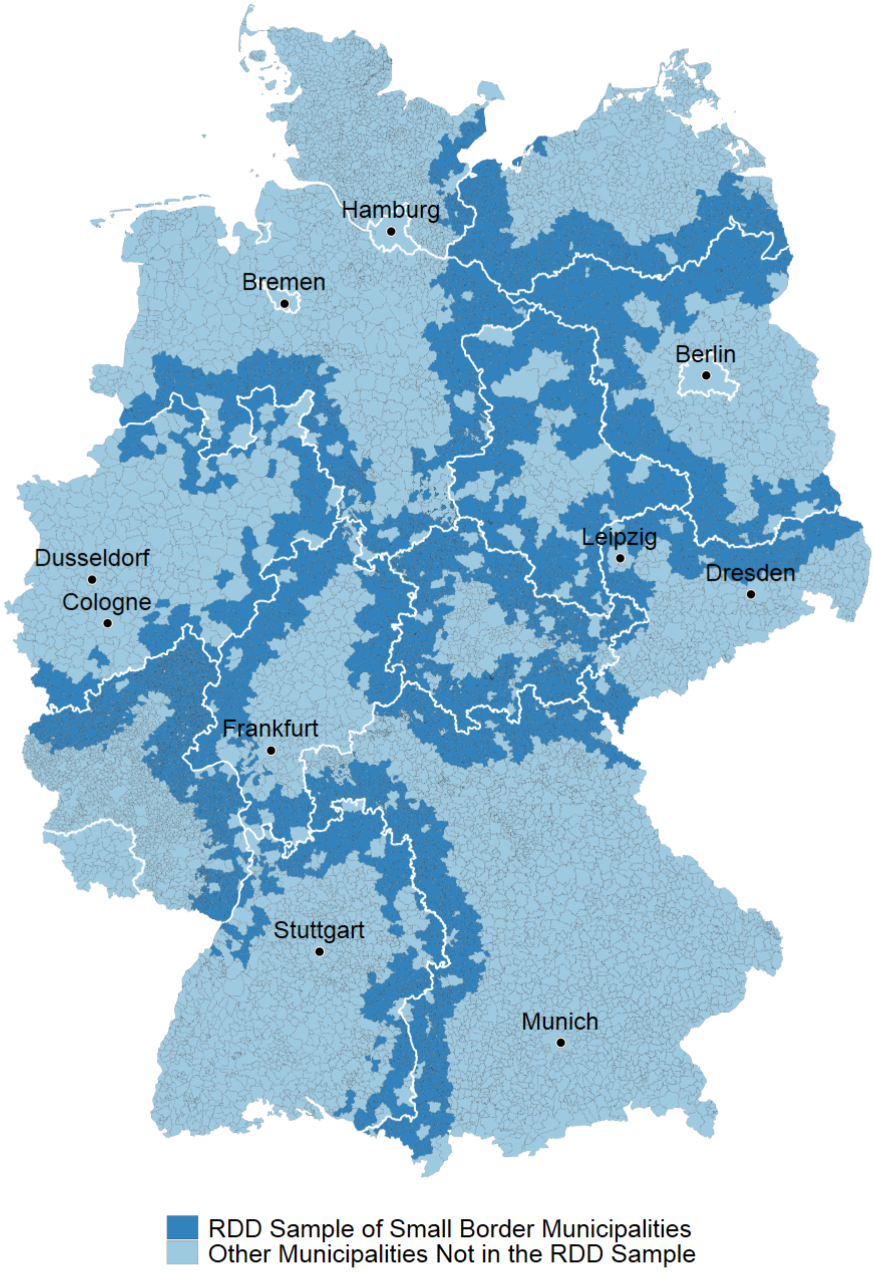
For municipal broadband availability, the outcome variable $y_{mt}$ represents broadband coverage in municipality $m$ in year $t$. At the property level, regressions estimate the effects on log sale prices and rents ($y_{imt}$). The key variable of interest, $highbroadbandstate_{mt}$, is an indicator equal to 1 if municipality $m$ belongs to a "high" broadband state in year $t$. The function $f(geographiclocation)_{b(m)}$ captures the RD polynomial (either in distance to the boundary or in longitude and latitude) for the discontinuity at state borders. The vector $X_{mt}$ controls for socioeconomic characteristics, while border-region-by-year fixed effects $\delta_{b(m)} \times \delta_t$ account for spatial and temporal variation. In the property-level estimations, we include property- and local-level controls $X_{imt}$ capturing observable attributes. Standard errors are clustered at the boundary-region-by-year level.

### 1.3.2 Sample and Summary Statistics

The sample comprises administrative broadband availability data, real estate offerings, as well as local socioeconomic and micro-census data described in subsection 1.2.3. In detail, we construct multiple samples along the following three dimensions: (1) sale versus rental properties, (2) broadband speeds (16 Mbit/s for main analysis, with heterogeneity analysis for 30 and 50 Mbit/s), and (3) bandwidth size around state borders (25 km for the baseline analysis, with robustness checks for 15 km and 50 km). These samples allow us to examine the differential effects of broadband access across markets, speeds, and space. We report descriptive statistics for all samples in section A.2.

For the main analyses, we construct two datasets covering 16 Mbit/s broadband availability in rural municipalities within 25 kilometers of the borders between policy-induced "high" and "low" broadband states from 2010 to 2019: one for properties offered for sale and another for rent. Rural municipalities are defined as those with fewer than 20,000 inhabitants, which excludes larger urban agglomerations and boundary regions of the three German city states. The sample comprises almost 1 million observations from 4,035 municipalities grouped into 57 distinct boundary regions. Figure 1.1 illustrates the sample, highlighting rural municipal-

**Figure 1.1:** Sample Illustration in a Map of Germany




*Note:* This map of Germany illustrates its 16 federal states, delineated by white lines, as well as its approximately 11,000 municipalities. Highlighted in dark blue, the RDD sample is comprised of 4,035 small municipalities that are located within 25 kilometers distance to the next state border of "high" and "low" broadband states. The municipalities not included in the RDD sample are shown in light blue. Those municipalities are either located further away from state boundaries or belong to larger urban agglomerations with many inhabitants.

ities (dark blue) along state borders (white lines). Appendix Figure A.2 provides a detailed view of the individual boundary regions.

Table 1.1 reports descriptive statistics for the main samples covering 16 Mbit/s broadband, including outcome variables, explanatory variables, and controls. The discontinuities in broadband availability and property prices between "high" and "low" broadband states are consistent with the spatial RDD design, while covariates appear largely balanced across state borders. Columns 1-4 report the full sample, columns 5–6 the "low" broadband states, and columns 7–8 the "high" broadband states. Broadband availability averages 53 percent across the sample, with higher coverage in "high" broadband states (59 percent) compared to "low" states (47 percent). Property sale prices average €1,360 per square meter, with a mean of €1,430 for properties in "high" broadband states and of €1,300 in "low" states. Similarly, rents average €5.9 per square meter, with slightly higher rents in "high" broadband states (€6.1) compared to "low" states (€5.6). For the control variables, which comprise individual property, municipal- and state-level characteristics, we find mostly similar characteristics on either side of the border.

Visual evidence supports these patterns. Appendix Figure A.3 and Figure A.6 show a balanced distribution of properties near state borders and over time for 16 Mbit/s broadband. The sample composition varies over time, as the RDD sample includes only municipalities near the borders of "high" and "low" broadband states with a broadband discontinuity in a given year. Appendix Figure A.9 highlights that availability in "high" broadband states started from a higher level and exhibits a steeper upward trend compared to "low" states. The summary statistics align with the spatial RDD design, showing discontinuities in broadband and property prices but largely balanced covariates at state borders. While the summary statistics provide initial support for the identifying assumption of the RDD, we test the smoothness of covariates around the spatial discontinuity in subsection 1.4.2.

The summary statistics for the higher broadband speeds 30 and 50 Mbit/s are reported in Appendix Table A.3 and Table A.4. Similarly, Appendix Figure A.4 and Figure A.5 show the spatial distribution of the sample in distance to the boundary, Appendix Figure A.7 and Figure A.8 present the distribution over time, and Appendix Figure A.10 and Figure A.11 report the distribution of 30 and 50 Mbit/s broadband availability over time.

**Table 1.1:** Descriptive Statistics of the Border Samples for 16 Mbit/s Broadband

| | Full Sample | | | | "Low" Broadband States | | "High" Broadband States | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Min | Max | Mean | SD | Mean | SD |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ***Outcome and Main Explanatory Variables*** | | | | | | | | |
| High Broadband States 16 Mbit/s | 0.49 | 0.50 | 0.00 | 1.00 | 0.00 | 0.00 | 1.00 | 0.00 |
| Broadband Availability Municipalities 16 Mbit/s | 0.53 | 0.32 | 0.00 | 1.00 | 0.47 | 0.33 | 0.59 | 0.30 |
| Property Sale Price Total | 188,030.60 | 121,773.21 | 8,800.00 | 2,950,000.00 | 181,621.52 | 113,848.10 | 194,832.86 | 129,308.80 |
| Property Sale Price per sqm | 1,364.31 | 715.67 | 244.28 | 7,175.00 | 1,302.30 | 660.27 | 1,430.12 | 764.64 |
| Property Rent Total (Monthly) | 484.91 | 240.80 | 98.00 | 3,500.00 | 461.31 | 218.98 | 505.03 | 256.25 |
| Property Rent per sqm (Monthly) | 5.87 | 1.60 | 3.53 | 20.00 | 5.62 | 1.42 | 6.09 | 1.71 |
| ***Control Variables*** | | | | | | | | |
| Property Type (ordinal indicator) | 1.77 | 0.56 | 1.00 | 3.00 | 1.80 | 0.55 | 1.75 | 0.58 |
| Number of Rooms in the Property | 4.84 | 2.54 | 0.00 | 57.00 | 4.90 | 2.51 | 4.76 | 2.57 |
| Log of Floor Space in sqm | 4.87 | 0.46 | 3.50 | 6.15 | 4.88 | 0.44 | 4.85 | 0.47 |
| Age of Property (ordinal indicator) | 8.40 | 5.98 | 1.00 | 18.00 | 8.54 | 6.07 | 8.26 | 5.88 |
| Newly Constructed Building | 0.13 | 0.34 | 0.00 | 1.00 | 0.12 | 0.33 | 0.13 | 0.34 |
| Renovation Status (ordinal indicator) | 3.59 | 1.06 | 1.00 | 5.00 | 3.60 | 1.05 | 3.58 | 1.07 |
| Equipped with Kitchen | 0.23 | 0.42 | 0.00 | 1.00 | 0.21 | 0.41 | 0.26 | 0.44 |
| Equipped with Garden | 0.29 | 0.45 | 0.00 | 1.00 | 0.28 | 0.45 | 0.30 | 0.46 |
| Equipped with Balcony or Terrace | 0.27 | 0.44 | 0.00 | 1.00 | 0.26 | 0.44 | 0.28 | 0.45 |
| Equipped with Basement | 0.41 | 0.49 | 0.00 | 1.00 | 0.40 | 0.49 | 0.42 | 0.49 |
| Parking Lot or Garage Available | 0.62 | 0.48 | 0.00 | 1.00 | 0.61 | 0.49 | 0.64 | 0.48 |
| Exclusive/Luxury Equipment or Villa | 0.04 | 0.18 | 0.00 | 1.00 | 0.03 | 0.18 | 0.04 | 0.19 |
| Equipped with Pool, Whirlpool, or Sauna | 0.06 | 0.24 | 0.00 | 1.00 | 0.06 | 0.23 | 0.07 | 0.25 |
| Bright Rooms | 0.16 | 0.37 | 0.00 | 1.00 | 0.15 | 0.36 | 0.18 | 0.38 |
| Heating Type | 0.29 | 0.95 | 0.00 | 5.00 | 0.28 | 0.94 | 0.30 | 0.96 |
| Central Heating | 0.88 | 0.98 | 0.00 | 2.00 | 0.85 | 0.98 | 0.90 | 0.99 |
| Quiet Location | 0.12 | 0.33 | 0.00 | 1.00 | 0.12 | 0.32 | 0.12 | 0.33 |
| Publicly Subsidized Housing | 0.04 | 0.19 | 0.00 | 1.00 | 0.04 | 0.20 | 0.04 | 0.19 |
| School Quality (PISA score) | -0.24 | 0.94 | -1.39 | 1.74 | -0.14 | 0.89 | -0.34 | 0.97 |
| Crime Rate per 10,000 Inhabitants | 0.07 | 0.01 | 0.05 | 0.09 | 0.07 | 0.01 | 0.07 | 0.01 |
| Mobile Internet Availability | 0.74 | 0.17 | 0.47 | 0.98 | 0.72 | 0.15 | 0.76 | 0.20 |
| Real Estate Transfer Tax Rate | 0.04 | 0.01 | 0.04 | 0.06 | 0.04 | 0.01 | 0.05 | 0.01 |
| Local Real Estate Tax Rate | 350.74 | 53.19 | 150.00 | 785.00 | 336.45 | 42.86 | 366.17 | 58.67 |
| Local Business Tax Rate | 356.69 | 35.78 | 200.00 | 490.00 | 345.47 | 27.11 | 368.81 | 39.82 |
| County Pre-Broadband Growth Trend (ordinal indicator) | -0.42 | 1.09 | -2.00 | 2.00 | -0.55 | 1.04 | -0.28 | 1.12 |
| Log Population Density per Sq. Km. | 5.17 | 0.89 | 1.56 | 7.88 | 5.12 | 0.90 | 5.21 | 0.89 |
| Female Population Share | 0.51 | 0.01 | 0.12 | 0.77 | 0.51 | 0.01 | 0.51 | 0.01 |
| Share of Inhabitants Aged 18 to 64 Years | 0.62 | 0.03 | 0.46 | 0.76 | 0.62 | 0.03 | 0.61 | 0.03 |
| Share of Inhabitants Older Than 65 Years | 0.22 | 0.04 | 0.03 | 0.46 | 0.21 | 0.04 | 0.22 | 0.04 |
| Log Purchasing Power | 18.90 | 0.75 | 14.11 | 20.78 | 18.75 | 0.73 | 19.05 | 0.74 |
| Unemployment Rate | 0.05 | 0.02 | 0.00 | 0.19 | 0.05 | 0.02 | 0.05 | 0.02 |
| *Observations* | 951,991 | | | | | | | |

*Notes:* The descriptive statistics of the border samples for 16 Mbit/s report information on properties for sale (N=741,369) and for rent (N=210,622) from 4,035 rural municipalities, which are located within 25 km of the borders of "high" and "low" broadband states. Columns 1 to 4 report the mean, standard deviation, minimum, and maximum for the full samples, whereas columns 5 to 6 state the mean and standard deviation for "low" broadband states only, and columns 7 to 8 report the analogous values for "high" broadband states.

## 1.4 Empirical Results

### 1.4.1 Results on Broadband Availability

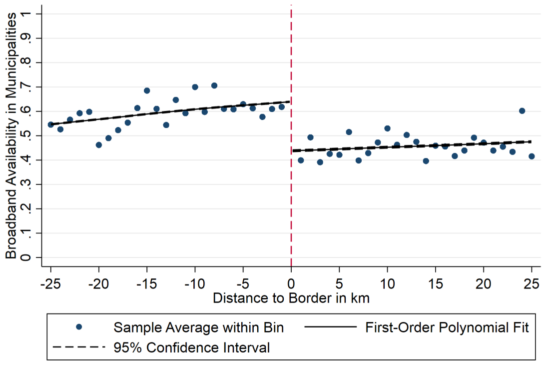
We provide graphical evidence to validate the spatial RD design by illustrating the relationship between broadband availability in municipalities and distance to the border between "high" and "low" broadband states. Figure 1.2 presents the spatial discontinuity in broadband availability for 16, 30, and 50 Mbit/s broadband speeds across state boundaries. In each panel, the y-axis represents broadband availability, while the x-axis measures the distance in kilometers to the nearest state border, with negative values indicating "high" broadband states. The RD plots are generated by an evenly spaced number of bins, representing the sample average within each bin, net of boundary-region-by-year fixed effects. The solid lines represent predicted values from a regression of the outcome variable on a first-order polynomial in distance to the boundary, with the corresponding 95 percent confidence intervals displayed by dotted lines. Thanks to the richness of the data, the confidence bands are very narrow.

The discontinuities in broadband availability at the state borders are visually evident for all three speed levels. This suggests that the spatial discontinuities in broadband availability at state borders are induced by differential state-level broadband expansion policies and not by endogenous local factors. The RD plots thus supports the validity of our quasi-experimental framework, demonstrating that neighboring municipalities on either side of the border exhibit significantly different broadband availability. This spatial discontinuity is plausibly exogenous to the individual municipalities and residents, enabling us to exploit this variation later on to estimate the causal effect of broadband access on property prices.

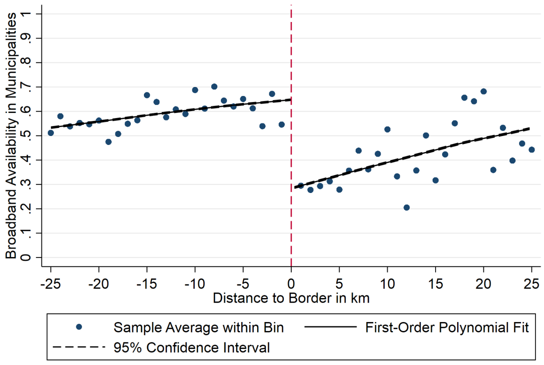
We estimate the spatial RD formally in Table 1.2, using various RD specifications with boundary-region-by-year fixed effects and standard errors clustered at the boundary-region-by-year level. Columns 1 to 3 use the log availability of 16, 30, and 50 Mbit/s connections respectively as dependent variables. Furthermore, this and the following two tables are divided into an upper and a lower panel to reflect the two different specifications of the spatial RDD. The upper Panel A presents the estimates for linear, quadratic, and linear interacted RDD polynomials in distance to border. In contrast, the lower Panel B reports results for estimations based on linear, quadratic, cubic, and quartic RDD polynomials in longitude and latitude. Since the latter specification uses two-dimensional geographic information, it more accurately controls for regional differences and thus constitutes our preferred specification (with a linear polyno-

**Figure 1.2:** Spatial RD Plots for Broadband Internet Availability in Municipalities

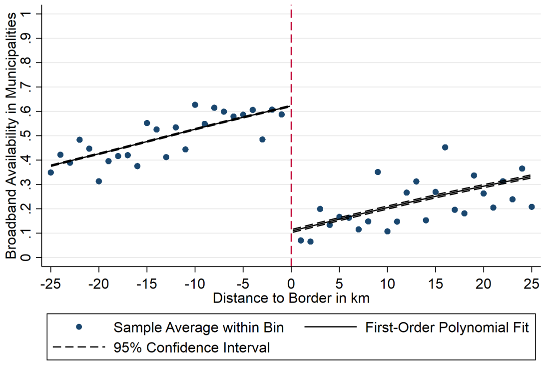
**(a)** 16 Mbit/s Broadband Availability in Municipalities




**(b)** 30 Mbit/s Broadband Availability in Municipalities




**(c)** 50 Mbit/s Broadband Availability in Municipalities




*Note:* Shown are spatial RD plots for broadband availability in municipalities for the Internet speeds 16 Mbit/s (Panel A), 30 Mbit/s (Panel B), and 50 Mbit/s (Panel C). The outcomes are plotted on the y-axis. "Distance to border in km" on the x-axis refers to the distance in kilometers from the closest state boundary, with negative values of distance indicating "high" broadband states. The RD plots are generated by an evenly spaced number of bins, representing the sample average within each bin, net of boundary-region-by-year fixed effects. The solid lines represent the predicted values from a regression of the outcome variable on a first-order polynomial in distance to the boundary. The corresponding 95 percent confidence intervals are displayed as dotted lines.

**Table 1.2:** Spatial RDD Results for Broadband Internet Availability in Municipalities

| Spatial RDD Estimates | Broadband Availability in Municipalities | Broadband Availability in Municipalities | Broadband Availability in Municipalities |
|---|---|---|---|
| | 16 Mbit/s | 30 Mbit/s | 50 Mbit/s |
| | (1) | (2) | (3) |
| *Panel A: RDD Polynomials in Distance to Boundary* | | | |
| **Linear** | 0.2804*** | 0.5239*** | 0.7751*** |
| | (0.0974) | (0.0792) | (0.1144) |
| **Quadratic** | 0.2774*** | 0.5613*** | 0.9298*** |
| | (0.0572) | (0.0724) | (0.1402) |
| **Linear Interacted** | 0.2780*** | 0.5444*** | 0.8818*** |
| | (0.0704) | (0.0745) | (0.1342) |
| *Panel B: RDD Polynomials in Longitude and Latitude* | | | |
| **Linear** | 0.2674*** | 0.5637*** | 0.9380*** |
| | (0.0611) | (0.0786) | (0.1619) |
| **Quadratic** | 0.2589*** | 0.5288*** | 0.9117*** |
| | (0.0562) | (0.0757) | (0.1585) |
| **Cubic** | 0.2382*** | 0.5354*** | 0.8580*** |
| | (0.0547) | (0.0676) | (0.1515) |
| **Quartic** | 0.2382*** | 0.5354*** | 0.8580*** |
| | (0.0547) | (0.0676) | (0.1515) |
| **Boundary Region by Year FE** | ✓ | ✓ | ✓ |
| **Municipalities** | 4,035 | 3,341 | 3,389 |
| **Data Availability Period** | 2011-2016 | 2014-2018 | 2011-2018 |

*Note:* Shown are the coefficients and standard errors for "high broadband state" under different specifications of the RDD polynomials, with each cell in the table reporting the result of a separate regression. Panel A displays estimates for linear, quadratic, and linear interacted RDD polynomials in distance to the state boundary, whereas Panel B presents the results for linear, quadratic, cubic, and quartic RDD specifications in longitude and latitude. Broadband availability in municipalities are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. *p<0.1; **p<0.05; ***p<0.01.

mial to avoid problems of higher-order polynomials). Within the tables, each cell shows the point estimates and standard errors of the "high" broadband state variable from a separate regression. Throughout the specifications in Table 1.2, boundary-region-by-year fixed effects are included and standard errors are clustered at the boundary-region-by-year level.

The estimates for the broadband speed of 16 Mbit/s in column 1 of Table 1.2 show throughout the RDD specifications a significantly positive effect of "high" broadband states on availability in municipalities in the range of 24 to 28 percentage points. This suggests that the boundary discontinuity of "high" and "low" broadband states indeed has sizable effects on households' local broadband access, even when controlling for regional characteristics through boundary-region-by-year fixed effects, and clustering the standard errors at the boundary-region-by-year level. The effect is identified from variation across boundary regions covering 4,035 municipalities over 6 years. The positive and significant result provides evidence that the "high" broadband state status is indeed relevant for municipality-level broadband availability.

For broadband speeds of 30 Mbit/s and 50 Mbit/s, the relationship is even stronger. The estimates range from 52 to 56 percentage points for 30 Mbit/s and 78 to 94 percentage points for 50 Mbit/s. The positive and significant results for these higher broadband speeds further underscore the impact of the "high" broadband state status on availability at the local level.[14]

### 1.4.2 Balanced Covariates

Given the evidence of a sharp spatial discontinuity in local broadband availability at the borders between "high" and "low" broadband states, the validity of the spatial RDD rests on the smoothness of other covariates (muncipality-, state-level, and property characteristics) across the boundary. Major discontinuities in these covariates would indicate potential confounding factors, violating the identifying assumption. Since differences in property prices should be attributable to broadband availability and not differences in other local characteristics, we test in this subsection for balanced covariates near the boundary to confirm smoothness.

Figure 1.3 shows the smoothness of covariates with only minor discontinuities across state borders, presenting evidence in three panels. Panel A shows various individual property char-

[14]Note that across columns, the years included in the sample differ due to data availability. The high/low state definition is also specific to the speed level. As a result, the number of municipalities in the sample differs as well.

acteristics, such as floor space, age, and type (apartment or house). For all of these 12 attributes, the RD plots exhibit minimal variation across the border, with averages on both sides being nearly identical and the trends appearing smooth.

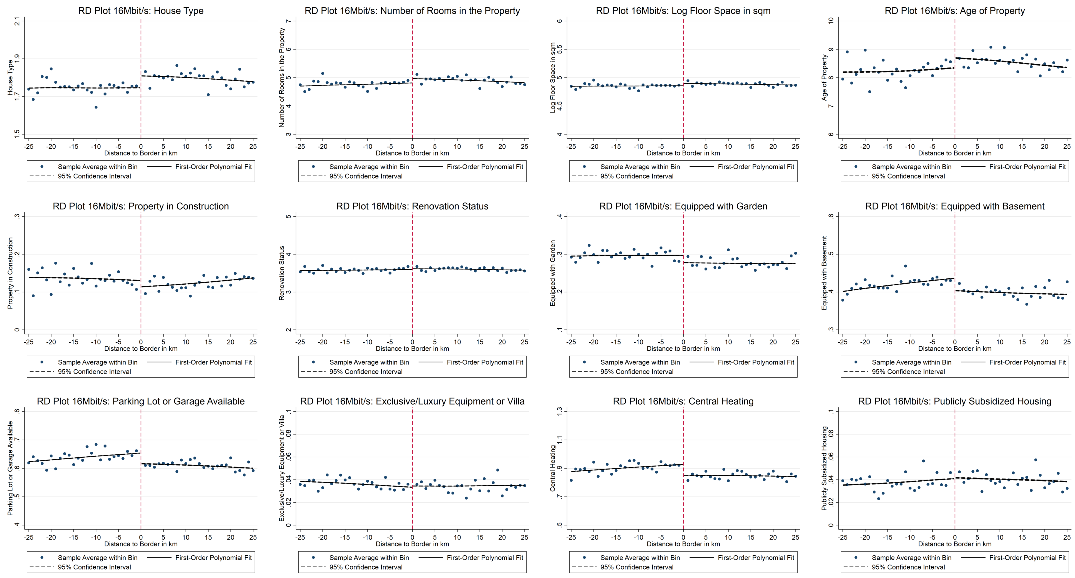
Panel B examines state-level institutional and policy characteristics. While school quality and crime rates show negligible differences between "high" and "low" broadband states, real estate transfer taxes are higher in "high" broadband states. This may have an ambiguous effect, since higher property transaction taxes suggest both greater fiscal capacity, which may be conducive to infrastructure expansion, but also negative capitalization effects of higher tax burdens into property prices. The share of households with mobile Internet, a variable related to broadband access, is balanced across the border. Although mobile Internet could substitute for broadband access in its absence, it is generally less relevant *at home* when broadband is available, since broadband typically provides faster and cheaper connectivity.

Panel C investigates municipality-level policy and economic characteristics. These include the real estate tax rate, business tax rate, log population density, pre-existing growth trend, and demographic characteristics (female, working age, and seniors' population shares). Higher tax rates and pre-existing growth trends in "high" broadband states demonstrate the importance of including these controls to ensure robust results. Population density, an important determinant of the costs of broadband expansion, is balanced around the border. Similarly, the population shares of females, working age people, and seniors are smoothly distributed around the boundary. Local economic controls comprise log purchasing power and the unemployment rate. While some differences are visually detectable, with slightly higher levels in "high" broadband states, they are economically small.

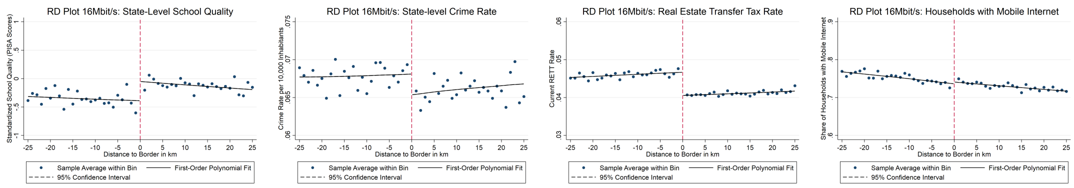
Overall, the broad set of municipality-, state-level, and property covariates displays smooth patterns across state borders, reinforcing the validity of the spatial RDD. Furthermore, these variables are included as controls in our regressions to enhance precision and ensure that the residual variation in property prices is plausibly attributable to differences in broadband availability.

**Figure 1.3:** Graphical Evidence of Balanced Covariates Around State Borders

**(a)** Panel A: Individual Property Characteristics




**(b)** Panel B: State-Level Institutional and Policy Characteristics




**(c)** Panel C: Municipality Policy and Local Economic Characteristics


*Note:* Shown are the spatial RD plots for property characteristics (Panel A), state-level policy characteristics (Panel B), and municipality policy and local economic characteristics (Panel C). The outcomes are plotted on the y-axis. "Distance to border in km" on the x-axis refers to the distance from the closest state boundary, with negative values indicating "high" broadband states. The RD plots were generated by an evenly spaced number of bins, representing the sample average, net of boundary-region-by-year fixed effects. Solid lines are the predicted values from regressions on a first-order polynomial in distance to the boundary. 95 percent confidence intervals are displayed as dotted lines.

### 1.4.3 Results on Real Estate Prices and Rents

To illustrate the impact of high-speed broadband access on real estate prices and rents, Figure 1.4 presents spatial RD plots for 16 Mbit/s broadband Internet. The plots demonstrate clear discontinuities in sale prices (Panel A) and rents (Panel B) at state borders, with higher values observed in municipalities located in "high" broadband states on the left side of the boundary. These discontinuities suggest a significant capitalization effect of broadband access on property prices. As before, the solid lines show predicted values from a first-order polynomial regression in distance to the boundary, while the dotted lines represent the corresponding 95 percent confidence intervals. In both panels, the confidence bands are very narrow.

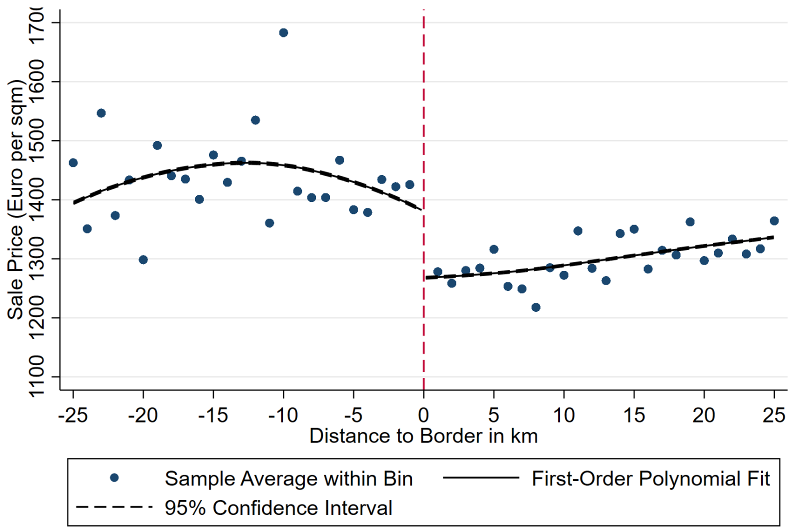
Moving towards more rigorous evidence, we present the main spatial RDD results on the effect of broadband availability on real estate sale prices and rents in Table 1.3 and Table 1.4. The tables report results under different specifications of the RDD (Equation 1.1), with Panel A using polynomials in distance to the boundary and Panel B using polynomials in longitude and latitude. The dependent variable are the log of real estate sale prices and rents, respectively. From columns (1) to (5), we start with boundary-region-by-year fixed effects and gradually add individual property controls, state policy controls, municipality policy controls, and local economic controls. Our preferred specification is the most restrictive in column (5), using a linear polynomial in longitude and latitude, fixed effects, and the full set of controls.

The results for sale prices in Table 1.3 consistently show significantly positive effects across all specifications. Under the most restrictive specification in column (5) using boundary-region-by-year fixed effects and the full set of controls, the estimated impact ranges from 4.9 to 9.7 percent. Our preferred RDD specification with linear polynomials in longitude and latitude yields an estimated increase of 8.1 percent. Using the mean property sale price in "low" broadband states of €181,622 (see Table 1.1), this corresponds to an approximate increase of €14,711 per property. In terms of sale price per square meter, where the mean is €1,302, the effect translates into an increase of €105.46 per square meter.

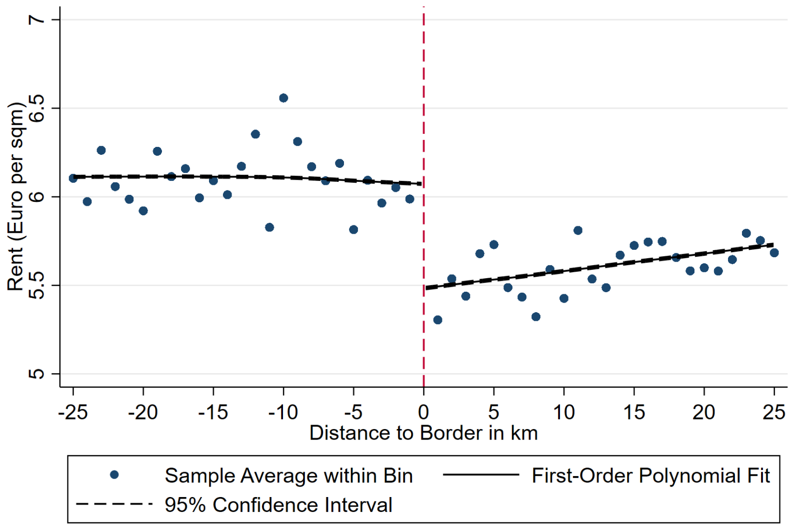
Table 1.4 provides complementary results for rents under various RDD specifications, again finding consistently positive and significant effects. Under the most restrictive specification in column (5), the estimated effect on property rents ranges from 2.2 to 4.4 percent. Our preferred specification with linear polynomials in longitude and latitude yields an estimated

**Figure 1.4:** Spatial RD Plots for Real Estate Sale Prices and Rents

**(a)** Spatial RD Plot for Real Estate Sale Prices (16 Mbit/s)




**(b)** Spatial RD Plot for Real Estate Rents (16 Mbit/s)




*Note:* These spatial RD plot show property sale prices (Panel A) and rents (Panel B) around the boundaries of "high" and "low" broadband states for 16 Mbit/s broadband Internet. Property prices and rents are measured in Euro per square meter and plotted on the y-axis. "Distance to border in km" on the x-axis refers to the distance in kilometers between the observation and the closest state boundary, with negative values of distance indicating "high" broadband states. The RD plots are generated by an evenly spaced number of bins, representing the sample average within each bin, net of boundary-region-by-year fixed effects. The solid lines represent the predicted values from a regression of the outcome variable on a first-order polynomial in distance to the boundary. The corresponding 95 percent confidence intervals are displayed as dotted lines.

**Table 1.3:** Main Results of the Spatial RDD for Real Estate Sale Prices (16 Mbit/s)

| **Spatial RDD Estimates** | **Real Estate Sale Prices** | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Panel A: RDD Polynomials in Distance to Boundary* | | | | | |
| **Linear** | 0.0475*** | 0.0407*** | 0.0866*** | 0.0573*** | 0.0493*** |
| | (0.0181) | (0.0139) | (0.0156) | (0.0172) | (0.0175) |
| **Quadratic** | 0.1087*** | 0.0948*** | 0.1355*** | 0.0959*** | 0.0786*** |
| | (0.0144) | (0.0118) | (0.0141) | (0.0170) | (0.0170) |
| **Linear Interacted** | 0.0485*** | 0.0457*** | 0.0897*** | 0.0471*** | 0.0408** |
| | (0.0177) | (0.0139) | (0.0156) | (0.0176) | (0.0175) |
| *Panel B: RDD Polynomials in Longitude-Latitude* | | | | | |
| **Linear** | 0.1120*** | 0.0973*** | 0.1392*** | 0.1000*** | 0.0810*** |
| | (0.0160) | (0.0129) | (0.0145) | (0.0154) | (0.0154) |
| **Quadratic** | 0.1118*** | 0.0964*** | 0.1501*** | 0.1105*** | 0.0943*** |
| | (0.0147) | (0.0119) | (0.0135) | (0.0151) | (0.0153) |
| **Cubic** | 0.1008*** | 0.0890*** | 0.1434*** | 0.1119*** | 0.0973*** |
| | (0.0143) | (0.0118) | (0.0131) | (0.0153) | (0.0153) |
| **Quartic** | 0.0711*** | 0.0634*** | 0.1117*** | 0.0923*** | 0.0812*** |
| | (0.0174) | (0.0142) | (0.0146) | (0.0166) | (0.0163) |
| **Boundary Region by Year FE** | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Individual Property Controls** | | ✓ | ✓ | ✓ | ✓ |
| **State Policy Controls** | | | ✓ | ✓ | ✓ |
| **Municipality Policy Controls** | | | | ✓ | ✓ |
| **Local Economic Controls** | | | | | ✓ |
| **Observations** | 741,369 | 741,369 | 741,369 | 723,881 | 723,881 |
| **Municipalities** | 4,035 | 4,035 | 4,035 | 3,983 | 3,983 |
| **Data Availability Period** | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 |

*Note:* Shown are the coefficients and standard errors for "high broadband state" under different specifications of the RDD polynomials, with each cell in the table reporting the result of a separate regression. Panel A displays estimates for linear, quadratic, and linear interacted RDD polynomials in distance to the state boundary, whereas Panel B presents the results for linear, quadratic, cubic, and quartic RDD specifications in longitude and latitude. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. *p<0.1; **p<0.05; ***p<0.01.

Table 1.4: Main Results of the Spatial RDD for Real Estate Rents (16 Mbit/s)

| Spatial RDD Estimates | Real Estate Rents | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Panel A: RDD Polynomials in Distance to Boundary* | | | | | |
| **Linear** | 0.0278** | 0.0283** | 0.0374*** | 0.0304*** | 0.0222** |
| | (0.0132) | (0.0120) | (0.0113) | (0.0104) | (0.0096) |
| **Quadratic** | 0.0552*** | 0.0561*** | 0.0628*** | 0.0491*** | 0.0355*** |
| | (0.0085) | (0.0078) | (0.0099) | (0.0103) | (0.0099) |
| **Linear Interacted** | 0.0290*** | 0.0319*** | 0.0390*** | 0.0248*** | 0.0172** |
| | (0.0107) | (0.0099) | (0.0098) | (0.0095) | (0.0086) |
| *Panel B: RDD Polynomials in Longitude-Latitude* | | | | | |
| **Linear** | 0.0587*** | 0.0592*** | 0.0664*** | 0.0536*** | 0.0378*** |
| | (0.0097) | (0.0090) | (0.0102) | (0.0087) | (0.0083) |
| **Quadratic** | 0.0581*** | 0.0581*** | 0.0723*** | 0.0580*** | 0.0436*** |
| | (0.0079) | (0.0073) | (0.0093) | (0.0090) | (0.0086) |
| **Cubic** | 0.0506*** | 0.0510*** | 0.0677*** | 0.0554*** | 0.0414*** |
| | (0.0069) | (0.0065) | (0.0080) | (0.0085) | (0.0083) |
| **Quartic** | 0.0338*** | 0.0351*** | 0.0477*** | 0.0400*** | 0.0299*** |
| | (0.0098) | (0.0092) | (0.0093) | (0.0094) | (0.0089) |
| **Boundary Region by Year FE** | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Individual Property Controls** | | ✓ | ✓ | ✓ | ✓ |
| **State Policy Controls** | | | ✓ | ✓ | ✓ |
| **Municipality Policy Controls** | | | | ✓ | ✓ |
| **Local Economic Controls** | | | | | ✓ |
| **Observations** | 378,348 | 378,348 | 378,348 | 369,335 | 369,335 |
| **Municipalities** | 3,628 | 3,628 | 3,628 | 3,579 | 3,579 |
| **Data Availability Period** | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 |

*Note:* Shown are the coefficients and standard errors for "high broadband state" under different specifications of the RDD polynomials, with each cell in the table reporting the result of a separate regression. Panel A displays estimates for linear, quadratic, and linear interacted RDD polynomials in distance to the state boundary, whereas Panel B presents the results for linear, quadratic, cubic, and quartic RDD specifications in longitude and latitude. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

increase of 3.8 percent. Using the mean property rent in "low" broadband states of €461 per month (see Table 1.1), this corresponds to an approximate increase of €17.52 per month. For rents per square meter, with a mean of €5.62, the effect implies an increase of €0.21 per square meter.[15]

Overall, the results for both sale prices and rents demonstrate that broadband availability strongly capitalizes into property values, reflecting households' high willingness to pay and underscoring the economic value of high-speed Internet compared to slower access in rural areas. The surplus from high-speed broadband access at home may be a combination of consumption value from activities such as streaming, information value derived from Internet access as a complement to local amenities, and labor market value through activities like working from home, which we further examine in section 1.5 on mechanisms. Regarding the heterogeneous effects between property sales and rentals, the smaller effect on rents (3.8 percent) likely reflects the immediate utility that households derive from high-speed Internet access. In contrast, the larger sale price increase (8 percent) may capture both the immediate benefits and the anticipated premium on future rental income as broadband coverage improves in neighboring low-broadband states. This difference aligns with buyers' stronger internalization of long-term benefits due to their greater commitment to properties, whereas more flexible renters prioritize short-term utility. Buyers likely anticipated these premiums to persist for several years, given uncertainty about when broadband speeds in low-broadband states would catch up. On average, this catch-up process took four years. As shown in Appendix Figure A.12, the broadband effect on property prices is strongest in those municipalities with the highest availability.

In comparison to previous studies on the capitalization effects of broadband in other countries, our findings for the German real estate market are consistent and of slightly higher magnitude. For instance, the estimated effects are higher but broadly in the same range as Ahlfeldt et al. (2017) who estimate 2.8 percent for 8 Mbit/s and 3.8 percent for 24 Mbit/s in the United Kingdom. They also compare well to the results by Molnar et al. (2019) of 3 percent for 25 Mbit/s in the United States. Combined, these findings highlight a rather uniform importance of broadband Internet across advanced economies. More broadly, our results for the capitalization effect of high-speed Internet correspond to improved school quality by ap-

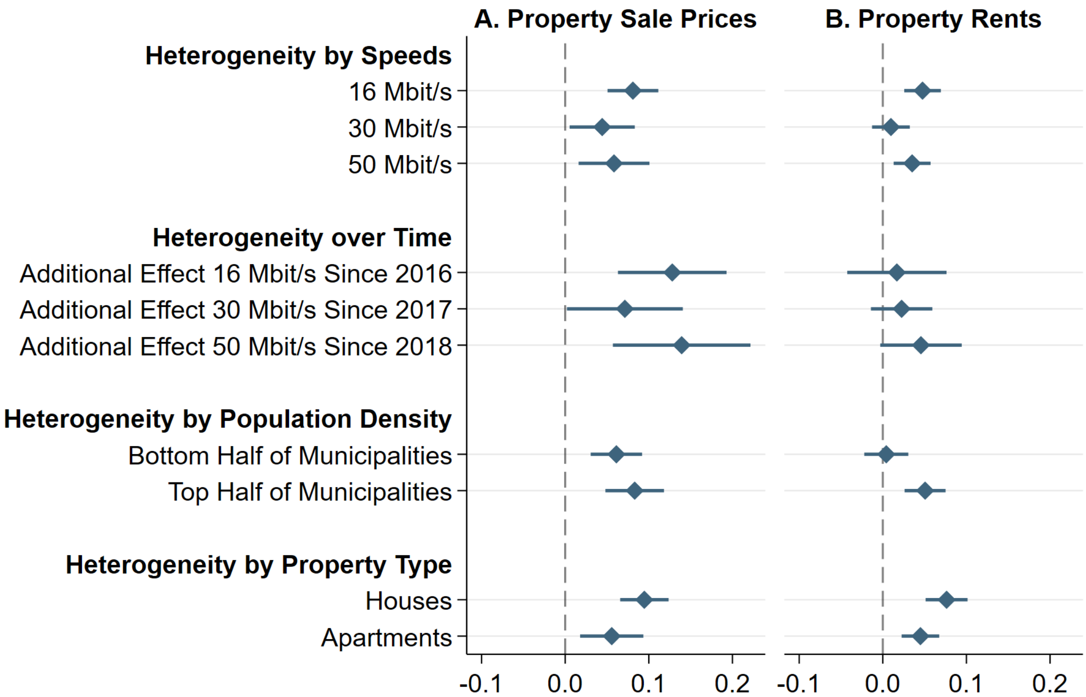
[15] Appendix Table A.11 reports the same regressions for sale prices and rents in levels, directly estimating euro values. The results closely align.

proximately half a standard deviation (Gibbons et al., 2013). They are higher than the introduction of air pollution regulations in affected American counties (Chay and Greenstone, 2005) as well as the removal of nearby toxic waste sites (Greenstone and Gallagher, 2008). The magnitude of the estimated effect in our rural setting is lower than the opening of new subway lines in New York City and Singapore (Diao et al., 2017; Gupta et al., 2022c).

### 1.4.4 Heterogeneity Analysis

Figure 1.5 provides an overview of the heterogeneity analysis, while detailed results are provided in section A.3.

**Figure 1.5:** Overview of Heterogeneity Analyses Results




*Note:* This coefficient plot provides an overview of the spatial RDD results for the heterogeneity analyses by different Internet speeds, over time, and by property types. The results for property sale prices are presented in Panel A and the results for property rents in Panel B. The plot reports the coefficients and 95 percent confidence intervals for regressions of "high broadband state" on property sale prices and rents using the preferred RDD specification with linear polynomials in longitude and latitude. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. The vertical dotted grey line marks zero. The detailed results are reported in section A.3.

**Positive But Diminishing Returns to Higher Internet Speeds** Having established the main results for broadband at 16 Mbit/s, we now turn to the effects of higher speeds, specifically 30 and 50 Mbit/s. The results in Figure 1.5 indicate that while the effects of "high" broadband states remain positive for these higher speeds, they are slightly smaller than those for the main broadband speed 16 Mbit/s.[16] It is important to note that these estimates capture the difference between a "high" and "low" broadband state *at the specific speed level* and do not directly compare higher speeds to a baseline of less than 16 Mbit/s as in our main analysis. These findings suggest that while consumers in the sample period value faster Internet speeds, the incremental benefits diminish at higher threshold speeds. The Internet speed upgrade to 16 Mbit/s appears to deliver the most substantial economic value.

**Increasing Value of High Internet Speeds over Time** Faster Internet speeds enable new applications that become more valuable as they develop and gain users through network effects. To examine this dynamic, we analyze how the capitalization effects of broadband access vary over time by estimating the spatial RDD with an additional interaction term between the indicator for "high" broadband states and a respective cutoff year for each broadband speed. Figure 1.5 summarizes the results (coefficients and confidence intervals on the interaction effects), with detailed estimates reported in Appendix Table A.6. For sale prices and 16 Mbit/s broadband, we find a significantly positive interaction effect between "high" broadband states and the time period since 2016. The coefficient estimate on this interaction term yields an additional effect of 12.8 percentage points in the preferred linear longitude-latitude specification. For rents, the estimates remain insignificant. For 30 and 50 Mbit/s, we also find significantly positive additional effects on sale prices in later years, while the effects on rents are insignificant. We interpret this as evidence of growing demand for bandwidth-intensive applications in more recent years, as households increasingly value faster Internet to support evolving digital activities. At the same time, the lack of high-speed broadband may be increasingly penalized, particularly in property sales where future expectations of broadband expansion play a larger role.

[16] Appendix Table A.5 reports the results for 30 and 50 Mbit/s, while Figure A.13 and Figure A.14 display RD plots for sale prices and rents at these speeds. The reduced significance for 30 Mbit/s is likely due, at least in part, to the smaller sample size relative to the 16 and 50 Mbit/s estimations.

**Stronger Effects in More Densely Populated Municipalities** Figure 1.5 provides another heterogeneity analysis, splitting the sample based on population density in municipalities (between bottom half and top half; see detailed results in Appendix Table A.7). The results show that capitalization effects are more pronounced in slightly more populated municipalities compared to their very rural counterparts for both sale prices and rents, suggesting a positive relationship between broadband's economic value and population density.

**Stronger Effects for Houses than Apartments** While the main analysis reports estimates for a pooled sample of houses and apartments, this heterogeneity analysis aims to identify differential effects by separately estimating the effects for houses and apartments. Figure 1.5 summarizes these results, with detailed estimates in Table A.8. We find significantly positive results for both houses and apartments, but the effects on sale prices and rents are higher for houses than for apartments. This difference may reflect lower average moving costs for apartments, which shorten the time horizon over which a fast Internet connection is valued (and uncertainty regarding the next buyer's valuation).

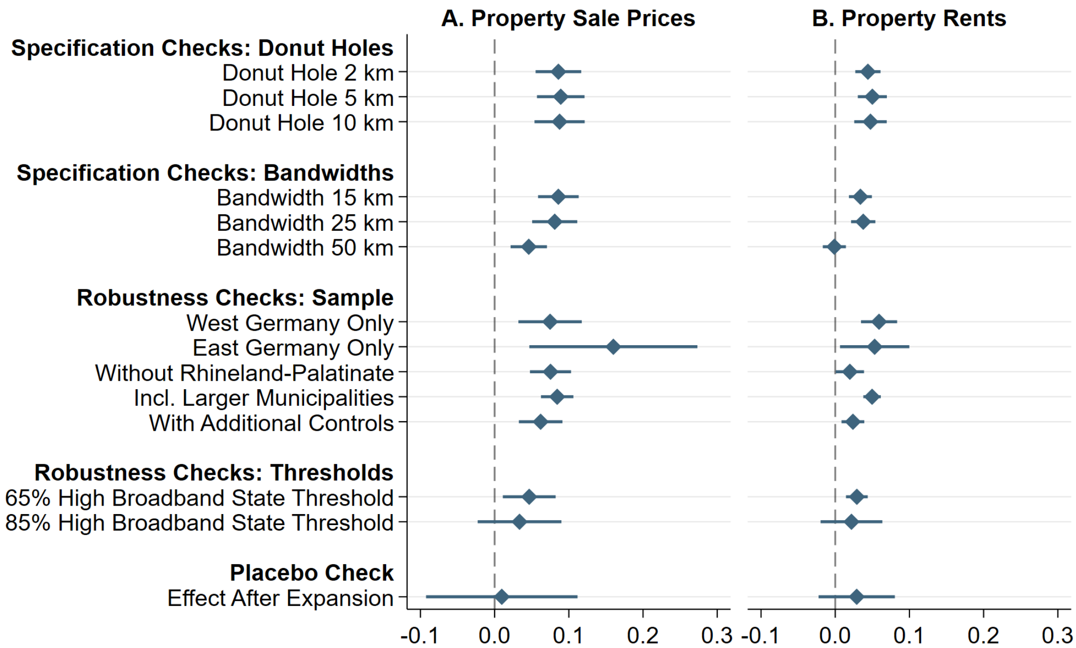
### 1.4.5 Specification, Robustness, and Placebo Checks

Figure 1.6 provides an overview of specification, robustness, and placebo checks, while detailed results are provided in section A.4.

**Specification Checks: Donut Hole Approach** To check the sensitivity of the estimates to the specific sample we select for our main analysis, we employ a "donut hole" approach. This addresses the concern that properties at the border may not be representative of rural municipalities overall. Furthermore, it excludes potential spillover effects near the border. While the bandwidth is again 25 kilometers, as in our main specification, properties which are very close to the border are excluded. Figure 1.6 shows that omitting a 2, 5, or 10 kilometer radius from the border does not substantially change the effect of "high" broadband states on sale prices and rents (see detailed results in Appendix Table A.10).

**Specification Checks: Bandwidths** The second set of specification checks uses different bandwidths, both larger and smaller than the main bandwidth of 25 kilometers around state borders. In Appendix Figure A.15 and Figure A.16, we present graphical evidence in RD plots for bandwidths of 15 and 50 kilometers, respectively. Table A.9 complements the

**Figure 1.6:** Overview of Specification, Robustness, and Placebo Checks of Spatial RDD




*Note:* This coefficient plot provides an overview of the spatial RDD results for the specification checks, robustness checks, and placebo checks. The results for property sale prices are presented in Panel A and the results for property rents in Panel B. The plot reports the coefficients and 95 percent confidence intervals for regressions of "high broadband state" on property sale prices and rents using the preferred RDD specification with linear polynomials in longitude and latitude. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. The vertical dotted grey line marks zero. The detailed results are reported in section A.4 Specification Checks, section A.5 Robustness Checks, and section A.6 Placebo Checks.

graphs with the corresponding estimates for the smaller and larger bandwidths, as well as the 25 kilometer bandwidth for comparison. Overall, the findings demonstrate that the estimated effects remain consistent in magnitude and statistically significant independent of the specific bandwidth choice. The main 25 km bandwidth strikes a balance between reducing bias and maintaining precision. A narrower bandwidth ensures greater comparability by focusing on locations with similar regional characteristics, but it also restricts the sample, potentially excluding important regions, such as East-West German state borders, where properties may be sparse near the boundary. In contrast, a larger bandwidth increases the sample size and statistical power but risks introducing bias by including more distant and less comparable properties.

**Robustness Checks on Sample** We conduct a series of robustness checks of the sample in Appendix Table A.12 and Table A.13 to confirm that our results are not driven by specific regions, states, or boundary regions.

First, we test whether the effects hold in West Germany only by excluding East German states to account for persistent structural differences. The estimates remain significantly positive, which suggests that East Germany does not drive the observed effects but rather that its inclusion may slightly attenuate the results.

Second, we analyze the effects of "high" and "low" broadband states in East Germany only. The estimates yield broadly similar results, although with higher standard errors, suggesting that the effects are not unique to either region.

Third, we remove Rhineland-Palatinate from the sample due to its unique regional structure with extremely small municipalities and status as a "low" broadband state for 16 Mbit/s until 2013. The results without Rhineland-Palatinate are consistent with the main findings, ruling out that its specific characteristics drive the effects.

Fourth, we expand the sample to include larger municipalities around state borders, relaxing the restriction of fewer than 20,000 inhabitants. Large municipalities are slightly more prevalent in "high" broadband states and exhibit higher property prices. Although the estimated effects are marginally larger than in the main sample, this exercise demonstrates that the results are robust to including more urbanized areas.

Fifth, we include additional control variables for commuting times to key infrastructure, such as airports, major cities, motorways, and hospitals. As shown in Appendix Figure A.19, they reflect minor regional differences in standard of living and accessibility of infrastructure. Adding these controls does not substantially alter the results.

Finally, we conduct a leave-one-out analysis in Appendix Figure A.17 and Figure A.18 by systematically excluding individual boundary regions from the sample. The results remain robust, confirming that no boundary region disproportionately influences the results.

**"High" Broadband State Threshold** Further results in Figure 1.6 show the robustness of our results to changing the cutoff for the classification of "high" broadband states (note that changing the cutoff also entails a change of the sample). Using a higher cutoff of

85 percent and a lower one of 65 percent, we find qualitatively similar results as with our main 75 percent cutoff (see Appendix Table A.14). Appendix Figure A.12 explores to which extent the effect size depends on the level of broadband availability further and shows a smooth curve around the 75 percent threshold used in our main analysis.

**Placebo Check: No Effect After Expansion** While the validity of an RDD can never be fully proven, a placebo check provides suggestive evidence for a causal effect (Cattaneo et al., 2019). If differences in property prices between "high" and "low" broadband states are driven by broadband availability, these effects should disappear once "low" broadband states catch up. We test this by examining 2019, the final year of the sample period, when differences in 16 Mbit/s availability between neighboring municipalities had largely disappeared. Persistent differences in property prices or rents would suggest the influence of other factors, undermining broadband availability as the primary driver. The results in Figure 1.6 and Appendix Table A.15 find no significant effects in 2019. This finding has two implications: First, it supports the validity of our RDD framework, suggesting that neighboring border municipalities are sufficiently comparable and that our estimates capture the effects of fast broadband as long as the spatial discontinuity at state borders exists. Second, it highlights the temporary nature of the capitalization effects. As the connectivity gaps close and 16 Mbit/s broadband access becomes universal, the property price premium diminishes. This is not because its benefits disappear, but because it is no longer a differentiating factor. Without a spatial discontinuity, our design can no longer identify capitalization effects, although households still benefit from high-speed Internet.

**Coarsened Exact Matching** We conduct a further robustness check using Coarsened Exact Matching (CEM) to address concerns about the similarity of neighboring municipalities in subsection A.7.1. By matching on unemployment rate, school quality, and crime rate terciles, we ensure that treatment and control municipalities are comparable while maintaining sufficient observations for estimation. The regression estimates using the CEM sample and weights yield estimates for sale prices and rents that are consistent with our main results, supporting the comparability of the two groups.

**Alternative Identification: Event Study Estimates** Finally, a rather different approach is presented with the event study design in Appendix Figure A.20. Note that the "event" in our setting happens when a municipality surpasses the threshold of providing 75 percent of households with at least 16 Mbit/s Internet. Since this share increases gradually over time, the observed pre-trend is expected. Nonetheless, the design intuitively illustrates that prices significantly increase as broadband coverage is expanded.

## 1.5 Mechanisms

This section examines the mechanisms driving the observed increases in property prices and rents from faster Internet access. Equilibrium price changes can result from shifts in demand and/or supply. However, the absence of significant differences in the number of property listings on the "high" broadband side of state borders (see Appendix Figure A.3 and Figure A.5) and the low short-term elasticity of housing supply (Baum-Snow and Han, 2024) suggest the effects are demand-driven. We thus focus on two key demand-side mechanisms: migration and Internet usage.

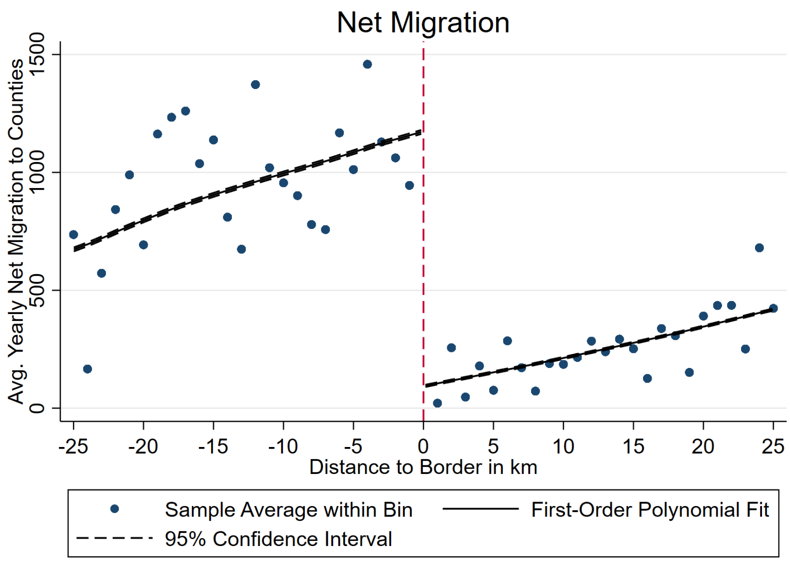
### 1.5.1 Migration

Based on administrative data, we study net domestic migration to municipalities in border regions of "high" and "low" broadband states as a potential indicator of increasing demand. As the spatial discontinuity in Figure 1.7 shows, municipalities in "high" broadband states for 16 Mbit/s exhibit higher net inflows than those in "low" states. The fact that real estate prices and rents increase with faster Internet availability suggests that there is higher demand increasing prices, rather than lower prices attracting new residents. In the next subsection, we explore further why faster Internet speeds may be attractive, i.e. to which extent they are being used and for what purposes.

### 1.5.2 Internet Usage

Any conceivable causal channel from broadband access to real estate prices and rents runs through Internet usage. Uptake is necessary for any capitalization effect of broadband's labor market, consumption, and information value. Since both current demand and expectations about future needs may influence capitalization, we examine the relationship between broadband availability and the speed levels households actually purchase.

**Figure 1.7:** Spatial RD Plot for Average Yearly Net Migration




*Note:* This spatial RD plot shows average yearly net migration to counties around the boundaries of "high" and "low" broadband states for 16 Mbit/s broadband Internet. "Distance to border in km" on the x-axis refers to the distance in kilometers between the observation and the closest state boundary, with negative values of distance indicating "high" broadband states. The RD plot was generated by an evenly spaced number of bins, representing the sample average within each bin, net of boundary-region-by-year fixed effects. The solid lines represent the predicted values from a regression of the outcome variable on a first-order polynomial in distance to the boundary. The corresponding 95 percent confidence intervals are displayed as dotted lines.

We use data from the 2018 German micro-census, which provides information on actual broadband usage, to correlate household usage with broadband availability.[17] Since all states were classified as "high" broadband states for 16 Mbit/s by 2018, we classify states based on whether they were "early adopters" of 16, 30, and 50 Mbit/s, defined as being among the earlier half of states to reach the "high" broadband threshold. This approach accounts for time lags in adoption due to contract expirations and delayed upgrades. For consistency, we apply the same classification to 30 and 50 Mbit/s. Thus, variation comes from the duration that these speeds have been available rather than their availability at the time of the micro-census.[18]

[17] Since micro-census responses are available at the county level, municipalities in our sample are assigned the survey responses from the county they belong to.

[18] Another reason for this approach is that uptake likely follows availability with some delay, e.g. households might switch provider and upgrade once their existing contracts expire. "Early adopter" states are clas-

**Uptake of Broadband Subscriptions** Figure 1.8 Panel A shows that the uptake of high-speed broadband subscriptions above 16 Mbit/s is approximately 10 percentage points higher in "high" municipalities at the boundary. Appendix Table A.18 complements the figure with further descriptive statistics on contractual speed levels in municipalities. The speed categories differ slightly from those for broadband availability in the main analysis due to the answer options provided in the survey. Taken together, the higher uptake in "high" municipalities suggests that broadband expansion addresses pre-existing demand for faster Internet speeds. We interpret this as a key mechanism driving the observed capitalization effects on property prices and rents.

The observed increase in the uptake of fast broadband subscriptions may reflect several channels. First, broadband expansion seems to address previously unmet demand for higher speeds in underserved areas. Second, local network effects, such as neighbors adopting faster connections, may additionally boost demand for higher speeds. Third, behavioral factors, such as the compromise effect, might incentivize users to select intermediate speeds, including those that were once the highest available. Finally, increased advertising and the salience of broadband access may elevate demand across all speeds.

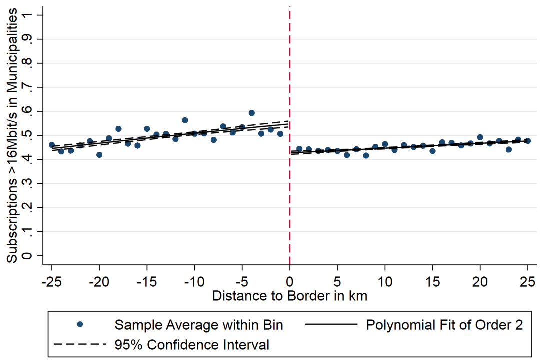
**Working from Home** The pandemic has led to a sudden increase in remote work, making fast Internet connections capable of supporting videoconferencing and other collaboration tools essential for many households. Evidence from the 2018 German micro-census indicates that the link between fast Internet and remote work was already evident even before the pandemic. Figure 1.8 Panel B shows the corresponding RD plot with the average share of the work week worked from home. A clear discontinuity is visible at the state border, with "high" broadband states exhibiting a 0.6 percentage point higher share of remote work, which is equivalent to a 12 percent increase. As Appendix Table A.18 reports, the difference is slightly larger when considering households working remotely at least part-time, at around one percentage point.

**Outbound Commuters** Remote work can reduce commuting frequencies, allowing workers to accept jobs at more distant workplaces. To explore this potential mechanism, we study outbound commuters in our sample in the RD plot in Figure 1.8 Panel C. A discontinu-

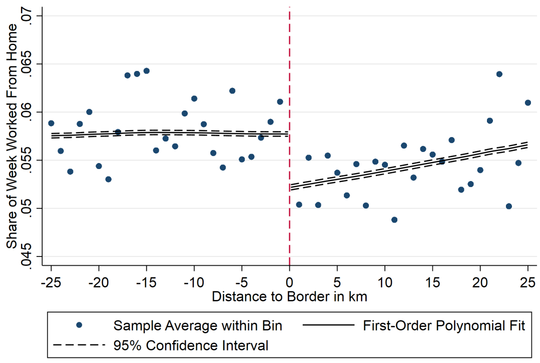
sified as "high" broadband states for 16 Mbit/s for more than six years in the sample, i.e. they have become a "high" broadband state in 2013 or earlier.

**Figure 1.8:** Spatial RD Plots for Broadband Subscriptions, Working From Home, and Outbound Commuters

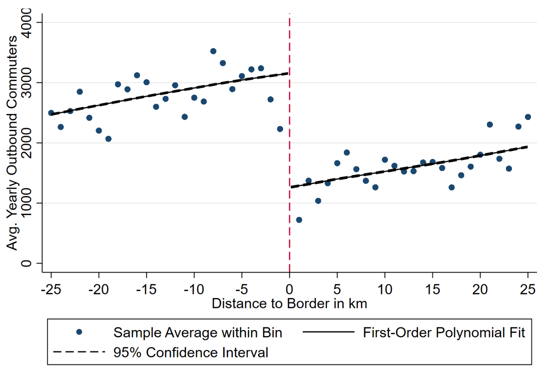
**(a)** Broadband Subscriptions >16 Mbit/s (2018)




**(b)** Working From Home (2018)




**(c)** Outbound Commuters




*Note:* Shown are spatial RD plots for the share of households with broadband subscriptions faster than 16 Mbit/s (Panel A), the share of the week worked from home (Panel B), both based on the 2018 German microcensus, and the number of average yearly outbound commuters from counties (Panel C). The outcomes are plotted on the y-axis. "Distance to border in km" on the x-axis refers to the distance in kilometers from the closest state boundary, with negative values indicating "high" broadband states. The RD plots are generated by an evenly spaced number of bins, representing the sample average within each bin, net of boundary-region-by-year fixed effects. Solid lines represent the predicted values from a regression on a first-order polynomial in distance to the boundary. The corresponding 95 percent confidence intervals are displayed as dotted lines.

ity at the state border is visible here as well, with many more outbound commuters in "high" broadband states. This is consistent with survey evidence showing that work from home has already been more common among long-distance commuters (Alipour et al., 2020). Thus, daily time savings when working from home for these commuters are likely even higher than the average for Germany of 65 minutes found by Aksoy et al. (2022).

**Discussion** Overall, the evidence suggests that capitalization effects are primarily driven by current demand rather than by expectations about future needs. One reason contemporary demand plays a larger role is the discounting of future utility from broadband access compared to its immediate value. Additionally, households likely anticipate that broadband availability will eventually improve universally, reducing the perceived scarcity of fast Internet.

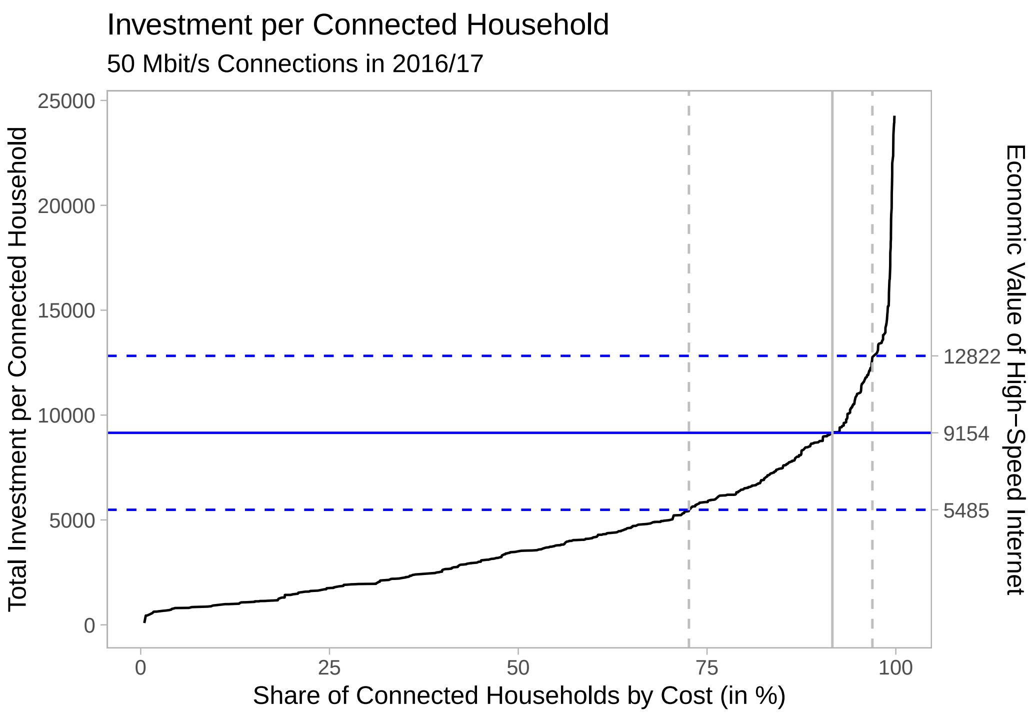
## 1.6 Policy Evaluation

In this section, we apply our results to evaluate broadband expansion policies. The extent of required government subsidies depends on whether the consumer surplus from fast broadband access exceeds deployment costs. In Germany, where the policy objective is universal access to fast Internet connections, the critical question is not whether rural broadband expansion is justified on welfare grounds but rather *how much subsidies are necessary* to achieve this goal efficiently.

Importantly, a smaller consumer surplus than deployment costs does not necessarily imply that subsidies are unwarranted. Broader economic benefits, such as spillovers or network externalities, may justify public investment. Subsidies can also address coordination failures among households or enable investments that would otherwise be constrained by credit limitations, even when the benefits exceed the costs. Conversely, if households' willingness to pay exceeds deployment costs, this indicates that subsidies are unnecessary and serve primarily as redistribution to property owners, provided no coordination problem exists.

**Cost-Benefit Analysis** While we do not have fine-grained data on the costs of a connection in our main sample period, we use data about costs from the later federal NGA program for a cost-benefit analysis. We rank the costs per connected households to estimate the share of households in municipalities (among those that applied for funding through the federal program, i.e., which were not yet sufficiently connected) that could arguably have been connected through private funds, as households' willingness to pay exceeded deployment costs. Note that this cost-benefit calculation compares data from the later federal program, which focused on 50 Mbit/s connections, with estimates from an earlier period based on 16 Mbit/s. Since our estimates are from an earlier period, the relevant and more comparable speed with respect to willingness to pay seemed to be 16 Mbit/s rather than 50 Mbit/s, since costs for a given speed level decrease over time. The calculation is carried out to provide a rough estimate of the share of households that may have been willing to fully finance broadband expansion privately had it not been subsidized. For the valuation, we show our main estimate with the 95 percent confidence interval in the graph. To get a euro value, we multiply the percentage increase in sales prices with the median house price in "low" broadband state municipalities.

**Figure 1.9:** Cost and Average Valuation per Connected Household (50 Mbit/s)




*Note:* Costs per connected 50 Mbit/s household in NGA program for applications filed 2016/17. Blue dashed lines indicate the highest and lowest estimated valuation of 16 Mbit/s connections in our main estimation in levels. The solid blue line indicates the estimate of our preferred specification. The corresponding grey lines indicate the share of households/connections covered at those values.

The results in Figure 1.9 show that at the main estimate of a valuation of 9154 euros, approximately 90 percent of projects could have been funded. The confidence interval of the share of households that could be connected ranges from approximately 72 to 97 percent.[19] While these calculations are not precise estimates and should be interpreted with caution, they still suggest that a sizable fraction of subsidized projects could potentially have been funded privately, as there may have existed sufficient demand from consumers.[20]

**MVPF Analysis** The public policy decision can also be studied in the context of the Marginal Value of Public Funds (MVPF) framework, which has been proposed in the public finance literature in recent years (Finkelstein and Hendren, 2020; Hendren and Sprung-Keyser, 2020, 2022). While a high MVPF typically indicates the efficiency of a public policy, in our context it suggests that broadband access could potentially have been provided privately without subsidies, given households' high willingness to pay.

$$MVPF = \frac{\text{Benefit to recipients}}{\text{Net costs for government}} \approx \frac{\text{WTP}}{\text{Costs of access}}$$

For simplicity, we can assume that the entire project is funded by the government, such that the total costs of a project are in the denominator of the equation.[21] This allows for a cost-benefit calculation to study the implications of a positive effect of broadband expansion on tax revenues through increased property transaction tax revenue in future sales.

In this exercise, we show the impact on MVPFs of a variety of realistic property transaction tax rates $\tau$ and interest rates $r$ to discount future revenue. The real estate transaction tax rate in German states varies from 3.5 to 6.5 percent. We use both, as well as an intermediate rate of 5 percent.

[19]Note that, while the constant valuation shown in the figure is a simplification, with the available data we cannot assign specific valuations to different cost levels. It is not clear whether more costly projects tend to belong to households that value faster Internet access more or less. While average valuation may in fact decrease with costs, the valuation curve cannot necessarily be assumed to be downward sloping (as a regular demand curve would be), which would decrease the share of projects that could be privately funded.

[20]Note that if redistribution were part of the goal of the policy, there are arguably more targeted approaches than a subsidy, which is appropriated mainly by real estate owners.

[21]Subtracting $x$ euros in the denominator from the costs to the government and subtracting the same amount in the numerator from the recipient's benefit would not change whether the MVPF is larger than one, for example, as long as further revenue implications of this change are negligible and can be disregarded.

We approximate the time to the next property sale $T$ based on the average mobility of the populations. Every year about one in ten Germans moves (EnBW, 2021). Thus the average time to the next move is five years. Again, this is a simplification, as not every move entails a property sale and for owners mobility may be lower. Moreover, mobility varies across regions. We assume that the added value of this particular broadband expansion for sales after the next one (which would be expected to happen in 15 years) is negligible due to technical progress and the possibility of leapfrogging to even better technologies.

We can then solve the following equation for the maximum costs for an MVPF larger than one:

$$\text{MVPF} = \frac{\text{WTP}}{\text{Cost} - (1+r)^{-T}\tau\text{WTP}} > 1$$

A shorter time to the next property sale implies a larger effect except in the case of a zero interest rate. The discount rate does not play a major role over a short time horizon of 5 years, but the table shows some cases around the interest rates set by the European Central Bank in our time period. Including positive effects on additional later sales would increase the effect.

The results are shown in Table A.19 in the Appendix. With realistic numbers, the relative increase of the maximum cost level ($(1+r)^{-T}\tau$) is slightly smaller than the tax rate (for low interest rates and a short number of years to the next sale). Hence there is some effect, but it is not large, with a maximum cost of access that is about 4 percent higher than in the absence of revenue effects. Thus, a few percent of projects "should" be financed in those cases that would not happen under private funding (which is the benchmark case in the first row of Appendix Table A.19).

**Discussion** The cost-benefit and MVPF analyses of broadband expansion subsidies in Germany reveal that the willingness to pay exceeds deployment costs for most households, suggesting that subsidies were unnecessary for many connections. This finding indicates that universal broadband access could likely have been achieved at a lower fiscal cost. However, subsidies may have addressed coordination failures among households willing to pay but unable to collectively finance broadband deployment.

The MVPF analysis further suggests that subsidies may be warranted for a small subset of households with a willingness to pay below deployment costs, provided the MVPF exceeds one. Evidence from Hendren and Sprung-Keyser (2020) highlights that educational policies benefiting children often generate higher returns.[22] In our setting, faster broadband may benefit entire households, including educational gains for children, which are not fully captured in households' willingness to pay. Our estimates do not factor in significant externalities such as network effects, reduced commuting, or broader economic benefits, which could justify broadband subsidies. Nonetheless, these externalities do not alter the finding that most households' willingness to pay exceeds costs.

Importantly, the broadband subsidies have uneven distributional consequences, at least as long as the discontinuity in availability persists. While residents benefit from faster Internet access, property owners disproportionately capture the gains through increased property values and rents, effectively redistributing some of the subsidies' benefits to them. This highlights distributive inequities in a policy aimed primarily at improving households' access to fast Internet. Overall, the findings suggest that Germany's objective of universal broadband access could have been achieved more efficiently with lower subsidies, reducing inefficiencies in the allocation of public funds.

## 1.7 Conclusion

This study demonstrates the significant impact of high-speed broadband Internet on real estate prices in Germany. Using a spatial RDD and rich micro-data, we exploit variation at state borders induced by broadband expansion policies to identify the causal effect. We find that property sale prices increase in "high" broadband states by up to 8 percent (€14,700 on average) and rents by 3.8 percent (€17 per month), underscoring the economic value households place on fast Internet access. Heterogeneity analyses reveal diminishing returns to higher speeds but growing effects over time. We show that the effects are primarily driven by current demand, including migration to high-broadband municipalities, more fast broadband subscriptions and higher remote work adoption.

[22] See https://www.policyinsights.org for an overview of MVPFs across policies. Hendren and Sprung-Keyser (2020) find MVPFs lower than one for housing voucher programs.

Our policy evaluation indicates that broadband subsidies were unnecessary for most households, since their willingness to pay exceeded deployment costs. However, subsidies may have addressed coordination failures or generated broader economic benefits, such as educational gains or network externalities. Importantly, the uneven distributional effects show that while residents benefit from faster Internet access, property owners capture much of the value through higher property prices and rents. Overall, our results suggest that Germany's goal of universal broadband access could be achieved at lower fiscal cost with better-targeted subsidies.

Our findings have several implications for public policy and future research. Policymakers should target subsidies more effectively to maximize social benefits and minimize inefficiencies, particularly by prioritizing regions with low willingness or ability to pay. The interplay between broadband expansion and spatial inequality is a potential avenue for future research. Future studies could also investigate how the value of broadband evolves with technological advancements, further speed upgrades and changing user demands, particularly in light of increasing reliance on digital infrastructure for work, education, and healthcare.

# 2

# Working from Home and Consumption in Cities

## Abstract

We estimate the impact of the Covid-induced shift to working from home (WFH) on offline consumer spending within 50 German metropolitan areas (MAs). We build a postcode-level panel (2019–2023) of cellphone mobility patterns and local card transaction volumes. The identifying variation comes from local differences in WFH potential: the fraction of residents with a teleworkable job. Difference-in-differences estimates show that higher WFH potential is associated with persistent morning-mobility declines and spending increases from 2019 to 2023. We estimate an elasticity of spending of -3.7 percent with respect to a WFH-induced decline in morning mobility by one percent, which is driven by large MAs. Neither firm turnover nor WFH-induced migration can explain the results. [1]

*Keywords*: Remote Work; Consumer Spending; Urban Agglomerations; Cities; Spatial Analysis; Cellphone Mobility

*JEL-Codes*: D1; E2; G2; J0

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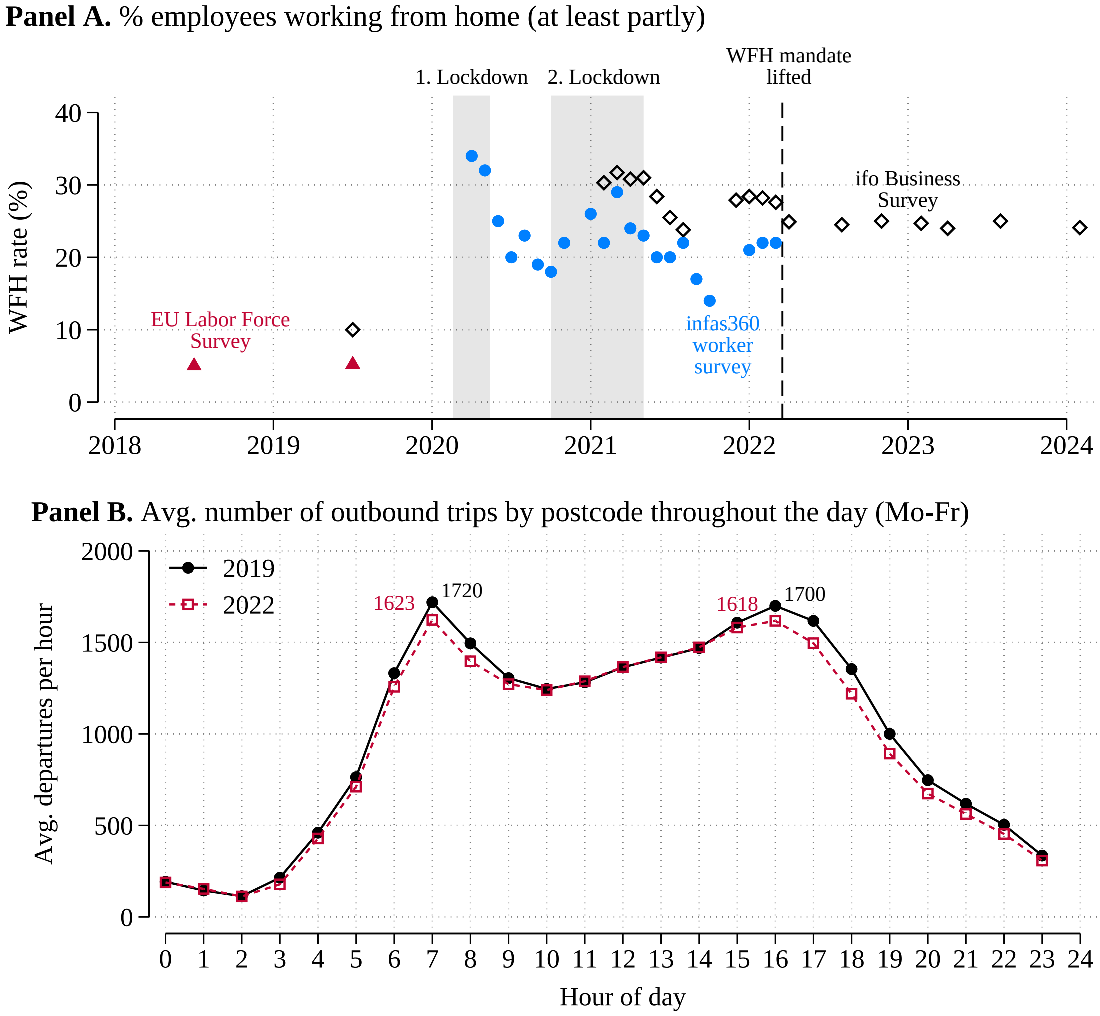
## 2.1 Introduction

The Covid-19 pandemic has disrupted traditional work organisation, inducing a sudden and lasting shift to working from home (WFH) (Barrero et al., 2023; Hansen et al., 2023). In Germany, WFH surged from below 10% before stabilising at 25% of employees after Covid restrictions were lifted in 2022 (Panel A, Figure 2.1). This shift has left its footprint in mobility patterns: Panel B of Figure 2.1 shows that the morning and evening rush hours register about 6% fewer trips. This reduction is consistent with the adoption of hybrid work schedules as the prevalent WFH model in most advanced economies (Aksoy et al., 2022). Studies have linked the WFH shock to flattening house price gradients, lower neighbourhood crime, or the urban exodus of high-skilled individuals (Althoff et al., 2022; Coven et al., 2023; Gupta et al., 2022a; Matheson et al., 2024; Mondragon and Wieland, 2022; Ramani et al., 2024). These rapid changes sparked speculations that the new geography of work may fundamentally alter the spatial distribution of economic activity in cities and even challenge their "survival" (De Fraja et al., 2022; Florida et al., 2021; Glaeser and Cutler, 2021; Glaeser, 2022; Gokan et al., 2022).

This paper presents new evidence on the geography of cities after the big shift to remote work: Using novel data covering geo-coded mobility and card transaction data from 2019 to 2023, we estimate WFH's impact on local consumer spending *within* 50 German metropolitan areas (MAs). Our setting allows us to go beyond the existing literature by establishing a causal link between WFH and shifts in consumer spending within agglomerations. The identifying variation comes from postcode-level differences in the exposure to the WFH shock. Specifically, we use a difference-in-differences (DiD) design that compares residential areas at a similar distance from the city centre but with different levels of *WFH potential*, i.e., the fraction of employed residents with a teleworkable job.

First, we find that a higher local WFH potential predicts stronger uptake of WFH (both intensive and extensive margin), as measured by a 2022 survey. Using newly available, geo-coded cellphone mobility data from Germany's largest carrier *Deutsche Telekom*, we also document a stronger and persistent decline in morning mobility in postcodes with a higher WFH potential, consistent with reduced commuting: A one percentage point higher WFH potential is associated with 0.16% fewer outbound trips on weekdays in 2023.

**Figure 2.1:** WFH Shock in Germany




*Notes:* Panel A reports the fraction of employees in Germany working from home at least partly based on surveys from the EU Labour Force Survey, the infas360 Casa Monitor Survey, and the ifo Business Survey. Panel B shows the average number of outbound trips by postcode and hour of day in 2019 and 2022. The data are based on cell phone pings from T-Systems by Deutsche Telekom (see section 2.2 for details).

Second, we estimate intention-to-treat (ITT) effects of WFH on local offline consumer spending. Spending data are supplied by *Mastercard* and comprise daily transaction volumes aggregated from merchants' locations to the postcode level. We find that spending trends sharply diverged after the pandemic outbreak: During lockdown periods, spending declined in areas with higher relative to lower WFH potential. Lockdowns were marked by transitory spikes in online commerce due to mandatory business closures. However, the pattern reversed as the economy recovered, with high-WFH areas persistently attracting more offline spending, and online shopping returning to the pre-pandemic level. Our estimates suggest a 0.77% increase in offline spending levels in 2023 for a one percentage point higher WFH potential.

Third, we estimate the elasticity of spending with respect to WFH-induced changes in mobility. To this end, we instrument 2019–23 changes in mobility with postcode-level WFH potential. Across different estimators (PPML versus OLS) and model specifications, we find that spending increases by 3.31% to 3.79% in response to a 1% decline in morning mobility. Our most demanding specification controls for postcodes' distance to the city centre, changes in population size (2019–23), and 2019 measures of mobility, spending per capita, industry composition, and mobility in neighbouring postcodes. Heterogeneity analyses reveal that the effects are driven by larger MAs, which are characterized by a higher share of teleworkable jobs. We find insignificant effects of WFH potential on mobility changes among the 35 smallest MA. This is consistent with theoretical arguments by Monte et al. (2023), who propose that smaller cities are likely to revert to their pre-Covid commuting equilibrium. Breaking down effects by spending category shows that WFH-induced spending shifts are strongest for the food service industry and grocery stores. In contrast, we find null effects for spending in apparel stores, likely due to limited purchase opportunities in residential neighbourhoods.

We find no evidence that spending differences are driven by WFH-induced migration: First, excess cross-county migration (2020–22) totalled 119 thousand, which is quantitatively negligible compared to 6 million employees transitioning to WFH after 2019.[2] Germany, like many advanced economies, saw a net urban population loss during the crisis. However, this is explained by a sharp decline in population inflows rather than an acceleration of outflows, consistent with models of domestic migration (Monras, 2020). Migration patterns are bolstered by DiD results showing that relative mobility between high versus low WFH areas returned to pre-Covid levels on Saturdays. These results reinforce that weekday gaps are driven by work-related mobility and that the population has not systematically changed across areas. Similarly, we find zero correlation between population change (2019–23) and WFH potential at the postcode or the municipality level. Together, the evidence does not support the popular narrative that remote work is causing an urban exodus in Germany.

[2]Counties (*Kreise and kreisfreie Städte*) correspond to the NUTS-3 level, which is geographically coarser than postcodes or municipalities (LAU-1/ LAU-2 level).

We explore supply-side changes as a second potential mechanism of spending shifts using information from Bureau van Dijk's Orbis database and administrative data on business notifications and insolvencies (*Gewerbeanzeigenstatistik*). Adopting our previous DiD framework, we find that firm entries and exits in relevant non-tradable industries evolved similarly across areas with different WFH potential throughout our observation period. Consequently, changes in purchase opportunities are unlikely to explain WFH impact estimates. Instead, the effect is fully driven by remote workers' shifting demand. These findings contrast with Duguid et al. (2023), who find that the number of establishments in large US cities grew in peripheral areas where remote workers tend to move to.

The final section focuses on workplace areas, defined as postcodes with high job density in 2019. These areas are closer to city centres, likely consumption hubs, and register higher evening rush hour outbound mobility. We find persistent spending declines in workplace areas mirrored by a decline in evening mobility. This is consistent with WFH shifting consumer spending away from workplaces into residential areas. These changes imply a reduction in spatial spending inequality within metro areas and relative spending gains in the city's periphery.

The article proceeds with a description of the main data sources in section 2.2. In section 2.3, our empirical strategy and the identifying assumptions are laid out. The results are presented in section 2.4. We conclude in section 2.5.

## 2.2 Data on Consumer Spending, WFH, and Mobility

**Sample** Our sample includes postcode-level observations covering all 50 German metropolitan areas and about 72% of the population. Metro areas are comparable to US Commuting Zones. They are centred around at least one urban core (i.e., a municipality with a population above 100,000) and extend to boundaries determined by 2019 commuting linkages with the core. MAs can have multiple cores if they are close to each other and interconnected (e.g., MA Berlin-Potsdam or MA Cologne-Bonn).[3] We define a "city centre" as the central postcode of an urban core and calculate the Euclidean distance between each postcode and the (closest) city centre. Figure B.1 maps the postcodes in Germany and highlights the MAs.

[3]The formal definition of German metropolitan areas (*Großstadtregionen*) is determined by the Federal Institute for Research on Building, Urban Affairs, Spatial Development (BBSR).

The average postcode hosts 14 thousand residents. The smallest MA is Salzgitter with a total population of 160 thousand; the largest MA is Berlin-Potsdam with more than 5 million residents.

**Card Transaction Data** We measure local offline consumer spending using anonymised and aggregated card transactions provided by *Mastercard Location Insights*. Offline spending refers to all card payments at brick-and-mortar establishments, such as restaurants and retail stores, cleared through the Mastercard network. This includes all payments at a physical point-of-sale (POS) with physical Mastercard credit, debit or Maestro cards as well as with their virtual counterparts (e.g., Apple Pay or Google Pay used with a smartphone or a smartwatch and a virtual Mastercard card in the background). [4] Transactions are grouped by industry using the merchant category codes (MCC) classification. We observe daily spending volumes, aggregated from the POS to the postcode-by-industry level from January 2019 to September 2023. [5] We exclude transactions from foreign cards to avoid distortions related to travel bans and tourism. Confidentiality restrictions mask values in day-by-industry-by-postcode cells with fewer than four transactions across less than four merchants. To minimise missing values, we focus on the "total spending" category in the main analysis, which contains the transaction volume across all MCC industries, and assume zero spending when values are masked. All our results are robust to excluding postcodes with missing values.

We also use data from *Mastercard Spending Pulse*, which provide daily national aggregates of spending volumes in brick-and-mortar stores versus e-commerce. The data take into account all payment modes (including cash), providing a high-frequency measure of aggregate private consumption that aligns closely with official statistics (Fourné and Lehmann, 2023).[6] The data can trace shifts between aggregate offline and online spending and offer insight into how shopping behaviour changed through the crisis.

**WFH Survey Data** WFH measures come from an employee survey conducted by *infas360*, a company specialised in micro-geographic survey and data collection methods. We

[4] Similar data at the US county level are used by Mian et al. (2013) to study the elasticity of consumption with respect to housing net worth.

[5] Absolute spending volume is divided by an unknown constant, preserving relative differences (over time and across space) within an industry but masking monetary values for data privacy reasons.

[6] Mastercard uses survey-based estimates for certain other payment forms, such as cash and checks, to improve representativeness.

introduced WFH-related questions into the spring 2022 wave of the infas360 CASA Monitor, a recurring survey of roughly 11,000 individuals, which is representative of the adult German population with internet access. We elicit whether respondents' primary job *could* be done at home at least one day per week, as well as their current and pre-Covid WFH status. To break down WFH measures by postcode, infas360 collapses WFH rates to the occupation level and then extrapolates to postcodes based on the local composition of employees' occupations. This approach is akin to the procedures used by Dingel and Neiman (2020) and Matheson et al. (2024) to calculate regional WFH measures from occupation-level information in the US and the UK, respectively. We define the fraction of employed residents with a job that can (at least partly) be done from home as a postcode's *WFH potential*. In B.5.1, we show that county-level aggregates of this index closely match the geographic pattern of alternative WFH potential measures from Alipour et al. (2023) and Dingel and Neiman (2020) for Germany.

**Cellphone Mobility Data** We obtain access to newly-available cellphone "ping" data provided by *T-Systems by Deutsche Telekom*, Germany's largest telecommunications company. Telekom uses a proprietary algorithm to identify users' movements based on mobile phone pings to cell towers. We observe hourly aggregates of the number of *outbound* trips, defined as movements crossing postcode $i$'s boundaries, from January 2019 to October 2023. To capture commuting for work, our analysis uses the total number of outbound trips between 6–9 am, covering typical morning mobility peaks (Figure 2.1, Panel B).

We report summary statistics in B.1.

### 2.3 Empirical Strategy

We aim to estimate the causal impact of WFH on the geography of offline spending within metro areas. The first challenge is that an upsurge in WFH affects spending in multiple locations simultaneously: We expect that consumption relocates from the vicinity of workplaces to residential areas. Additionally, locations along commuting routes are likely affected, as non-commuting trips often occur along these paths (Miyauchi et al., 2022; Oh and Seo, 2023). A sensible approach is to focus on "at-home" consumption: Our thought experiment compares changes in local spending between "similar" residential postcodes that differ with respect to the severity of the WFH shock while (for now) neglecting the origin of potential spending relocations.

The second challenge is that *observed* WFH rates may be driven by other determinants of spending changes, creating an endogeneity issue. Indeed, the crisis prompted an array of disruptions, from behavioural changes to economic policies, which are nearly impossible to disentangle and possibly correlated with WFH. We address this by comparing postcodes with different levels of WFH potential: The idea is to approximate the pre-existing local capacity to expand WFH after Covid forced the economy into the WFH experiment. As such, the measure is unaffected by other sources of spending disruptions after the outbreak. We use our mobility data to verify whether WFH capacity constraints have bite and explain changes in morning commuting. We expect that a higher WFH potential relates to lower morning mobility and more local spending.

**Difference-in-Differences Approach** The reasoning motivates a DiD design that compares high vs. low-WFH-potential postcodes over time. As WFH effects are likely to vary through different stages of the Covid crisis and the recovery, we consider a dynamic DiD that tracks differences across postcodes over time:

$$y_{it} = \sum_{k \neq 2020m2} 1(k = t) \times [\beta^k WFHPOT_i + \mu^k dist_i] + \gamma_i + \gamma_{r(i)t} + \varepsilon_{it}, \qquad (2.1)$$

where $y_{it}$ denotes an outcome (spending or mobility) for postcode $i$ in month $t$. $WFHPOT_i$ denotes postcode $i$'s WFH potential (0-100), and $dist_i$ is the log distance to the city centre. Both variables are interacted with time dummies to capture differences by month-year. Controlling for proximity to the city centre is important to account for possible confounding due to the location of postcodes along commuting routes. $\gamma_i$ denotes postcode fixed effects. To ensure that we compare changes among postcodes located in the *same* metro area $r$, we interact month-year with MA fixed effects $\gamma_{r(i)t}$. The error term $\varepsilon_{it}$ captures unobserved shocks, which are assumed to be uncorrelated with the regressors of interest. Then, the coefficients $\beta^k$ trace outcome differences associated with a one percentage point higher WFH potential over time, conditional on trend differences by distance to the city centre. February 2020 is the reference period.

As the left-hand side of Equation 2.1 is a non-negative (count) variable, we estimate the model using the Poisson Pseudo Maximum Likelihood (PPML) estimator (Santos Silva and Tenreyro, 2006). PPML imposes proportional effects and can handle zeros in the dependent variables, which is occasionally the case for spending (especially during lockdowns) (Chen and Roth, 2024).[7] We also report OLS estimates for models with log-transformed dependent variables as a robustness check. For these specifications, we drop all postcodes that record zero spending from the sample. The findings are qualitatively and quantitatively consistent.

In the baseline, we cluster standard errors by postcode, which corresponds to the level of treatment "assignment" (Abadie et al., 2023). Inference is robust to alternative assumptions about the variance-covariance matrix; in particular, to two-way clustering at the postcode level (allowing for serial correlation) and the metro-area-by-month-year level, allowing for arbitrary error correlation across postcodes of the same MA in each period (Cameron et al., 2011). We also consider corrections for spatial correlation by Conley (1999) and Müller and Watson (2022) (B.5.3).

Our setting involves a continuous treatment where all postcodes are treated at varying intensities. Consequently, the validity of the DiD design rests on the *strong* parallel trends (SPT) assumption (Callaway et al., 2024): We assume that the observed trend of postcodes with a given WFH potential corresponds to the (unobserved) average trend across all postcodes had they been assigned the same WFH potential, conditional on trend differences by distance to the city centre. Strong parallel trends ensure that lower-WFH-potential areas are a valid counterfactual for higher-WFH-potential areas (and vice versa). The assumption is met, for instance, if we rule out that postcodes select into levels of WFH potential based on expected treatment effects. Like standard parallel trends, this assumption cannot be tested directly. We provide visual verification of parallel pre-trends while acknowledging that these do not necessarily inform about postcodes' treated potential outcomes.

A concern for the validity of SPT is other determinants of spending shifts that are correlated with WFH potential. For instance, our estimates may pick up differences in the severity of supply-side disruptions if local WFH potential and industry composition are co-determined. We address this by successively adding controls that may explain diverging spending trends after the outbreak. Our most demanding specification controls for postcodes' distance to the

[7] Using OLS requires a $\log(y + 1)$ transformation or excluding zeros from the sample. Both approaches can be problematic; see Chen and Roth (2024) for a thorough discussion.

city centre, changes in population size (2019–23), and 2019 measures of mobility, spending per capita, industry composition, and mobility in neighbouring postcodes. As we do not observe cash payments, another potential concern is heterogeneity in the shift from cash to card. Payment card usage in Germany has steadily increased from 37% to 54% of all domestic payments between 2017 and 2023, without disruption from the pandemic (see B.3). In contrast, the number of POS terminals remained stable, indicating a steady card payment infrastructure. By including MA-by-time-period fixed effects, we control for MA-specific time shocks, including heterogeneous shifts in payment methods across MAs. Additionally, by controlling for changes in spending trends by proximity to the city centre, we capture potential trend breaks related to different degrees of urbanisation within MAs. Finally, additional controls account for differential shifts driven by industry composition.

**Instrumental Variable Approach** The DiD estimates deliver intention-to-treat effects because of non-compliance in the sense that WFH potential is not fully realised. For example, varying local conditions and incentives to realise WFH opportunities can mediate how WFH rates actually change in regions that have similar WFH potential. To account for this, we estimate an IV model. Specifically, we instrument changes in morning outbound mobility with WFH potential, yielding an estimate of the elasticity of spending with respect to WFH-induced mobility changes. The IV approach delivers local effects for regions that adjust their mobility *because* they have a higher scope to work from home.

Focusing on the changes between 2019 and 2023 (the post-Covid economy), our relationship of interest is given by

$$spending_{i\tau} = \alpha \times log\ mobility_{i\tau} + Post_\tau \times \mathbf{X}_i'\rho + \lambda_i + \lambda_{r(i)\tau} + \varepsilon_{i\tau}, \qquad (2.2)$$

with the corresponding first stage:

$$log\ mobility_{i\tau} = \pi \times Post_\tau \times WFHPOT_i + Post_\tau \times \mathbf{X}_i'\delta + \gamma_i + \gamma_{r(i)\tau} + \vartheta_{i\tau}, \qquad (2.3)$$

where $log\ mobility_{i\tau}$ is a postcode's log morning mobility in year $\tau \in \{2019, 2023\}$ and $Post_\tau$ is a dummy equal to one in 2023. [8] $\mathbf{X}_i$ is a vector of controls interacted with the post dummy

[8] With two time periods, Equation 2.2 is equivalent to a "long differences" specification that uses $\Delta spending_i$ on the left-hand side.

(excluded instruments). As before, we include postcode and MA-by-time-period fixed effects. The validity of this approach hinges on a strong first stage, i.e., that a higher scope for WFH reduces morning mobility ($\hat{\pi} < 0$).

We show results using a control function approach (CFA) and the 2SLS estimator to estimate the IV model. The CFA is appropriate for non-linear models with non-negative outcomes such as spending (Wooldridge, 2015). Specifically, the CF corresponds to the first-stage residuals $\widehat{\vartheta}_{it}$ from estimating Equation 2.3 by OLS. Equation 2.2 is estimated via PPML and introduces the control function as an additional covariate (Lin and Wooldridge, 2019). [9] Both approaches deliver an estimate of the spending elasticity with respect to WFH-induced changes in morning mobility ($\hat{\alpha}$). To account for the two-step procedure, the standard errors of the CF estimates are cluster-bootstrapped by postcode.

## 2.4 Results

### 2.4.1 Higher WFH Potential Boosts Remote Work and Lowers Mobility

We first probe the premise that WFH potential properly captures spatial differences in the exposure to the WFH shock induced by Covid-19.

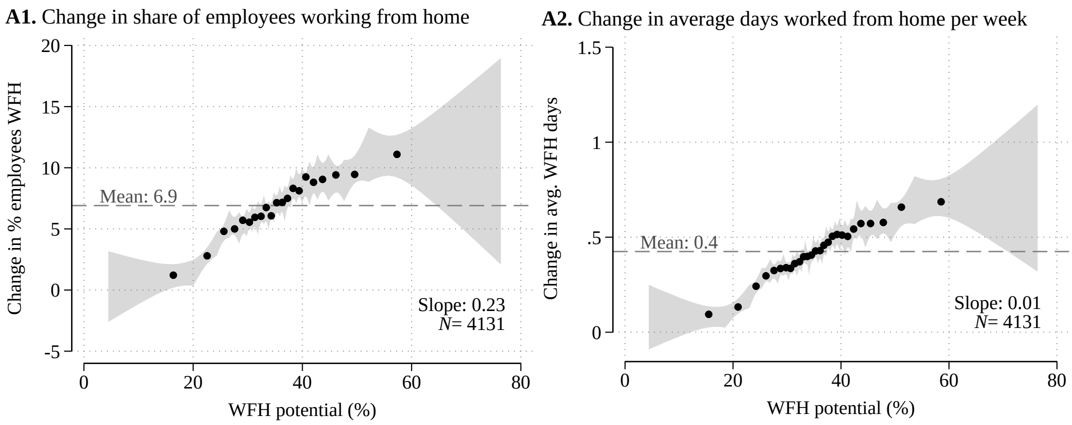
**Changes in Actual WFH 2019–22** Panel A of Figure 2.2 plots extensive and intensive margin changes in local WFH prevalence against WFH potential. We use the methodology by Cattaneo et al. (2024) to group observations into equal-sized bins and construct 95% confidence bands for the conditional mean functions, controlling for MA fixed effects. Panel A1 shows a positive relationship between postcodes' WFH potential and the 2019–22 change in the share of residents working 1+ days per week from home. The horizontal line, which marks the average change of (6.9 percentage points), clearly lies outside the confidence band. Panel A2 shows that average days worked remotely increased by 0.4 days and that WFH intensified more in high-WFH potential areas.

**Changes in Morning Mobility** Panel B of Figure 2.2 reports DiD-PPML results based on Equation 2.1. The dependent variable is the average number of outbound trips between 6 and 9 am per month. We plot results separately for weekdays (Mo-Fr) and Sat-

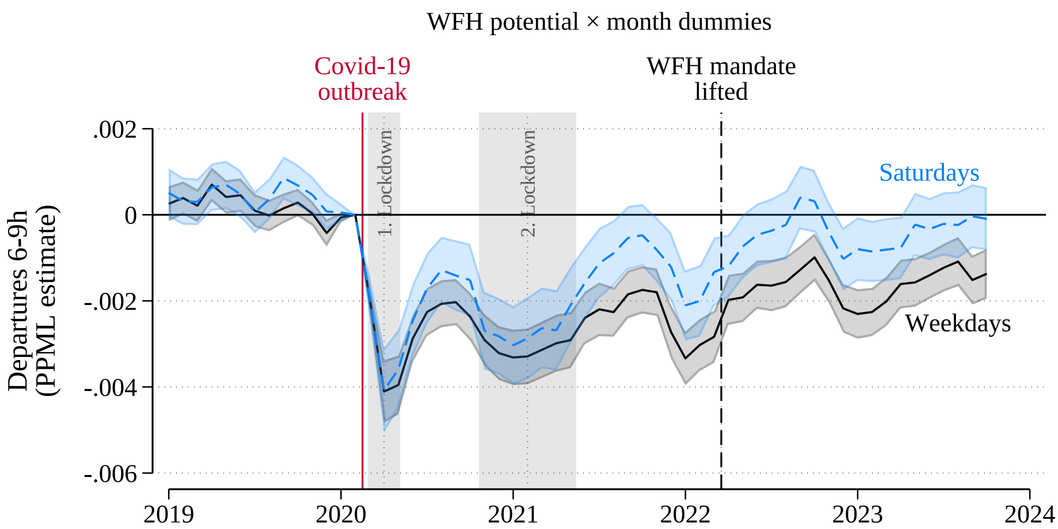
[9] Note that the CFA is numerically equivalent to 2SLS in the linear case.

**Figure 2.2:** Link Between WFH Potential and WFH Uptake

**Panel A.** WFH potential and WFH growth during the pandemic (2019-2022)




**Panel B.** WFH potential and change in morning mobility




*Notes:* Panel A reports binned scatterplots conditional on MA fixed effects using the methodology by Cattaneo et al. (2024). The shaded areas highlight 95% confidence bands of the conditional mean functions. Horizontal lines correspond to the mean of the dependent variable. Survey data on WFH practices are from the infas360 Casa Monitor. Panel B shows DiD results based on Equation 2.1 estimated by PPML. The dependent variable is the number of outbound trips between 6-9 am at the postcode level. Estimates are transformed by $\exp(\hat{\beta}^k) - 1$ to reflect proportional changes. Confidence bands are drawn at the 95% level based on standard errors clustered by postcode.

urdays. We exclude Sundays as stores are generally closed in Germany. PPML estimates are transformed to reflect proportional changes associated with higher WFH potential.[10] The estimates show parallel trends in 2019, followed by a sharp mobility drop in areas with higher WFH potential after the crisis reached Germany. The mobility gap narrowed as the economy recovered and the federal WFH mandate was lifted in April 2022. Yet, a sizeable difference persists: In 2023, morning mobility on weekdays is about 0.16% lower for a one percentage point increase in WFH potential. This is consistent with reduced commuting due to stabilising WFH levels in the economy. By contrast, average mobility differences on Saturdays returned to their pre-Covid level, corroborating the notion that weekday changes are driven by work-related mobility.

**WFH-Induced Migration** Closing mobility gaps on Saturdays is also important because we would expect differences to persist if WFH systematically increased the likelihood of moving. Perhaps surprisingly, the data do not substantiate this channel. We examine Saturday mobility gaps throughout the day and find that they closed at virtually all times (Appendix Figure B.14). This finding contradicts the popular narrative that remote workers were driving the "urban flight" seen in many cities. We therefore thoroughly investigate the link between WFH and domestic migration in B.6. The evidence bolsters the case that WFH-induced migration played a negligible role at best: First, population outflow from cities *slowed* during the crisis. The observed urban flight is explained by the even sharper decline in population inflow. Indeed, these patterns are anticipated by models of domestic migration responses to local economic shocks (Monras, 2020). Second, origin-destination data on domestic migration reveal that excess net migration from more to less central counties between 2020–22 totalled only 59 thousand. This amounts to less than one percent of the 6 million employees who transitioned to remote work after 2019. Third, using panel data on employees' municipality of residence, we estimate a version of the DiD in Equation 2.1: We find no significant link between WFH potential and changes in the log number of employed residents. Again, this conflicts with the view that remote worker outmigration drives urban decline. Our findings corroborate evidence based on administrative information about employees' home and workplace municipality: Coskun et al. (2024) report no association between changes in commuting distances among workers in high versus low WFH potential

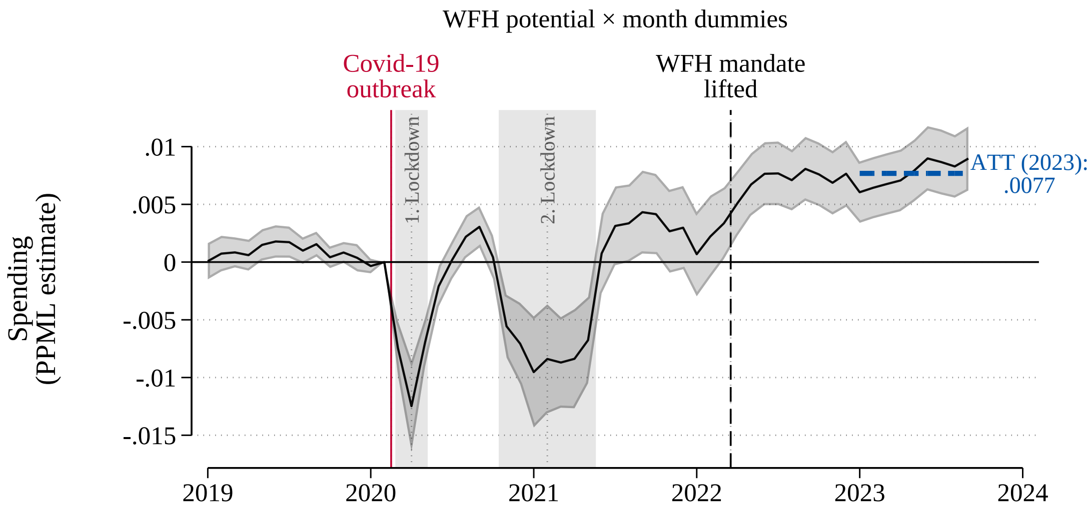
[10]Specifically, we report $\exp(\hat{\beta}^k) - 1$.

occupations in 2020. Although higher WFH potential is linked to increased commuting distance in 2021, this change is almost entirely due to job transitions, not relocations. Overall, the evidence indicates that migration dynamics during this period are influenced by factors other than WFH.

### 2.4.2 Higher WFH Potential Increases Local Spending

Next, we turn to the ITT effects of WFH potential on local spending. Figure 2.3 reports PPML estimates of trend differences in weekday spending associated with differences in WFH potential (Equation 2.1). Postcodes are on similar spending trends before the shock and sharply diverge during the crisis: spending in postcodes with higher WFH potential dropped relatively more during the two lockdown periods, with a brief recovery in between. The pattern reversed as the economy recovered. In 2023, the average effect among treated postcodes amounts to a 0.77% increase in local spending for a one percentage point higher WFH potential.

**Figure 2.3:** WFH Potential and Change in Local Spending




*Notes:* The figure shows DiD results based on Equation 2.1 estimated by PPML. The dependent variable is average spending on weekdays (Mo-Fr) at the postcode level. Estimates are transformed by $\exp(\hat{\beta}^k) - 1$ to reflect proportional changes. Confidence bands are drawn at the 95% level based on standard errors clustered by postcode.

At first glance, the negative DiD estimates during the pandemic seem inconsistent with the WFH story, given that WFH rates surged during lockdowns (Figure 2.1). Two mechanisms may explain this pattern. First, mandatory business closures in non-essential industries temporarily prevented most offline transactions. The estimates reflect this supply-side disruption. Indeed, we document notable spikes in e-commerce as demand shifted online during these periods: Appendix Figure B.21 plots aggregate trends of offline and online spending since 2018 using data from Mastercard Spending Pulse. During lockdowns, the fraction of online spending nearly doubled from 14% to 26%. Remarkably, e-commerce returned to its pre-Covid level both in absolute and relative terms in 2023, suggesting that supply-side disruptions in offline commerce were largely transitory. Second, the crisis created unprecedented spikes in short-time work (STW).[11] The number of short-time workers peaked at 6 million (18% of all employees) in April 2020 and spiked again in February 2021 (Appendix Figure B.20). The numbers dropped quickly after the second lockdown and returned to near zero in 2022. Because WFH demonstrably shielded workers from STW and the associated wage losses (Adams-Prassl et al., 2020; Alipour et al., 2021; Ben Yahmed et al., 2024), the estimates may also reflect a spurious negative correlation between WFH and spending, driven by more STW in areas where fewer people could work remotely.

Importantly, mandatory closures, online spikes, and STW were transitory phenomena. WFH has stuck. The positive DiD estimates following the removal of Covid restrictions suggest that WFH caused spending to shift into remote workers' neighbourhoods. The effect stabilises in parallel with the recovering economy and the stabilising WFH rates.

**Supply-Side Responses** A key question is whether supply-side adaptations could explain these effects. For instance, mandatory closures may have permanently scarred regions by boosting firm exits. Then, our WFH impact estimates would be smaller compared to a scenario without temporary closures. For US cities, Delventhal and Parkhomenko (2023) show theoretically and Duguid et al. (2023) find empirically that retail establishments follow population growth caused by remote worker migration.[12] The authors find that areas with higher residential WFH potential experience a *decline* in the number of establishments due to WFH-induced outmigration. Because WFH did not boost migration out of German cities,

[11] The short-time work scheme (*Kurzarbeit*) is designed to prevent layoffs while allowing companies to reduce labour costs during an economic downturn. The government partially compensates for wage losses due to reductions in working hours. The German STW scheme was generously expanded during the Covid crisis such that unemployment barely increased (Ben Yahmed et al., 2024).

[12] The authors examine 16 large US cities and find moderate effects overall: average establishment growth (2019Q4–2021Q4) was -2% in city centres mirrored by 2% growth in outer suburban rings.

this channel is likely negligible. Remarkably, Duguid et al. (2023) find that WFH potential still predicts establishment losses, conditional on population changes. A possible explanation is the changing shopping behaviour of remote workers, including a shift to online commerce (Alcedo et al., 2024). Indeed, the US shows a lasting increase in the online share of retail spending, in contrast to the trend reversal observed in Germany (Alcedo et al., 2024).

We examine whether the supply side reacted to the WFH shock in B.2. We draw on two datasets to track firm turnover, Bureau van Dijk's Orbis database, and administrative data on business notifications and insolvencies from the German Federal Statistical Office (Statistics of Business Notification, *Gewerbeanzeigenstatistik*). Adopting our DiD framework, we find that firm entries and exits in relevant non-tradable industries followed similar patterns across areas with varying WFH potential throughout the observation period. This suggests that changes in purchase opportunities cannot account for our WFH impact estimates. Instead, the entire effect appears to result from demand-side shifts following the transition to remote work.

### 2.4.3 Instrumental Variable (IV) Results

We turn to our IV results in Table 2.1. We report results for the non-linear model estimated by PPML and the control function estimator. Results for the linear model estimated by OLS/2SLS are presented in Appendix Table B.5.

Column 1 gives the reduced-form estimates of WFH potential on the 2019–23 change in weekday spending, conditional on log distance to the city centre. The PPML and OLS estimates are close and significant: a one percentage point increase in WFH potential implies a 0.66% (0.80%) increase in spending.[13] The coefficient on log distance is positive, indicating that peripheral postcodes saw increased spending relative to closer areas. In Column 2, we add pre-determined controls for morning mobility, spending per capita, and industry composition (spending share in 'food services', 'grocery & food stores', and 'apparel', respectively). We also include 2019 mobility in neighbouring postcodes, measured as inverse-distance-weighted mobility in *other* postcodes of the same MA. The idea is to account for

[13] Recall that the proportional changes implied by PPML and OLS carry different interpretations. As spending is log-transformed in the OLS regression, the proportional change is unit-specific. PPML delivers the average level effect rescaled by the outcome mean. Thus, OLS places higher weight on effects for postcodes with lower initial spending (Chen and Roth, 2024).

**Table 2.1:** Main Results (Non-Linear Model)

| | Spending (Mo-Fr) | | | | | |
|---|---|---|---|---|---|---|
| | Reduced Form (PPML) | | Main Equation (PPML) | | Instrumental Variable (CFA) | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| WFH potential (%) | 0.007*** | 0.007*** | | | | |
| | (0.001) | (0.001) | | | | |
| Log departures 6-9h | | | -0.141 | -0.718*** | -3.369*** | -3.816*** |
| | | | (0.103) | (0.100) | (0.672) | (0.666) |
| Control function | | | | | 3.303*** | 3.152*** |
| | | | | | (0.686) | (0.667) |
| Log distance to city centre | 0.113*** | -0.030** | 0.083*** | -0.047*** | 0.168*** | -0.002 |
| | (0.013) | (0.015) | (0.010) | (0.013) | (0.022) | (0.014) |
| 2019 log departures 6-9h | | -0.401*** | | -0.421*** | | -0.461*** |
| | | (0.019) | | (0.019) | | (0.023) |
| Net migration (2019-23) | | 0.125 | | 0.118 | | 0.140 |
| | | (0.237) | | (0.229) | | (0.229) |
| 2019 log departures (6-9h) of neighbours | | -0.320** | | -0.394*** | | -0.433*** |
| | | (0.130) | | (0.127) | | (0.127) |
| 2019 log spending p.c. | | -0.334*** | | -0.344*** | | -0.349*** |
| | | (0.020) | | (0.020) | | (0.020) |
| 2019 spending share Food Services | | 0.066*** | | 0.075*** | | -0.017 |
| | | (0.020) | | (0.018) | | (0.029) |
| 2019 spending share Grocery and Food Stores | | -0.025*** | | -0.023*** | | -0.007 |
| | | (0.009) | | (0.009) | | (0.010) |
| 2019 spending share Apparel | | 0.141*** | | 0.150*** | | 0.133*** |
| | | (0.042) | | (0.039) | | (0.039) |
| First stage coef. | | | | | -0.0019 | -0.0018 |
| | | | | | $F$ =62.04 | $F$ =51.82 |
| Implied prop. effect (%) | 0.66 | 0.71 | -0.14 | -0.72 | -3.31 | -3.74 |
| Tot. obs. | 8,124 | 8,124 | 8,124 | 8,124 | 8,124 | 8,124 |
| No. Postcodes | 4,062 | 4,062 | 4,062 | 4,062 | 4,062 | 4,062 |

*Notes:* The table presents results based on Equations 2.2 and 2.3. All columns include postcode and metro-area×post-dummy fixed effects. The implied proportional effect (IPE) corresponds to the percentage change in spending associated with a percentage-point change in WFH potential or a percent change in departures 6-9h, respectively, and is calculated as $100 \times [\exp(\cdot) - 1]$. Standard errors are clustered by postcode and reported in parentheses. Columns 5 and 6 report cluster-bootstrapped standard errors (1,000 repetitions). $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

postcodes' location along commuting routes. [14] Finally, we include the 2019–23 change in population as a proxy for net migration. Reassuringly, adding the controls does not affect the reduced-form estimates.

Columns 3 and 4 report the results of Equation 2.2. The estimated elasticity of spending with respect to morning mobility is negative but insignificant without additional controls. Including controls severely impacts the point estimate, indicating that mobility is correlated with observable and likely unobservable determinants of spending.

Columns 5 and 6 address endogeneity by instrumenting mobility by WFH potential. The coefficient on the control function is statistically significant, implying that we can reject that mobility is exogenous (Lin and Wooldridge, 2019). The elasticity of spending to mobility implied by the IV estimates is negative 3.31–3.74 and consistent with the 2SLS results (negative 3.41–3.79). The first-stage $F$-statistic is above 50, suggesting that WFH potential is a strong instrument. [15]

The estimates imply that a WFH-induced reduction in morning outbound mobility leads to a disproportionate increase in local spending. This finding is consistent with the observation that WFH adoption is driven by those at the top of the wage distribution: We document an hourly wage premium of 7.6% for jobs that can (at least partly) be worked remotely based on 2018 data. The share of teleworkable jobs is increasing almost monotonically through the wage distribution (see B.7.1 for details).[16] Thus, as WFH is adopted disproportionately by higher-income workers in areas with a higher WFH potential, spending appears highly elastic to mobility.

It is worth noting that the inclusion of population change (2019–23) does not affect the reduced-form or IV estimates, nor is it correlated with spending changes (conditional on the other covariates). Indeed, we find that the regression function of population change (2019–23) over WFH potential is flat (Appendix Figure B.18). This corroborates our results of no

[14] Mobility in neighbouring postcodes corresponds to the number of trips in other postcodes of the same MA, weighted by the inverse distance between postcodes' centroids.

[15] Lee et al. (2022, 2023) show that confidence intervals of the 2SLS estimate need to be adjusted in case the first-stage $F$-statistic is below 104.67. We report their proposed $VtF$-95% confidence intervals, which smoothly translate the value of the $F$-statistic into appropriate interval length, in square brackets. The coefficients remain significant.

[16] Pre-Covid data for the US also show that workers who can work remotely enjoy a wage premium on average (Delventhal and Parkhomenko, 2023; Dingel and Neiman, 2020).

systematic outmigration from high-WFH areas following the Covid shock (see B.6).[17] In B.5.3, we show that inference in the linear and non-linear models is robust to different approaches correcting spatial correlation in model errors.

**Heterogeneity by Metro Area Size** We explore effect heterogeneity by metro area size in B.4.1. MA size positively correlates with the concentration of teleworkable jobs in the core city (Appendix Figure B.8). Network effects from greater concentrations of teleworkable jobs could increase incentives to realise WFH opportunities (Monte et al., 2023).[18] Thus, we compare impact estimates among small, medium, and large MAs to see if the WFH shock hits larger MAs more severely. We find that it does. Among the smallest 35 MAs, the reduced-form estimate of WFH potential on spending is close to zero and barely significant. Moreover, WFH potential is a poor predictor of morning mobility changes ($F < 10$), suggesting weak incentives or capabilities to take up WFH in smaller MAs. By contrast, we find significant reduced-form and IV estimates for mid-sized MAs. The mobility elasticity of spending is negative 2.46–3.14. We estimate the largest effects for the five largest MAs with an elasticity of negative 3.66–4.88. This result is consistent with theoretical arguments by Monte et al. (2023), who find that, given productivity spillovers among individuals working in person, a coordinated switch to remote work is more likely to be permanent in larger cities; in contrast, smaller cities tend to converge back to their commuter equilibrium.

**Heterogeneity Across Industries** Finally, we assess whether WFH impacts industries differently in B.4.2. Postcodes with fewer than four merchants in a given category drop out of the sample due to data privacy restrictions. Thus, to ensure enough power, we focus on the largest industries: food services, grocery stores, and apparel stores. Results show that the WFH impact on apparel stores is zero, suggesting that remote workers do not shift spending on clothing and accessory products to the vicinity of their homes. This could also be explained by limited purchase opportunities in residential areas and the lack of new store openings in areas with increased WFH (see B.2). By contrast, we estimate significant elasticities for spending on food services and groceries: A percent decline in morning mobility

[17] Note that, in principle, population change should be considered a "bad control" if we expect WFH to affect spending via migration. As the point estimates are insensitive to the inclusion of this variable, we report the even columns with all covariates for expositional brevity.

[18] The concentration of teleworkable jobs corresponds to the 2019 fraction of jobs that could be done from home at least partly, as measured by Alipour et al. (2023).

increases restaurant spending by 3.92% compared to 2.65% in grocery stores. This is unsurprising, given that eating out for lunch is a common feature of working at the office. Transactions are not time-stamped in our data. But it is plausible that some of the saved lunch money is redirected towards restaurant visits during the evenings or even spent on groceries near workers' homes instead. Thus, the effect estimate for grocery stores may also reflect some substitution between spending categories after workers transition to remote work.

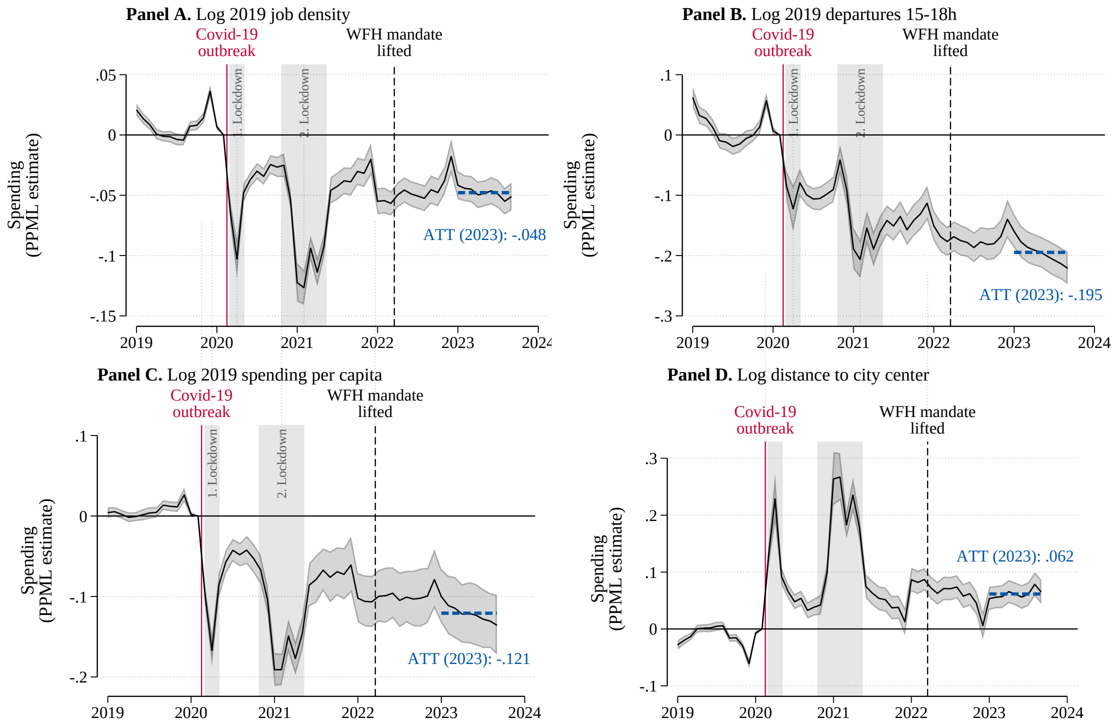
**Income Effects** Besides substitution across spending categories, the estimates may also reflect income effects. Cheaper lunches on home days, but also different wage growth dynamics by WFH status may directly influence spending constraints. For instance, Barrero et al. (2022) suggest that WFH reduces wage growth pressure because employers share its amenity value with employees. Wages may also respond to the changing competitive landscape for teleworkable jobs after employers realise their WFH potential. Similarly, wages will likely respond to WFH-induced productivity changes. Recent evidence suggests that hybrid WFH models tend to deliver neutral or positive productivity effects (Angelici and Profeta, 2024; Bloom et al., 2024; Choudhury et al., 2024), whereas shifting to fully remote generates losses (Emanuel and Harrington, 2024; Gibbs et al., 2023). Thus, income effects could go different ways and potentially bear significant distributional consequences at the macro level (Autor et al., 2023). We cannot disentangle spending shifts from income effects with our data and leave this question to future research.

### 2.4.4 Consequences for Workplace Areas

Our estimates exploit variation in WFH-induced changes in morning commuting to estimate spending changes across home areas. By design, this approach abstracts from the locations from which spending is redirected to remote workers' neighbourhoods. While compelling for causally identifying spending effects, it ignores a crucial aspect of the impact of WFH on the geography of consumption in cities: the consequences for workplace areas. We turn to these in this section.

We explore spending trends since 2019 by adopting the DiD framework introduced in section 2.3. Here, we do not include any controls but explore trend differences across several dimensions separately. Note that WFH does not necessarily fully mediate spending effects. Thus, we are cautious about causal claims. We define workplace areas as postcodes with a high job density, defined as employment per square kilometre in 2019. Thus, the DiD estimates reflect the (relative) spending shift from workplace to residential areas. Binscatter regressions show that a higher job density is associated with nearly monotonic increases in the proximity to the city centre, outbound mobility in 2019 (a proxy for home commutes), and 2019 spending per capita (Appendix Figure B.22).

**Figure 2.4:** Consequences for Workplace Areas




*Notes:* Panels A–D report DiD estimates from a PPML regression of monthly weekday spending on DiD interaction terms of month dummies with a time-invariant variable $Z$, month$\times$MA fixed effects, and postcode fixed effects. $Z$ corresponds to log 2019 job density in Panel A, log 2019 departures between 3 and 6 pm (Panel B), log 2019 spending per capita (Panel C), and log distance to the city centre (Panel D). Estimates are transformed by $\exp(\cdot)-1$ to reflect proportional changes. Shaded areas highlight 95% confidence bands using standard errors clustered at the postcode level.

Panel A of Figure 2.4 plots the PPML-DiD estimates from the interaction of log 2019 job density with month dummies. The results show that job sites were severely hit by the crisis. Weekday spending plummeted during the lockdowns and only partially recovered in the post-pandemic economy. On average, spending is 4.8% lower for a one percent increase in the 2019 job density. Spending trends similarly diverged when comparing areas by their pre-crisis evening outbound mobility (Panel B): In 2023, local spending is 19.5% lower among areas with one percent more evening commuting in 2019. Panel C shows that these changes affect the regional inequality in economic activity: Areas with a higher spending per capita in 2019 persistently attract less spending in the post-Covid economy. We estimate an elasticity of spending with respect to 2019 per capita spending of -12.1%. Finally, we explore the spatial implications of the shock. Panel D reports trend differences across postcodes' distance to the city centre. We find persistent gains in less versus more central areas. On average, spending in 2023 is 6.2% higher for a percent distance increase. Appendix Figure B.23 plots analogue DiD estimates using outbound mobility between 3 and 6 pm as the dependent variable. The results confirm that workplace areas persistently experience reduced evening mobility, as expected with higher levels of remote work.

Breaking down the results by industry reveals that spending in all categories (Food Services, Grocery Stores, Apparel Stores) declined in areas with higher versus lower job concentration between 2019 and 2023 (Appendix Table B.8). Spending losses in apparel stores seem at odds with the result from subsection 2.4.3 that variation in WFH potential does not explain different spending trends in this category. Note that this is not necessarily a contradiction as the causal WFH estimates capture differences among residential postcodes, whereas these estimates capture relative changes between workplace and residential areas. Thus, the loss could be explained by increases in WFH that are not driven by WFH potential.

## 2.5 Conclusion

We study the consequences of the big shift to remote work for local consumer spending within German agglomerations. The analysis builds on a novel panel (2019–23) of cellphone mobility patterns and local card spending volumes in brick-and-mortar establishments at the postcode level. Our identifying variation comes from postcode-level differences in WFH potential, i.e., the ability of the resident population to transition to WFH after February 2020.

DiD estimates suggest persistent declines in mobility, paralleled by increases in spending, in areas with higher WFH potential in 2023. Instrumenting 2019–23 mobility changes by WFH potential, we estimate an elasticity of spending with respect to WFH-induced mobility changes of -3.31% to -3.79%. The effects are driven by larger metro areas and spending in food services and grocery stores. We do not find evidence that WFH-induced migration, firm turnover, or persistent shifts to online commerce can explain these effects. Finally, we show that workplace areas (high job density postcodes) saw persistent spending losses. These areas are more likely consumption hubs and close to the city centre. Consequently, the WFH shock reduced spatial inequality in economic activity by generating relative gains in residential and more peripheral areas of the city.

Our findings inform at least three areas: First, recent research on determinants of agglomerations reinforced the notion that serendipitous exchange among workers from different firms is crucial for cluster success (Atkin et al., 2022). Thus, companies must learn how to foster such interactions in future. Second, for municipalities that levy local business taxes and receive federal funds per resident, understanding spatial changes in economic activity and resident population is essential. Third, urban planning for public transport and zoning policies relies on micro-geographic evidence on shifts in economic activity and how people allocate time within the city. Indeed, a debate has emerged over possible interventions to reinvigorate urban spaces for leisure, as millions of workers no longer commute regularly (Glaeser and Ratti, 2023). The high-resolution and near real-time data used in this paper can support policymakers in promptly evaluating the consequences of local policy experimentation and enhance the understanding of effective strategies.

# 3

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

## Abstract

We study the impact of working from home (WFH) on the spatial distribution of urban housing prices. Using geocoded data on over 20 million residential property offerings in 50 German metropolitan areas from 2014 to 2023, our difference-in-differences analysis leverages postcode-level variation in the exposure to the WFH shock caused by the Covid-19 pandemic. Our results show that WFH has led to a sustained reduction in the price premium associated with proximity to urban centers. Importantly, WFH explains housing price changes even after controlling for distance from city centers. This novel finding suggests that WFH induced a reduction in spatial inequality within cities beyond flattening the urban gradient. The impact of WFH is driven by demand-side mechanisms, including shifts in migration patterns and increased demand for larger homes, while housing supply remains unaffected. Urban price declines reflect dampened expectations about future demand, since the pre-pandemic trend of net in-migration to central, high-WFH-potential areas abruptly halted, reducing future rental cash flows. Our findings highlight the need for urban resilience policies, including adaptive zoning, infrastructure investment, and increased housing supply. [1]

*Keywords*: Working from Home, Urban Housing Prices, Real Estate, Spatial Inequality, Cities

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

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## 3.1 Introduction

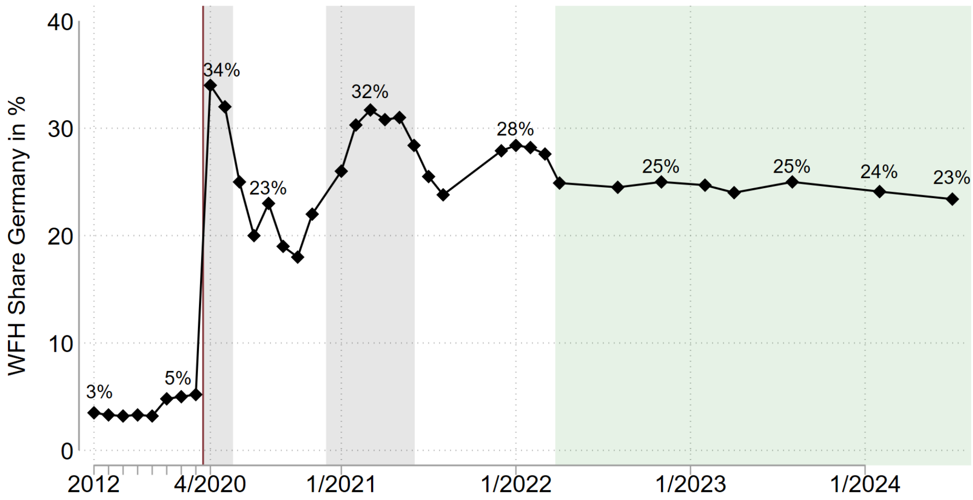
The sustained increase in working from home (WFH) since the Covid-19 pandemic is one of the most substantial transformations of the labor market in recent years (Aksoy et al., 2022; Barrero et al., 2021b, 2023; Bloom et al., 2024; Hansen et al., 2023). Positive experiences and investments in enabling technologies have made this shift enduring, with many employees favoring a hybrid work model that blends office and remote work (Aksoy et al., 2022; Barrero et al., 2021b, 2023). Reflecting the global trend, Figure 3.1a shows that the proportion of the German workforce who WFH at least partly has increased from 5 percent in 2019 to about 25 percent and has stabilized at this level since 2022.

Research shows that WFH is concentrated in cities, where its effects are likely to be most pronounced (Alipour et al., 2023; Dingel and Neiman, 2020). Cities thrive on agglomeration economies, with dense, amenity-rich urban centers attracting high-skilled workers and productive firms that drive both innovation and economic growth (Glaeser et al., 1992). However, the Covid-19 pandemic disrupted these dynamics, with net population losses and declining housing prices in city centers indicating a reduced appeal of urban living (Brueckner et al., 2023; Delventhal et al., 2022; Delventhal and Parkhomenko, 2023; Gupta et al., 2022a; Mondragon and Wieland, 2022; Monte et al., 2023; Ramani et al., 2024; Rosenthal et al., 2022). Most studies link urban housing price shifts to WFH, but establishing causality is challenging due to confounding pandemic effects and limited evidence at finer spatial levels. Furthermore, most research focuses on the United States, leaving evidence from other countries, such as Germany, relatively scarce. Since German cities are generally more monocentric, denser, and public transit-oriented, while U.S. cities tend to be more sprawling, polycentric, and car dependent, we expect a differential impact of WFH in these urban geographies. Figure 3.1b shows that the shift to WFH in Germany coincided with a flattening of the urban housing price gradient. Between 2019 and 2023 prices fell in city centers and rose in suburbs and peripheries. However, wide confidence bands demonstrate substantial within-city variation, suggesting that the spatial dynamics of WFH within cities remain heterogeneous and not yet fully understood.

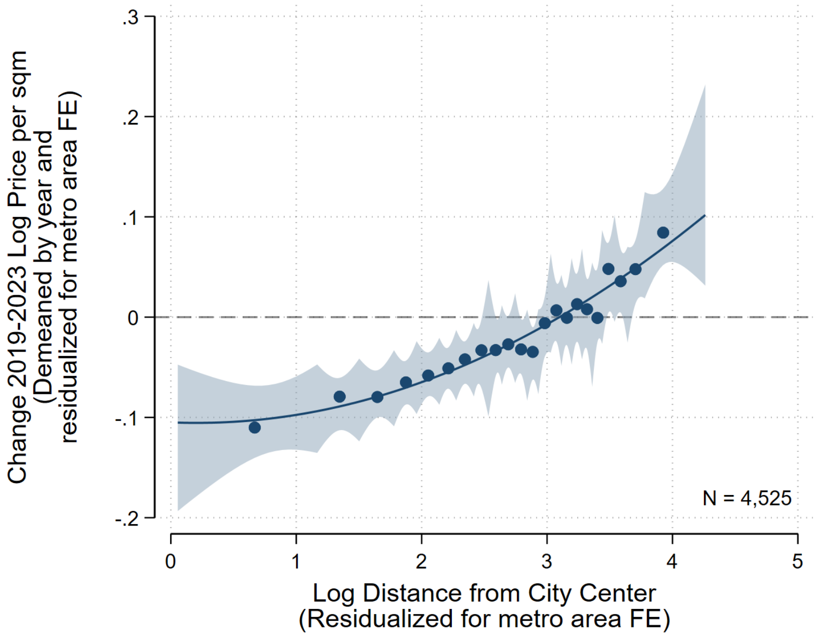
This paper investigates the impact of WFH on the spatial distribution of housing prices within metropolitan areas (MAs). We use data on more than 20 million residential prop-

**Figure 3.1:** Persistent WFH Increase and Spatial Changes in Housing Prices

**(a)** Development of WFH Share of German Workforce 2012–2024




**(b)** Changes in Urban Housing Price Gradient 2019–2023




*Note:* In Panel A, WFH data for Germany are from Eurostat (2012-2019), infas360 (2020-2021) and ifo Institute (2021-2023). The red line marks the outbreak of the Covid-19 pandemic in March 2020, the shaded gray areas highlight "lockdown" periods, and the shaded green area the post-pandemic period since April 2022. Panel B displays a binned scatter plot following the methodology by Cattaneo et al. (2024) on the postcode-level relationship between log distance from the city center and the change in log residential sale prices. The shaded areas highlight 95% confidence bands of the conditional mean functions. Log property prices and log distance are residualized for metro area fixed effects, and prices are demeaned by year fixed effects.

erty offerings from 2014 to 2023, geocoded at the postcode level. The identifying variation comes from differences in postcodes' *WFH potential*, defined as the fraction of employed residents with a teleworkable job, applying an established method in calculating regional WFH measures (Alipour et al., 2023; Dingel and Neiman, 2020; Matheson et al., 2024). We use a difference-in-differences (DiD) approach to compare the evolution of house prices across postcodes *within* the same MA. We focus on price changes by postcodes' distance from the metro center and their WFH potential, separately and in the same specification. Identification relies on the assumption that these areas would have followed parallel trends in housing prices, absent the WFH shock. We confirm parallel pre-trends and probe robustness to including pre-determined controls interacted with time trends.

Our analysis reveals three key findings. First, the shift to WFH has significantly contributed to the flattening of the urban housing price gradient. DiD results show that house prices moved in parallel until 2019, started diverging in 2020 and stabilized by 2023. Areas closer to urban centers and with higher WFH potential saw price declines relative to peripheral and low-WFH-potential areas. Specifically, our results show that a 10 percent greater distance from the city center is associated with a 0.5 percent increase in sale prices and rents in 2023, while a one percentage point higher WFH potential decreases them by 0.4 and 0.3 percent, respectively. The effects are strongest in the most expensive areas and commuting belts of the largest cities. While our results align with findings from the U.S., the magnitude of the effects in Germany is notably smaller. This suggests that European cities remain attractive places to live for high-income households, potentially due to better amenities and quality of life.

Second, our analysis shows that WFH reduces spatial inequality in housing prices beyond flattening the price gradient. Using a long DiD approach (2019-2023), we find that within-metro variation in WFH potential explains housing price changes across postcodes, even after absorbing trends by distance from the city centers. Notably, the interaction between WFH potential and distance reveals that the price-reducing effects of WFH are stronger in peripheral regions of the MAs. Approximately 25 percent of the change in the urban price gradient can be attributed to differences in WFH potential. These findings highlight the distributional effects of WFH, as remote work shifts housing demand away from central, high-cost areas and toward more affordable, peripheral neighborhoods.

Third, we find that WFH impacts urban housing markets through demand- rather than supply-side adjustments. Theoretically, WFH weakens the link between home and work, reducing the need to live near urban centers and making longer commutes more acceptable. Empirically, urban centers have seen a net population loss after 2019. Remarkably, this is driven by a decline in moves toward cities rather than by an urban exodus. The migration patterns in Germany differ from those in the U.S., where WFH has led to more substantial urban out-migration, as population shifts relative to local WFH potential have been minimal. This is consistent with theoretical models on internal migration responses to local shocks (Monras, 2020). Analyzing population changes by WFH potential within metro areas, we find that higher-WFH-potential areas grew faster until 2019. The trend abruptly stopped with the pandemic's onset. From 2019 to 2023, higher-WFH areas did not grow faster than lower-WFH areas, on average. We confirm this finding using granular cell-phone ping data obtained from Deutsche Telekom. Thus, the WFH shock dampened expectations about future demand, since the anticipated increase in net in-migration to central, high-WFH-potential areas failed to materialize, reducing expected future rental cash flows. This results in falling prices in urban cores relative to peripheral, lower-WFH-potential regions despite parallel population trends between 2019 and 2023. Our result aligns with recent findings that WFH primarily increases the commuting distances via job transitions rather than relocations (Akan et al., 2024; Boeri and Rigo, 2024; Coskun et al., 2024). Finally, we find no differential trends in housing quantities and liquidity by WFH potential or distance from urban centers, indicating low housing supply elasticity.

Our findings have implications for the future of cities. As WFH persists beyond the pandemic, the reduced premium on urban proximity and the decline in spatial inequality of housing costs have stabilized and are expected to endure. By lowering prices in urban cores, WFH improves housing affordability also for lower-income, non-remote workers, who live close to city centers. Contrary to previous studies that find either positive or negative welfare effects of WFH, our results suggest that the impact varies by location. While Davis et al. (2024b); Richard (2024) argue that WFH reduces welfare for non-WFH workers by driving up overall housing prices due to increased demand and inelastic supply, Delventhal et al. (2022) observe that WFH improves welfare through falling real estate prices. In contrast, we find that WFH improves affordability in urban cores but drives up housing demand and thus prices in suburban and peripheral areas, with an overall reduction of spatial inequality that extends beyond the flattening of the urban gradient. Overall, these shifts underscore the need for urban resilience policies, including adaptive zoning, infrastructure investment, and increased housing supply. Rising demand in suburban and peripheral areas necessitates expanded infrastructure and public transit to maintain housing affordability.

Our paper expands on two key strands of the literature. First, we contribute to the literature on the economic and societal impacts of WFH by showing how it reshapes the spatial distribution of housing costs. Previous studies have assessed the feasibility and inequality associated with WFH (Aksoy et al., 2022; Alipour et al., 2022; Althoff et al., 2022; Barrero et al., 2021b; Davis et al., 2024a,b; Dingel and Neiman, 2020; Hansen et al., 2023), as well as its effects on productivity and the labor market (Bamieh and Ziegler, 2022; Bloom et al., 2024, 2015; Choudhury et al., 2024; De Fraja et al., 2021; Emanuel and Harrington, 2024; Gokan et al., 2022), neighborhood choice (Ferreira and Wong, 2022), and crime (Matheson et al., 2024). Our paper is closely aligned with research on the impact of WFH on the spatial distribution of economic activity, city structure, and urban amenities (Delventhal et al., 2022; Delventhal and Parkhomenko, 2023; Duranton and Handbury, 2023; Glaeser and Cutler, 2021; Rosenthal et al., 2022). Our novel finding is that WFH reduces spatial disparities in urban housing costs beyond flattening the urban price gradient.

Second, we contribute to the literature on the consequences of WFH for urban real estate by examining the causal link between local WFH potential and housing prices *within* German cities. This geography is representative of other European cities but differs from the structure of U.S. cities. While prior studies have primarily focused on broad metro-level impacts (Delventhal et al., 2022; Delventhal and Parkhomenko, 2023; Gupta et al., 2022a; Kyriakopoulou and Picard, 2023; Liu and Su, 2021; Mondragon and Wieland, 2022; Monte et al., 2023), with Brueckner et al. (2023) distinguishing between inter- and intra-city effects, the novelty of our analysis is that we leverage within-city variation of WFH potential. We provide empirical evidence that WFH flattens the urban gradient and drives the emergence of the "donut effect," initially observed in U.S. cities (Gupta et al., 2022a; Ramani et al., 2024). Since the German cities in our study are more monocentric, denser, and public transit-oriented than their U.S. counterparts, our results differ significantly from previous U.S. evidence, particularly in the smaller magnitude of the effect and the reduction of spatial disparities in housing prices. Our finding that WFH effects persist in both large and small cities contradict Monte et al. (2023), who predict a return pre-pandemic conditions in smaller metros. Complementary research shows substantial impacts of WFH on the office real estate market (Bergeaud et al., 2023; Gupta et al., 2023, 2022b).

The paper proceeds with a description of the data in section 3.2. Next, section 3.3 presents descriptive evidence. Based on our framework in section 3.4, section 3.5 details our empirical results on WFH and urban housing prices. We investigate the mechanisms in section 3.6. Finally, section 3.7 discusses our findings and concludes.

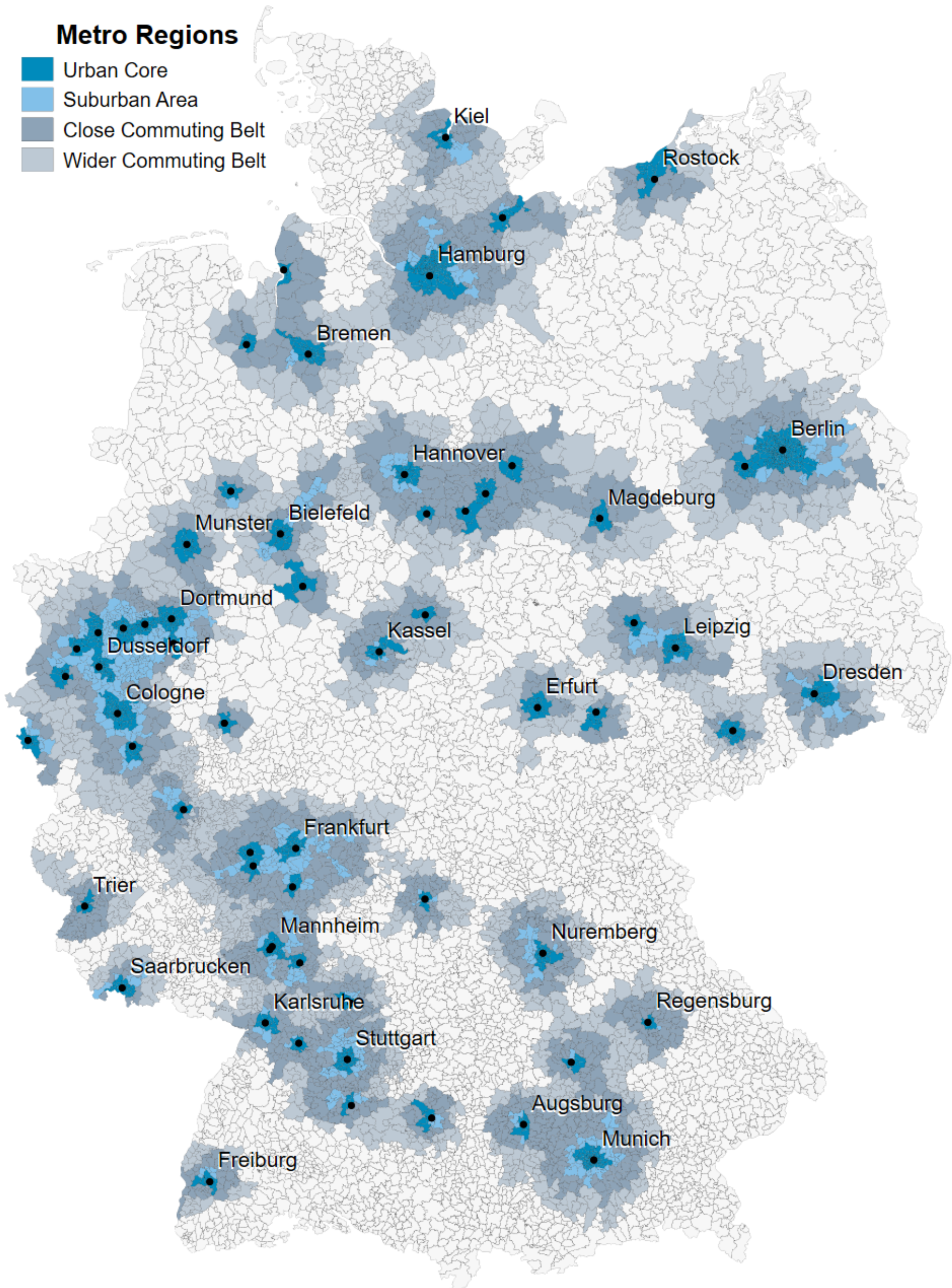
## 3.2 Postcode-Level Data on the Housing Market and WFH in German Metro Areas

**Sample** Our sample includes 4,543 postcodes in Germany's 50 metropolitan areas (MAs), covering about two-thirds of the population (56 million people). The metro areas, similar to U.S. commuting zones, are administratively defined by the German Federal Office for Building and Regional Planning (BBSR) as municipalities where at least 25 percent of employed residents commute to the central city. In general, German cities are more monocentric, denser, and transit-oriented than U.S. cities that are more sprawling, polycentric, car-dependent, and economically segregated (Ahlfeldt et al., 2015; Glaeser et al., 1992; Heblich et al., 2020; Lucas and Rossi-Hansberg, 2002; Roback, 1982). 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. For each postcode, we calculate the Euclidean distance from the nearest MA center. Figure 3.2 illustrates our sample of 50 MAs on a map of Germany. For each postcode, we observe monthly real estate prices, WFH potential, and local characteristics, aggregated at the month-postcode level by averaging listing-level observations. Figure 3.3 illustrates our spatial data, mapping postcode-level changes in real estate prices and WFH potential for the Berlin metro area, representative of other regions. The study period spans 2014–2023.[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 December 2023, covering over 20 million list-

[2] In 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.

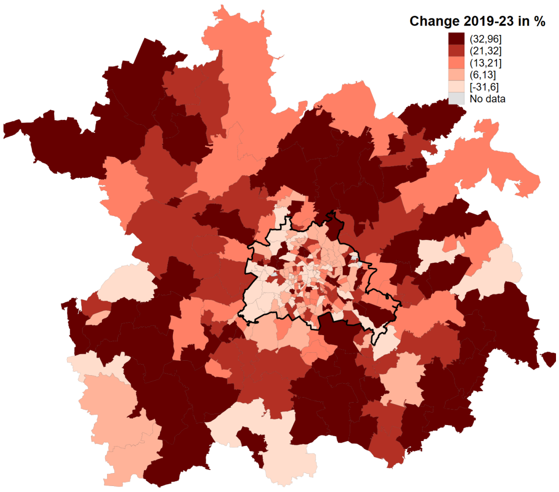
**Figure 3.2:** Sample Illustration of 50 German Metro Regions



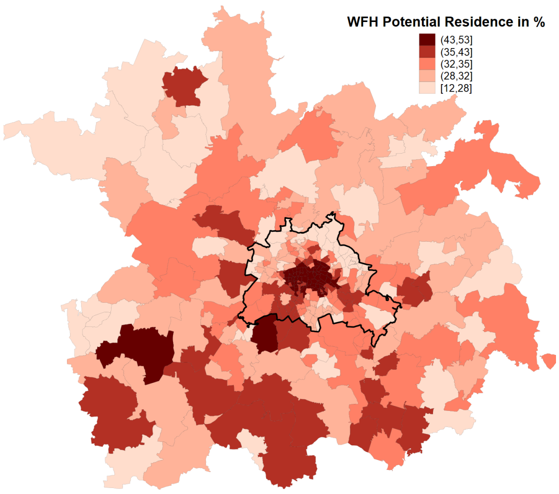

*Notes:* This figure displays the sample comprised of the 50 largest metro regions in Germany with the corresponding urban core (dark blue), the suburban area (blue), as well as the close and wider commuting belt (dark gray / light gray). The administrative classification of the metro areas and the catchment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

**Figure 3.3:** Spatial Data on Housing Price Changes and WFH Potential

**(a)** Changes in Residential Property Prices in Berlin Metro Area Q4 2019 – Q4 2023




**(b)** WFH Potential at the Place of Residence in Berlin Metro Area




*Note:* The map in Panel A visualizes nominal changes of residential property sale prices in the Berlin metropolitan area between 2019 Q4 and 2023 Q4. The different shades of red reflect the level of price changes in the respective zip codes. The table below reports the 2023 Q4 values of the nominal residential property price index (normalized to index value of 100 in 2019 Q4) for sale prices in column (1) and rents in column (2). Postcodes are grouped into four categories: low, medium, high density, and central business district. In Panel B, the different shades of red depict the WFH potential at the place of residence in the Berlin metropolitan area.

ings 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 (sale or rent), type (e.g., single-family house, 3-bedroom apartment), asking price, listing date, size (e.g., rooms, floor space) age (construction year), and features (e.g., heating type, kitchens, gardens, balconies, parking). 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 C.3 shows the distribution of log sale prices and rents per square meter. Appendix Figure C.4 and Figure C.5 demonstrate that the offering prices align closely with publicly recorded transaction prices in major cities, confirming their validity as a proxy for actual market transactions.

**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 online survey of roughly 11,000 individuals, which is representative of the adult German population with Internet access. 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 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 C.6 shows that county-level aggregates of our measure align 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. (2022). 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** Furthermore, we 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 (Destatis, 2023; German Federal Employment Agency, 2024).

Summary statistics are reported in Table C.1 of the Appendix. The mean postcode size in our sample is 12,950 inhabitants.

## 3.3 Descriptive Evidence on Spatial Changes in Urban Housing Prices

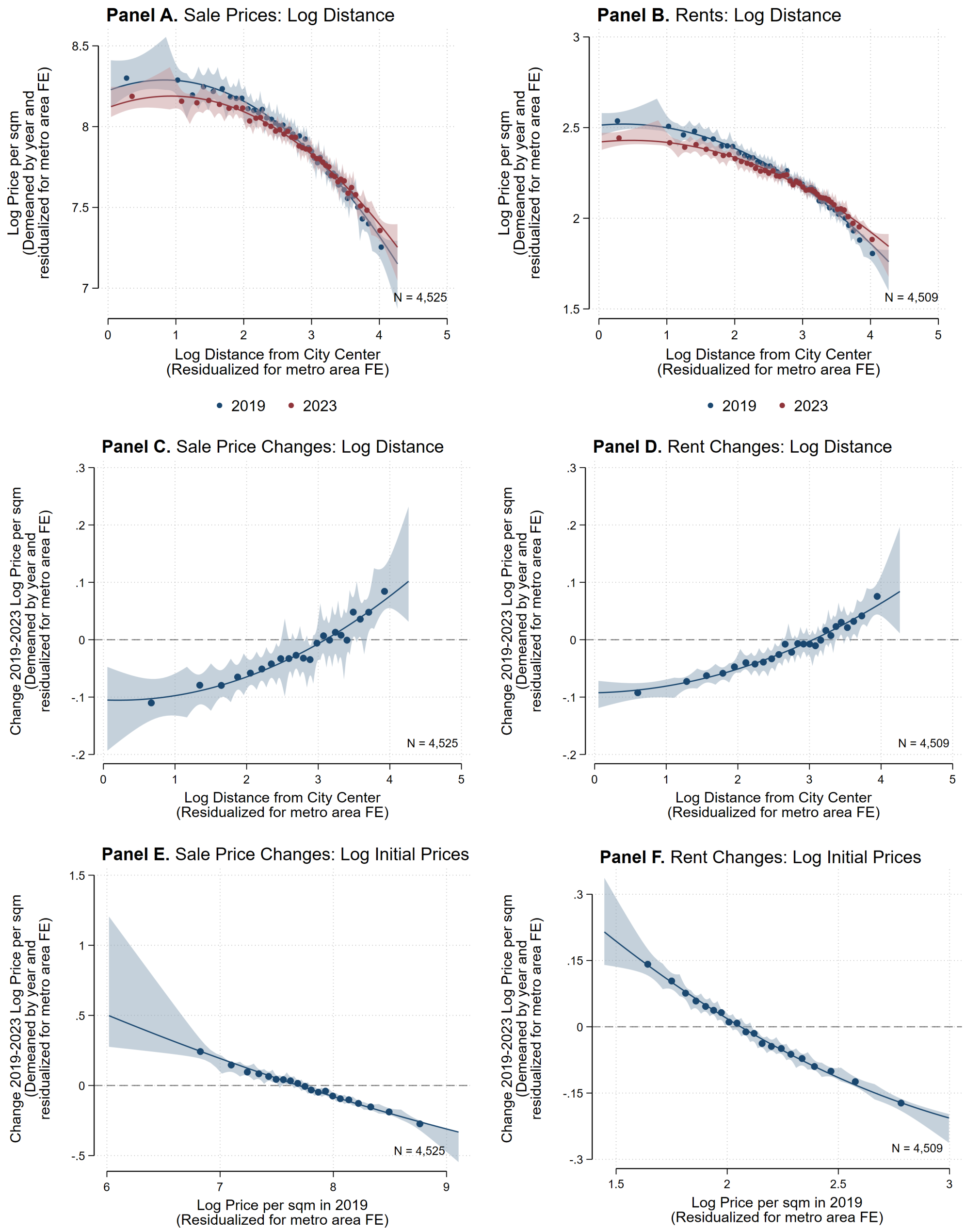
### 3.3.1 Flattening of the Urban Price Gradient

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, this gradient has undergone significant flattening. We provide empirical evidence that WFH contributes to this flattening and creates a "donut effect" in Germany, similar to patterns observed in major U.S. cities (Gupta et al., 2022a; Ramani et al., 2024), but with a lower magnitude (see Appendix Figure C.7).

Figure 3.4 presents binned scatter plots of housing price changes (2019–-2023) against log distance from the city center and log 2019 price levels. Panels A and B of Figure 3.4 present the house price gradients in 2019 and 2023 for sale prices and rents, respectively. The binned scatterplots are conditional on MA and year fixed effects and use equal-sized bins based on the method by Cattaneo et al. (2024). The shaded regions mark the 95% confidence bands of the conditional mean functions. The plots show a clear flattening of the gradients. Panels C and D plot changes in log prices against log distance from the city center. The mean of the changes is normalized to zero. The plot shows stronger price growth the further the distance from the urban core. The relationship appears to be non-linear, with steeper slope for more peripheral areas. Panels E and F highlight that the gradient flattening coincides with a reduction in regional house price inequality: Price growth strongly declines with higher 2019 price levels.

These patterns are similar for other agglomeration measures (population density, purchasing power), pointing to a remarkable decline in the value of density (see Appendices Figure C.8 to Figure C.11). Still, we observe substantial heterogeneity in price adjustments, even at similar

**Figure 3.4:** Flattening of the Urban Housing Price Gradient




*Notes:* This figure displays binned scatter plots following the methodology proposed by Cattaneo et al. (2024) on the postcode-level relationship between the log distance from the city center and the log sale prices (Panel A) and rents (Panel B) of residential properties in 2019 (blue) and 2023 (red). Panels C and D show the relationship between log distance and the change in log sale prices and residential rents from 2019 to 2023, respectively. Panels E and F show the relationship between the pre-pandemic log sale prices and rents in 2019 and the change in log prices from 2019 to 2023. The shaded areas highlight 95% confidence bands of the conditional mean functions. Log property prices are demeaned by year fixed effects and residualized for metro area fixed effects. Log distance is residualized for metro area fixed effects.

distances from the city center, as evidenced by the wide confidence bands. This underscores the need to better understand housing price dynamics at finer spatial levels. In particular, we address whether the sudden shift to WFH can explain heterogenous price trends *within* the city.

### 3.3.2 DiD Analysis on Price Changes Relative to Distance from City Centers

Building on the descriptive results from the binned scatter plots, we conduct a dynamic difference-in-differences (DiD) analysis to examine how urban housing prices evolved from 2014 to 2023. We examine price changes relative on distance from city centers and pre-pandemic price levels, while also identifying potential pre-trends.

We estimate two dynamic DiD specifications, which exploit spatial variation in postcodes' log distance from the nearest urban center and their log pre-pandemic housing price level:

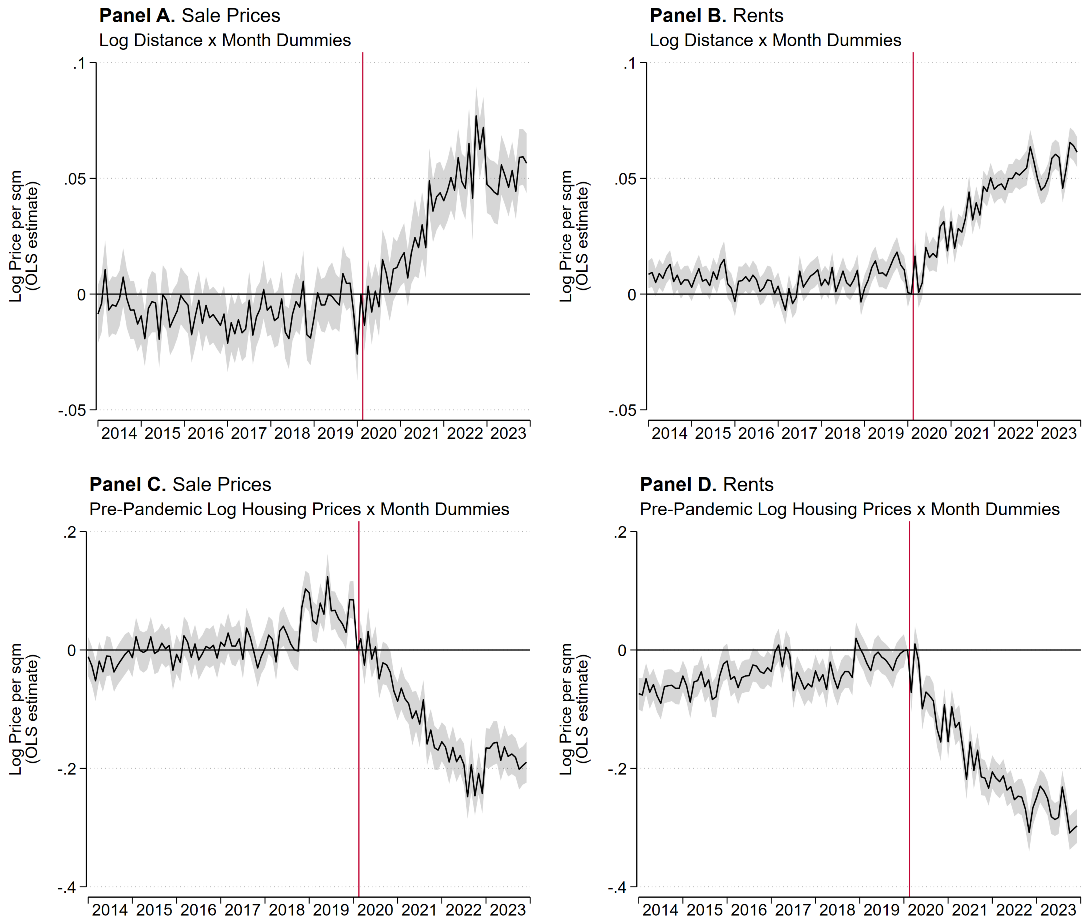
$$Log\_Price_{ct} = \sum_{k \neq Feb\_2020} \beta^k [1(k = t) \times Log\_Distance\_City\_Center_c] + \gamma_c + \delta_{m(c)t} + \varepsilon_{ct}, \quad (3.1)$$

$$Log\_Price_{ct} = \sum_{k \neq Feb\_2020} \beta^k [1(k = t) \times Log\_2019\_Housing\_Price_c] + \gamma_c + \delta_{m(c)t} + \varepsilon_{ct}, \quad (3.2)$$

where $Log\_Price_{cmt}$ is the log average sale price or rent in postcode $c$, metro area $m$ and month $t$. $Log\_Distance\_City\_Center_c$ denotes the logarithm of postcode $c$'s distance from the nearest city center in kilometers (plus 1). $Log\_2019\_Housing\_Price_c$ captures the log of the postcode $c$'s housing price level in 2019. Distance and pre-pandemic price levels are time-invariant and thus orthogonal to the Covid shock. We include postcode and metro-area-by-month-year fixed effects $\gamma_c$ and $\delta_{m(c)t}$ to absorb time-invariant factors and common shocks. We use February 2020 as the reference period and cluster standard errors at the postcode level to account for spatial spillovers.

Figure 3.5 plots the DiD coefficients $\hat{\beta}_k$ for log distance from the city center (Panels A and B) and pre-pandemic housing prices (Panels C and D). We find that the pre-trends until 2019

**Figure 3.5:** DiD Results on Housing Price Changes Relative to Distance from Urban Centers and Pre-Pandemic Housing Prices




*Notes:* This figure presents DiD estimates $\hat{\beta}_k$ from separate regressions of Equation 3.1, in which the interaction terms are between monthly dummies from January 2014 until December 2023 and log distance from the city center in Panels A and B as well as between monthly dummies and the pre-pandemic log housing prices in Panels C and D. The dependent variable is the postcode-level average log sale price per square meter in Panels A and C as well as 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.

are centered around zero and largely statistically insignificant. In the post-pandemic period, the DiD estimates deviate from zero and become significant, stabilizing in 2023. The proximity premium to urban centers has declined and areas with higher pre-pandemic housing prices have experienced slower price growth. 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 in 2023, while 10 percent higher pre-pandemic housing prices correlate with a 2 percent drop in sale prices and a 2.5 percent decrease in rents. The persistence of the effects suggests that temporary pandemic containment measures, which disproportionately impacted city centers, are unlikely to explain these trends.

Our results are consistent with previous findings from the U.S., but the magnitude of the effects in Germany is notably smaller. For instance, Gupta et al. (2022a) find that in the largest 30 U.S. metropolitan during the first nine months of the pandemic (until December 2020), a 1 percent higher distance from the city center is associated with increases of house prices by 1 percent and rents by 3 percent. In contrast, the corresponding effects in Germany during this period are less than 1 percent.

Appendix Figure C.12 shows that these effects are strongest in the commuting belts of the largest ten metros but remain significant across all regions. We further confirm the flattening of the urban price gradient and absence of pre-trends by using normalized distance and population density in Appendix Figure C.13.

Overall, our descriptive findings show that the pandemic has permanently changed the microgeography of urban housing markets. The housing price gradient has flattened, with significant spatial dispersion suggesting that factors like local differences in WFH *within* cities may impact the spatial distribution of urban housing prices.

## 3.4 Empirical Framework: WFH Impact on Urban Housing Prices

### 3.4.1 Conceptual Framework

The impact of WFH on urban housing markets can be analyzed through the Rosen-Roback urban spatial equilibrium model (Roback, 1982; Rosen, 1974), where workers choose locations by balancing wages, housing costs, and local amenities to equalize utility across space. In this framework, high-productivity, amenity-rich cities command higher wages to offset urban living costs. The rise of WFH disrupts this equilibrium by partially decoupling workplace and residence, enabling workers to reoptimize their location choices.

This *partial decoupling* arises from the widespread adoption of hybrid work arrangements, where employees alternate between remote and on-site workdays (Barrero et al., 2023; Bloom et al., 2024). In contrast, fully remote work, which would enable a complete decoupling of residence and workplace, is feasible only a for a small fraction of the workforce.[3]

WFH reduces the need for frequent commuting, allowing employees to live farther from their workplaces or accept jobs in distant locations in exchange for lower housing costs or larger living spaces. Since hybrid work still necessitates some proximity to workplaces, WFH reshapes residential preferences and the spatial distribution of housing demand *within* rather than across cities. Empirical evidence confirms that WFH-driven relocations occur mostly within metro areas rather than between them (Althoff et al., 2022; Brueckner et al., 2023; Gupta et al., 2022a; Ramani et al., 2024).

We expect WFH to impact urban housing markets through two demand-side adjustment mechanisms. First, hybrid workers may relocate to suburban or peripheral areas in search of better affordability or larger homes. This directly reduces housing demand in urban cores, which have the highest WFH potential. We therefore expect a negative impact of the residential WFH potential on local housing prices. Second, WFH weakens the traditional link between workplace proximity and residential location by allowing workers to accept urban jobs without relocating. This decoupling lowers expectations about future rental cash flows in central locations, as owners and landlords anticipate reduced in-migration to central, high-WFH-potential areas. This reduction in expected demand for urban living exerts downward pressure on property values and rents. Notably, this expectation effect is not directly captured by residential WFH potential measured in 2022, as it reflects broader labor market adjustments rather than individual relocations. Given Germany's overall low labor mobility, we expect this shift in expectations to have a particularly strong impact on urban housing markets. 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).

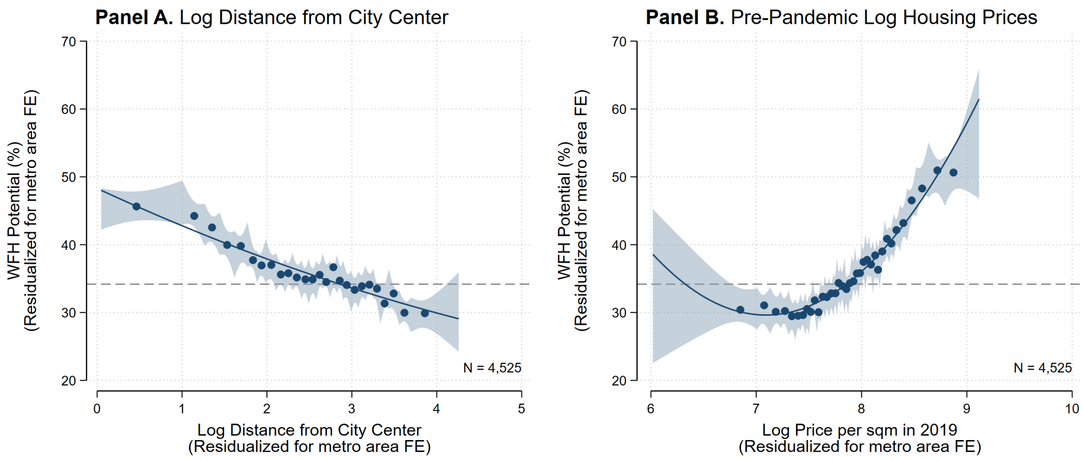
[3] According to the German micro-census, a quarter of the German workforce worked at least partly remotely in 2023 (Destatis, 2024). Among them, 74 percent followed a hybrid model, while only 26 percent worked fully remotely.

These shifts in housing demand are expected to produce two spatial effects. First, WFH may *contribute to flattening* the urban housing price gradient. Second, it is expected to *reduce spatial inequality* in housing costs within cities by narrowing price differences among neighborhoods located at similar distances from the urban core. However, the extent of these effects is likely heterogeneous and moderated by local characteristics, such as urban amenities.

### 3.4.2 Identification Strategy

The empirical results from section 3.3 suggest that the trends in urban housing prices reflect structural shifts, such as the widespread adoption of remote work, rather than temporary, pandemic-related factors. Building on the theoretical considerations in subsection 3.4.1, our empirical strategy tests whether WFH reshapes the spatial distribution of urban housing prices through two key channels: (i) *flattening the urban price gradient* and (ii) *reducing spatial inequality in housing costs*.

**Figure 3.6:** Association of WFH Potential with Distance, Pre-Pandemic Housing Prices and Price Changes 2019-2023




*Notes:* This figure displays binned scatter plots following the methodology proposed by Cattaneo et al. (2024) on the postcode-level relationship between the WFH potential at the place of residence with the log distance from the city center in Panel A as well as with the pre-pandemic log housing prices in 2019 in Panel B. The shaded areas highlight 95% confidence bands of the conditional mean functions. 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 dashed line in Panels A and B marks the average WFH Potential at the place of residence of 34.18 %. WFH potential, log distance and log housing prices in 2019 are residualized for metro area fixed effects.

To illustrate spatial differences in WFH potential within cities, Figure 3.6 presents binned scatter plots of postcode-level correlations: WFH potential vs. log distance from the urban center (Panel A) and WFH potential vs. pre-pandemic log housing prices (Panel B). We use equal-sized bins, 95 percent confidence intervals, and metro area fixed effects (Cattaneo et al., 2024). WFH potential is defined as the share of employed residents who can work remotely at least one day per week, consistent with Dingel and Neiman (2020). The binscatter regressions show that WFH potential decreases almost monotonically with distance from the urban center, indicating that workers with WFH-feasible jobs tend to live closer to city centers. Higher WFH potential is also associated with higher pre-pandemic housing prices, consistent with evidence from the U.S. that WFH workers earn higher incomes (Delventhal and Parkhomenko, 2023; Dingel and Neiman, 2020).[4]

Our analysis employs a continuous treatment approach with postcode-level variation in WFH potential. The validity of the DiD design relies on the strong parallel trends (SPT) assumption, which asserts that postcodes with different WFH potentials provide valid counterfactuals for one another. This assumption holds unless postcodes self-select WFH levels based on anticipated treatment effects. While we cannot directly test this, we provide visual evidence of parallel pre-trends, recognizing that this does not fully account for potential post-treatment outcomes.

A threat to identification is the presence of unobserved confounders correlated with both WFH potential and housing price changes, such as local economic shocks or differential policy interventions. To mitigate this, we incrementally control for postcodes' distance from the city center, population density, industry composition, and sociodemographic characteristics, ensuring that our estimates capture the causal effect of WFH. Additionally, we include postcode fixed effects to absorb time-invariant factors and metro-area-by-month-year fixed effects to account for differential time trends and shocks across metropolitan areas.

We use two complementary approaches in our analysis. First, a dynamic DiD approach estimates the effect of WFH potential on the urban housing price gradient over time, checking for pre-trends and capturing dynamic effects. Second, a long DiD approach assesses the persistent impact of WFH on the spatial distribution of housing prices beyond the gradient flattening.

[4] Appendix Figure C.14 further shows that WFH potential is concentrated in dense urban centers, while Appendix Figure C.15 reveals the flattening of the urban housing price gradient relative to WFH potential.

**Dynamic DiD Analysis** We examine the causal effect of WFH on urban housing prices by leveraging spatial variation in exposure to the WFH shock induced by the Covid-19 pandemic. Specifically, we compare changes in housing prices between high- and low-WFH-potential postcodes *within* metropolitan areas. To ensure robust estimates, we control for postcode-level characteristics, such as distance from the urban center, population density, industry composition, and sociodemographic factors. Since the WFH potential was largely determined before the pandemic, it is relatively independent of the Covid shock. Formally, we estimate the following dynamic DiD regression:

$$\begin{aligned}
Log_Price_{ct} = & \sum_{k \neq Feb_2020} [\beta^k 1(k=t) \times WFH_Potential_c \\
& + \gamma^k 1(k=t) \times Log_Distance_c + \zeta^k 1(k=t) \times Log_Density_c \\
& + \eta^k 1(k=t) \times Industry_c + \theta^k 1(k=t) \times Sociodemographic_c] \\
& + \gamma_c + \delta_{m(c)t} + \varepsilon_{ct},
\end{aligned} \tag{3.3}$$

where $Log\_Price_{cmt}$ is the log average sale price or rent in postcode $c$, metro area $m$ and month $t$. $WFH\_Potential_c$ denotes postcode $c$'s WFH potential, measured as the percentage of employed residents with WFH-feasible jobs. $Log\_Density_c$ refers to log population density, $Log\_Distance_c$ to log distance from the urban center, $Industry_c$ to local industry structure, and $Sociodemographic_c$ to local sociodemographic characteristics, each at the postcode level. We include postcode and metro-area-by-month-year fixed effects $\gamma_c$ and $\delta_{m(c)t}$ to absorb time-invariant factors and common shocks. We use February 2020 as the reference period, weight by employment at the postcode level and cluster standard errors at postcodes to account for spatial spillovers.

**Long DiD Analysis** We employ a long DiD approach from 2019 to 2023 to examine the long-run effects of WFH potential on the spatial distribution of urban housing prices. This analysis tests whether WFH reduces spatial inequality in housing prices within metros *beyond* flattening the urban price gradient. Specifically, we assess whether variation in WFH potential explains housing price changes, even conditional on distance from the city center. Formally, we estimate the following regression:

$$
\begin{aligned}
\Delta_{2019-2023} Log\_Price_c = \ & \beta_1 \times WFH\_Potential_c + \beta_2 \times Log\_Distance_c \\
& + \beta_3 \times (WFH\_Potential_c \times Log\_Distance_c) + \beta_4 \times Log\_Distance_c^2 \\
& + \gamma_c + \varepsilon_c,
\end{aligned}
\tag{3.4}
$$

where $\Delta_{2019-2023} Log\_Price_c$ represents the change in log sale prices and rents in postcode $c$ from 2019 to 2023. $WFH\_Potential_c$ denotes postcode $c$'s WFH potential, and $Log\_Distance_c$ reflects its log distance from the nearest urban center. The variable $Log\_Distance_c^2$ reflects the quadratic nature of the spatial relationship between WFH and distance from the urban center. We include either metro area or metro-by-catchment-area fixed effects $\gamma_c$ to absorb time-invariant city characteristics. Again, we weight by employment at the postcode level and cluster standard errors at postcodes to account for spatial spillovers.

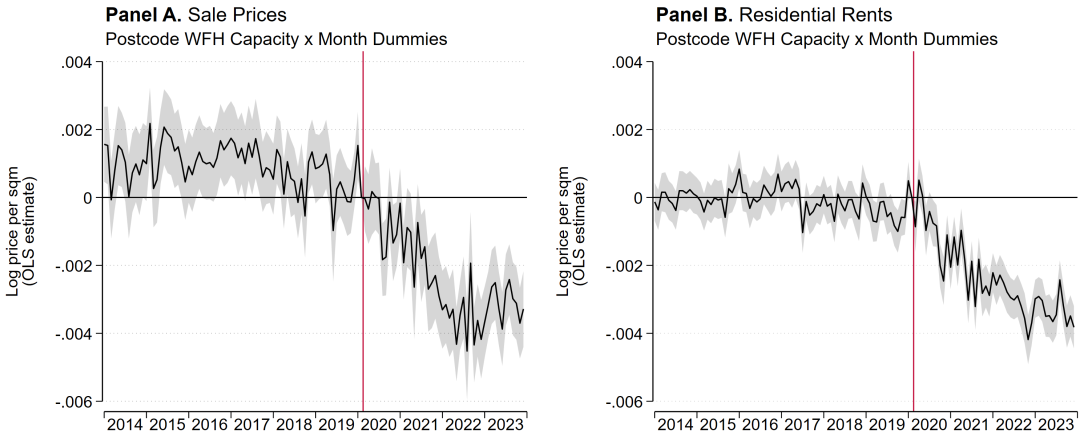
In Equation 3.4, the coefficient $\beta_1$ captures the effect of WFH potential on housing price changes within a metropolitan area. We hypothesize that postcodes with higher WFH potential become relatively cheaper, either through relocations or fewer moves toward the city. When controlling for distance, $\beta_1$ captures differences in housing cost changes between postcodes with similar distance but differing WFH potential. As shown in Figure 3.6, there is significant variation in WFH potential among equidistant postcodes. We focus on the coefficient $\beta_3$, which captures the interaction between WFH potential and distance from the city center. We hypothesize that WFH causes larger housing price reductions in more expensive, central postcodes.

## 3.5 Results: WFH Impact on Urban Housing Prices

### 3.5.1 Dynamic DiD Results

The dynamic effect of WFH potential on urban housing prices is shown with monthly DiD coefficients in Figure 3.7, where the charts illustrate the impact on log sale prices (Panel A) and rents (Panel B). 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 – areas close to the city center with high housing costs – 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. 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.

**Figure 3.7:** DiD Results on the Impact of WFH Potential on Urban Housing Prices




*Notes:* This figure presents DiD estimates $\hat{\beta}_k$ from separate regressions of Equation 3.3, in which the interaction terms are between monthly dummies from January 2014 until December 2023 and postcode-level WFH potential of residents. 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 Panel A and the average log rent per square meter 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.

We formalize the analysis in Appendix Table C.2, grouping monthly time indicators into annual bins to reflect pre- and post-Covid periods. The table presents estimates for the interaction terms between WFH potential and yearly post-Covid periods, with columns (1) to (4) showing results for sale prices and columns (5) to (8) for rents. Columns (1) and (5) include controls for postcode and metro-area-by-year-month fixed effects, revealing significantly negative coefficients both sale prices and rents in the post-Covid period that correspond to Figure 3.7.

The results are heterogeneous within and across metropolitan areas, as shown in Appendix Figure C.16. 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 metropolitan areas, but the effects remain significant across all metropolitan areas. Our evidence therefore contrasts with findings by Monte et al. (2023) from the U.S., where the WFH impact is concentrated in large cities.

### 3.5.2 Long DiD Results

The long DiD analysis from 2019 to 2023 examines the persistent effect of WFH, providing novel evidence that WFH significantly affects the spatial distribution of housing prices in metropolitan areas beyond flattening the urban gradient.

The results in Table 3.1 show that WFH explains spatial differences in housing price changes, even after controlling for distance from city centers. Panel A presents results for sale prices and Panel B for rents. The negative and significant coefficient on WFH potential shows that postcodes with higher WFH potential experienced larger declines in housing prices. This indicates high housing price elasticity to WFH potential, especially in central, high-cost locations. In addition, column (2) demonstrates that, even among postcodes at similar distances from the city center, higher WFH potential is linked to greater reductions in housing prices. This finding implies that WFH not only flattens the urban price gradient but also reduces spatial disparities in housing costs within metropolitan areas. Furthermore, the positive interaction coefficient indicates that the impact of WFH on reducing house prices is more pronounced in central, high-cost neighborhoods. Overall, these findings reveal that WFH flattens the urban price gradient and reduces spatial disparities, highlighting the distributional impact of remote work on urban housing markets.

Comparing the log distance coefficient in column (2) with the descriptive analyses in section 3.3 suggests that approximately 25 percent of the distance gradient change comes from variation in WFH potential. This suggest that while WFH plays a significant role in reshaping urban housing prices, other factors, such as changes in amenities or emerging disamenities – potentially influenced by WFH – account for the majority of the effect. In particular, the increase in urban disamenities, such as crime, drugs, and business closures, may have diminished city center attractiveness post-Covid. However, in Germany, WFH potential is not significantly linked to business closures (Alipour et al., 2022). Given the magnitude and persistence of the WFH impact, it plausibly remains the most important single driver of spatial housing price changes in cities.

**Table 3.1:** Long DiD Results on Effect of WFH Potential and Log Distance on Urban Housing Price Changes 2019–2023

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| ***Panel A Dependent Variable: 2019-2023 Change in Log Property Sale Prices*** | | | | | | |
| WFH Potential Residence | -0.0035*** | -0.0018*** | -0.0013** | -0.0039*** | -0.0030*** | -0.0055*** |
| | (0.0003) | (0.0003) | (0.0006) | (0.0008) | (0.0007) | (0.0009) |
| Log Distance from Center | | 0.0369*** | 0.0446*** | -0.0146 | -0.0538*** | -0.1009*** |
| | | (0.0029) | (0.0095) | (0.0134) | (0.0187) | (0.0220) |
| WFH Potential × Log Distance | | | -0.0002 | 0.0008*** | 0.0005** | 0.0015*** |
| | | | (0.0002) | (0.0003) | (0.0003) | (0.0003) |
| Log Distance Squared | | | | | 0.0158*** | 0.0152*** |
| | | | | | (0.0026) | (0.0030) |
| *Number Postcodes* | 4,523 | 4,523 | 4,523 | 4,518 | 4,523 | 4,518 |
| ***Panel B Dependent Variable: 2019-2023 Change in Log Property Rents*** | | | | | | |
| WFH Potential Residence | -0.0028*** | -0.0011*** | -0.0011*** | -0.0026*** | -0.0022*** | -0.0032*** |
| | (0.0001) | (0.0001) | (0.0003) | (0.0004) | (0.0003) | (0.0004) |
| Log Distance from Center | | 0.0360*** | 0.0365*** | -0.0011 | -0.0261*** | -0.0360*** |
| | | (0.0015) | (0.0047) | (0.0071) | (0.0093) | (0.0119) |
| WFH Potential × Log Distance | | | -0.0000 | 0.0006*** | 0.0004*** | 0.0009*** |
| | | | (0.0001) | (0.0001) | (0.0001) | (0.0002) |
| Log Distance Squared | | | | | 0.0100*** | 0.0061*** |
| | | | | | (0.0013) | (0.0015) |
| *Number Postcodes* | 4,507 | 4,507 | 4,507 | 4,502 | 4,507 | 4,502 |
| 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 3.4. Panel A displays the results for the 2019-2023 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 3.3 portrayed in Figure 3.7. 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 3.4. 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.

The heterogeneity of the effects within metropolitan areas is shown in Appendix Table C.3, which underscores the impact of WFH on reducing housing prices particularly in urban cores, while the effect in the suburbs and periphery are less negative. Appendix Table C.4 demonstrates that the effects are strongest in the 10 largest metros but remain significant in smaller metropolitan areas.

### 3.5.3 Robustness Checks

We test the robustness of both the dynamic and long DiD results by systematically introducing additional controls and using residualized property prices as outcomes.

For the dynamic DiD results, we incrementally add controls to account for potential confounders in Appendix Table C.2. Columns (2) and (6) control for population density and distance from the city center, with the corresponding dynamic DiD charts presented in Appendix Figure C.17. Columns (3) and (7) further incorporate industry composition and sociodemographic structure, while columns (4) and (8) additionally control for migration flows. The complete set of dynamic DiD estimates, including all controls, is visualized in Appendix Figure C.18. Although the inclusion of these variables attenuates the coefficient on WFH potential, it remains significantly negative across all specifications, reinforcing the robustness of our findings.

For the long DiD results, we conduct similar robustness checks (see Appendix Table C.5). We sequentially add controls for postcode-level population density, industry composition, and sociodemographic structure. The results remain largely consistent with our main findings, confirming that the observed effects are not driven by omitted local characteristics.

Furthermore, we verify the robustness of the estimated WFH impact by using residualized property prices as outcomes, which account for property characteristics through a hedonic adjustment. The results remain largely unchanged (see Appendix Figure C.19).

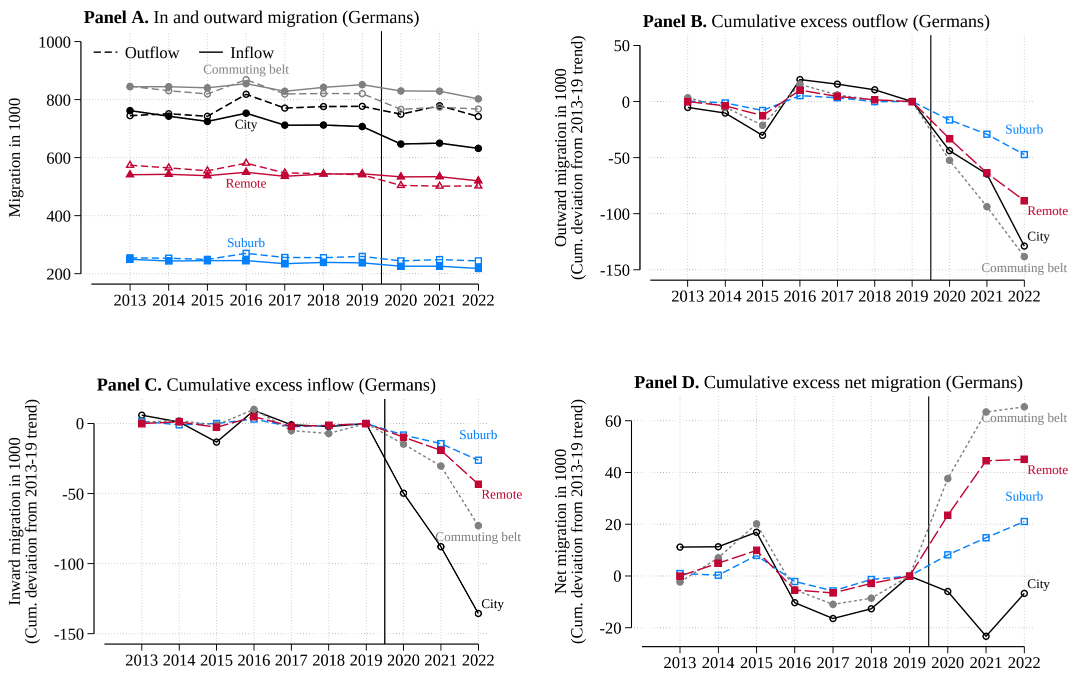
## 3.6 Mechanisms Driving the WFH Effect

This section analyzes the mechanisms through which WFH reshapes urban housing markets, focusing on three demand-side drivers: migration, employment trends and space demand. While housing demand is expected to adjust in response to WFH and we find evidence for this hypothesis, there is an absence of supply-side mechanisms.

### 3.6.1 Changes in Migration Flows Within Metros

We examine migration patterns as the first demand-side mechanism. Using administrative data from 2013 to 2022, we analyze net domestic migration flows both within and across metropolitan areas. As outlined in section 3.4, WFH affects migration patterns in two ways: First, hybrid workers may relocate to suburban or peripheral areas for better affordability or larger homes, directly reducing housing demand in urban cores. Second, WFH allows workers to accept jobs in cities without relocating, lowering expectations about the long-term demand for urban living. Since property prices represent the net present value of expected future cash flows from rents, both mechanisms impact urban housing prices.

**Figure 3.8:** Changes in Urban Net Migration Flows




*Notes:* This figure displays total domestic migration flows across county borders in Germany between 2013 and 2022. Panel A depicts the evolution of inflows and outflows for the urban catchment areas: city, suburb, commuting belt, remote area. Panel B and C detail cumulative excess outflows and inflows since the pandemic relative to the trend from 2013-2019. Panel D illustrates cumulative excess net migration by urban catchment areas. Administrative data on migration statics are provided by the German Federal Statistical Office.

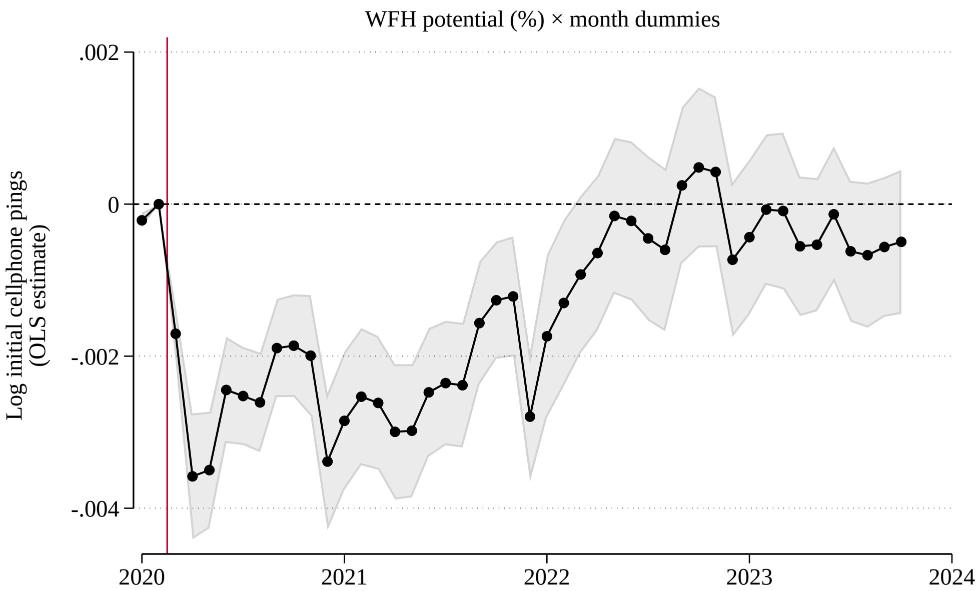
Figure 3.8 Panel A shows the evolution of total migration flows in urban cores, suburbs, commuting belts, and peripheral regions. Since the pandemic, population flows have slowed, with both outflows (Panel B) and inflows (Panel C) declining relative to pre-pandemic levels. However, the decrease in inflows was sharper, particularly into urban areas. This sharper drop in inflows has led to a post-pandemic increase in net outward migration, with the largest population gains in commuting belts and remote areas. Our findings challenge the "urban exodus" narrative, as urban population loss is due to reduced inflows rather than increased outflows. These altered migration patterns suggest shifting residential preferences and reduced proximity needs, as WFH allows workers to accept jobs in cities without relocating. This aligns with prior studies (Akan et al., 2024; Boeri and Rigo, 2024; Coskun et al., 2024), showing that WFH increases the distance between home and workplace for job transitions without significantly affecting current job holders. Our results are also consistent with models of households' reactions to local economic shocks that do not expect substantial migration responses (Monras, 2020).

Using the origin-destination features of the migration data, Appendix Figure C.20 shows that population flows have occurred predominantly within rather than across metro regions. Two dominant trends emerge: the largest net migration flows were from urban cores to commuting belts and to remote areas. However, the scale of migration remains modest. Excess net migration from more to less central counties between 2020 and 2022 totaled just 59 thousand people. This represents less than one percent of the six million workers who transitioned to WFH since 2019.

To address the limitations of county-level administrative migration data, we additionally use granular cellphone mobility data from T-Systems by Deutsche Telekom to analyze population changes at the postcode level. In Figure 3.9, we apply a version of our dynamic DiD framework to measure postcode-level population changes through the number of users' first-morning pings within their home zones relative to local WFH potential over time. While we find a decline during the pandemic, morning pings post-Covid show no significant differences compared to pre-pandemic patterns. Reassuringly, these granular spatial data confirm that population shifts within cities relative to WFH potential have been minimal.

Overall, our analysis of migration patterns suggests that WFH has impacted urban housing demand primarily through altered expectations rather than large-scale population shifts. While population changes within metropolitan areas have been modest, the sharp decline in inflows to urban cores reflects altered residential preferences. Importantly, this reduced inflow has likely reshaped expectations about long-term urban housing demand. As a result, housing demand has declined in urban cores and risen in suburban and peripheral areas, as workers gain flexibility to live farther from city centers while having urban jobs. 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.

**Figure 3.9:** DiD Estimates of Changes in Cellphone Pings Relative to WFH Potential

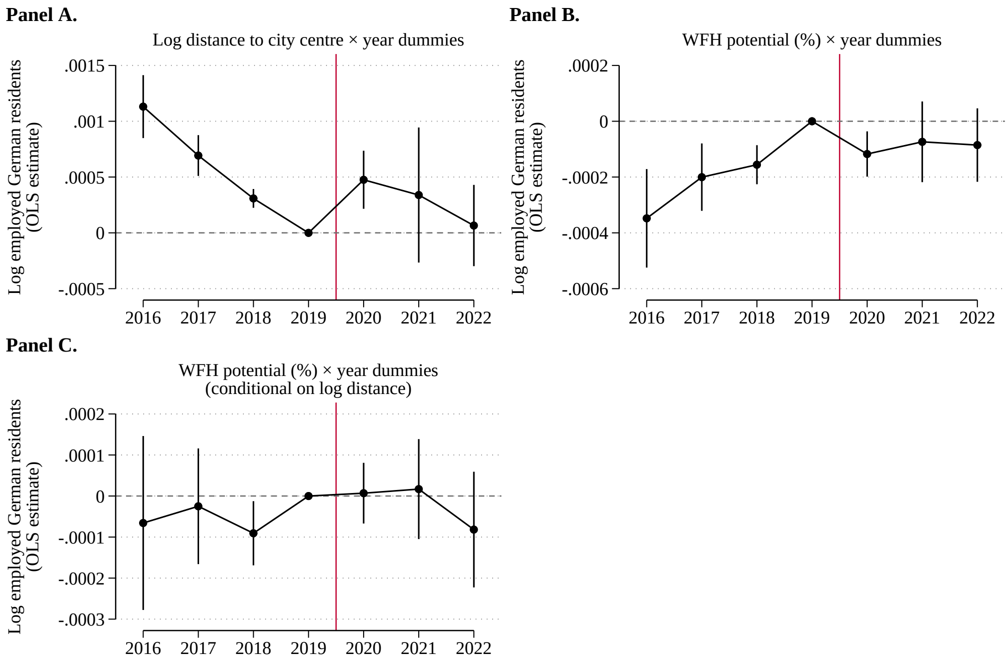



*Note:* This figure reports monthly DiD estimates of the changes in cellphone users' first-morning pings within their home zones relative to WFH potential at the postcode level. The estimates use postcode and metro-area-by-month fixed effects. Standard errors are clustered at the postcode level. The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

### 3.6.2 Broken Urbanization Trend in Employment Growth

We analyze spatial changes in employment patterns as the second demand-side mechanism. The recent literature documents a broader shift of economic activity toward the suburbs and periphery of cities due to WFH, which is likely to influence employment dynamics, such as an increase in service jobs, as consumer spending moves to local businesses in these areas (Alipour et al., 2022; Althoff et al., 2022; Duguid et al., 2023; Rosenthal et al., 2022).

**Figure 3.10:** Spatial Employment Trends in Metro Areas




*Notes:* This figure depicts spatial employment trends across metropolitan areas from 2013 to 2022, based on the log employment of Germans at their place of residence. Panels A–C report DiD estimates from OLS regressions of the log number of employed German residents on DiD interaction terms, year×MA fixed effects, and municipality fixed effects. DiD interactions equal year-dummies×log distance from the city center in Panel A and year-dummies×WFH potential in Panel B. Panel C reports the DiD coefficients from WFH potential×year dummy interactions, conditional on log distance×year fixed effects. 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*).

Figure 3.10 illustrates spatial employment trends in German metropolitan areas from 2013 to 2022, applying our dynamic DiD framework based on administrative data. Panel A shows DiD estimates from OLS regressions of the log number of employed German residents on an interaction term of log distance from the city center and year dummies. Until 2019, the negative pre-trend indicates stronger employment growth in urban cores relative to suburbs and commuting belt. However, since 2020 this urbanization trend in employment growth has reversed, with growth in suburban and peripheral areas now paralleling that of urban cores. Panel B highlights that before the pandemic, employment growth was also faster in high-WFH-potential areas, which are typically urban and high-cost locations. Since 2020, this trend has flattened, with high- and low-WFH-potential areas showing parallel growth. Panel C finds no significant direct link between WFH potential and employment changes after controlling for distance, indicating that employment shifts are primarily spatial.

These findings reveal two key breaks in employment trends: the end of the pre-pandemic urbanization trend and the slowing of faster employment growth in high-WFH-potential areas. The trend breaks align with the interpretation that WFH has weakened the traditional link between workplace location and residence. WFH enables suburban and remote residents to accept urban jobs without relocating, reducing the necessity of living near workplaces. This interpretation is consistent with evidence from Germany (Coskun et al., 2024), which shows that WFH increases the distance between home and workplace primarily for job transitions.

Ultimately, by altering where people can work, WFH has contributed to the spatial redistribution of housing demand. The reduced concentration of employment growth in urban cores has eased housing pressure in these areas while increasing demand in suburban and peripheral regions.

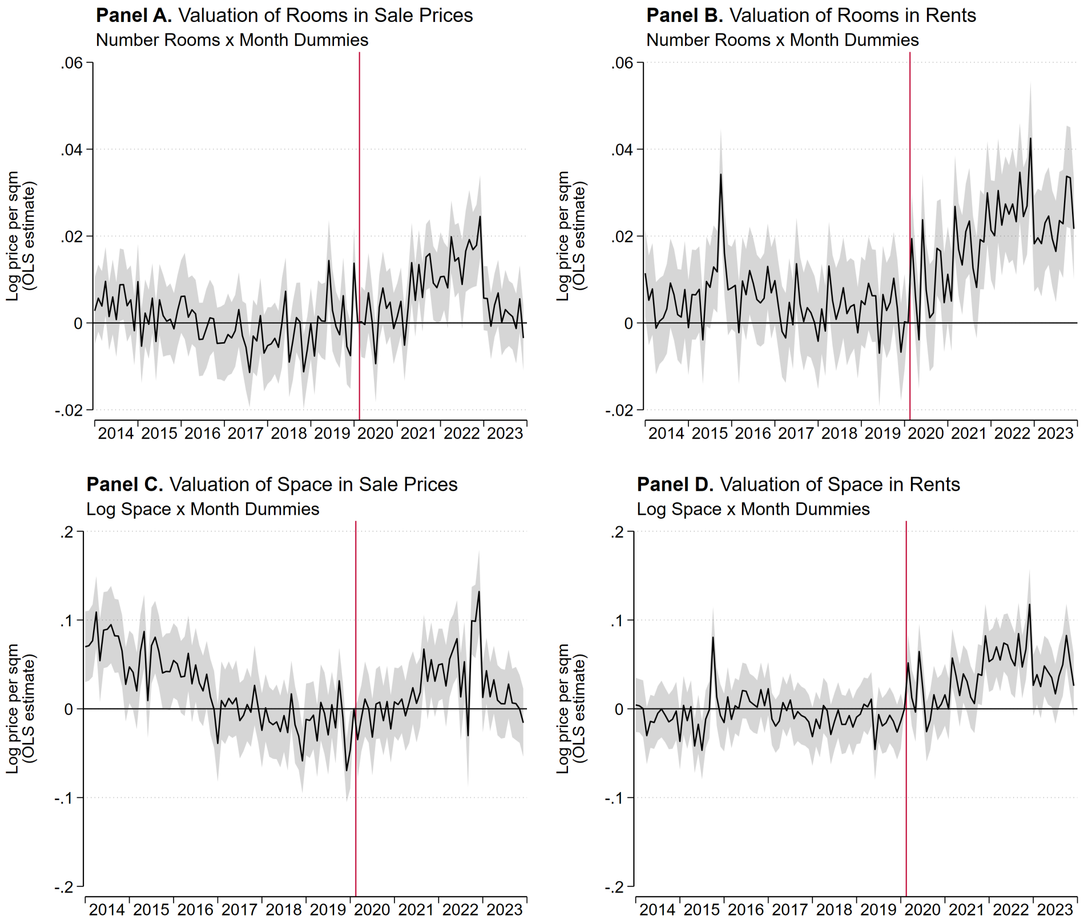
### 3.6.3 Increased Valuation of Larger Properties Suitable for WFH

As a third demand-side mechanism, we examine how WFH has revalued residential properties better suited for remote work, particularly larger homes. Greater WFH adoption likely increases demand for space, such as dedicated home offices, driving up demand for larger properties.

In Figure 3.11, we analyze the changing valuation of floor space and the number of rooms of residential properties. We again employ a dynamic DiD approach over the period from 2014 to 2023. The results reveal mostly insignificant pre-trends, followed by a significant increase in the valuation of larger properties since the pandemic and the rise in WFH. We find an increased valuation of space particularly in rents. The heterogeneity analysis by property type in Appendix Figure C.21 compares the effects across 1-bedroom, 3-bedroom and garden apartments. While there is an increase in sale prices of garden apartments, we do not find significant differences for rents.

Overall, the rising valuation of larger properties is a channel through which WFH influences urban housing prices. Since these larger properties are mostly located in the suburbs and periphery, this contributes to the flattening of the urban price gradient.

**Figure 3.11:** Increased Valuation of Space and Rooms




*Notes:* This figure presents DiD estimates $\hat{\beta}_k$ from separate regressions in the form of Equation 3.1, Equation 3.2 and Equation 3.3, in which the interaction terms are between monthly dummies from January 2014 until December 2023 and postcode-level average number of rooms per property in Panels A and B as well as between monthly dummies and postcode-level average log floor space per property in Panels C and D. The dependent variable is the postcode-level average log sale price per square meter in Panels A and C as well as 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.

### 3.6.4 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. (2022a), 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 log distance from the urban center and WFH potential have a differential effect on these outcomes over the period from 2014 to 2023.

We find that neither housing quantity nor liquidity changes meaningfully over time with respect to distance and WFH potential. Detailed results for housing quantity and liquidity are provided in Appendices Figure C.22 and Figure C.23, 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).

## 3.7 Discussion and Conclusion

Our study provides causal evidence that WFH has significantly reshaped the spatial distribution of housing prices within metropolitan areas. Exploiting postcode-level variation in exposure to the WFH shock across Germany's 50 largest metropolitan areas, we find that WFH has flattened the urban housing price gradient and reduced spatial disparities in housing costs. A 10 percent greater distance from the city center is associated with a 0.5 percent increase in sale prices and rents in 2023, while a one percentage point higher WFH potential lowers them by 0.4 and 0.3 percent, respectively. Importantly, within-city variation in WFH potential explains significant differences in housing price changes, even after controlling for distance from city centers. The impact of WFH on urban housing markets is driven by demand-side mechanisms as remote work partially decouples workplaces and residences. We find reduced inflows to urban cores, increasing housing demand and employment growth in suburban and peripheral areas as well as rising valuations for larger, WFH-suitable properties.

We show that WFH drives the "donut effect" in Germany, similar to U.S. cities (Gupta et al., 2022a; Ramani et al., 2024), but with a smaller magnitude. This suggests that German – and likely other European – cities remain desirable places to live for high-income households thanks to superior amenities and quality of life. Our novel finding is that WFH not only flattens the urban price gradient but also diminishes spatial disparities in housing costs within cities, reducing price differences even at similar distances from urban centers.

Contrary to previous studies, our findings suggest that the welfare effects of WFH depend on location. While Davis et al. (2024b) and Richard (2024) find that remote work reduces welfare for non-WFH workers by driving up overall housing prices due to increased demand and inelastic supply, Delventhal et al. (2022) observe that WFH improves welfare through falling real estate prices. In contrast, we show that WFH improves affordability in urban cores but drives up housing demand and thus prices in suburban and peripheral areas, with an overall reduction of spatial inequality that extends beyond the flattening of the urban gradient.

Our findings have important implications for the future of cities. As WFH continues to reshape the geography of urban housing markets, policymakers need to account for shifting demand patterns to ensure efficient and equitable urban development. The reduced premium on proximity challenges the viability of urban centers, affecting consumption amenities, commercial real estate, and the provision of local public goods. In urban cores, declining housing costs improve affordability, but urban resilience may require adjustments in land use policies, investments in amenities, and the conversion of commercial properties. In contrast, rising demand in suburban and peripheral areas highlights the need for expanded infrastructure, improved public transit, and greater housing supply to accommodate population growth without worsening affordability.

Future research could explore how WFH-induced shifts in housing demand affect labor mobility, firm location decisions, and urban wage premia, as well as the long-term implications for housing affordability and spatial inequality.

# 4

# The Centralization Effect: Working from Home and Urban Office Real Estate

## Abstract

This paper examines how working from home (WFH) reshapes urban office real estate, focusing on firm-level office space and within-city location decisions in Germany's seven largest metropolitan areas. Using a difference-in-differences approach and a novel dataset of 35,000 office leases and WFH survey data, I exploit industry-level WFH variation to estimate its effect on office leasing from 2019 to 2023. I find that a one percentage point increase in the industry-level WFH rate reduces total newly leased office space by two percent and average office size by one percent in 2023 relative to 2019. The impact is heterogeneous, with newer and high-quality offices remaining unaffected, while older, lower-quality buildings experience the largest declines. Spatially, WFH leads to a centralization effect, with increased demand for centrally located offices. The urban rent gradient remains stable, while vacancies rise in suburban and peripheral areas. These shifts are driven by firm-level demand rather than supply-side adjustments or employment changes, as WFH-intensive firms downsize space and prioritize location quality. These findings suggest a reallocation of office demand rather than a uniform decline, with implications for urban planning, real estate markets, and firm location choice. [1]



*Keywords*: Working from Home, Commercial Real Estate, Office Space Demand, Agglomeration Economies, Cities

*JEL-Codes*: D1, E2, J0, R0



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## 4.1 Introduction

One of the most profound shifts in labor markets in recent years has been the rise of working from home (WFH). Initially driven by the Covid-19 shock, WFH has persisted well beyond the pandemic, marking a structural change in work organization (Aksoy et al., 2022; Barrero et al., 2021b; Bloom et al., 2024; Hansen et al., 2023). The predominant WFH model today is hybrid work, with employees alternating between home and office days (Bloom et al., 2024; Destatis, 2024).[2] The post-pandemic WFH rate has stabilized at an elevated level globally. In the U.S., around 27 percent of paid workdays are remote, while in Germany, about 25 percent of employees work from home at least part-time – a fivefold increase compared to 2019 (Figure 4.1). Prior research shows that WFH is prevalent in occupations that cluster in large cities, where its effects on firms, workers, and real estate markets are most pronounced (Alipour et al., 2023; Dingel and Neiman, 2020).

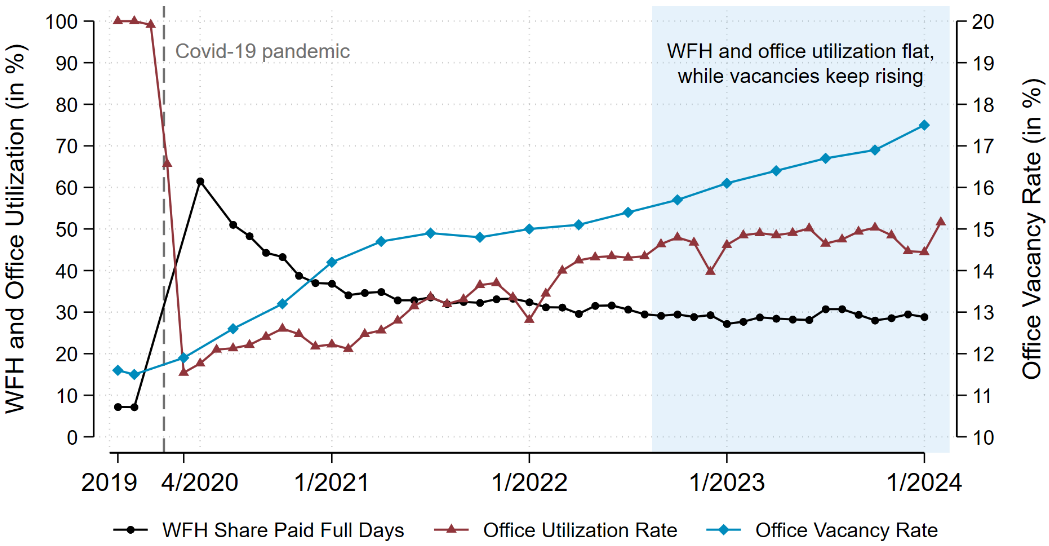
Cities benefit from agglomeration economies, where dense urban centers attract high-skilled workers and productive firms that gain from proximity, knowledge spillovers, and shared amenities. However, WFH weakens the link between workplaces and residences, as fewer people commute daily to city centers. This shift has reduced office utilization, contributing to a "donut effect" of declining central foot traffic and raising concerns about an "urban doom loop," in which rising office vacancies, falling commercial real estate (CRE) values, and lower economic activity create negative spillovers for retail, services, and employment. Office utilization has plateaued at about half of the pre-pandemic level, and vacancy rates have doubled in Germany (Figure 4.1). In the U.S., Gupta et al. (2022b) find an "apocalypse" in office valuations amid even higher vacancies. However, little is known about how WFH affects office demand at the firm and spatial level, particularly outside the U.S. WFH may reshape firms' location preferences, leading to a reallocation of office demand rather than a uniform decline. Understanding these dynamics is essential for assessing the impact of WFH on urban structure, firm location choices, and CRE markets.

This paper examines how WFH reshapes firm-level and spatial office demand in Germany's seven largest metropolitan areas. I first document trends in urban office leases and WFH

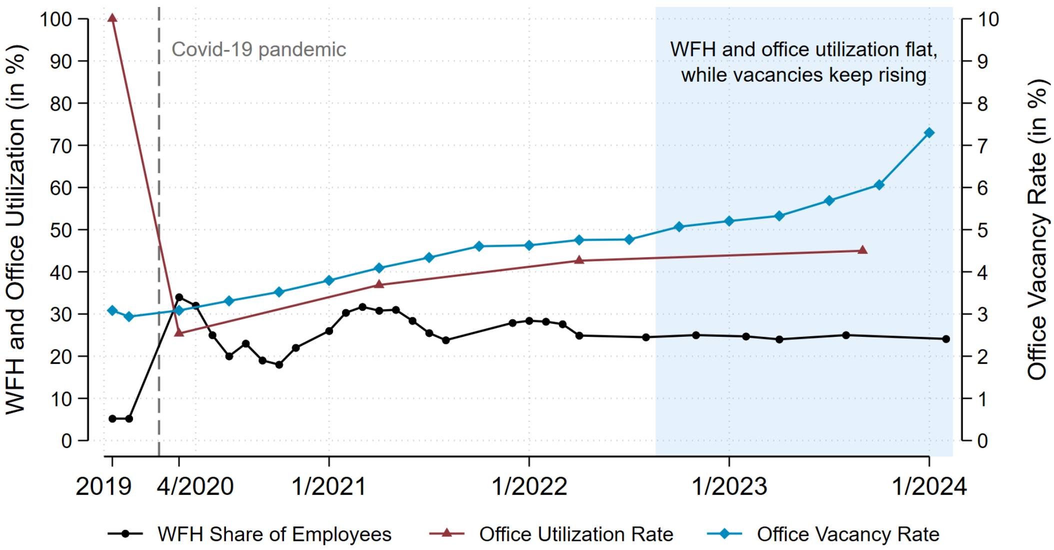
[2] According to the German micro-census, 25 percent of the German workforce worked remotely in 2023; among them, 74 percent were hybrid and 26 percent fully remote (Destatis, 2024).

**Figure 4.1:** WFH, Office Occupancy, and Office Vacancies 2019 – 2024

**(a)** United States




**(b)** Germany




*Note:* The panels report the development of the WFH rate over time in black, the office utilization rate in red, and the office vacancy rate in blue. Panel A depicts the evolution in the U.S., while Panel B captures the trends in Germany. The dashed grey line marks the outbreak of the Covid-19 pandemic in March 2020. The shaded blue area highlights the post-pandemic stabilization in WFH and office utilization. WFH data for the U.S. are from Barrero et al. (2021b), while WFH data for Germany are from Eurostat (2012-2019), infas360 (2020-2021) and ifo Institute (2021-2023). The office utilization data are normalized to an index value of 100 percent for 2019, although offices were not fully utilized before the pandemic. Data sources are Kastle (2019-2024) for the U.S., and Combine (2019-2022) and Savills (2023) for Germany. The office vacancy rates are from Colliers USA and Germany (2024).

using cross-sectional micro-data from the *ifo Business Survey* (7,000+ firms) and office lease data from *Colliers* (35,000+ leases) from 2014 to 2023.[3] This study focuses on leasing rather than sales, as leasing decisions better reflect firms' office space demand. The analysis builds on urban economics models, where firms balance agglomeration benefits against office costs. In response to increased WFH, firms may (i) downsize if cost savings outweigh productivity and agglomeration benefits, (ii) upgrade to higher-quality offices if productivity gains justify higher rents, or (iii) relocate centrally if access to amenities and agglomeration benefits outweigh higher costs. To test these hypotheses, I use a difference-in-differences (DiD) strategy that exploits variation in pandemic-induced WFH growth (2019–2023) across industries as an external shift in office demand. A dynamic DiD specification links leasing outcomes (2017–2023) to pre-pandemic (2019) industry WFH rates, which strongly predict post-pandemic WFH growth. A long DiD specification captures the cumulative effect by comparing office leasing changes between 2019 and 2023. The estimates control for metro-area-by-year fixed effects, within-metro variation in business and property tax rates, postcode characteristics, and industry employment shifts. The urban analysis examines office moves and the spatial distribution of vacancies. I conduct extensive heterogeneity analyses and robustness checks and assess demand- and supply-side mechanisms using firm-level survey information on office leasing preferences as well as data on office supply and employment. By providing evidence on firm-level and spatial adjustments, this study advances the understanding of how urban office markets adapt to hybrid work.

The analysis yields four main results. First, WFH growth has a significantly negative impact on office space demand, driven by fewer leases and space downsizing. At the industry level, a one percentage point WFH growth from 2019 to 2023 is associated with a two percent decline in total office space leased, along with a decline in the number of leases. WFH growth (2019-2023) is linked to a one percent reduction in average space per office lease. This indicates that firms adjust their space needs both by leasing smaller offices and signing fewer leases. Notably, rents remain unaffected by WFH at both the industry and firm levels, suggesting that reduced office space demand in WFH-intensive industries has not led to rent declines. The heterogeneity analysis reveals that the effect is strongest for WFH-intensive firms within

[3] *Colliers Germany* advises CRE users, owners, investors, and developers. Their market intelligence team tracks all known office leases in the market, not just those brokered by Colliers.

industries experiencing above-average WFH growth, reinforcing the role of hybrid work in reshaping office demand.

Second, the WFH impact on office markets is heterogeneous. Older and lower-quality buildings experience the strongest negative impact, while newer and high-quality buildings are largely unaffected. Given the ongoing shift toward environmental, social, and governance (ESG) standards in corporate real estate, this trend cannot be attributed solely to WFH. However, survey evidence indicates that WFH accelerates this transition by making office quality a more critical factor in leasing decisions, as hybrid firms may prefer better office spaces for office days. This finding aligns with Gupta et al. (2022b), who show that prime office spaces in the U.S. are shielded from WFH-induced demand declines. This suggests that firms increasingly prioritize office space quality over quantity.

Third, contrasting with findings of a "donut effect" in residential real estate and urban consumer spending (Alipour et al., 2022; Brueckner et al., 2023; Duguid et al., 2023; Ramani et al., 2024), the evidence points to a centralization effect in urban office real estate. Within metro areas, I find a positive impact of WFH on office leases in central business districts (CBDs), whereas the strongest declines occur in suburban areas. WFH growth is negatively associated with office distance from the city center, with a one percentage point increase in WFH reducing distance by about 0.6 percent. The urban gradient for office leasing outcomes remains stable, particularly for rents. This reflects the persistent amenity and accessibility value of central locations. Furthermore, the analysis of recent office moves complements this result. While relocations in 2020, which were likely initiated before the pandemic, exhibit an increase in city-center distance, moves since then show a minor centralization effect. Similarly, vacancy rates have risen the most in suburbs and peripheral areas but remained stable in urban cores, confirming the shift in office demand toward central locations.

Fourth, the WFH effect on office leasing is driven by demand-side mechanisms, while there is an absence of significant supply-side adjustments. There is a strongly positive relationship between WFH growth and office downsizing, affecting both small and large firms. Survey evidence suggests that firms with high WFH adoption revise their leasing criteria, favoring more central locations, higher office quality, increased desk sharing, and expanded social spaces. These changes reflect shifts in work organization in hybrid firms. The spatial analysis of office stock changes finds no significant supply adjustments across CBDs, cities, suburbs, and peripheries. Lastly, I explore employment as a potential channel through which WFH impacts office demand. By controlling for employment changes, the main specification isolates the impact of WFH from this channel. WFH growth is positively but insignificantly associated with employment growth, and employment changes do not differ significantly between cities and their surroundings. Thus, employment shifts do not explain the impact of WFH.

These findings have important implications for office real estate, urban planning, and the CRE industry. As hybrid work reshapes office demand, firms prioritize higher-quality spaces in newer, centrally-located buildings, reinforcing the office as a collaboration hub rather than a daily workspace. Coordinated office and remote work days create uneven urban dynamics, filling city centers on office days and leaving them emptier on remote work days. Policymakers need to adjust public transportation, retail planning, and zoning to accommodate these shifts. Furthermore, increasing office vacancies highlight the need for conversion policies to support residential or mixed-use redevelopment of empty office buildings. This is particularly relevant in suburban and peripheral areas, where vacancies are concentrated despite housing shortages. Additionally, targeted strategies are needed to revitalize urban centers.

This study contributes to the growing literature on WFH and real estate markets by examining its impact on firm-level office demand and the spatial distribution of office leases. While most research focuses on the U.S., this study provides long-term post-pandemic evidence from Germany, where urban structure, public transit reliance, and commercial real estate dynamics differ. Studies have documented declining office valuations (Gupta et al., 2022b), a flattening of urban rent gradients (Althoff et al., 2022; Gupta et al., 2022a; Ramani et al., 2024; Rosenthal et al., 2022), and broader shifts in urban economic geography (Delventhal et al., 2022; Delventhal and Parkhomenko, 2023; Duranton and Handbury, 2023; Monte et al., 2023). Gupta et al. (2022b) find that WFH drives declines in U.S. office valuations, while Bergeaud et al. (2023) show a similar effect in France. Much of the literature emphasizes a "donut effect," where WFH shifts housing demand and consumer spending outward (Alipour et al., 2022; Brueckner et al., 2023; Duguid et al., 2023; Gupta et al., 2022a; Mondragon and Wieland, 2022; Ramani et al., 2024). However, evidence on office markets, particularly outside the U.S., remains scarce. While previous studies focus on metro-level changes, my analysis of within-city variation in Germany over an extended post-pandemic period shows that WFH leads to a reallocation of office space demand rather than a uniform decline. My findings complement Gupta et al. (2022b), who show that prime office spaces are more resilient to the negative impact of WFH, and extend the literature by examining spatial heterogeneity in office demand within cities.

Finally, this study contributes to the debate on the future of cities in the WFH era. While some predict a decline in urban agglomeration due to WFH (Duranton and Handbury, 2023; Glaeser and Cutler, 2021), my findings suggest that proximity and accessibility remain valuable. Rather than eroding agglomeration, WFH reconfigures office demand, with firms adapting their location strategies to balance flexibility with the benefits of urban density.

The remainder of the paper is organized as follows: Section 4.2 describes the sample and data and presents descriptive evidences on recent trends in urban office markets and WFH. Section 4.3 outlines the empirical framework of the analysis, embedding it within a broader theoretical foundation. Section 4.4 conducts the firm-level analysis of WFH and office demand. Section 4.5 carries out the spatial analysis of the WFH impact on urban offices. Section 4.6 investigates the mechanisms behind the WFH effect. Finally, section 4.7 discusses the findings, policy implications, and concludes.

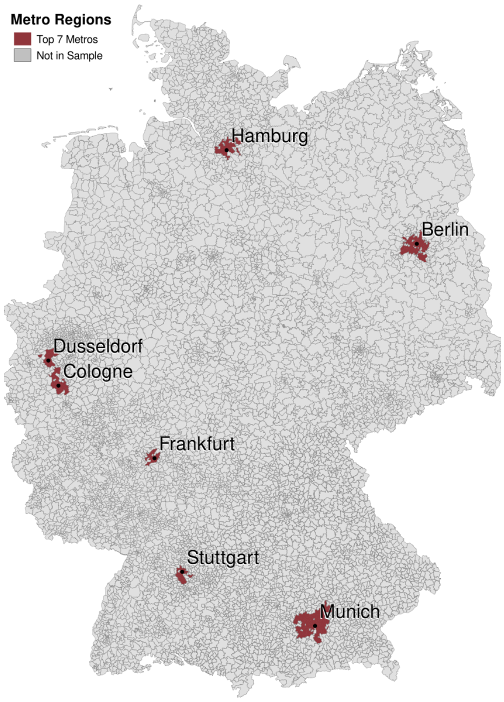
## 4.2 Data and Descriptive Evidence on WFH and Urban Office Markets in Germany

### 4.2.1 Sample

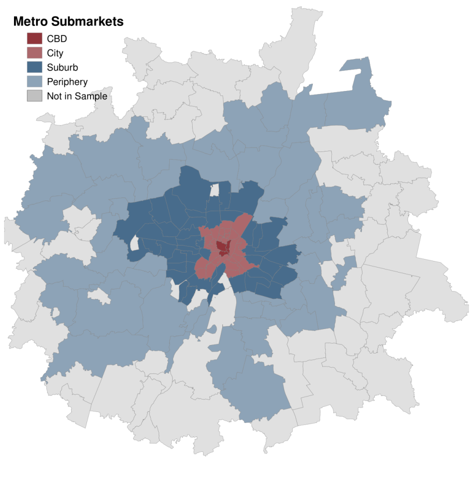
This study combines firm-, industry-, and postcode-level data on WFH prevalence, office leases, and local economic conditions in Germany's seven largest metropolitan areas: Berlin, Hamburg, Munich, Cologne, Frankfurt, Stuttgart, and Dusseldorf. These regions are home to about 17 million people (20 percent of the population) and account for almost 10 million jobs (22 percent of the workforce). These metropolitan areas serve as regional economic hubs and are similar to U.S. commuting zones. Covering the period from January 2014 to December 2023, the analysis encompasses approximately 500 postcodes within these regions. I leverage repeated cross-sectional WFH micro-data from the *ifo Business Survey* with more than 7,000 German firms and office lease data from *Colliers*, a commercial real estate consulting firm, with more than 35,000 new leases in the seven metropolitan areas. WFH data are collected at the firm level and aggregated to the industry level, where they are matched to individual office leases based on tenants' reported industries. Additionally, I incorporate administrative data on municipality-level business and property tax rates, as well as industry-

**Figure 4.2:** Sample of Urban Office Leases and WFH Growth in Germany

**(a)** Sample of 7 Largest German Metro Areas




**(b)** Metro Area Submarkets Example: Munich




*Note:* These maps illustrate the sample, consisting of Germany's seven largest metropolitan areas: Berlin, Hamburg, Munich, Cologne, Frankfurt, Stuttgart, and Dusseldorf. Panel A highlights these metropolitan areas in red, where I combine firm-, industry- and postcode-level data on office leases and WFH. Areas marked in gray are not included in the sample. Panel B provides a detailed breakdown of postcodes in the metropolitan areas into four submarket categories: central business district (CBD), city, suburb, and periphery. The map shows the Munich metropolitan area as an example, which is representative of the other cities.

level and spatial employment data. At the postcode level, I observe distance of the leased office space from the city center and population density, allowing for a detailed spatial analysis of office market dynamics.

Figure 4.2 Panel A presents a map of Germany highlighting the seven metropolitan areas included in the sample. As shown in Panel B for the Munich metropolitan regions, postcodes are categorized into four submarket types: central business district (CBD), city, suburb, and periphery (see Appendix Figure D.1 for a map of all cities and submarkets). Summary statistics are reported in Appendix Table D.1.

### 4.2.2 Data and Trends in Urban Office Leases

**Office Leases Data** I use repeated cross-sectional transaction data on new office leases provided by Colliers (2024). *Colliers Germany* advises commercial real estate users, owners, investors and developers. Their market intelligence division tracks the office real estate market in the seven major German cities, gathering data on all office leases known to the market, not only those brokered by Colliers. This ensures that their data accurately capture deals on the office leasing market and are not affected by shifting dynamics due to the WFH increase. The dataset includes over 35,000 recorded office leases across Germany's seven largest office markets (Berlin, Hamburg, Munich, Cologne, Frankfurt, Stuttgart, and Dusseldorf) from 2014 to 2023. For the main analysis, I focus on new leases signed between January 2018 and December 2023, around the Covid-induced WFH shock in 2020.

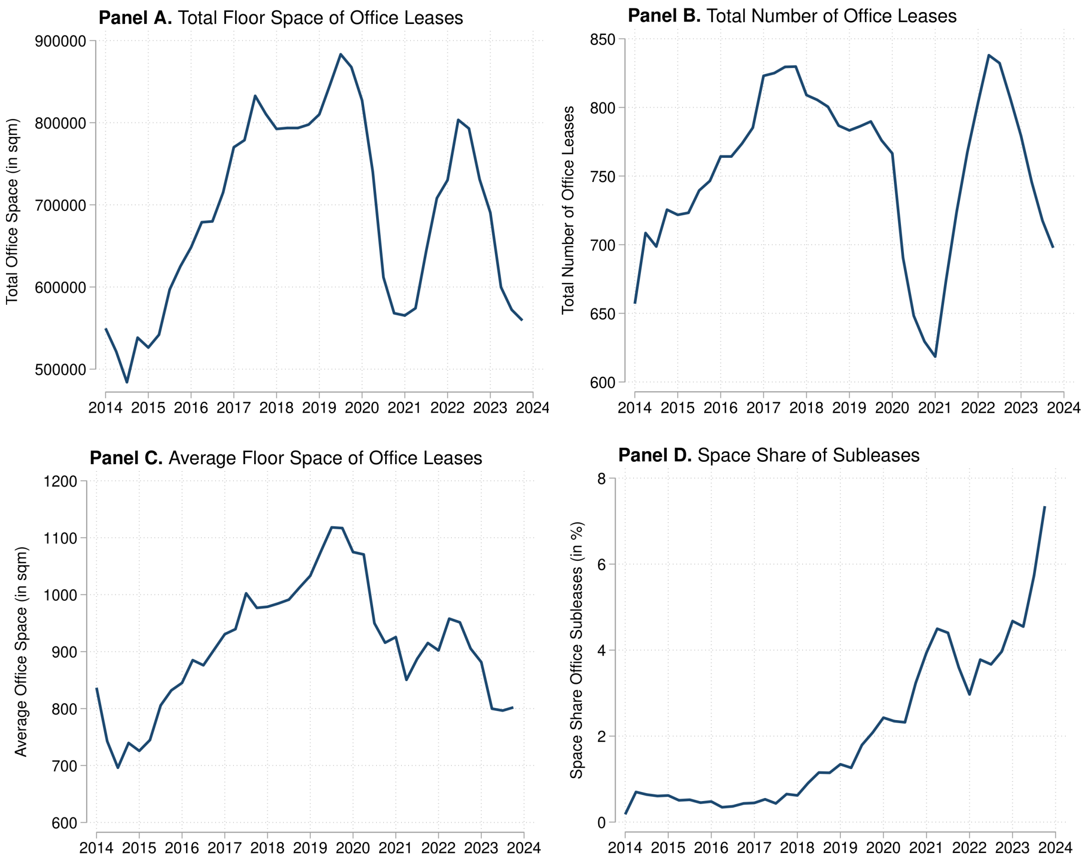
The dataset provides detailed leasing information, including leased space, rent, building quality, age, postcode-level location, and tenant industry. Unlike datasets based on property listings, which reflect asking prices and available spaces, these data capture actual contractual terms and identify the industry of the leasing firms. For the empirical analysis, the raw data undergo cleaning and validation, ensuring that observations with missing rent or area values are excluded.

Importantly, the dataset does not track the stock of office leases or a panel of lease agreements over time, but rather a cross-section of newly signed leases in each year. This includes extensions of existing leases if a new contract was signed upon expiration. Furthermore, data for the Hamburg and Cologne metropolitan regions are incomplete before 2017 and 2019, respectively.

Beyond lease transactions, the Colliers database also provides submarket-level data on office inventory and vacancy rates, allowing for a broader assessment of office market dynamics.

**Descriptive Evidence** This subsection documents recent trends in new office leases across Germany's seven largest metropolitan areas. Figure 4.3 presents quarterly data, which were smoothed using a four-quarter moving average, to highlight shifts before and after the Covid-induced WFH shock.

**Figure 4.3:** Trends in Urban Office Leases 2014-2023




*Notes:* This figure displays trends in the space of office leases in the metropolitan areas between 2014 and 2023. Panel A reports the total aggregate floor space of office leases in square meters, panel B shows the total number of individual lease agreements. Panel C reports the average floor space of single lease agreements. Panel D reports the percentage of total space that is leased under a sublease agreement. Data are from Colliers (2024).

Panel A shows total floor space of new office leases, revealing a steady upward trend from 2014 to 2019 before dropping sharply in 2020. Although leasing activity partially recovered in 2022, it fell again in 2023 to levels comparable to the peak of the pandemic, indicating persistent office demand weakness. Panel B plots total lease counts, which follow a similar pattern, but the decline is less pronounced. This suggests that firms primarily downsize rather than not leasing new office space any more.

Panel C illustrates average office size per lease, which rose from 800 to 1,100 square meters (2014–2019), but has declined steadily since 2020, returning to 800 square meters by 2023. This suggests a shift toward smaller office spaces, potentially reflecting firms adapting to hybrid work models with less office space. Panel D tracks subleasing as a share of total leased space, an indicator of firms seeking to reduce office space in the short-run while maintaining existing leases. From a stable subleasing share of about one percent pre-pandemic, subleasing surged to eight percent by late 2023. This increase indicates that more firms have recently reduced their office footprint.

Figure 4.4 presents trends in office leasing revenue and rents from 2014 to 2023. Panel A shows that total leasing revenue nearly doubled from 2014 to 2019 before dropping sharply in 2020. Although it briefly recovered in 2022, it fell again in 2023, mirroring the decline in total leased space.

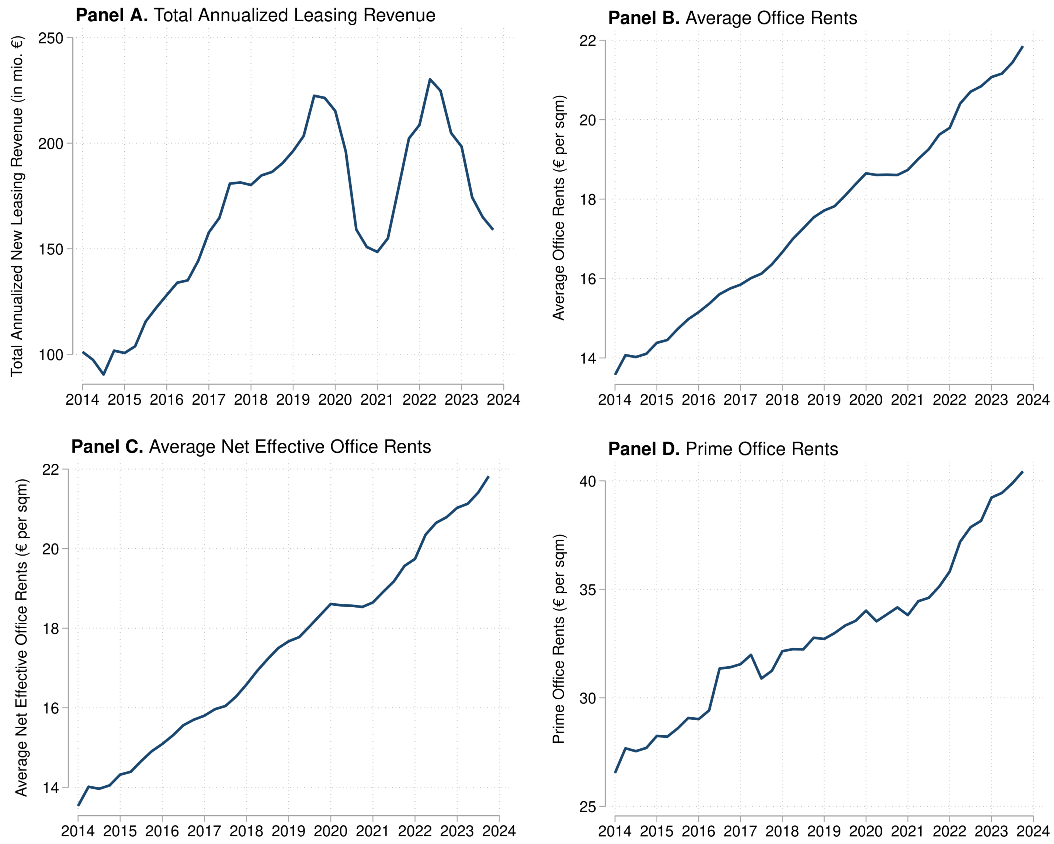
Despite this contraction, Panels B to D show that rents have remained rigid. Average office rents (Panel B) increased from 14 euros per square meter in 2014 to 22 euros per square meter in 2023. Average net effective rents (Panel C), which adjust for incentives such as rent-free months, follow the same pattern. Prime office rents (Panel D), defined as the top three percent of rents in each metro and period, have also steadily increased over time, reaching an average of 40 euros per square meter in 2023.[4]

Appendix Figure D.3 to Figure D.9 present the same trends for each of the seven metropolitan areas. While there is some heterogeneity, the overall patterns are consistent across cities.

Taken together, these trends indicate a structural contraction in office demand, as firms lease less space, downsize, and turn to subleasing. However, rents remain rigid, likely due to fixed lease agreements, landlords' reluctance to lower prices, or firms' willingness to pay premiums for high-quality office space.

[4]Appendix Figure D.2 visualizes the urban rent gradient of office rents, with the highest rents in the CBD and the lowest rents in the periphery.

**Figure 4.4:** Trends in Urban Office Rents 2014-2023




*Notes:* This figure displays trends in the rents paid for office leases in the observed metropolitan areas between 2014 and 2023. Panel A reports the total aggregate leasing revenue per annum in millions of euros. Panel B shows the average rent per square meter in euros. Panel C reports the average net effective rent per square meter in euros. Panel D reports the rent per square meter for prime office spaces. Data are from Colliers (2024).

### 4.2.3 Data and Trends in WFH

**WFH Survey Data** I use firm-survey micro-data on industry-level WFH prevalence from 2019 to 2023, drawn from the *ifo Business Survey* (EBDC-BEP, 2023; Sauer et al., 2023). Conducted monthly among 9,000 firms across services, manufacturing, construction, and retail, the survey produces the ifo Business Climate Index, a widely used economic indicator.

Since 2021, survey waves have regularly included questions on WFH prevalence, measured as the share of employees working from home at least partly. The WFH data are repeated cross-sectional, with more than 7,000 firms responding on average. In April 2023, the survey introduced a retrospective question on pre-pandemic WFH rates (2019), providing the baseline for my analyses. While recall bias is a potential concern, the pre-Covid reference point is well-defined. Furthermore, the 2019 WFH rate of the ifo data aligns closely with administrative records (Destatis, 2024).

Due to anonymity requirements, it is not possible to link ifo Business Survey data at the firm level with Colliers office lease data, limiting the analysis to industry-level WFH variation. Since the ifo dataset excludes the financial and public sectors, WFH rates for these industries are imputed using the service sector average.[5] Appendix Table D.2 details the mapping of ifo industry classifications to Colliers industry categories.

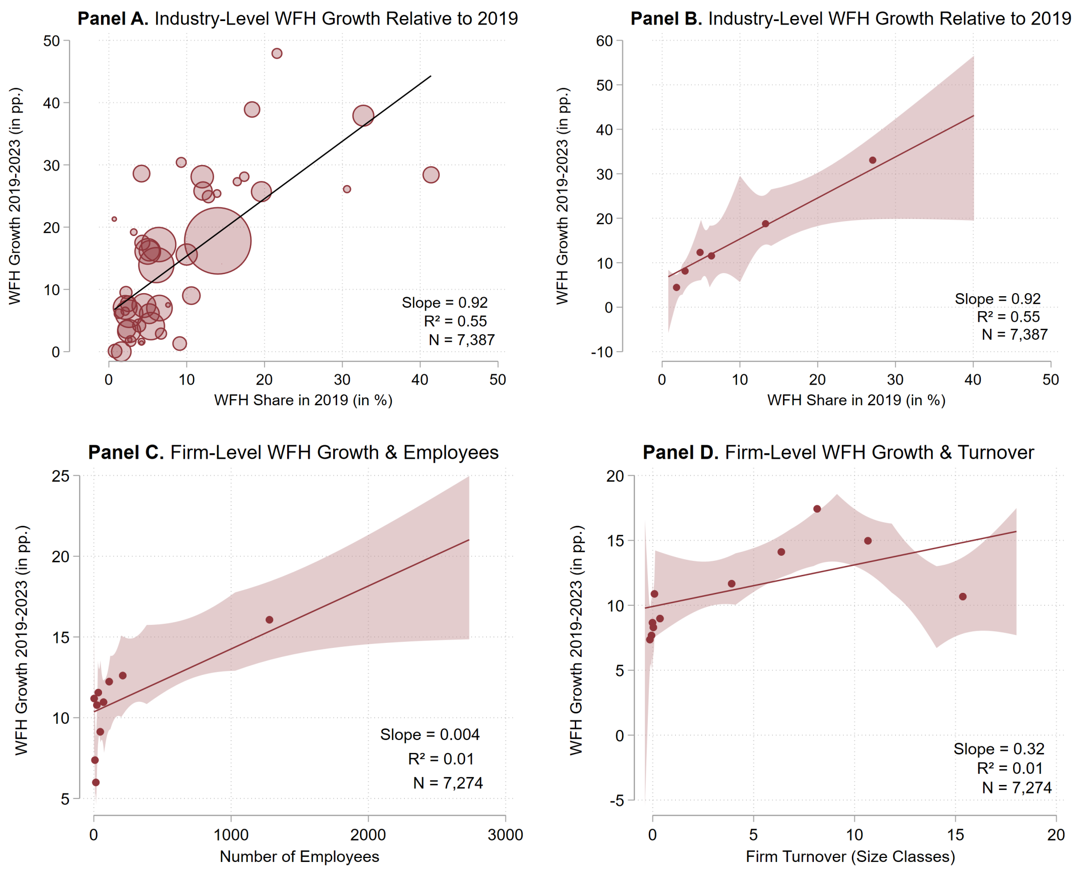
**Descriptive Evidence** The descriptive analysis in Figure 4.5 shows substantial industry-level variation in both the level and growth of WFH between 2019 (pre-pandemic) and 2023 (post-pandemic). As established by previous research (Alipour et al., 2023; Dingel and Neiman, 2020), the prevalence of WFH across industries is largely determined by task characteristics, digital adaptability, and the feasibility of remote collaboration.

Panels A and B display the industry-level relationship between pre-pandemic WFH rates in 2019, measured as the share of employees per industry that works from home at least partly, and WFH growth from 2019 to 2023. The scatter plot in Panel A shows that industries with higher WFH adoption in 2019 experienced the largest increases in WFH. The strong positive relationship highlights that the Covid-induced shift to remote work was proportional to pre-pandemic WFH levels. This suggests that the pandemic reinforced existing patterns, rather than equalizing WFH adoption across industries. One possible explanation is that industries with established remote work infrastructure or job tasks conducive to WFH were better positioned to expand WFH when pandemic lockdowns and WFH mandates in 2020 made it necessary. In fact, the largest increases occurred in knowledge-based industries such as IT, advertising, information services, travel agencies, and consulting, whose job tasks allow for a high share of remote work. In contrast, industries with little pre-pandemic WFH may have faced and still face structural barriers, as their job tasks requires in-person work, which prevents more WFH adoption. This applies to industires, such as hospitality, postal and courier

[5] Both the financial and public sectors account for about five percent of the total sample. The imputed WFH rates in 2023 (service-sector average) align closely with micro-census data on WFH adoption from the German micro-census (Destatis, 2024). Additonally, I conduct a robustness check in Appendix Table D.12, which shows that the main estimates are robust to excluding observations from these two industries.

services, retail, and construction, which saw only little WFH growth. Panel B confirms this pattern using a binned scatter plot. The positive relationship is significant, as the fitted line lies within the confidence band for the entire distribution.

**Figure 4.5:** Trends in Working From Home 2019-2023




*Notes:* This figure displays industry- and firm-level relationships of WFH growth. Panel A shows a scatter plot of the 2019-2023 growth of the share of employees working partially or fully from home relative to the baseline WFH rate in 2019. The size of the bubbles represent industry size weights. Panel B presents the same relationship in a binned scatter plot using the methodology by Cattaneo et al. (2024) with evenly spaced bins (quantiles), a fitted line, and the 95 percent confidence interval. Panels C and D illustrate binscatter regression estimates on the firm-level relationship between WFH growth and firm size measured in the number of employees and turnover, respectively. Data are from the ifo Business Survey (EBDC-BEP, 2023).

At the firm level, Panels C and D examine how WFH growth correlates with firm size, measured by employees (Panel C) and turnover (Panel D). Larger firms have higher WFH growth, but the confidence intervals indicate substantial variation. Since large firms, particularly in service-sector industries, account for the majority of office leasing, their increased WFH adoption likely influences office demand.

Overall, WFH growth followed pre-pandemic adoption patterns, with Covid accelerating rather than reshaping industry trends. While differential firm strategies and policy responses have likely played a role, pre-existing industry characteristics appear as the main driver. The results suggest that WFH growth was largely externally driven by the pandemic, making it a plausible although not entirely exogenous treatment variable.

### 4.2.4 Connecting WFH Growth and Urban Office Leases

Figure 4.6 investigates the industry-level relationship between WFH growth and distance from the city center with office market outcomes from 2019 to 2023.

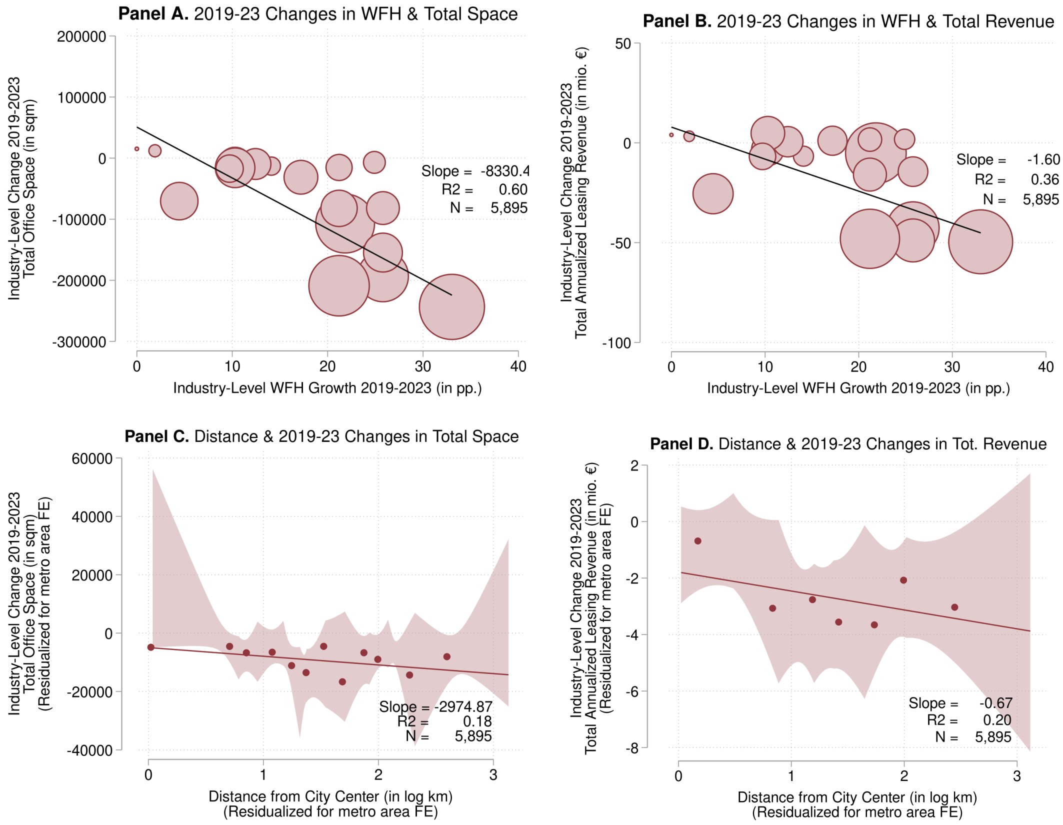
Panels A and B show scatter plots of WFH growth against changes in total office space leased and total annualized leasing revenue, respectively. Both plots reveal a strongly negative relationship, indicating that industries with higher WFH growth saw larger declines in office demand and revenue from new office leases. As the bubble sizes reflect industry weights, the charts show that larger industries drive the negative relationship.

Panels C and D present binned scatter plots of postcode-level distance from the city center against changes in office space leased and leasing revenue, respectively. The slightly negative relationship suggests that WFH-driven office demand reductions are distributed rather evenly across urban areas. However, there is a weaker or even slightly positive effect in the CBD.

In Appendix Figure D.10, I use firm-level data on individual office leases to examine the same relationships between WFH growth, distance, and office outcomes at a more granular level. While the overall patterns persist, there is larger variation in outcomes at the firm-level than at the industry-level.

While these patterns suggest a link between WFH growth and changes in urban office leases, they are not causal. Many factors, including industry composition, economic conditions, and firm-specific decisions, may simultaneously influence both WFH adoption and office leasing outcomes. Therefore, the further analysis adopts a more rigorous empirical approach to isolate the effects of WFH on urban office markets.

**Figure 4.6:** Industry-Level Correlation of WFH Growth and Distance with Changes in Office Space and Rents 2019-2023




*Notes:* This figure shows industry-level relationships between WFH growth, distance and office market outcomes. Binscatter regression estimates are residualized for metro area fixed effects, using evenly spaced bins (quantiles), fitted lines, and 95 percent confidence intervals (Cattaneo et al., 2024). Panel A plots WFH growth against changes in total office space leased (2019-2023), while Panel B relates WFH growth to changes in total annualized leasing revenue (2019-2023). In both scatter plots, the bubble sizes reflect industry weights. Panels C and D display binned scatter plots of postcode-level distance from the city center and changes in total office space leased (Panel C) and total annualized leasing revenue (Panel D) over the period 2019-2023. Data are from the ifo Business Survey (EBDC-BEP, 2023) and Colliers (2024).

## 4.3 Empirical Framework: WFH Impact on the Urban Office Leases

### 4.3.1 Conceptual Framework

This paper builds on standard urban economics models, where firms and workers optimize location decisions by balancing agglomeration benefits, office costs, and commuting considerations. In the *Rosen-Roback model* (Roback, 1982; Rosen, 1974), urban wages and rents adjust to equalize utility across locations. Changes in work arrangements, such as the increase in WFH, can alter firms' demand for office space and the spatial structure of cities. Similarly, in *quantitative spatial models* (e.g. Ahlfeldt et al. (2015)), equilibrium outcomes depend on the distribution of firms, workers, and amenities – all of which are affected by WFH adoption.

The shift to WFH weakens the traditional link between firms' office locations and city centers by reducing the need for daily commuting. However, if in-person collaboration remains valuable, as in the predominant hybrid work model, firms may still prioritize high-quality, well-located offices. This implies persistent agglomeration forces in central areas rather than a uniform decline in office demand.

A stylized model in section D.3 provides a simple framework that captures the main mechanisms through which WFH affects urban office leases. The following presents the essence of the model. Specifically, I consider a **two-step process**:

1. **Work arrangements:**
    - Firms and workers determine their optimal mix of on-site, hybrid, or remote work to maximize profits and utility.
    - Firms balance the productivity benefits of in-office work ($\theta_i(A)$) and agglomeration advantages in urban centers ($\mu(d)$) against the cost of office space ($C_i(A, d)$).
    - Workers trade off commuting costs ($C_j(d)$) with access to urban amenities and professional advantages of working in a central location ($\nu(d)$).
    - With Cobb-Douglas preferences, there is positive demand for both in-office and remote work, which implies hybrid work as the optimal work arrangement. This aligns with the real economy, where hybrid work is the dominant WFH model.
2. **Office space decisions:** Based on work arrangements, firms adjust their office spaces, optimizing for size, quality, and location.

The stylized model yields three **testable hypotheses**:

1. **Office downsizing:** Firms in WFH-intensive industries lease less total office space, reducing dedicated workspaces as hybrid work lowers in-office demand. Downsizing oc-

curs when cost savings from reduced office space outweigh the productivity benefits of in-office work and agglomeration economies.

2. **Flight to quality:** Rather than abandoning office space, firms may prioritize higher-quality office spaces, favoring modern buildings with better amenities and flexible layouts. This shift occurs if the productivity benefits of upgrading outweigh the higher costs, particularly when downsizing frees up budget for higher-quality spaces.

3. **Centralization effect:** Firms may relocate toward central locations if the benefits of agglomeration, in-office productivity, and worker amenities outweigh the higher costs of office rents in the CBD. This reallocation of office demand toward urban centers suggests that WFH reshapes the spatial distribution of office leasing.

I empirically test these hypotheses by examining how WFH growth affects office leasing at the industry and firm levels, as well as how these effects vary across space within cities. The next subsection outlines the identification strategy in detail.

### 4.3.2 Identification Strategy

**Empirical Approach** To analyze the effect of WFH on office leasing, I use a difference-in-differences (DiD) strategy that exploits exploits industry-level variation in WFH growth induced by the pandemic as an external shift in office demand. In a dynamic DiD specification, I relate office leasing outcomes from 2017 to 2023 to pre-pandemic (2019) WFH rates across industries, which strongly predict WFH growth since the pandemic. A long DiD specification captures the cumulative effect of WFH growth by comparing changes in office leasing between 2019 and 2023. The treatment intensity of WFH is measured continuously, comparing industries with higher versus lower WFH adoption. The estimates reflect intent-to-treat (ITT) effects, since WFH adoption is observed at the industry level. This mitigates concerns about selection into WFH and office space adjustments at the firm level. Furthermore, industry-level WFH rates are not driven by individual firms, reducing endogeneity concerns. To account for broader office market dynamics, I include metro-area-by-year fixed effects to absorb local shocks and macroeconomic trends. Additionally, I control for within-metro variation in business and property tax rates, postcode characteristics, and industry-level employment. These controls ensure that the estimated WFH effect reflects shifts in office demand rather than differences in local policies, location attributes, or employment trends.

**Estimation** I estimate the impact of WFH on several office leasing outcomes, using industry-level variation in WFH adoption as the treatment variable. The outcomes include total office space leased and total leasing revenue at the industry level. At the firm level, I analyze average office space, average rent, and prime office rent. At the firm-postcode level, I examine how WFH growth affects office lease distance from the urban center. For consistency, all outcome variables are log-transformed. All specifications include metro-area-by-year fixed effects. The estimations with individual office leases as outcomes control for municipality-level business and property tax rates, postcode characteristics (distance from city center, population density), and industry-level employment. Including these controls in the industry-level estimates provides little additional explanatory power. For regressions with log distance from the city center as the outcome, postcode characteristics are excluded as controls. Standard errors are clustered at the industry-by-submarket level, assuming industry-level WFH growth has location-specific effects given spatial clustering of industries in different city areas (Abadie et al., 2023). In a robustness check, I test alternatives, including clustering at the industry-by-year level (with fewer clusters), which confirm the stability of the results (see Appendix Table D.9).

I estimate two specifications:

**Dynamic DiD** Firstly, I estimate a dynamic DiD model from 2017 to 2023 with annual interaction terms of the pre-pandemic WFH rate in 2019:

$$Outcome_{ict} = \sum_{k \neq 2019} \left[ \beta^k 1(k = t) \times WFH2019_i \right] + X'_{it}\gamma + \delta_{m(c)} \times \lambda_t + \varepsilon_{ict}, \tag{4.1}$$

where $Outcome_{ict}$ is the log office outcome variable of industry or firm $i$ in postcode $c$ and year $t$. $WFH2019_i$ denotes the pre-pandemic industry-level WFH rate in 2019, measured as the percentage of employees who work from home at least partly. $X'_{it}$ is a vector of controls for business and property tax rates, postcode characteristics, and industry employment. I include metro-area-by-year fixed effects $\delta_{m(c)} \times \lambda_t$ to absorb regional trends and common shocks. The reference period is 2019, just before the pandemic-induced WFH increase. I cluster standard errors at the industry-by-submarket-type level, accounting for correlation within industries and locations over time.

**Long DiD** Secondly, I estimate a long DiD model that compares office market outcomes in 2023 to their pre-pandemic levels in 2019, using industry-level WFH growth from 2019 to 2023 as the treatment variable:

$$\Delta_{2019-2023}Outcome_{ic} = \beta WFHGrowth_i + X'_{ic}\gamma + \delta_{m(c)} + \varepsilon_{ic}, \tag{4.2}$$

Unlike the dynamic specification, the long DiD collapses the analysis into a single post-period (2023). This approach estimates the cumulative effect of the industry-level $WFHGrowth_i$ on office leasing outcomes between 2019 and 2023. $WFHGrowth_i$ measures every industry's increase of the WFH rate in percentage points, i.e. the percentage point change of employees who work from home at least partly in 2023 compared to 2019. Therefore, it provides a more aggregated measure of the long-term impact, abstracting from yearly fluctuations while applying the same treatment definition and control structure.

**Identifying Assumptions and Threats to Identification** The central assumption is parallel trends, which implies that, without WFH growth, treated and control industries would have followed similar office leasing trajectories. If high- and low-WFH industries were already diverging pre-pandemic, the estimates could capture pre-existing differences rather than the treatment effect. However, pre-trend tests in my dynamic DiD design confirm that high- and low-WFH industries exhibited similar office leasing behavior before the pandemic, supporting the parallel trends assumption.

Another potential concern is that industry-level WFH growth may be endogenous if it correlates with unobserved factors affecting office demand. If WFH-intensive industries were already on different leasing trajectories due to pre-existing structural trends, the estimated effects could reflect broader industry shifts, rather than the impact of WFH itself. However, industries with the highest WFH growth from 2019 to 2023 had already adopted more remote work before the pandemic. This suggests that their post-pandemic WFH increase was shaped by existing industry characteristics. In particular, industries with established remote work infrastructure and job tasks conducive to WFH, such as IT, advertising, and consulting, were better positioned to expand WFH in response to disruptions caused by the pandemic. A robustness check using pre-determined industry-level WFH potential from 2018 (Alipour et al., 2023) further supports this argument (see Appendix Table D.14). In addition, my control for industry-level employment changes ensures that the estimated WFH effect isolates shifts in office demand from employment changes.

Spillover effects could be an issue if WFH growth in one industry may indirectly affect firms in other industries through changes in office rents or equilibrium effects. If this occurs, the control group may not represent a valid counterfactual. However, metro-area-by-year fixed effects as well as controls for within-metro differences and employment absorb local shocks and time trends. Additionally, I conduct a robustness check with both postcode and metro-area-by-year fixed effects, which leaves the main results largely unchanged.

A final concern is potential reverse causality. One might worry that WFH growth itself could have been shaped by pre-existing office leasing trends. However, the analysis of pre-trends indicates that industry-level WFH adoption before Covid was not associated with differential office leasing patterns.

## 4.4 Empirical Results: Industry- and Firm-Level Impact of WFH on Office Leases

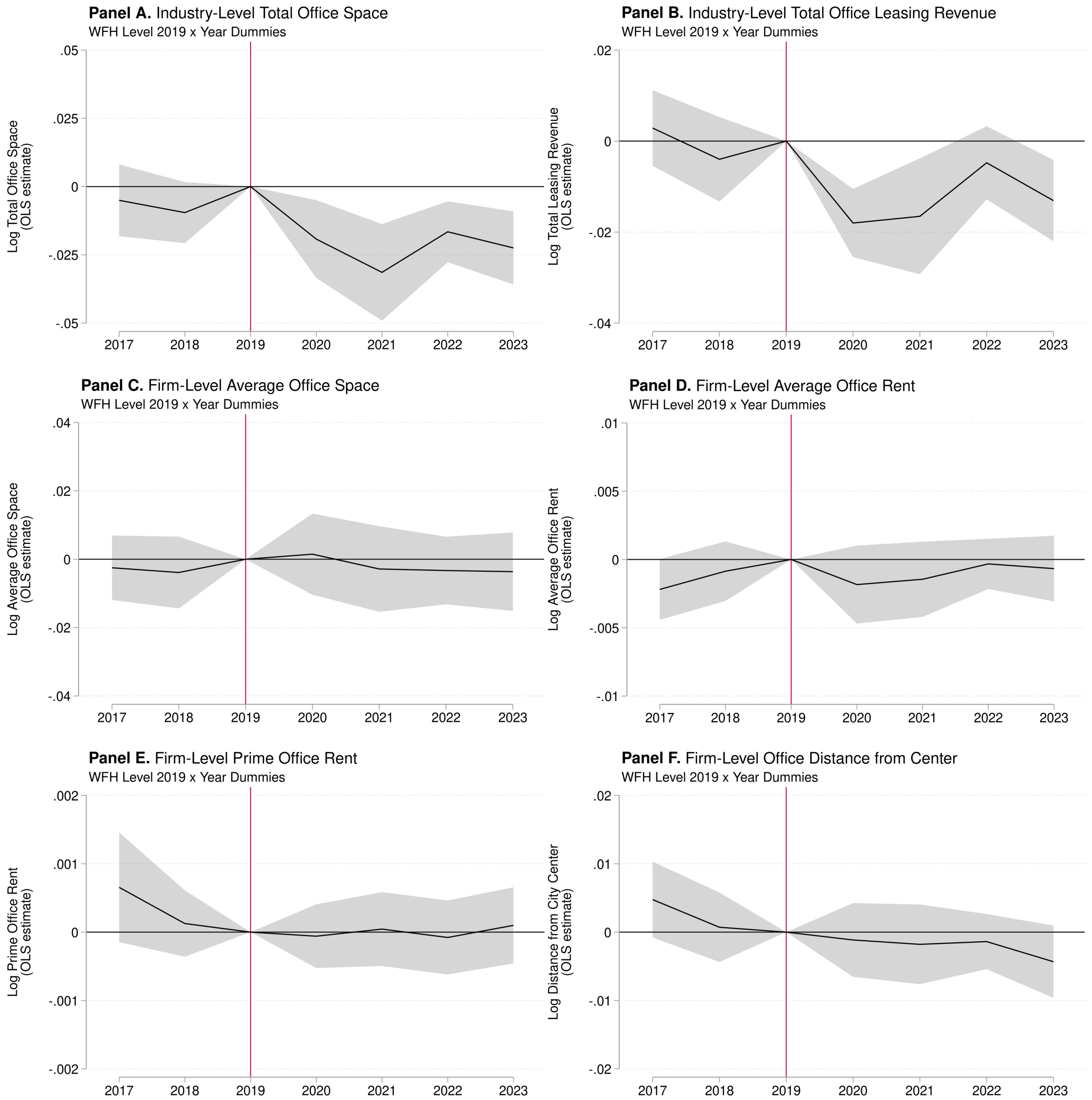
### 4.4.1 Industry- and Firm-Level DiD Results

Figure 4.7 presents the dynamic DiD results at both the industry and firm levels from 2017 to 2023. The main findings are that higher pre-pandemic WFH adoption (2019) is associated with significant downsizing of office space and a shift toward central locations.

At the industry level, WFH is associated with a significant decline in total newly leased office space (Panel A). The estimates show insignificant pre-trends and an immediate negative effect following the pandemic outbreak in 2020. Total leasing revenues (Panel B) also decrease, but the effect is only significant in 2020, 2021, and 2023. These results suggest that the shift in office leasing reflects a structural change due to increased WFH adoption rather than a temporary shock.

A detailed look at leasing quantities in Appendix Figure D.11 reveals that the reduction in leased office space and lease revenues is primarily driven by fewer leases and downsized offices, rather than by declining rents. This indicates that WFH affects office markets through quantity adjustments rather than price changes.

**Figure 4.7:** Industry- and Firm-Level Dynamic DiD Estimates 2017-2023




*Notes:* This figure presents dynamic DiD estimates $\hat{\beta}_k$ from separate regressions of Equation 4.1 on the association between WFH growth and office outcomes. All dependent variables are regressed onto an interaction term of WFH growth and year dummies from 2017 to 2023. Panel A reports effects on total industry-level office space leased (log square meters), while Panel B shows total industry-level annualized leasing revenue (log euros). Panel C presents firm-level average office space (log square meters), Panel D shows firm-level average office rent (log euros), and Panel E focuses on prime office rents (log euros). Panel F shows log distance from the city center of firms' office locations. The estimates are conditional on metro-area-by-year fixed effects, municipality tax controls, postcode controls, and employment controls. 95 percent confidence intervals are displayed in gray with standard errors clustered at the industry-by-submarket-type level. The vertical red line marks 2019, the reference year before the Covid-19 pandemic. Data are from the ifo Business Survey (EBDC-BEP, 2023) and Colliers (2024).

WFH leads to smaller average office spaces (Panel C), which suggests that downsizing is an adjustment mechanism, although the dynamic DiD results are insignificant. Despite weaker demand, both average and prime office rents (Panels D and E) remain largely unchanged. This suggests lease rigidity or landlord expectations of market recovery may be preventing price adjustments.

By 2023, WFH-intensive firms also relocate closer to the city center (Panel F), indicating a shift in office preferences toward premium central locations. This trend may reflect efforts of firms with hybrid work arrangements to consolidate space, leverage agglomeration benefits, or improve accessibility of their office locations.

Turning to the long DiD results, Table 4.1 quantifies the cumulative effects by comparing outcomes and WFH adoption in 2023 (post-pandemic) to 2019 (pre-pandemic baseline). At the industry level, column (1) shows that a one percentage point increase in WFH growth (2019-2023) is associated with a significant reduction of total office space demand by two percent. Column (2) indicates a modest decline in total leasing revenue, but the effect is statistically insignificant. Column (3) finds that average leased office space decreases by one percent per percentage point of WFH growth, confirming the downsizing trend. Average and prime office rents (columns 4 and 5) remain unaffected.

The estimates imply that the industry-average WFH growth of 15 percentage points from 2019 to 2023 corresponds to a 30 percent decrease in total newly leased office space and a 15 percent reduction in average office size. While the magnitude of these effects appears large, it captures a multi-year transition rather than an immediate adjustment, as firms have adapted their office needs to new work arrangements. Survey evidence indicates that most firms have already completed the majority of their space reductions (ifo Institute for Economic Research, 2024). This suggests that the most significant phase of office downsizing has likely passed and that the impact may moderate in the coming years.

Column (6) reveals that higher WFH growth significantly reduces firms' distance from the city center by about 0.6 percent, confirming the centralization effect seen in the dynamic DiD results. With the average industry-level WFH growth, this corresponds to a shift toward the urban center of about 8 percent or slightly more than 1 kilometer. This indicates that while WFH reduces total office demand, firms maintaining office space tend to relocate to more central locations.

**Table 4.1:** Industry- and Firm-Level Long DiD Results

| | Industry-Level | | Firm-Level | | | |
|---|---|---|---|---|---|---|
| | **Log Total Office Space Demand** | **Log Total Office Rent Revenue** | **Log Average Office Space** | **Log Average Office Rent** | **Log Prime Office Rent** | **Log Distance from City Center** |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **WFH Growth × Post (2023)** | -0.0216*** | -0.0050 | -0.0095*** | -0.0011 | 0.0006 | -0.0056*** |
| | (0.0031) | (0.0039) | (0.0034) | (0.0007) | (0.0005) | (0.0021) |
| $N$ | 5,895 | 5,895 | 5,875 | 5,875 | 5,875 | 5,875 |
| $R^2$ | 0.22 | 0.21 | 0.04 | 0.50 | 0.92 | 0.18 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |

*Notes:* This table reports long DiD estimates $\hat{\beta}$ of WFH growth on office characteristics based on Equation 4.2. Time dummies are grouped into two bins: the year 2019 as the pre-Covid reference period and the year 2023 as the only post-period. Columns (1) and (2) display industry-level estimates of the WFH growth effect on log total office space demand and log total office leasing revenue. The firm-level results in columns (3) to (6) report the results for log average office space, log average office rent, log prime office rent, and log distance from city center, respectively. The estimates are conditional on metropolitan area fixed effects, municipality tax controls, postcode controls, and employment controls. Standard errors are clustered at the industry-by-submarket-type level. *p<0.1; **p<0.05; ***p<0.01.

Overall, the long DiD results confirm a structural shift in office demand in response to WFH growth, driven by smaller and fewer leases. At the same time, demand reallocates toward centrally located office spaces, while rents remain stable.

### 4.4.2 Heterogeneity Analysis

The impact of WFH on office leasing is heterogeneous regarding firms' WFH intensity, building characteristics, and location.

First, the effect of WFH on office leases is concentrated among firms with the highest WFH adoption. Appendix Table D.3 compares industries with below- and above-average WFH growth. The results show that firms with higher WFH adoption experience significantly stronger reductions in leased office space and average rents, suggesting that the observed effects are actually driven by WFH. Notably, for WFH-intensive firms, prime office rents increase slightly while average office rents decline. This could indicate a minor "flight to quality," as firms consolidate space while upgrading to premium office spaces. However, this result should be interpreted with caution.

Second, the WFH has a differential impact on the office market, as its effects vary by building quality and age. Appendix Table D.4 shows that high-quality buildings (category A) remain largely unaffected by WFH. For those prime buildings, the estimated effects on leased space and rents are insignificant. This finding aligns with Gupta et al. (2022b), who show that prime office buildings in the U.S. are shielded from WFH-induced declines. In contrast, lower-quality buildings (categories B and C) experience significant reductions in leased space and rents. This suggests that the WFH-induced demand reductions are concentrated in lower-quality office buildings.

A similar pattern is evident for building age (see Appendix Table D.5). Building age is defined either as the building year or the year of the last major renovation, indicating the current age of a property. WFH does not negatively affect new buildings (constructed or renovated since 2020), but older buildings. Properties built before 1990 are subject to the largest declines. This trend may coincide with lower energy efficiency in older buildings. Given the ongoing shift toward environmental, social, and governance (ESG) standards in corporate real estate, WFH may accelerate the transition toward higher-quality, newer offices, as hybrid firms prioritize modern, well-equipped spaces for in-office workdays.

Third, WFH reshapes firms' office demand within cities. Appendix Table D.6 shows that WFH has a positive effect on office leasing in central business districts (CBDs), both in terms of total leased space and rents. In contrast, WFH is associated with a strongly negative effect on office demand in urban and suburban locations, while peripheral areas experience a smaller decline. The relatively weaker impact in peripheral areas may be due to other locational advantages that my controls (property and business taxes, postcode characteristics) do not fully capture. This finding suggests a centralization rather than a "donut effect" in urban office leasing.

Across metro regions, Appendix Table D.7 reveals that the negative WFH effect is stronger in Germany's mid-sized metro areas (bottom four of the top seven: Cologne, Frankfurt, Stuttgart, and Dusseldorf). On the other hand, the three largest agglomerations (Berlin, Hamburg, and Munich) appear somewhat shielded from the WFH-induced decline. This may be due to stronger agglomeration economies and higher overall demand for office space in these larger cities.

### 4.4.3 Robustness Checks

I conduct seven robustness checks to test the sensitivity of my results to alternative specifications, clustering methods, additional controls, fixed effects, leaving out industries, and alternative WFH measures.

First, Appendix Table D.8 replaces the annual industry-level log employment controls with a single control for employment in 2019, the pre-Covid reference year. The results remain unchanged, which suggests that industry-level employment shifts correlated with WFH growth do not drive the estimates.

Second, Appendix Table D.9 tests the robustness of my standard errors to alternative clustering levels. Panel A reports the baseline estimates, clustered at the industry-by-submarket-type level (up to 72 clusters). Panels B through E apply alternative clustering at the industry-by-year (108 clusters), metro-area-by-submarket-type (28 clusters), submarket level within cities (101 clusters), and postcode level (500+ clusters), respectively. The main findings of significant estimates on total office space leased, average office space, and distance from the city center remain significant across all specifications.

Third, Appendix Table D.10 introduces additional controls: an indicator for subleasing, car distance from the city center, metro area GDP, postcode-level 2019 employment, municipality-level property and business tax revenue. The additional controls have minimal impact on office space and rent estimates. However, the coefficient on distance shrinks while remaining significant. This indicates that the additional controls capture some channels through which WFH affects location choices.

Fourth, Appendix Table D.11 investigates the effect of more restrictive fixed effects. In addition to metro-area-by-year fixed effects, I add postcode fixed effects instead of postcode-level controls. The main estimates remain largely unchanged, which suggests that my findings are not driven by omitted spatial or temporal variation.

Fifth, Appendix Table D.12 tests the robustness of the results by re-estimating the regressions without observations from the financial and public sectors. Since these industries are not covered in the WFH survey data, their values were previously imputed using the service-sector average. Excluding these sectors does not meaningfully alter the results. This shows that the main findings are not driven by office leasing dynamics in these two industries.

Sixth, Appendix Table D.13 checks the differences in outcomes when using industries' WFH rate in 2019 from the ifo Business Survey as alternative treatment variable instead of WFH growth (2019-2023). The motivation is that the 2019 WFH rate is independent of the pandemic, which drove subsequent WFH growth. The estimates largely confirm the main long DiD results, although the coefficients differ due to differences in scaling of the treatment variables. The only change is that the effect on average office space becomes statistically insignificant, but the coefficient still suggests downsizing.

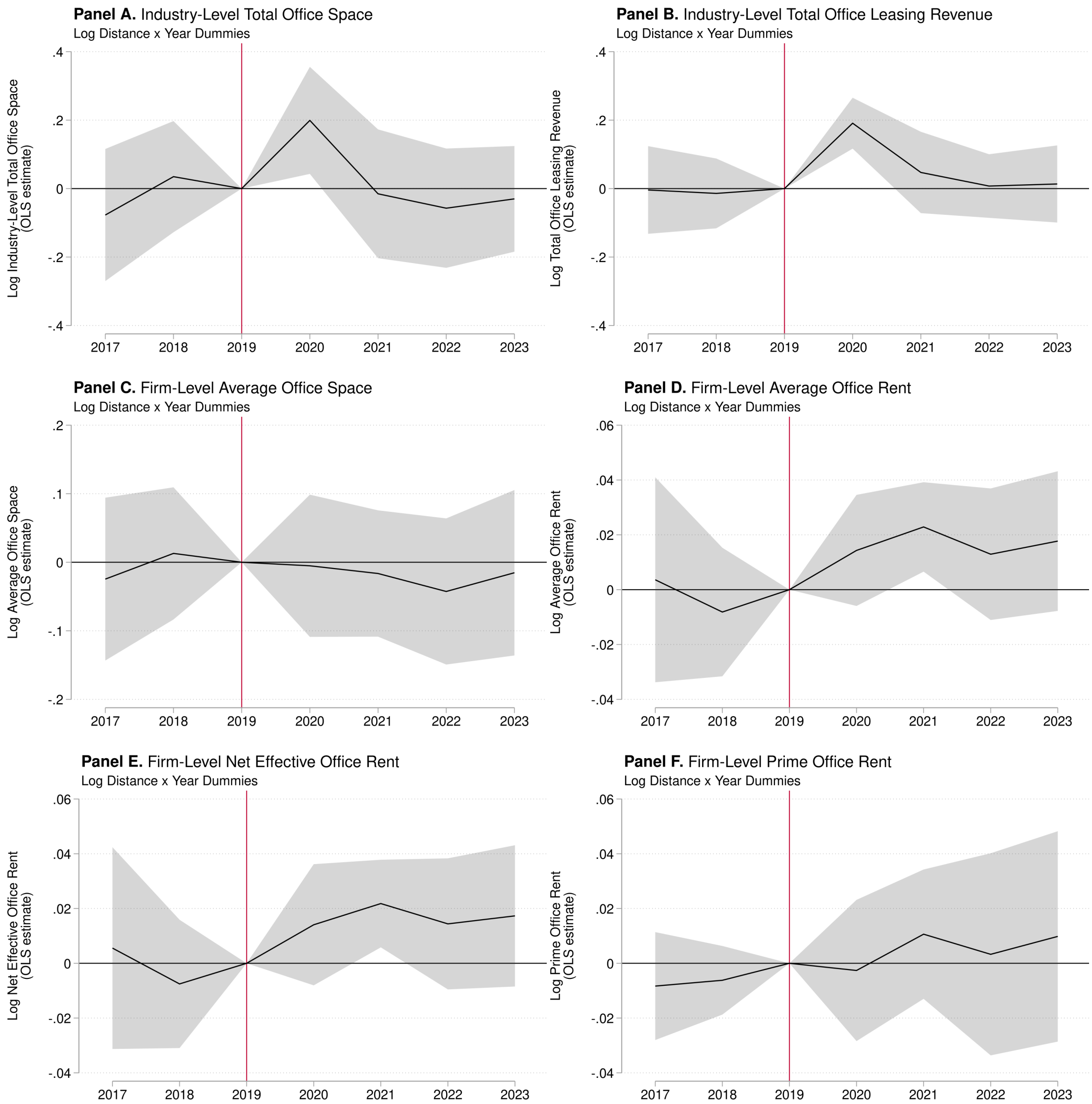
Finally, Appendix Table D.14 replaces WFH growth (2019–2023) with an industry-level pre-pandemic WFH potential measure from Alipour et al. (2023). Their approach estimates job-level WFH feasibility based on task content. While my treatment period is subject to post-pandemic shifts, their WFH potential measure is based on 2018 data and unaffected by these shifts. The estimates for WFH potential are consistent with the main results for WFH growth, which validates the empirical approach. The WFH effect on office space downsizing remains significant, but coefficient shrinks due to different scaling of the WFH variables. Notably, total leasing revenue and average office rent estimates turn significantly negative. The negative effect on office location distance remains robust.

## 4.5 Empirical Results: Urban Impact of WFH on Office Leases

### 4.5.1 Urban DiD Results

The firm- and industry-level analysis shows that WFH growth is significantly associated with firms leasing smaller office space closer to the city center, suggesting downsizing and a modest centralization effect. However, these findings do not capture how the *geography of office leasing* within metro areas has changed. To examine these broader urban implications, I conduct a descriptive urban DiD analysis that focuses on whether office demand has moved toward or away from central locations post-pandemic, rather than estimating the direct effect of WFH on office leasing.

**Figure 4.8:** Urban Dynamic DiD Estimates 2017-2023




*Notes:* This figure presents dynamic DiD estimates $\hat{\beta}_k$ from separate regressions on the association between distance from the city center and office outcomes. All dependent variables are regressed onto an interaction term of distance and year dummies from 2017 to 2023. Panel A reports effects on total industry-level office space leased (log square meters), while Panel B shows total industry-level annualized leasing revenue (log euros). Panel C presents firm-level average office space (log square meters), Panel D shows firm-level average office rent (log euros), Panel E displays net effective rents, and Panel F focuses on prime office rents (log euros). The estimates are conditional on metro-area-by-year fixed effects, municipality tax controls, postcode controls, and employment controls. 95 percent confidence intervals are displayed in gray with standard errors clustered at the industry-by-submarket-type level. The vertical red line marks 2019, the reference year before the Covid-19 pandemic. Data are from Colliers (2024).

Unlike the previous analyses, which use industry-level WFH growth as the treatment variable, the descriptive urban analysis instead employs postcode-level distance from the city center as the explanatory variable. The outcome variables remain consistent with the main specifications, including total and average office space leased, leasing revenues, and rents. However, rather than using distance from the city center as an outcome, I include net effective rents. Since these urban DiD regressions use log distance as the explanatory variable, postcode-level controls are excluded.

Figure 4.8 reveals a temporary outward shift in 2020 and 2021, as indicated by significantly positive estimates for office space and revenue relative to distance. Since then, the trend has reversed back to pre-pandemic levels and turned even slightly negative. The long DiD estimates in Appendix Table D.15 confirm this pattern.

This raises a question: Given the centralization of WFH-intensive firms, why do overall urban leasing patterns remain largely unchanged? The answer lies in compositional shifts. WFH-intensive firms move toward city centers but lease less space overall, reducing demand in suburban and peripheral areas. At the same time, firms with lower WFH adoption continue to lease office space. Their location preferences remain relatively stable, with a slight outward shift. These opposing trends offset each other, keeping the broader landscape of urban office demand unchanged.

In addition, the observed stability in office rents (Panels D–F of Figure 4.8) suggests that there are no local price adjustments associated with the changing composition of office leasing firms across locations. Selection effects may play a role, as WFH-intensive firms that move closer to the center lease smaller offices or fill vacancies rather than driving up prices.

Overall, the spatial patterns in urban office demand have remained relatively stable despite the increase in WFH. While there is a modest centralization effect among WFH-intensive firms, the broader structure of urban office leasing has not been fundamentally reshaped.

### 4.5.2 Stable Urban Gradient for Office Leases

Two important concepts in urban economics are that real estate rents reflect the value of locations and that they decline with distance from the city center. Central locations command higher rents due to agglomeration economies, superior amenities, and better accessibility relative to suburbs and the periphery. Despite the increase in WFH, my central finding is that the urban gradient for office leases in major German cities has remained remarkably stable between 2019 and 2023.

Figure 4.9 presents changes in the urban gradient for office leases, comparing estimates for 2019 (blue) and 2023 (red). The figure shows the effect of distance from the city center on total office space (Panel A) and total leasing revenue (Panel B). Panels C to E display the effects for average office space, average rents, net effective rents, and prime office rents, respectively. Across all panels, the estimates for 2023 closely resemble those from 2019, with largely overlapping confidence intervals. While there is local variation, the overall urban gradients for office space and rents remain largely unchanged.

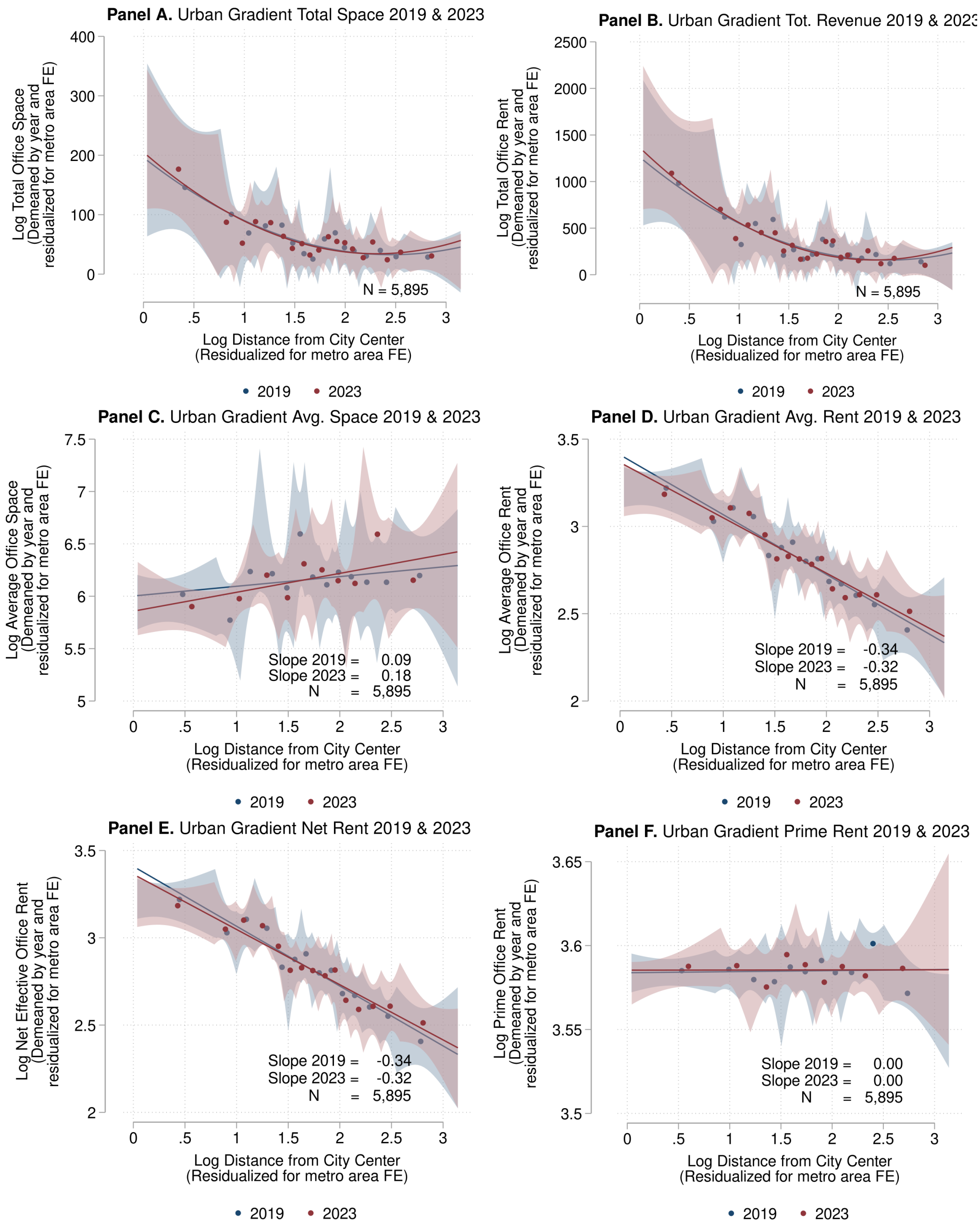
The stability of these urban gradients contrasts with the "donut effect" observed in urban housing markets and consumer spending (Alipour et al., 2022; Duguid et al., 2023; Gupta et al., 2022a; Ramani et al., 2024), where demand has shifted outward. This result suggests that firms continue to value proximity to city centers, even as hybrid work alters office utilization. However, these aggregate trends mask the shifts between WFH-intensive firms, whose office location preferences have shifted toward the urban core, and less WFH-intensive firms that continue to lease office space as before.

### 4.5.3 Minor Centralization Effect in Office Moves

While the stability of urban gradients indicates that overall urban office demand has remained steady, this subsection investigates marginal spatial shifts by analyzing office relocations. Specifically, I analyze 206 within-metro office moves between 2020 and 2024. Unfortunately, due to anonymization, I cannot link these office relocations with industry-level WFH growth.

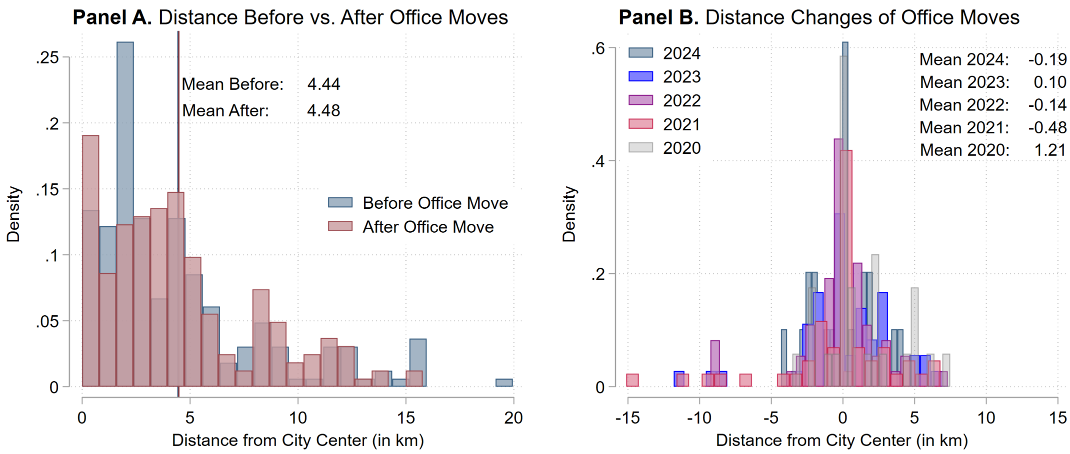
Figure 4.10 presents two main findings. Panel A shows the distribution of firms' office locations before and after relocations (2020–2024) in terms of distance from the city center. On average, the mean distance remains largely unchanged. Panel B, however, reveals notable annual changes that are masked in the aggregate analysis. Firstly, office relocations in 2020 show an increase in distance. Since office moves are typically planned years in advance, the outward shift in 2020 likely reflects pre-pandemic leasing decisions rather than a direct response to WFH. This suggests that urban office moves followed a slight suburbanization trend before the pandemic-induced WFH increase. Since 2021, however, there has been a

**Figure 4.9:** Urban Gradient for Office Leases




*Notes:* This figure shows changes in the estimates of the urban gradient of office characteristics between 2019 and 2023. Binscatter regression estimates are residualized for metro area fixed effects and demeaned by year, using evenly spaced bins (quantiles), fitted lines, and 95 percent confidence intervals (Cattaneo et al., 2024). Estimates for 2019 are reported in blue, and for 2023 in red. All dependent variables are regressed on log distance from city center. Panel A reports effects on total office space leased (log sqm), and Panel B on total office leasing revenue (euros). Panel C shows average office space (log sqm), Panel D displays average office rent (log euros/sqm), Panel E reports net effective rents (log euros/sqm), and Panel F focuses on prime office rents (log euros/sqm). Data are from Colliers (2024).

**Figure 4.10:** Spatial Changes in Office Moves Within Metros 2020–2024




*Notes:* This figure analyzes within-metro office moves in the seven largest German office real estate markets between 2020 and 2024. Panel A presents a histogram of the distance from the city center for both old and new office locations. The vertical lines illustrate the mean distance before and after office moves. Panel B displays a histogram of the change in distance, shown separately for each year using different colors. The data include 206 office moves, provided by Colliers (2024).

trend reversal, with relocations exhibiting a gradual shift toward centralization. From 2021 to 2024, the average distance from the city center decreased by 0.2 kilometers.

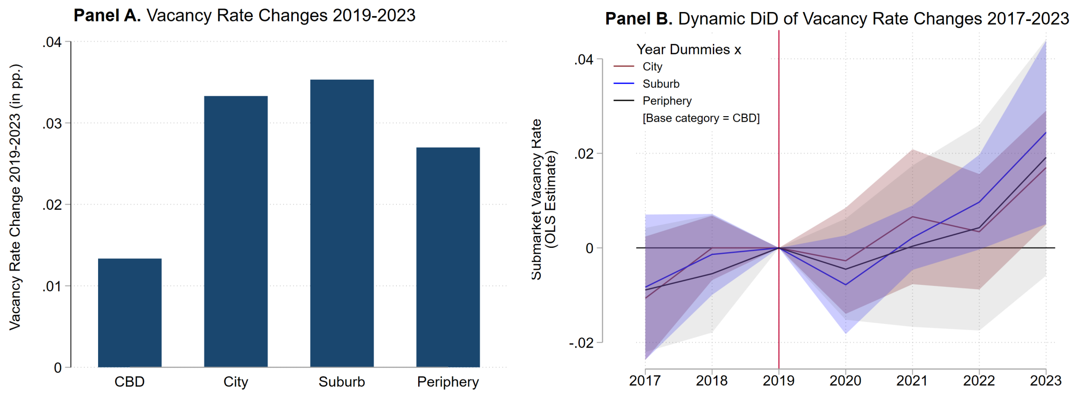
Still, this shift cannot be attributed solely to WFH, as the ongoing trend toward environmental, social, and governance (ESG) standards in corporate real estate has directed office leasing decisions toward newer, higher-quality buildings. This trend could have been further amplified by WFH, which increases demand for those buildings, as shown in subsection 4.4.2.

### 4.5.4 Concentration of Vacancies in Suburbs and the Periphery

Another implication of the WFH-driven reduction in office demand is an increase in office vacancies. This analysis thus shifts the focus from office leasing to vacancies. Specifically, I examine whether there are spatial trends across city submarkets. While vacancies have increased across all metropolitan areas, I find that the rise has been significantly more pronounced in suburban and peripheral locations compared to CBDs.

Figure 4.11 analyzes spatial trends in office vacancies. Panel A shows that vacancy rates in the city outskirts, suburbs, and periphery increased by about three percentage points between 2019 and 2023, whereas vacancies in the CBD rose by just over one percentage point. In

**Figure 4.11:** Spatial Changes in Office Vacancy Rates Within Metros




*Notes:* This figure presents within-metro changes in vacancy rates at the level of submarkets in the seven largest German office real estate markets. Panel A presents the average change in vacancy rates in percentage points between 2019 and 2023 for the central business district (CBD), city, suburb, and periphery. Panel B displays the changes in submarket vacancy rates from 2017 to 2023 relative to the CBD in 2019, which is set as the base category. The annual DiD estimates are drawn with 95 percent confidence intervals. Standard errors are clustered at the metro-area-by-submarket-type level. Data on submarket vacancy rates are from Colliers (2024).

Panel B, I employ a dynamic DiD analysis, which compares growth trends across submarket types over time relative to the CBD in 2019. The estimates show no significant pre-trends, initial stability following the Covid shock, and a significant increase in vacancies in the city outskirts and suburbs by 2023.

Overall, these findings indicate that urban centers have been more resilient to rising office vacancies than suburban and peripheral areas. While vacancy trends could theoretically reflect both weaker demand and excess supply, they are primarily driven by demand shifts, to which WFH has contributed. As the subsequent analysis shows, there have been no significant differences in new office supply across submarkets. Therefore, weaker demand explains the higher vacancy rates outside central locations.

## 4.6 Mechanisms Driving the WFH Impact on Office Leases

This section analyzes the mechanisms that drive the WFH effect on urban office markets. Using firm-level survey data, I show WFH-induced shifts in demand for office space. Meanwhile, the analysis finds that neither supply-side mechanisms nor industry or spatial trends in employment can explain the results.

### 4.6.1 Firm-Level Demand: WFH Growth Drives Office Downsizing

Using firm-level data from 7,274 companies in the August 2023 ifo Business Survey (EBDC-BEP, 2023), I investigate the relationship between WFH growth and office downsizing (both already implemented and planned).

Figure 4.12 presents the results in binscatter regression plots. Across all firms (Panel A), there is a statistically significant positive relationship between firms with greater WFH growth and the share of firms that downsize office space. This pattern holds for service-sector firms (Panel B), which account for most office leases, as well as for both large firms (Panel C) and small and medium-sized enterprises (Panel D). This result suggests that firms with greater WFH adoption are more likely to reduce their office footprint.

Furthermore, this finding helps mitigate concerns about reverse causality. Specifically, one might worry that office downsizing drives WFH growth rather than the other way around. However, WFH had largely stabilized across the economy by 2023. Therefore, the observed downsizing is more likely a response to sustained higher WFH adoption than a driver of it.

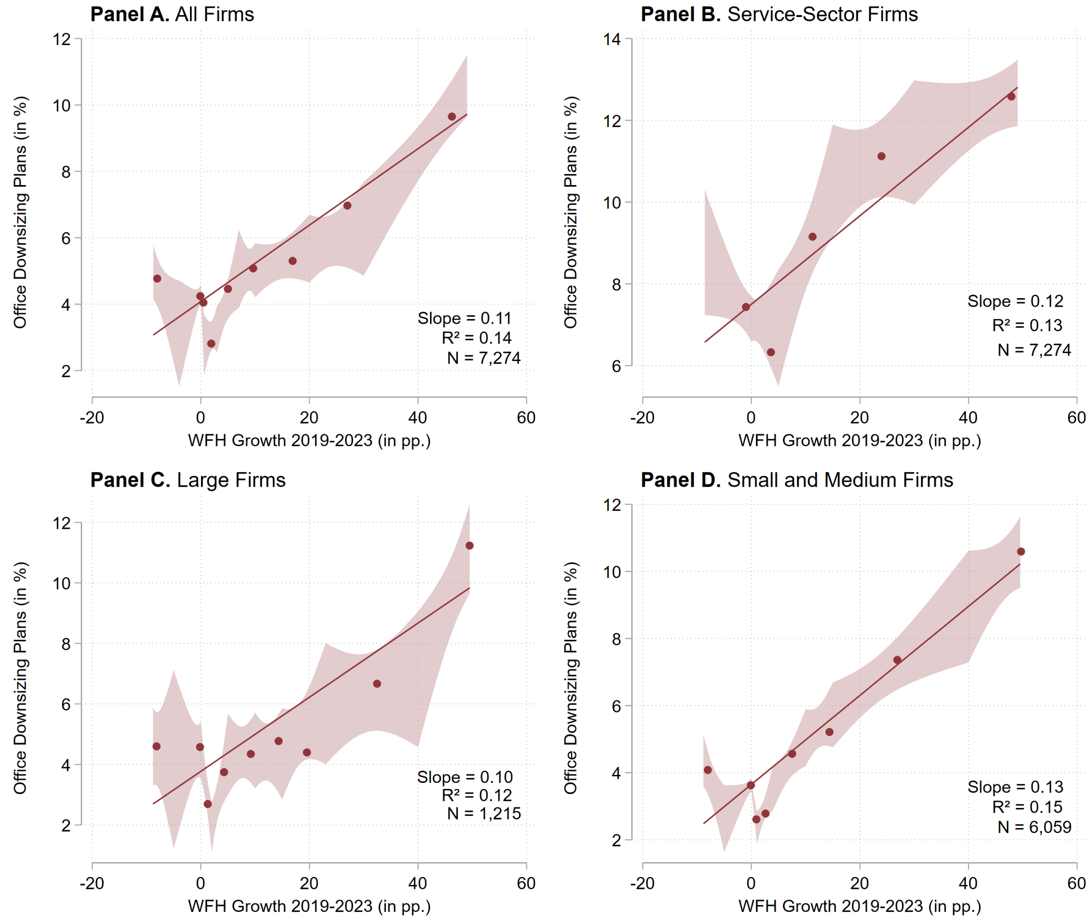
### 4.6.2 Shifting Demand: WFH Firms Prioritize Centrality, Quality, and Flexibility

**Shift toward Central, High-Quality, Flexible Office Spaces** Appendix Figure D.12 presents binscatter regression plots of the industry-level association of WFH growth with changes in office characteristics based on the ifo Business Survey (ifo Institute for Economic Research, 2024).

Panel A shows that industries with higher WFH growth have a higher share of companies that want to relocate offices closer to city centers. Panel B finds a positive association between WFH growth and the share of firms that upgrade the quality of their office spaces. Panel C illustrates that WFH-intensive industries are more likely to adopt desk-sharing models, which optimize space utilization when fewer employees are in the office. Finally, Panel D indicates that these industries are also expanding social spaces, such as adding more communication zones and meeting rooms.

These findings suggest that WFH not only influences the size and location of offices, but also leads to changes in office design and the organization of work.

**Figure 4.12:** Firm-Level Relationship Between WFH Growth and Office Downsizing




*Notes:* This figure displays the firm-level relationship between WFH growth and intentions for office space downsizing. All panels show binscatter regression plot using the methodology by Cattaneo et al. (2024) with evenly spaced bins (quantiles), a fitted line, and the 95 percent confidence interval. Panel A reports the estimates for all firms, while Panel B shows service-sector firms only. Panel C presents estimates for large firms, and Panel D for small and medium firms. Data are from the ifo Business Survey (EBDC-BEP, 2023).

**Revised Criteria in Firms' Office Leasing Decisions** With the shift to hybrid work, the role of the office has evolved from a traditional workspace to a hub for interaction. Insights from structured expert interviews with CRE brokers highlight that an office's ability to complement the new work arrangements has become a key leasing criterion.

Appendix Figure D.13 illustrates the rising importance of flexible office designs. Since the pandemic, the share of leases prioritizing adaptability to hybrid work has increased from 6 to

33 percent. Firms increasingly seek office spaces with open layouts, expanded communication zones, and dedicated collaboration areas, replacing traditional individual offices.

### 4.6.3 Supply-Side: Spatial Changes in Office Stock

While the two previous subsections have documented demand-side mechanisms behind the WFH impact on urban office markets, supply-side factors could also play an important role. More precisely, if new office construction or demolitions of old buildings vary systematically across urban submarkets over time, this could influence the observed outcomes in office space leased and rents. To test this hypothesis, I examine spatial changes in office stock between 2017 and 2023.

Appendix Figure D.14 presents the results. I measure office supply as the total stock of office space in log square meters.[6] Panel A shows that office supply increased at similar rates across the CBD, city outskirts, suburbs, and periphery from 2019 to 2023 (before vs. after the WFH increase). Panel B reports the results of a dynamic DiD, which compares spatial changes in office supply across submarket types over time relative to the CBD in 2019. The analysis finds insignificant pre-trends and, importantly, no statistically significant difference in office supply growth across submarkets in the post-period.

These findings indicate that differential supply trends are unlikely to be driving the observed WFH effects on urban office markets.

### 4.6.4 Industry-Level and Spatial Changes in Employment

Finally, I investigate shifts in employment across industries and within metropolitan regions, which may correlate both with WFH growth and office space demand. In the main analysis, the specifications control for annual industry-level employment, which ensures that employment changes do not drive the estimated WFH effects. However, these controls do not account for potential spatial employment shifts within cities. To test this hypothesis, I use administrative employment statistics from the German Federal Employment Agency (2025), both at the industry and spatial levels.

[6] Across the seven metropolitan areas, the total stock of office space stands stood at approximately 90 million square meters (sqm) in 2017, 92 million square meters in 2019, and 96 million square meters in 2023. This indicates a stable positive trend in office supply (Colliers, 2024).

As shown in Appendix Figure D.15 Panel A, I find no significant relationship between WFH growth and industry-level employment. While employment growth is slightly higher in WFH-intensive industries, the binscatter estimates are statistically indistinguishable from zero for the majority of the distribution. Since the main analysis already controls for industry-level employment, this channel does not explain the observed WFH effects.

Regarding the spatial shifts in employment, Panel B of Appendix Figure D.15 conducts a dynamic DiD analysis that compares employment growth in the metro surroundings over time to the urban core in 2019. I use the administrative labor market area classification of Germany's seven largest metro regions, which comprise a total of 39 municipalities (7 urban cores and 32 metro surroundings).[7] The analysis shows that employment in urban cores and metro surroundings has evolved in parallel over time, although there is a slight but statistically insignificant downward trend in the metro surroundings in 2022 and 2023. Importantly, the results find no significant differences in employment growth between these two areas.

Overall, despite the weak correlation of employment growth with WFH-intensive industries and central locations, the estimates suggest that employment shifts are not a major driver of the observed WFH effects on urban office markets.

## 4.7 Discussion and Conclusion

This study provides evidence on the impact of WFH on urban office leases at the industry, firm, and spatial levels. Using detailed micro-data on WFH adoption and office leases, it documents how hybrid work reshapes firms' office space decisions and the broader urban office market. The first finding is that WFH growth significantly reduces office space demand, primarily through fewer leases and downsizing of average office space, while rents remain stable. Secondly, the impact is highly uneven across office types, as firms prioritize quality over quantity. Older and lower-quality buildings see the strongest declines, whereas prime office spaces are largely unaffected. Thirdly, WFH has led to a modest centralization effect in office real estate, with an overall stable urban gradient. Leasing demand has shifted toward central locations, while vacancies have risen the most in suburban and peripheral areas. Finally, the

[7] Due to data limitations, I cannot analyze employment trends at the more granular metro submarket level.

WFH impact is driven by demand-side mechanisms, as firms downsize and prioritize central, high-quality offices, while changes in office supply and employment play no significant role.

These findings provide new evidence that WFH has reshaped office demand in cities – and differently than in the U.S. While WFH in the U.S. has driven substantial office devaluations and suburbanization in consumer spending and housing markets (Gupta et al., 2022a,b; Ramani et al., 2024), my results show a centralization effect in Germany. Leasing demand has shifted toward central locations, with WFH even increasing space demand in CBDs. Although the overall decline in office space demand likely contributes to lower valuations in Germany as well, the resilience of central office markets suggests that agglomeration economies remain important. At the same time, hybrid work has introduced new temporal patterns of office utilization, reducing daily commuter flows and concentrating office activity on fewer days. This may contribute to the "donut effect" in urban consumer spending. The contrasting patterns between the U.S. and Germany, as well as between commercial and residential real estate, underscore how institutional factors and urban structure shape cities' adaptation to hybrid work.

There are several implications for urban office real estate, urban planning, and the CRE industry. First, firms continue to prioritize central locations for their agglomeration benefits, accessibility, and high-quality office environments. However, WFH has altered mobility patterns, reducing daily commuter flows and concentrating office activity on fewer days. To revitalize urban centers, policymakers may need to adjust public transportation schedules, retail planning, and zoning regulations.

Second, rising office vacancies raise concerns about an "urban doom loop," where falling CRE values and lower economic activity create negative spillovers for retail, services, and employment. Targeted and proactive conversion policies can help prevent this scenario by facilitating the residential or mixed-use redevelopment of empty office buildings. This is particularly relevant in suburban and peripheral areas, where vacancies are concentrated despite housing shortages. Converting vacant office space and space no longer needed due to WFH could create about 60,000 new apartments in Germany's seven largest cities (Krause et al., 2024). These office-to-residential conversions could provide housing for up to 102,000 people, mitigating both housing shortages and rising office vacancies.

Finally, hybrid work changes the organization of work. This transforms the role of the office from a daily workspace into a collaboration hub. Many firms now coordinate office presence on certain weekdays, typically Tuesday through Thursday, to reap the benefits of face-to-face collaboration. This shift drives up peak office utilization and cushions the negative impact on WFH on total space demand. It also reinforces demand for high-quality, flexible office spaces that are designed for hybrid work.

Avenues for future research include open questions on the long-term implications of WFH for urban office markets. One important area is how lease structures, pricing, and tenant preferences adapt as hybrid work stabilizes. Another key question is how reduced office utilization affects urban industries, particularly retail, hospitality, and transportation.

# A

# Appendix to Chapter 1

## A.1 Institutional Background: Broadband Expansion Policies in German States

**Table A.1:** Broadband Expansion Policies in German States: Part I

| Federal State | Time Period | State's Broadband Program | Program Type | Program Details |
|---|---|---|---|---|
| **Baden-Württemberg** | 2008-2009 | Rural Broadband Initiative [1]-[4] | Financial funding as an investment cost subsidy | Financial funding for municipalities in rural areas with no or insufficient broadband coverage of EUR 20 million. |
| | 2015-2022 | Baden-Württemberg Broadband initiative II / Baden-Württemberg NGA funding regulation [5]-[8] | Financial funding in the operator model | Financial funding for municipalities, associations of municipalities and rural districts in rural-and commercial areas on the outskirts of towns that are in "NGA white and grey areas", after an internal revision by a specialist office or by the Landesanstalt für Kommunikation Baden-Württemberg and an approval from the European Commission in the case of "NGA grey areas", amounting to EUR 253.6 million. |
| | | | Support of a simplified legal framework | Financial funding of coordination and management operations in inter-municipal cooperations in the construction of NGA networks, leading to economies of scale of public authorities and thus speeding up the application process. |
| **Bavaria** | 2008-2010 | Broadband development in rural areas of Bavaria [9] | Financial funding in the profitability gap model | Financial funding for small and medium-sized enterprises in rural areas of Bavaria with little or no existing broadband use, after a verification by public authorities regarding the project's profitability gap, amounting to EUR 20 million. |
| | 2012-2019 | Directive on the funding of the establishment of high-speed networks in the Free State of Bavaria [10]-[11] | Financial funding in the profitability gap model | Financial funding for municipalities, associations of municipalities and municipal associations in the Free State of Bavaria where an improvement in existing broadband coverage can be achieved, amounting to EUR 1.5 billion. |
| | | | Support of a simplified legal framework | Financial funding in the form of an increase in the maximum funding amount in the case of inter-municipal cooperation. |
| **Berlin** | 2014-2020 | Law on the Joint Task "Improvement of the Regional Economic Structure" (GRW Law) [12] | Financial funding in the profitability gap model and operator model | Financial funding for the measure sponsors, Berlin districts, natural persons or legal entities that are not profit-oriented in "NGA white" commercial areas/commercial collections, after a market investigation procedure and an application to the Senate Department for Economic Affairs, Energy and Operations. |
| | | | Support of a simplified legal framework | Direct funding of network operators, eliminating thus administrative burdens on districts. |
| **Brandenburg** | from 2013 onwards | Brandenburg Fiber Optics 2020 [13]-[15] | Financial funding as an investment cost subsidy | Financial funding for TC companies in areas with no connection to backhaul fiber-optic networks and in which broadband coverage cannot be attributed to competing broadband infrastructures, amounting to EUR 94 million. |
| **Bremen** | 2014-2021 | GA/GRW funding program [16] | Financial funding in the profitability gap model | Financial funding in areas that lack NGA infrastructure and in "NGA white areas". The determination of "NGA white areas" must be verified within the scope of a market investigation procedure. The classification of Bremen into a C or D funding area, according to which the funding rate can vary, should be noted. Bremen remains a GRW eligible area beyond 2021. |
| **Hamburg** | from 2015 onwards | Federal funding program for broadband expansion [17]-[18] | Financial funding in the profitability gap model, operator model and in consulting services | Financial funding for local authorities in which the project area is located, especially municipalities, city states, administrative districts, municipal special-purpose associations or another local authority or an association under the respective local authority law of the federal states. |
| **Hesse** | 2016-2020 | Directive on the funding of broadband supply in the state, Hesse-Part 6: Federal state funding for broadband infrastructure expansion [19]-[20] | Financial funding in the profitability gap model and operator model | Financial funding for municipalities, associations of municipalities, local authorities and 100 publicly owned private companies in areas with no broadband coverage, amounting to EUR 46 million from the digital dividend II and from federal state funds. |
| | | | Support of a simplified legal framework | Financial funding of coordination and management operations in inter-municipal cooperations in the construction of NGA networks, leading thus to economies of scale of public authorities and speeding up the application process. |

*Note:* All federal states offer financial funding as project share financing in the form of a non-repayable grant. Baden-Württemberg also offers the possibility of a fixed grant as funding. In the states Berlin, Bremen, Hamburg and Mecklenburg-Western Pomerania the programs are not state funding programs, but federal funding programs for broadband expansion or other, such as the GRW funding program.

**Table A.2:** Broadband Expansion Policies in German States: Part II

| Federal State | Time Period | State's Broadband Program | Program Type | Program Details |
|---|---|---|---|---|
| **Mecklenburg-Western Pomerania** | from 2015 onwards | Federal funding program for broadband expansion [21]-[22] | Financial funding in the profitability gap model, operator model and in consulting services | Financial funding for local authorities in which the project area is located, especially municipalities, city states, administrative districts, municipal special-purpose associations or another local authority or an association under the respective local authority law of the federal states, amounting to EUR 520 million as co-financing for the government funds and for the municipal share. |
| **Lower Saxony** | 2016-2021 | Directive Broadband Expansion Lower Saxony [23]-[27] | Financial funding in the operator model | Financial funding for local authorities, joint municipalities and municipal associations, after an application to the Nbank, amounting to EUR 58 million from the digital dividend II. |
| | from 2019 onwards | Directive Giganet Expansion Lower Saxony [28] | Financial funding in the profitability gap model and operator model | Financial funding in counties, independent cities, the Hanover region and local authorities (first-time recipients) that are "NGA white areas". |
| **North Rhine-Westphalia** | 2016-2021 | Directive on the granting of subsidies to promote NGA in rural areas [29] | Financial funding in the profitability gap model and operator model | Financial funding for municipalities, associations of municipalities and districts in residential areas, mixed areas and rural areas in North Rhine-Westphalia with a funding volume taken from the digital dividend II and the Eler. |
| **Rhineland-Palatinate** | 2015-2020 | Directive on the funding of the roll-out of high-speed broadband networks [30]-[31] | Financial funding in the profitability gap model and operator model | Financial funding for administrative districts, associations of associations, municipalities not belonging to associations, special-purpose associations and legally responsible institutions under public law in "NGA white areas", after a review by the Ministry of the Interior, Sports and Infrastructure and often a feasibility study, amounting to EUR 124.7 million. |
| **Saarland** | 2019-2022 | Directive on the funding of individual fiber-optic connections for high-demand customers in the Saarland ("Gigabit Premium") [32] | Financial funding | Financial funding for businesses, cultural institutions, and non-profit organizations in the Saarland that need a fiber-optic connection ("high-need users"). |
| **Saxony** | 2018-2023 | Directive Digital Offensive Saxony [33]-[34] | Financial funding in the profitability gap model, operator model and in consulting services | Financial funding, based on the federal funding program, for consulting services of broadband projects and for hot spots/WLAN in public areas relevant to tourism, amounting to EUR 200 million from state funds, EUR 80 million from EU funds and EUR 32 million from the digital dividend II. |
| **Saxony-Anhalt** | from 2015 onwards | Directive on the granting of subsidies to fund next generation access - broadband expansion in Saxony-Anhalt [35]-[36] | Financial funding in the profitability gap model, operator model and in consulting services | Financial funding for municipalities, including administrative districts, and special-purpose municipal associations, amounting to EUR 350 million (70 million from EAFRD, 24 million from EFRD, 4 million from federal government, other funds). |
| | | | Support of a simplified legal framework | Funding for certified broadband consultants who support and advise grantees on broadband investments. Funding for planning services only if these are provided by certified broadband consultants. |
| **Schleswig-Holstein** | 2017-2021 | Directive on the promotion of broadband supply in rural areas of Schleswig-Holstein (Broadband Directive) [37]-[38] | Financial funding in the profitability gap model, operator model and in consulting services | Financial funding for municipalities and associations of municipalities in rural areas, with proof of a lack of or inadequate broadband supply, amounting to EUR 71 million (EUR 36 million from GAK, EAFRD, GRW, EUR 14 million from the state of Schleswig-Holstein, EUR 21 million from the digital dividend II). |
| **Thuringia** | 2017-2020 | Directive of the Free State of Thuringia to promote the expansion of high-performance broadband infrastructures (Broadband Expansion Directive) [39]-[40] | Financial funding in the profitability gap model, operator model and in consulting services | Financial funding for local authorities, associations of local authorities or mergers of local authorities in the Free State of Thuringia, public-law companies, companies organized under private law and owned by public-law bodies, and private TC companies, amounting to EUR 520 million (175 million of which from federal state funds). |
| | | | Support of a simplified legal framework | Financial funding of inter-municipal cooperation. |

*Note:* All federal states offer financial funding as project share financing in the form of a non-repayable grant. Baden-Württemberg also offers the possibility of a fixed grant as funding. In the states Berlin, Bremen, Hamburg and Mecklenburg-Western Pomerania the programs are not state funding programs, but federal funding programs for broadband expansion or other, such as the GRW funding program.

## Information Sources on Broadband Expansion Programs in Tables I and II[1]:


[1] https://mlr.baden-wuerttemberg.de/de/unser-service/presse-und-oeffentlichkeitsarbeit/pressemitteilungen/pressemitteilung/pid/erstmalig-landesfoerderung-zum-ausbau-der-breitbandinfrastruktur-im-laendlichen-raum-1/

[2] https://mlr.baden-wuerttemberg.de/de/unser-service/presse-und-oeffentlichkeitsarbeit/pressemitteilungen/pressemitteilung/pid/initiative-baden-wuerttembergs-bei-der-agrarministerkonferenz-erfolgreich-1/

[3] https://mlr.baden-wuerttemberg.de/de/unser-service/presse-und-oeffentlichkeitsarbeit/pressemitteilungen/pressemitteilung/pid/ministerrat-gibt-gruenes-licht-fuer-deutschlands-umfassendste-breitband-initiative-laendlicher-raum-1/

[4] https://www.baden-wuerttemberg.de/fileadmin/redaktion/m-im/intern/dateien/publikationen/20200911_Breitbandbericht_Baden-Württemberg.pdf

[5] https://mlr.baden-wuerttemberg.de/de/unser-service/presse-und-oeffentlichkeitsarbeit/pressemitteilungen/pressemitteilung/pid/leben-und-arbeiten-40-breitbandausbau-kommt-nach-baden-wuerttembergischem-modell-mit-hochgeschwind/

[6] https://mlr.baden-wuerttemberg.de/de/unser-service/presse-und-oeffentlichkeitsarbeit/pressemitteilungen/pressemitteilung/pid/breitbandausbau-laeuft-gruen-rot-hat-jetzt-schon-mehr-projekte-bewilligt-als-alle-vorgaengerregieru/

[7] https://www.baden-wuerttemberg.de/fileadmin/redaktion/m-im/intern/dateien/publikationen/20200911_Breitbandbericht_Baden-Württemberg.pdf

[8] https://ec.europa.eu/competition/state_aid/cases/257876/257876_1719703_130_2.pdf

[9] https://ec.europa.eu/competition/state_aid/cases/225952/225952_885446_30_2.pdf

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[24] https://www.bznb.de/fileadmin/dokumente/A__nderung_RL_Breitbandausbau_NI_Endfassung.pdf
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[26] https://www.bundestag.de/resource/blob/436906/329bc7b4229cb1191cde4890942a9c77/wd-5-056-16-pdf-data.pdf
[27] https://www.mw.niedersachsen.de/download/109532/Breitbandausbau_in_Niedersachsen_-_Strategie_und_Foerderkulisse_des_Landes.pdf
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[33] https://www.revosax.sachsen.de/vorschrift/17836-Richtlinie-Digitale-Offensive-Sachsen
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[35] https://breitband.sachsen-anhalt.de/fileadmin/Bibliothek/Politik_und_Verwaltung/StK/Breitband/Ausbau_NGA/allg._Dokumente/15-10-27-RL_NGA_LSA_NEU-nach_Kabinettbeschluss.pdf
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## A.2 Descriptives

### A.2.1 Descriptive Statistics

Table A.3 and Table A.4 on the following two pages report the summary statics of the border samples for 30 Mbit/s and 50 Mbit/s broadband, respectively.

**Table A.3:** Descriptive Statistics of the Border Samples for 30 Mbit/s Broadband

| | Full Sample | | | | "Low" Broadband States | | "High" Broadband States | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Min | Max | Mean | SD | Mean | SD |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ***Outcome and Main Explanatory Variables*** | | | | | | | | |
| High Broadband States 30 Mbit/s | 0.56 | 0.50 | 0.00 | 1.00 | 0.00 | 0.00 | 1.00 | 0.00 |
| Broadband Availability Municipalities 30 Mbit/s | 0.57 | 0.32 | 0.00 | 1.00 | 0.49 | 0.33 | 0.64 | 0.29 |
| Property Sale Price Total | 184,277.81 | 125,378.25 | 8,800.00 | 2,500,000.00 | 176,387.12 | 120,150.29 | 190,516.23 | 129,021.28 |
| Property Sale Price per sqm | 1,352.27 | 813.36 | 244.28 | 7,180.00 | 1,297.79 | 763.88 | 1,395.34 | 847.96 |
| Property Rents Total (Monthly) | 459.90 | 236.64 | 90.00 | 3,450.00 | 439.09 | 219.48 | 479.42 | 250.12 |
| Property Rents per sqm (Monthly) | 5.94 | 1.66 | 3.53 | 20.00 | 5.75 | 1.51 | 6.11 | 1.77 |
| ***Control Variables*** | | | | | | | | |
| Property Type | 1.79 | 0.55 | 1.00 | 3.00 | 1.79 | 0.54 | 1.78 | 0.56 |
| Number of Rooms in the Property | 4.78 | 2.65 | 0.00 | 40.00 | 4.71 | 2.60 | 4.84 | 2.70 |
| Log of Floor Space in sqm | 4.87 | 0.46 | 3.50 | 6.15 | 4.86 | 0.44 | 4.87 | 0.47 |
| Age of Property | 8.56 | 6.05 | 1.00 | 18.00 | 8.66 | 6.22 | 8.48 | 5.91 |
| Newly Constructed Building | 0.15 | 0.36 | 0.00 | 1.00 | 0.15 | 0.36 | 0.16 | 0.36 |
| Renovation Status | 3.50 | 1.15 | 1.00 | 5.00 | 3.48 | 1.16 | 3.51 | 1.15 |
| Equipped with Kitchen | 0.28 | 0.45 | 0.00 | 1.00 | 0.27 | 0.44 | 0.29 | 0.45 |
| Equipped with Garden | 0.35 | 0.48 | 0.00 | 1.00 | 0.35 | 0.48 | 0.36 | 0.48 |
| Equipped with Balcony or Terrace | 0.35 | 0.48 | 0.00 | 1.00 | 0.33 | 0.47 | 0.36 | 0.48 |
| Equipped with Basement | 0.41 | 0.49 | 0.00 | 1.00 | 0.41 | 0.49 | 0.42 | 0.49 |
| Parking Lot or Garage Available | 0.61 | 0.49 | 0.00 | 1.00 | 0.61 | 0.49 | 0.61 | 0.49 |
| Exclusive/Luxury Equipment or Villa | 0.05 | 0.22 | 0.00 | 1.00 | 0.05 | 0.22 | 0.05 | 0.22 |
| Equipped with Pool, Whirlpool, or Sauna | 0.07 | 0.26 | 0.00 | 1.00 | 0.06 | 0.24 | 0.08 | 0.27 |
| Bright Rooms | 0.18 | 0.38 | 0.00 | 1.00 | 0.18 | 0.38 | 0.18 | 0.39 |
| Heating Type | 0.39 | 1.07 | 0.00 | 5.00 | 0.37 | 1.04 | 0.41 | 1.09 |
| Central Heating | 0.94 | 0.99 | 0.00 | 2.00 | 0.88 | 0.98 | 0.99 | 0.99 |
| Quiet Location | 0.12 | 0.33 | 0.00 | 1.00 | 0.12 | 0.33 | 0.12 | 0.33 |
| Publicly Subsidized Housing | 0.01 | 0.10 | 0.00 | 1.00 | 0.01 | 0.10 | 0.01 | 0.10 |
| School Quality (PISA) | -0.21 | 1.03 | -1.39 | 1.74 | -0.02 | 0.92 | -0.36 | 1.09 |
| Crime Rate per 10,000 Inhabitants | 0.07 | 0.01 | 0.05 | 0.09 | 0.07 | 0.01 | 0.07 | 0.01 |
| Mobile Internet Availability | 0.96 | 0.02 | 0.88 | 0.99 | 0.96 | 0.02 | 0.96 | 0.03 |
| Real Estate Transfer Tax Rate | 0.05 | 0.01 | 0.04 | 0.06 | 0.05 | 0.01 | 0.05 | 0.01 |
| Local Real Estate Tax Rate | 378.50 | 60.46 | 150.00 | 785.00 | 368.63 | 43.23 | 386.49 | 70.43 |
| Local Business Tax Rate | 361.77 | 36.00 | 200.00 | 490.00 | 357.04 | 33.30 | 365.61 | 37.61 |
| County Pre-Broadband Growth Trend | -0.93 | 1.10 | -2.00 | 2.00 | -1.20 | 1.00 | -0.73 | 1.13 |
| Log Population Density per Sq. Km. | 4.76 | 0.92 | 1.56 | 7.88 | 4.70 | 0.95 | 4.81 | 0.90 |
| Female Population Share | 0.50 | 0.01 | 0.18 | 0.77 | 0.50 | 0.01 | 0.50 | 0.01 |
| Share of Inhabitants Aged 18 to 64 Years | 0.61 | 0.03 | 0.46 | 0.74 | 0.61 | 0.03 | 0.61 | 0.03 |
| Share of Inhabitants Older Than 65 Years | 0.24 | 0.04 | 0.03 | 0.45 | 0.23 | 0.04 | 0.24 | 0.04 |
| Log Purchasing Power | 18.81 | 0.78 | 14.17 | 20.78 | 18.83 | 0.71 | 18.80 | 0.83 |
| Unemployment Rate in Percent | 0.05 | 0.02 | 0.00 | 0.17 | 0.05 | 0.02 | 0.05 | 0.02 |
| *Observations* | 464,092 | | | | | | | |

*Notes:* The descriptive statistics of the border samples for 30 Mbit/s report information on properties for sale (N=287,967) and for rent (N=176,125) from 3,341 rural municipalities, which are located within 25 km of the borders of "high" and "low" broadband states. Columns 1 to 4 report the mean, standard deviation, minimum, and maximum for the full samples, whereas columns 5 to 6 state the mean and standard deviation for "low" broadband states only, and columns 7 to 8 report the analogous values for "high" broadband states.

**Table A.4:** Descriptive Statistics of the Border Samples for 50 Mbit/s Broadband

| | Full Sample | | | | "Low" Broadband States | | "High" Broadband States | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Min | Max | Mean | SD | Mean | SD |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ***Outcome and Main Explanatory Variables*** | | | | | | | | |
| High Broadband States 50 Mbit/s | 0.49 | 0.50 | 0.00 | 1.00 | 0.00 | 0.00 | 1.00 | 0.00 |
| Broadband Availability Municipalities 50 Mbit/s | 0.44 | 0.35 | 0.00 | 1.00 | 0.30 | 0.33 | 0.57 | 0.32 |
| Property Sale Price Total | 211,663.53 | 131,273.37 | 9,000.00 | 2,950,000.00 | 206,176.08 | 126,956.38 | 217,320.16 | 135,347.25 |
| Property Sale Price per sqm | 1,560.54 | 788.44 | 244.28 | 7,180.00 | 1,515.03 | 736.19 | 1,607.45 | 836.31 |
| Property Rents Total (Monthly) | 512.98 | 250.50 | 90.00 | 2,800.00 | 495.96 | 236.88 | 528.83 | 261.55 |
| Property Rents per sqm (Monthly) | 6.21 | 1.68 | 3.53 | 20.00 | 5.99 | 1.56 | 6.43 | 1.76 |
| ***Control Variables*** | | | | | | | | |
| Property Type | 1.74 | 0.57 | 1.00 | 3.00 | 1.74 | 0.56 | 1.73 | 0.58 |
| Number of Rooms in the Property | 4.75 | 2.50 | 0.00 | 57.00 | 4.75 | 2.47 | 4.76 | 2.53 |
| Log of Floor Space in sqm | 4.85 | 0.46 | 3.50 | 6.15 | 4.86 | 0.45 | 4.85 | 0.47 |
| Age of Property | 7.97 | 6.05 | 1.00 | 18.00 | 8.05 | 6.16 | 7.89 | 5.94 |
| Newly Constructed Building | 0.17 | 0.38 | 0.00 | 1.00 | 0.17 | 0.38 | 0.17 | 0.38 |
| Renovation Status | 3.49 | 1.16 | 1.00 | 5.00 | 3.48 | 1.16 | 3.50 | 1.16 |
| Equipped with Kitchen | 0.23 | 0.42 | 0.00 | 1.00 | 0.21 | 0.41 | 0.25 | 0.43 |
| Equipped with Garden | 0.31 | 0.46 | 0.00 | 1.00 | 0.30 | 0.46 | 0.32 | 0.47 |
| Equipped with Balcony or Terrace | 0.30 | 0.46 | 0.00 | 1.00 | 0.29 | 0.45 | 0.32 | 0.47 |
| Equipped with Basement | 0.43 | 0.50 | 0.00 | 1.00 | 0.42 | 0.49 | 0.45 | 0.50 |
| Parking Lot or Garage Available | 0.61 | 0.49 | 0.00 | 1.00 | 0.60 | 0.49 | 0.62 | 0.49 |
| Exclusive/Luxury Equipment or Villa | 0.04 | 0.20 | 0.00 | 1.00 | 0.04 | 0.19 | 0.04 | 0.20 |
| Equipped with Pool, Whirlpool, or Sauna | 0.06 | 0.24 | 0.00 | 1.00 | 0.06 | 0.23 | 0.07 | 0.25 |
| Bright Rooms | 0.19 | 0.39 | 0.00 | 1.00 | 0.18 | 0.38 | 0.20 | 0.40 |
| Heating Type | 0.30 | 0.94 | 0.00 | 5.00 | 0.29 | 0.93 | 0.31 | 0.96 |
| Central Heating | 0.93 | 0.99 | 0.00 | 2.00 | 0.91 | 0.99 | 0.95 | 0.99 |
| Quiet Location | 0.13 | 0.33 | 0.00 | 1.00 | 0.13 | 0.34 | 0.13 | 0.33 |
| Publicly Subsidized Housing | 0.02 | 0.14 | 0.00 | 1.00 | 0.02 | 0.14 | 0.02 | 0.15 |
| School Quality (PISA) | 0.08 | 0.99 | -1.39 | 1.74 | 0.25 | 1.01 | -0.09 | 0.93 |
| Crime Rate per 10,000 Inhabitants | 0.06 | 0.01 | 0.05 | 0.09 | 0.06 | 0.01 | 0.06 | 0.01 |
| Mobile Internet Availability | 0.79 | 0.20 | 0.47 | 0.99 | 0.78 | 0.18 | 0.80 | 0.22 |
| Real Estate Transfer Tax Rate | 0.05 | 0.01 | 0.04 | 0.06 | 0.04 | 0.01 | 0.05 | 0.01 |
| Local Real Estate Tax Rate | 359.50 | 65.47 | 150.00 | 876.00 | 343.91 | 48.07 | 375.55 | 76.24 |
| Local Business Tax Rate | 354.89 | 34.11 | 200.00 | 515.00 | 346.25 | 28.49 | 363.78 | 37.01 |
| County Pre-Broadband Growth Trend | -0.26 | 1.13 | -2.00 | 2.00 | -0.28 | 1.12 | -0.23 | 1.15 |
| Log Population Density per Sq. Km. | 5.17 | 0.91 | 1.43 | 7.88 | 5.13 | 0.92 | 5.20 | 0.91 |
| Female Population Share | 0.50 | 0.01 | 0.20 | 0.77 | 0.50 | 0.01 | 0.50 | 0.01 |
| Share of Inhabitants Aged 18 to 64 Years | 0.62 | 0.03 | 0.43 | 0.76 | 0.62 | 0.03 | 0.61 | 0.03 |
| Share of Inhabitants Older Than 65 Years | 0.22 | 0.04 | 0.09 | 0.49 | 0.21 | 0.04 | 0.22 | 0.04 |
| Log Purchasing Power | 18.84 | 0.77 | 14.11 | 20.73 | 18.72 | 0.76 | 18.96 | 0.77 |
| Unemployment Rate in Percent | 0.04 | 0.02 | 0.00 | 0.14 | 0.04 | 0.02 | 0.04 | 0.02 |
| *Observations* | 695,234 | | | | | | | |

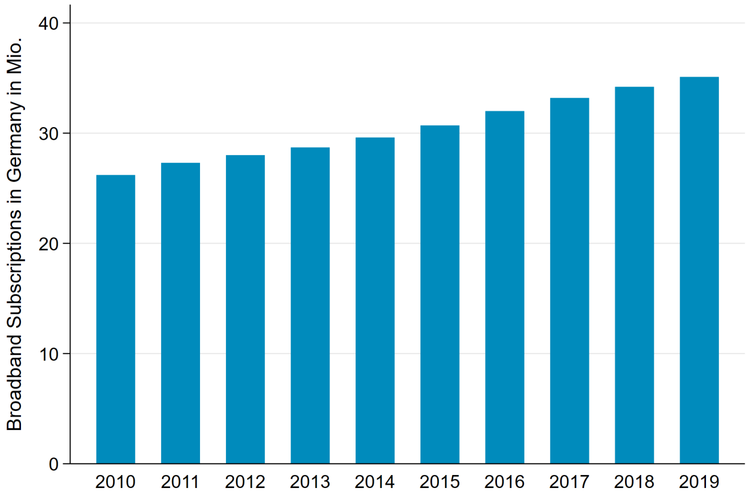
*Notes:* The descriptive statistics of the border samples for 50 Mbit/s report information on properties for sale (N=467,432) and for rent (N=227,802) from 3,389 rural municipalities, which are located within 25 km of the borders of "high" and "low" broadband states. Columns 1 to 4 report the mean, standard deviation, minimum, and maximum for the full samples, whereas columns 5 to 6 state the mean and standard deviation for "low" broadband states only, and columns 7 to 8 report the analogous values for "high" broadband states.

### A.2.2 Descriptive Figures

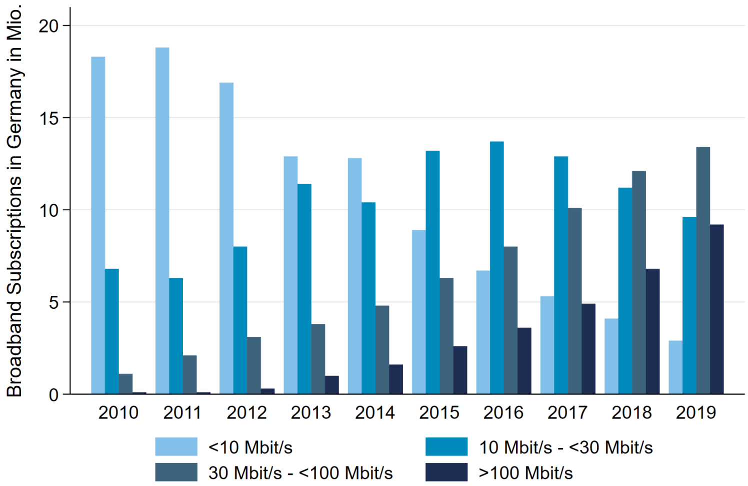
#### Administrative Data on Germany's Broadband Expansion

**Figure A.1:** Trends in Broadband Subscriptions in Germany 2010-2019

**(a)** Number of Broadband Subscriptions in Germany 2010-2019



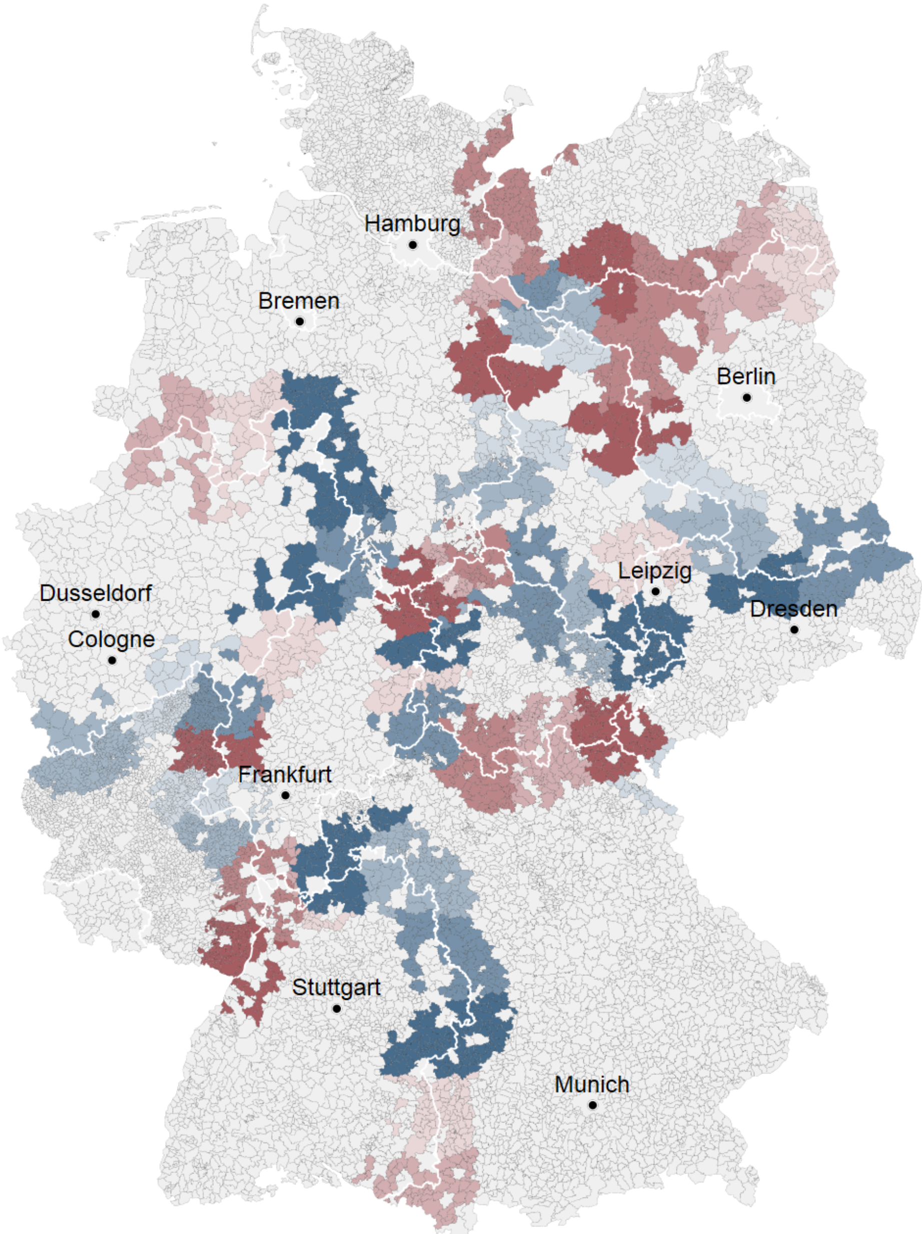

**(b)** Speed Distribution of Broadband Subscriptions in Germany 2010-2019




*Note:* Panel A shows the number of registered broadband subscriptions in Germany from 2010 to 2019, indicating a gradual increase over time. Panel B displays the annual distribution of broadband subscriptions by Internet speeds during the same period, illustrating a shift towards faster broadband. Data source: Bundesnetzagentur, 2010-2020.

## Illustration of Boundary Regions in RDD Sample

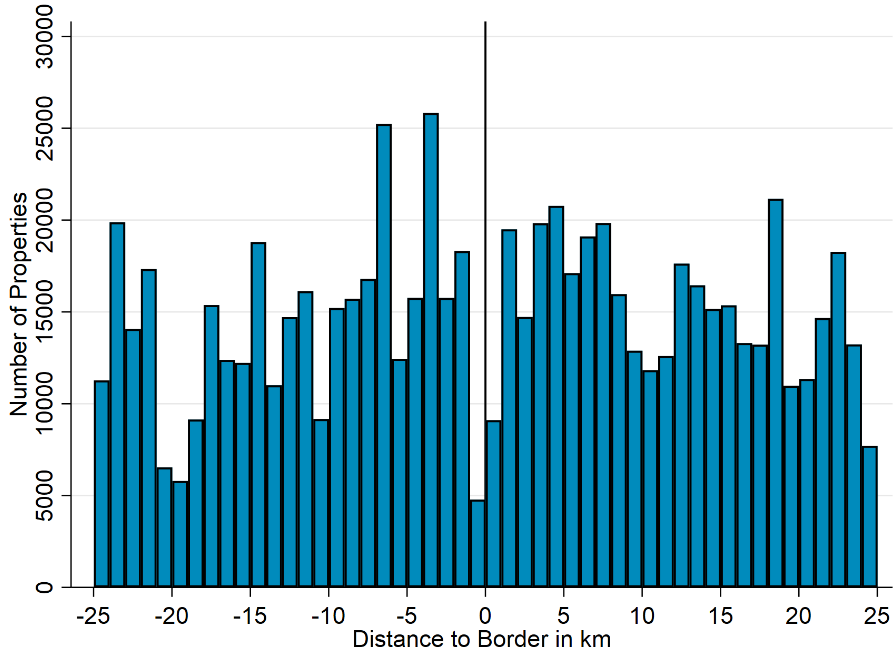
**Figure A.2:** Illustration of Boundary Regions in a Map of Germany




*Note:* This map of Germany illustrates its 16 federal states, delineated by white lines, as well as its approximately 11,000 municipalities. The RDD sample is comprised of small municipalities located around state orders of "high" and "low" broadband states. These sample municipalities are grouped in 59 boundary regions, which are highlighted in different shades of blue and red.

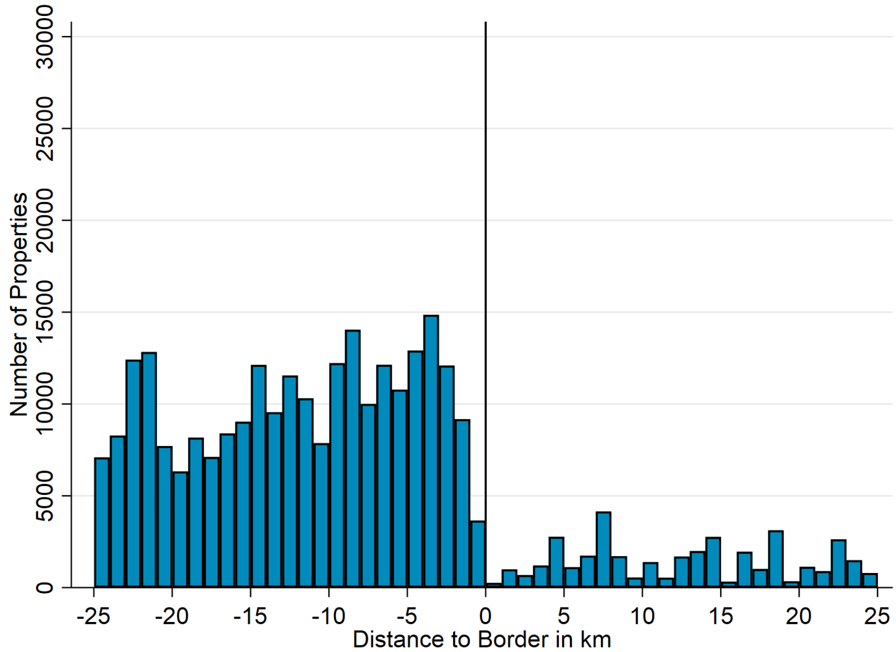
## Sample Distribution in Distance to Boundary

**Figure A.3:** Sample Distribution in Distance to Boundary for 16 Mbit/s Broadband Internet



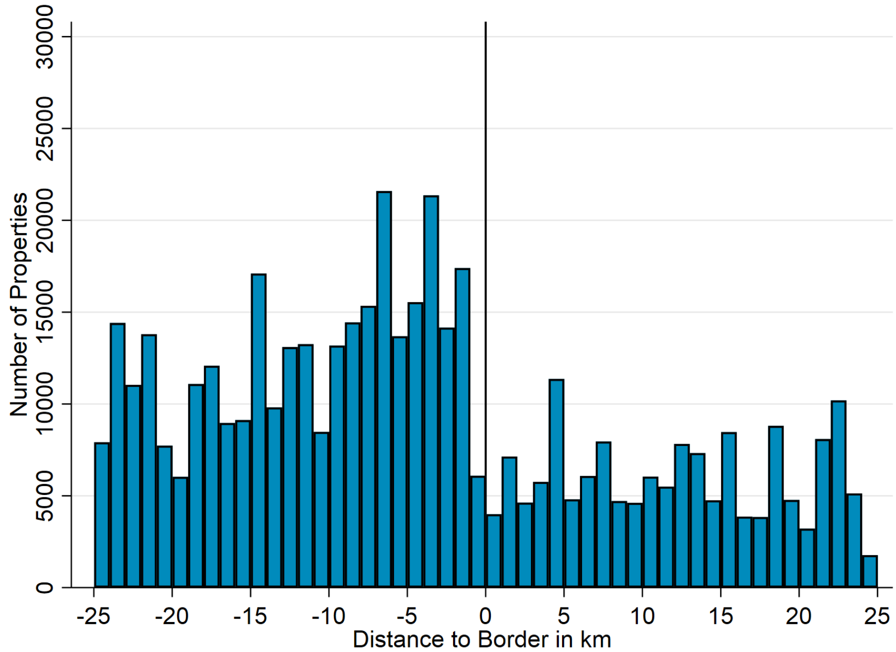

*Note:* This graph shows the spatial distribution of the RDD sample around the boundaries of "high" and "low" broadband states for 16 Mbit/s broadband Internet. The number of properties, i.e. the number of observations in the RDD sample, are plotted on the y-axis. "Distance to border in km" on the x-axis refers to the distance in kilometers between the observation and the closest state boundary, with negative values of distance indicating "high" broadband states. The plot was generated by an evenly spaced number of bins, representing the sum of observations within each bin.

**Figure A.4:** Sample Distribution in Distance to Boundary for 30 Mbit/s Broadband Internet




*Note:* This graph shows the spatial distribution of the RDD sample around the boundaries of "high" and "low" broadband states for 30 Mbit/s broadband Internet. The number of properties, i.e. the number of observations in the RDD sample, are plotted on the y-axis. "Distance to border in km" on the x-axis refers to the distance in kilometers between the observation and the closest state boundary, with negative values of distance indicating "high" broadband states. The plot was generated by an evenly spaced number of bins, representing the sum of observations within each bin.

**Figure A.5:** Sample Distribution in Distance to Boundary for 50 Mbit/s Broadband Internet

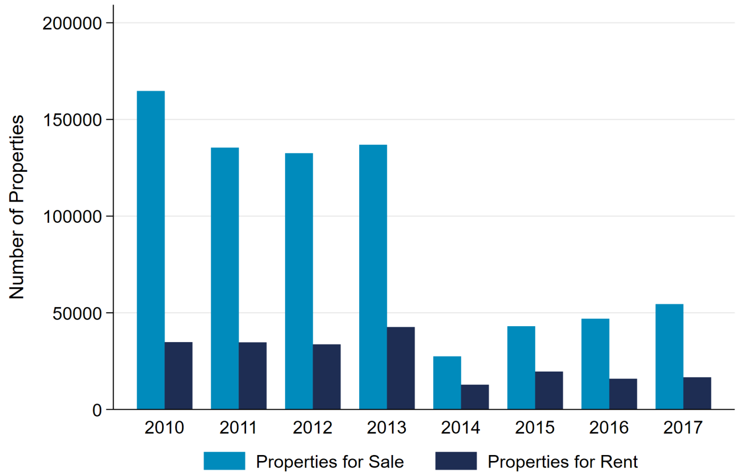



*Note:* This graph shows the spatial distribution of the RDD sample around the boundaries of "high" and "low" broadband states for 50 Mbit/s broadband Internet. The number of properties, i.e. the number of observations in the RDD sample, are plotted on the y-axis. "Distance to border in km" on the x-axis refers to the distance in kilometers between the observation and the closest state boundary, with negative values of distance indicating "high" broadband states. The plot was generated by an evenly spaced number of bins, representing the sum of observations within each bin.

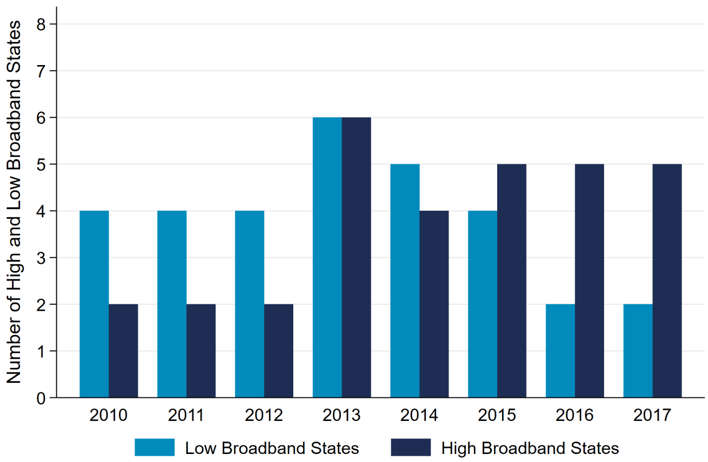
## Sample Distribution Over Time

**Figure A.6:** Distribution of RDD Sample and Broadband Status Over Time for 16 Mbit/s

**(a)** Sample Distribution Over Time for 16 Mbit/s



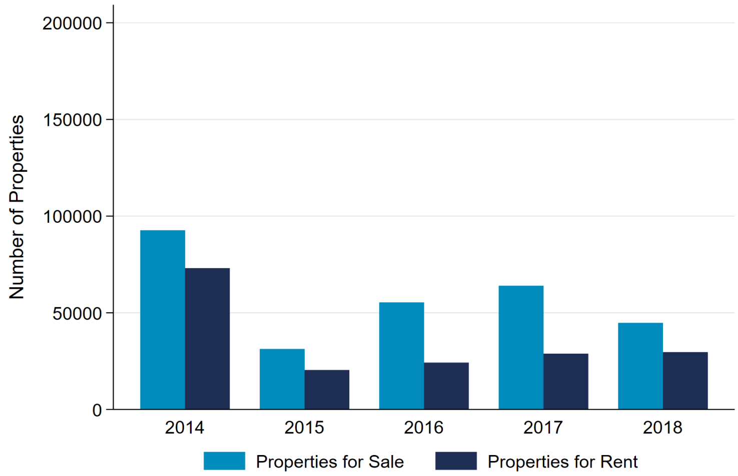

**(b)** Number of "High" and "Low" Broadband States Over Time for 16 Mbit/s



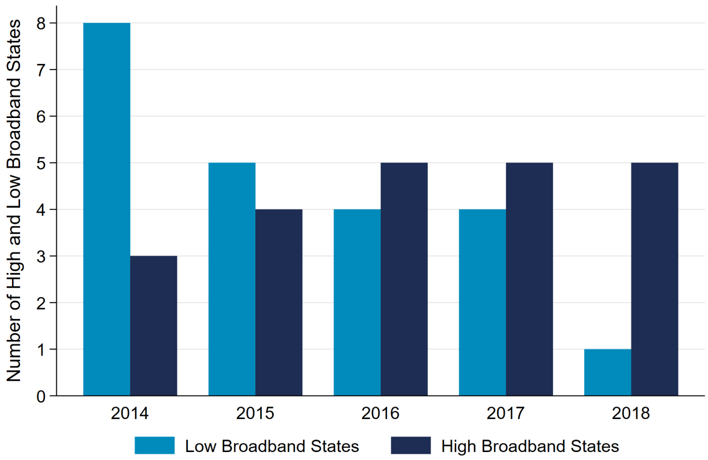

*Note:* Panel A shows the annual distribution of the RDD sample over time for 16 Mbit/s broadband Internet from 2010 to 2017. The y-axis displays the number of properties offered for sale and rent, and the x-axis shows the years included in the RDD sample. Panel B presents the number of "high" and "low" broadband states for 16 Mbit/s broadband Internet from 2010 to 2017. The RDD sample each year consists only of municipalities near the borders of states with a discontinuity in broadband status, leading to variation in sample composition over time.

**Figure A.7:** Distribution of RDD Sample and Broadband Status Over Time for 30 Mbit/s

**(a)** Sample Distribution Over Time for 30 Mbit/s



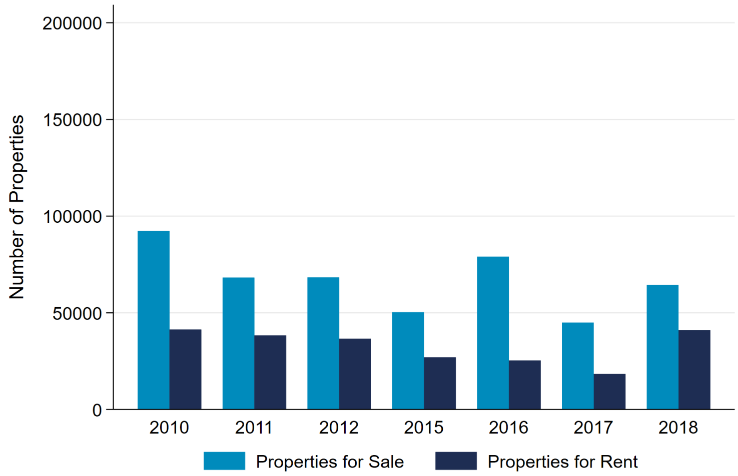

**(b)** Number of "High" and "Low" Broadband States Over Time for 30 Mbit/s



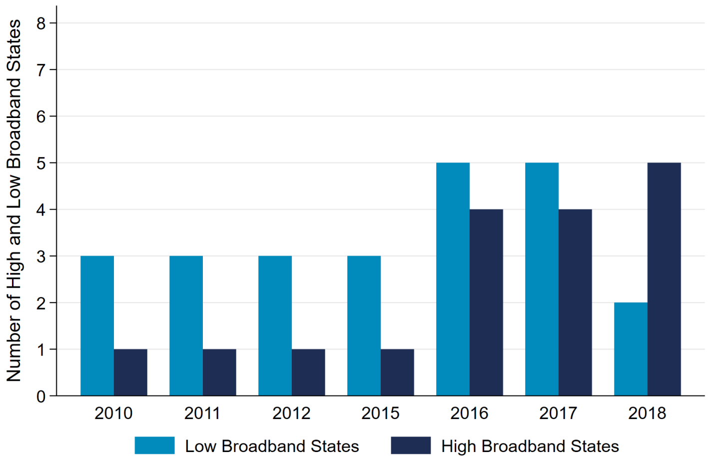

*Note:* Panel A shows the annual distribution of the RDD sample over time for 30 Mbit/s broadband Internet from 2010 to 2017. The y-axis displays the number of properties offered for sale and rent, and the x-axis shows the years included in the RDD sample. Panel B presents the number of "high" and "low" broadband states for 30 Mbit/s broadband Internet from 2010 to 2017. The RDD sample each year consists only of municipalities near the borders of states with a discontinuity in broadband status, leading to variation in sample composition over time.

**Figure A.8:** Distribution of RDD Sample and Broadband Status Over Time for 50 Mbit/s

**(a)** Sample Distribution Over Time for 50 Mbit/s



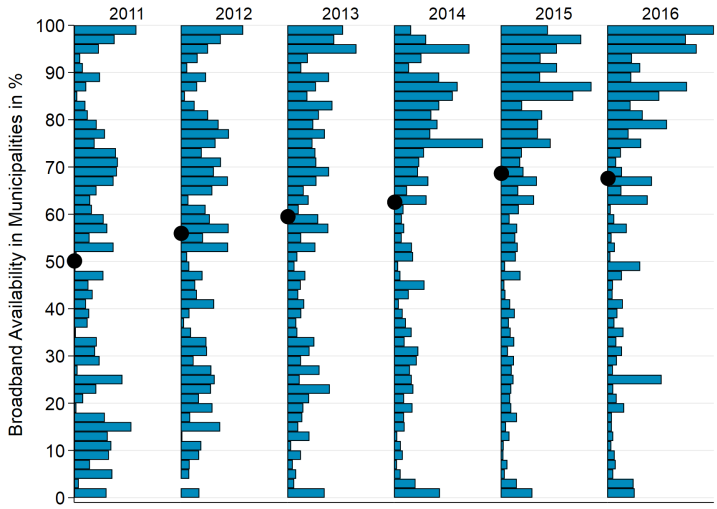

**(b)** Number of "High" and "Low" Broadband States Over Time for 50 Mbit/s



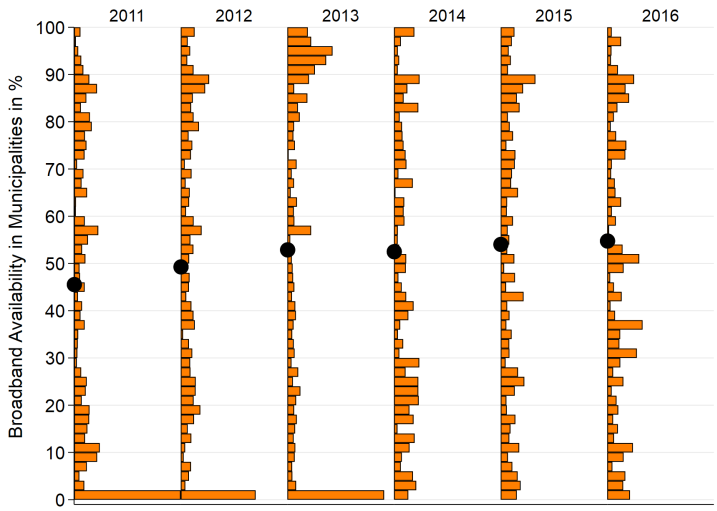

*Note:* Panel A shows the annual distribution of the RDD sample over time for 50 Mbit/s broadband Internet from 2010 to 2017. The y-axis displays the number of properties offered for sale and rent, and the x-axis shows the years included in the RDD sample. Panel B presents the number of "high" and "low" broadband states for 50 Mbit/s broadband Internet from 2010 to 2017. The RDD sample each year consists only of municipalities near the borders of states with a discontinuity in broadband status, leading to variation in sample composition over time.

**Figure A.9:** High-Speed Internet Availability 16 Mbit/s in "High" and "Low" Broadband States

**(a)** "High" Broadband States



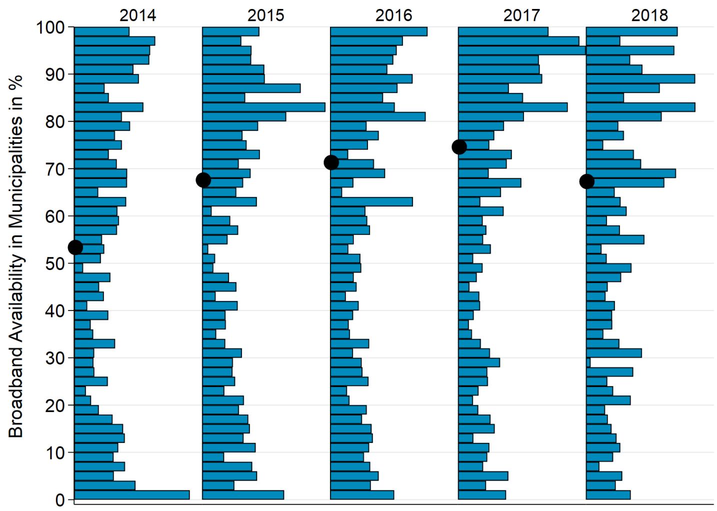

**(b)** "Low" Broadband States



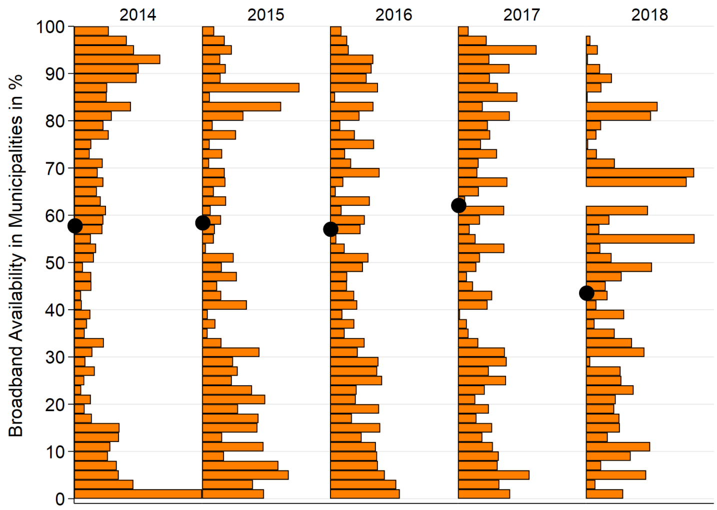

*Note:* This figure shows annual histograms of the availability of 16 Mbit/s broadband Internet in municipalities (measured as share of households per municipality with access to this Internet speed). Panel A portrays fast Internet availability in municipalities located in "high" broadband states while Panel B displays broadband access in "low" broadband states. The black dots represent yearly population-weighted means across all municipalities. The figure indicates differences in both level and time trend of Internet availability between "high" and "low" broadband states.

**Figure A.10:** High-Speed Internet Availability 30 Mbit/s in "High" and "Low" Broadband States

**(a)** "High" Broadband States



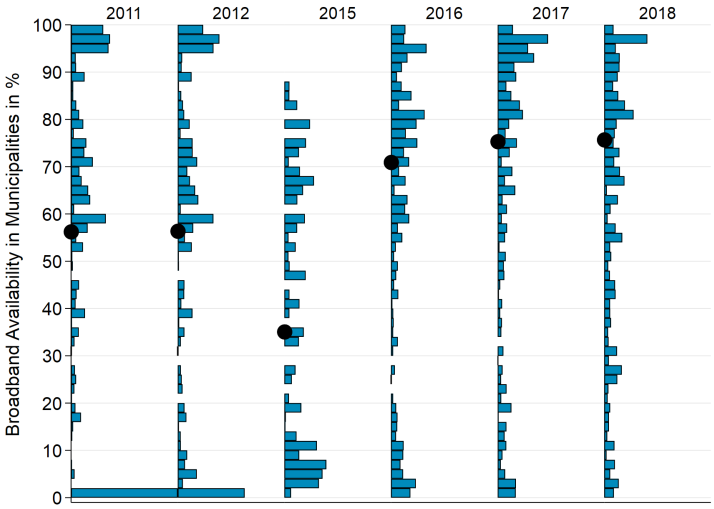

**(b)** "Low" Broadband States



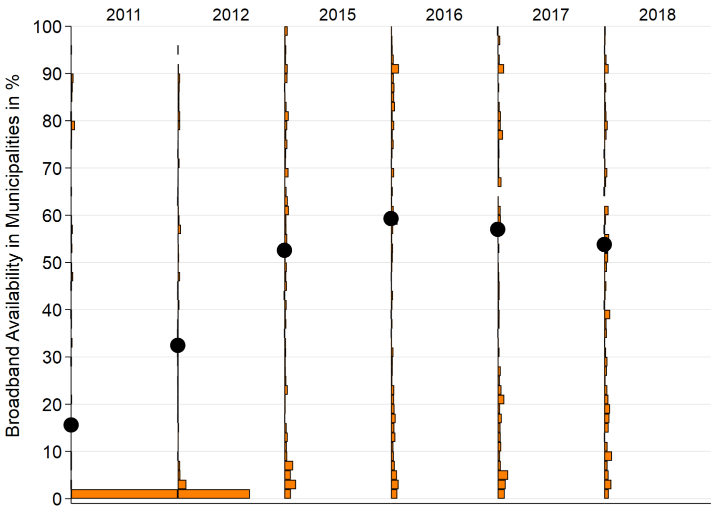

*Note:* This figure shows annual histograms of the availability of 30 Mbit/s broadband Internet in municipalities (measured as share of households per municipality with access to this Internet speed). Panel A portrays fast Internet availability in municipalities located in "high" broadband states while Panel B displays broadband access in "low" broadband states. The black dots represent yearly population-weighted means across all municipalities. The figure indicates differences in both level and time trend of Internet availability between "high" and "low" broadband states.

**Figure A.11:** High-Speed Internet Availability 50 Mbit/s in "High" and "Low" Broadband States

**(a)** "High" Broadband States




**(b)** "Low" Broadband States



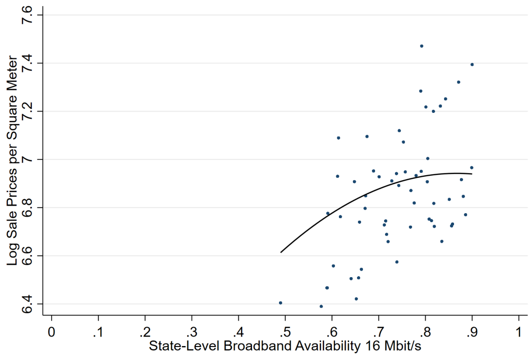

*Note:* This figure shows annual histograms of the availability of 50 Mbit/s broadband Internet in municipalities (measured as share of households per municipality with access to this Internet speed). Panel A portrays fast Internet availability in municipalities located in "high" broadband states while Panel B displays broadband access in "low" broadband states. The black dots represent yearly population-weighted means across all municipalities. The figure indicates differences in both level and time trend of Internet availability between "high" and "low" broadband states.

## A.3 Heterogeneity Analysis

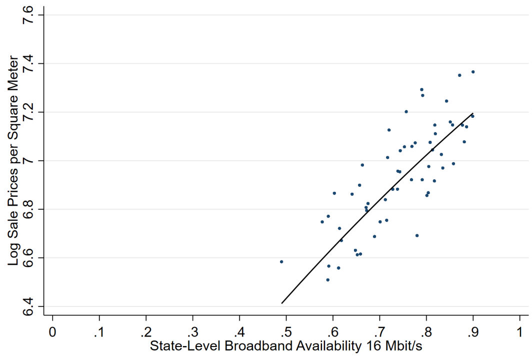
### A.3.1 Effect Size Heterogeneity

**Figure A.12:** Effect Size Heterogeneity of Property Sale Prices and Rents

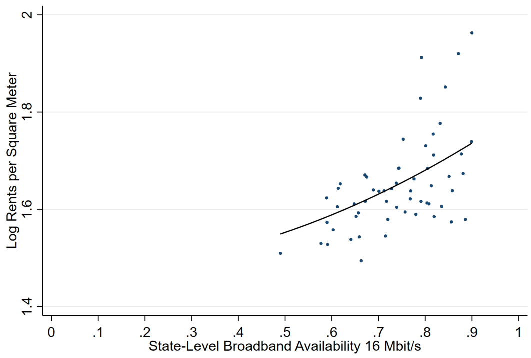
**(a)** Sale Prices: Unconditional Correlation



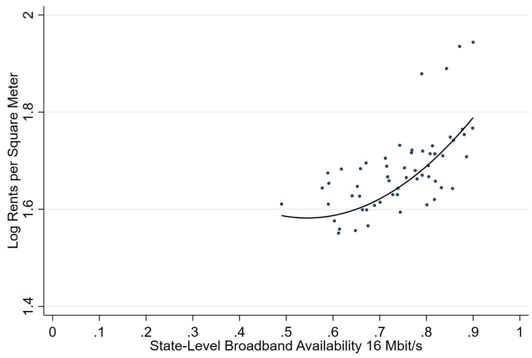

**(b)** Sale Prices: Conditional Correlation




**(c)** Rents: Unconditional Correlation




**(d)** Rents: Conditional Correlation

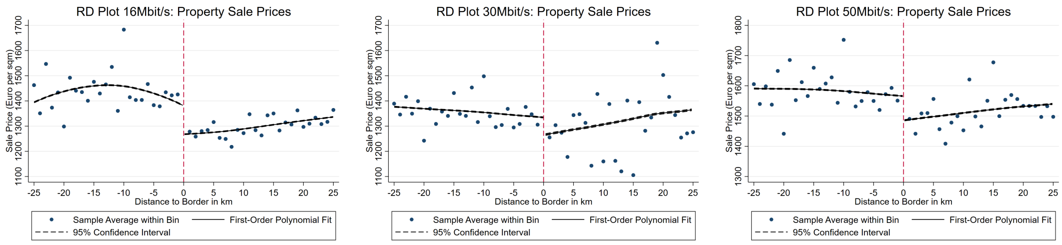



*Note:* This figure illustrates the effect size heterogeneity by correlating state-level broadband availability and property sale prices / rents. The state-level broadband availability of 16 Mbit/s on the x-axis is the determinant of "high" broadband states with the threshold of providing at least 75 percent of households with fast Internet. Log sale prices / log rents per square meter are on the y-axis. The shown conditional correlation is the result of a regression with control variables for individual property, state-level, municipality-level, and local economic characteristics as well as boundary-region-by-year fixed effects. The solid line represents the quadratic fit.

### A.3.2 Heterogeneity by Internet Speeds

**Figure A.13:** Spatial RD Plots of Property Sale Prices for Different Internet Speeds

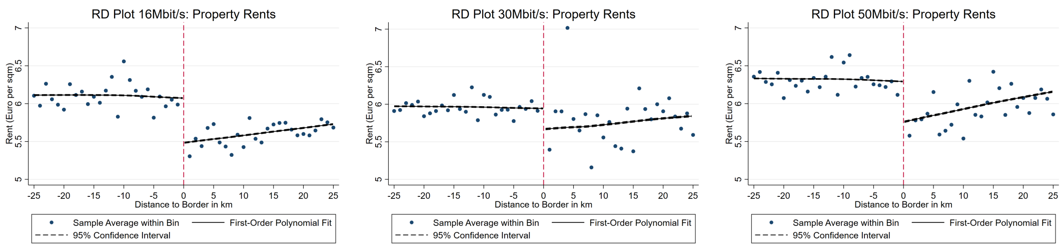
**(a)** Sale Prices 16 Mbit/s **(b)** Sale Prices 30 Mbit/s **(c)** Sale Prices 50 Mbit/s




*Note:* Shown are spatial RD plots for property sale prices (measured in Euro per square meter) for the Internet speeds 16 Mbit/s (Panel A), 30 Mbit/s (Panel B), and 50 Mbit/s (Panel C). The outcomes are plotted on the y-axis. "Distance to border in km" on the x-axis refers to the distance in kilometers between the observation and the closest state boundary, with negative values of distance indicating "high" broadband states. The RD plots are generated by an evenly spaced number of bins, representing the sample average within each bin, net of boundary-region-by-year fixed effects. The solid lines represent the predicted values from a regression of the outcome variable on a first-order polynomial in distance to the boundary. The corresponding 95 percent confidence intervals are displayed as dotted lines.

**Figure A.14:** Spatial RD Plots of Property Rents for Different Internet Speeds

**(a)** Rents 16 Mbit/s **(b)** Rents 30 Mbit/s **(c)** Rents 50 Mbit/s




*Note:* Shown are spatial RD plots for property rents (measured in Euro per square meter) for the Internet speeds 16 Mbit/s (Panel A), 30 Mbit/s (Panel B), and 50 Mbit/s (Panel C). The outcomes are plotted on the y-axis. "Distance to border in km" on the x-axis refers to the distance in kilometers between the observation and the closest state boundary, with negative values of distance indicating "high" broadband states. The RD plots are generated by an evenly spaced number of bins, representing the sample average within each bin, net of boundary-region-by-year fixed effects. The solid lines represent the predicted values from a regression of the outcome variable on a first-order polynomial in distance to the boundary. The corresponding 95 percent confidence intervals are displayed as dotted lines.

**Table A.5:** Heterogeneity of Spatial RDD Results by Internet Speeds (16, 30, & 50 Mbit/s)

| **Spatial RDD Estimates** | **Sale Prices** | | | **Rents** | | |
|---|---|---|---|---|---|---|
| | **16 Mbit/s** | **30 Mbit/s** | **50 Mbit/s** | **16 Mbit/s** | **30 Mbit/s** | **50 Mbit/s** |
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| ***Panel A: RDD Polynomials in Distance to Boundary*** | | | | | | |
| **Linear** | 0.0493*** | 0.0282 | 0.0552** | 0.0222** | 0.0035 | 0.0324*** |
| | (0.0175) | (0.0209) | (0.0214) | (0.0096) | (0.0116) | (0.0108) |
| **Quadratic** | 0.0786*** | 0.0416** | 0.0569*** | 0.0355*** | 0.0080 | 0.0319*** |
| | (0.0170) | (0.0205) | (0.0204) | (0.0099) | (0.0116) | (0.0102) |
| **Linear Interacted** | 0.0408** | 0.0319 | 0.0517** | 0.0172** | 0.0050 | 0.0287*** |
| | (0.0175) | (0.0205) | (0.0209) | (0.0086) | (0.0116) | (0.0103) |
| ***Panel B: RDD Polynomials in Longitude and Latitude*** | | | | | | |
| **Linear** | 0.0810*** | 0.0443** | 0.0584*** | 0.0378*** | 0.0097 | 0.0351*** |
| | (0.0154) | (0.0197) | (0.0214) | (0.0083) | (0.0114) | (0.0111) |
| **Quadratic** | 0.0943*** | 0.0404** | 0.0600*** | 0.0436*** | 0.0126 | 0.0379*** |
| | (0.0153) | (0.0191) | (0.0197) | (0.0086) | (0.0115) | (0.0113) |
| **Cubic** | 0.0973*** | 0.0455** | 0.0640*** | 0.0414*** | 0.0076 | 0.0382*** |
| | (0.0153) | (0.0196) | (0.0217) | (0.0083) | (0.0121) | (0.0118) |
| **Quartic** | 0.0812*** | 0.0365* | 0.0469** | 0.0299*** | 0.0075 | 0.0269*** |
| | (0.0163) | (0.0200) | (0.0195) | (0.0089) | (0.0136) | (0.0099) |
| **Boundary Region by Year FE** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Individual Property Controls** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **State Policy Controls** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Municipality Policy Controls** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Local Economic Controls** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Observations** | 723,881 | 277,859 | 460,871 | 369,335 | 170,719 | 225,055 |
| **Municipalities** | 4,035 | 3,341 | 3,389 | 3,628 | 2,953 | 2,973 |
| **Data Availability Period** | 2010-2017 | 2014-2018 | 2010-2018 | 2010-2017 | 2014-2018 | 2010-2018 |

*Note:* Shown are the coefficients and standard errors for "high broadband state" under different specifications of the RDD polynomials, with each cell in the table reporting the result of a separate regression. Panel A displays estimates for linear, quadratic, and linear interacted RDD polynomials in distance to the state boundary, whereas Panel B presents the results for linear, quadratic, cubic, and quartic RDD specifications in longitude and latitude. Columns (1) to (3) report the results for property sale prices, while columns (4) to (6) show the results for rents. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

### A.3.3 Heterogeneity Over Time

**Table A.6:** Heterogeneity of Spatial RDD Results Over Time (16, 30, & 50 Mbit/s)

| **Spatial RDD Estimates** | **Sale Prices** | | | **Rents** | | |
|---|---|---|---|---|---|---|
| | **16 Mbit/s** | **30 Mbit/s** | **50 Mbit/s** | **16 Mbit/s** | **30 Mbit/s** | **50 Mbit/s** |
| | **>= 2016** | **>= 2017** | **>= 2018** | **>= 2016** | **>= 2017** | **>= 2018** |
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| *Panel A: RDD Polynomials in Distance to Boundary* | | | | | | |
| **Linear** | 0.1220*** | 0.0839** | 0.1502*** | 0.0084 | 0.0300* | 0.0507** |
| | (0.0363) | (0.0344) | (0.0415) | (0.0333) | (0.0175) | (0.0243) |
| **Quadratic** | 0.1209*** | 0.0730** | 0.1416*** | 0.0080 | 0.0241 | 0.0487** |
| | (0.0356) | (0.0341) | (0.0408) | (0.0336) | (0.0175) | (0.0227) |
| **Linear Interacted** | 0.1198*** | 0.0802** | 0.1516*** | 0.0081 | 0.0277 | 0.0548** |
| | (0.0365) | (0.0340) | (0.0413) | (0.0334) | (0.0174) | (0.0232) |
| *Panel B: RDD Polynomials in Longitude and Latitude* | | | | | | |
| **Linear** | 0.1280*** | 0.0714** | 0.1393*** | 0.0168 | 0.0225 | 0.0457* |
| | (0.0329) | (0.0350) | (0.0415) | (0.0301) | (0.0185) | (0.0246) |
| **Quadratic** | 0.1380*** | 0.0605* | 0.1564*** | 0.0480* | 0.0227 | 0.0680** |
| | (0.0298) | (0.0344) | (0.0426) | (0.0274) | (0.0210) | (0.0271) |
| **Cubic** | 0.1736*** | 0.0601* | 0.1740*** | 0.0690** | 0.0232 | 0.0786*** |
| | (0.0322) | (0.0334) | (0.0437) | (0.0286) | (0.0212) | (0.0280) |
| **Quartic** | 0.1482*** | 0.0392 | 0.1307*** | 0.0631** | 0.0214 | 0.0593** |
| | (0.0314) | (0.0319) | (0.0401) | (0.0285) | (0.0209) | (0.0283) |
| **Boundary Region by Year FE** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Individual Property Controls** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **State Policy Controls** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Municipality Policy Controls** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Local Economic Controls** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Observations** | 723,881 | 277,859 | 460,871 | 369,335 | 170,719 | 225,055 |
| **Municipalities** | 4,035 | 3,341 | 3,389 | 3,628 | 2,953 | 2,973 |
| **Data Availability Period** | 2010-2017 | 2014-2018 | 2010-2018 | 2010-2017 | 2014-2018 | 2010-2018 |

*Note:* Shown are the coefficients and standard errors for "high broadband state" under different specifications of the RDD polynomials, with each cell in the table reporting the result of a separate regression. Panel A displays estimates for linear, quadratic, and linear interacted RDD polynomials in distance to the state boundary, whereas Panel B presents the results for linear, quadratic, cubic, and quartic RDD specifications in longitude and latitude. Columns (1) to (3) report the results for property sale prices, while columns (4) to (6) show the results for rents. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. *p<0.1; **p<0.05; ***p<0.01.

### A.3.4 Heterogeneity by Population Density

**Table A.7:** Heterogeneity of Spatial RDD Results by Population Density

| Spatial RDD Estimates | Sale Prices | | Rents | |
|---|---|---|---|---|
| | Lower Half Pop. Density | Upper Half Pop. Density | Lower Half Pop. Density | Upper Half Pop. Density |
| | (1) | (2) | (3) | (4) |
| *Panel A: RDD Polynomials in Distance to Boundary* | | | | |
| **Linear** | 0.0357* | 0.0508** | 0.0296 | 0.0119 |
| | (0.0199) | (0.0216) | (0.0297) | (0.0256) |
| **Quadratic** | 0.0701*** | 0.0780*** | 0.0074 | 0.0504*** |
| | (0.0153) | (0.0197) | (0.0127) | (0.0160) |
| **Linear Interacted** | 0.0269 | 0.0468** | -0.0174 | 0.0436** |
| | (0.0188) | (0.0212) | (0.0242) | (0.0180) |
| *Panel B: RDD Polynomials in Longitude and Latitude* | | | | |
| **Linear** | 0.0612*** | 0.0831*** | 0.0041 | 0.0506*** |
| | (0.0156) | (0.0177) | (0.0134) | (0.0124) |
| **Quadratic** | 0.0689*** | 0.0966*** | 0.0130 | 0.0568*** |
| | (0.0155) | (0.0169) | (0.0137) | (0.0124) |
| **Cubic** | 0.0732*** | 0.0976*** | 0.0027 | 0.0602*** |
| | (0.0164) | (0.0165) | (0.0184) | (0.0118) |
| **Quartic** | 0.0482*** | 0.0824*** | 0.0198 | 0.0526*** |
| | (0.0184) | (0.0189) | (0.0164) | (0.0156) |
| **Boundary Region by Year FE** | ✓ | ✓ | ✓ | ✓ |
| **Individual Property Controls** | ✓ | ✓ | ✓ | ✓ |
| **State Policy Controls** | ✓ | ✓ | ✓ | ✓ |
| **Municipality Policy Controls** | ✓ | ✓ | ✓ | ✓ |
| **Local Economic Controls** | ✓ | ✓ | ✓ | ✓ |
| **Observations** | 153,833 | 570,048 | 37,508 | 167,862 |
| **Municipalities** | 2,017 | 2,018 | 1,048 | 1,048 |
| **Data Availability Period** | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 |

*Note:* Shown are the coefficients and standard errors for "high broadband state" under different specifications of the RDD polynomials, with each cell in the table reporting the result of a separate regression. Panel A displays estimates for linear, quadratic, and linear interacted RDD polynomials in distance to the state boundary, whereas Panel B presents the results for linear, quadratic, cubic, and quartic RDD specifications in longitude and latitude. Columns (1) to (3) report the results for property sale prices, while columns (4) to (6) show the results for rents. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

### A.3.5 Heterogeneity by Property Types

**Table A.8:** Heterogeneity of Spatial RDD Results by Property Types

| **Spatial RDD Estimates** | **Sale Prices** | | **Rents** | |
|---|---|---|---|---|
| | **Houses** | **Apartments** | **Houses** | **Apartments** |
| | (1) | (2) | (3) | (4) |
| ***Panel A: RDD Polynomials in Distance to Boundary*** | | | | |
| **Linear** | 0.0543*** | 0.0461** | 0.0487*** | 0.0204** |
| | (0.0179) | (0.0192) | (0.0150) | (0.0092) |
| **Quadratic** | 0.0969*** | 0.0494** | 0.0609*** | 0.0336*** |
| | (0.0163) | (0.0205) | (0.0125) | (0.0097) |
| **Linear Interacted** | 0.0494*** | 0.0301 | 0.0466*** | 0.0151* |
| | (0.0175) | (0.0195) | (0.0113) | (0.0085) |
| ***Panel B: RDD Polynomials in Longitude and Latitude*** | | | | |
| **Linear** | 0.0946*** | 0.0557*** | 0.0600*** | 0.0363*** |
| | (0.0147) | (0.0192) | (0.0096) | (0.0083) |
| **Quadratic** | 0.1028*** | 0.0770*** | 0.0674*** | 0.0421*** |
| | (0.0151) | (0.0184) | (0.0093) | (0.0088) |
| **Cubic** | 0.1051*** | 0.0887*** | 0.0678*** | 0.0391*** |
| | (0.0152) | (0.0174) | (0.0089) | (0.0084) |
| **Quartic** | 0.0877*** | 0.0788*** | 0.0482*** | 0.0292*** |
| | (0.0165) | (0.0194) | (0.0099) | (0.0089) |
| **Boundary Region by Year FE** | ✓ | ✓ | ✓ | ✓ |
| **Individual Property Controls** | ✓ | ✓ | ✓ | ✓ |
| **State Policy Controls** | ✓ | ✓ | ✓ | ✓ |
| **Municipality Policy Controls** | ✓ | ✓ | ✓ | ✓ |
| **Local Economic Controls** | ✓ | ✓ | ✓ | ✓ |
| **Observations** | 507,349 | 216,531 | 42,477 | 326,856 |
| **Municipalities** | 4,017 | 3,485 | 2,764 | 3,509 |
| **Data Availability Period** | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 |

*Note:* Shown are the coefficients and standard errors for "high broadband state" under different specifications of the RDD polynomials, with each cell in the table reporting the result of a separate regression. Panel A displays estimates for linear, quadratic, and linear interacted RDD polynomials in distance to the state boundary, whereas Panel B presents the results for linear, quadratic, cubic, and quartic RDD specifications in longitude and latitude. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. *p<0.1; **p<0.05; ***p<0.01.

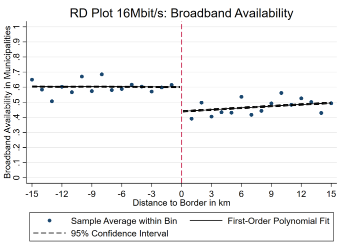
## A.4 Specification Checks

### A.4.1 Graphical Evidence

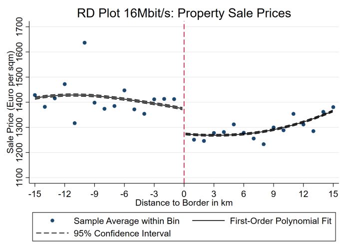
#### RD Plots of Main Outcomes for 15km Bandwidth

**Figure A.15:** Spatial RD Plots of Main Outcomes for Alternative 15km Bandwidth

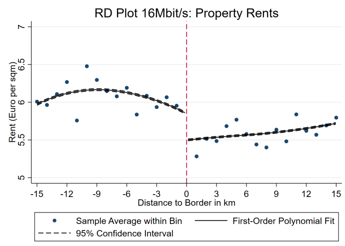
**(a)** Broadband Availability




**(b)** Property Sale Prices




**(c)** Property Rents

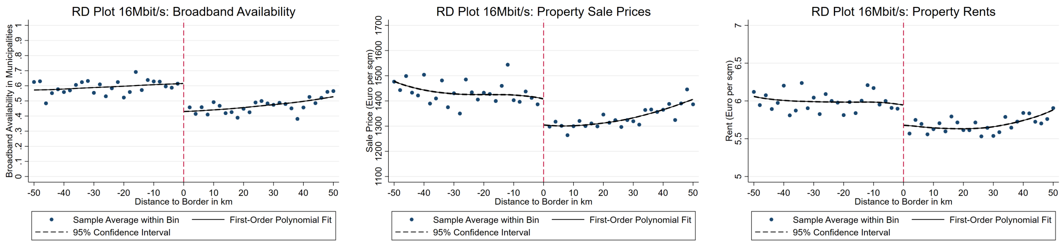



*Note:* Shown are spatial RD plots for broadband availability in municipalities (Panel A), property sale prices (Panel B), and property rents (Panel C) for the Internet speed of 16 Mbit/s using an alternative bandwidth of 15 kilometers around the state borders. The outcomes are plotted on the y-axis. "Distance to border in km" on the x-axis refers to the distance in kilometers between the observation and the closest state boundary, with negative values of distance indicating "high" broadband states. The RD plots are generated by an evenly spaced number of bins, representing the sample average within each bin, net of boundary-region-by-year fixed effects. The solid lines represent the predicted values from a regression of the outcome variable on a first-order polynomial in distance to the boundary. The corresponding 95 percent confidence intervals are displayed as dotted lines.

## RD Plots of Main Outcomes for 50km Bandwidth

**Figure A.16:** Spatial RD Plots of Main Outcomes for Alternative 50km Bandwidth

**(a)** Broadband Availability **(b)** Property Sale Prices **(c)** Property Rents




*Note:* Shown are spatial RD plots for broadband availability in municipalities (Panel A), property sale prices (Panel B), and property rents (Panel C) for the Internet speed of 16 Mbit/s using an alternative bandwidth of 50 kilometers around the state borders. The outcomes are plotted on the y-axis. "Distance to border in km" on the x-axis refers to the distance in kilometers between the observation and the closest state boundary, with negative values of distance indicating "high" broadband states. The RD plots are generated by an evenly spaced number of bins, representing the sample average within each bin, net of boundary-region-by-year fixed effects. The solid lines represent the predicted values from a regression of the outcome variable on a first-order polynomial in distance to the boundary. The corresponding 95 percent confidence intervals are displayed as dotted lines.

### A.4.2 Tables

Sensitivity of Spatial RDD Results to Bandwidths Around State Boundaries

**Table A.9:** Sensitivity of Spatial RDD Results to 15, 25, and 50km Bandwidths

| **Spatial RDD Estimates** | **Sale Prices** | | | **Rents** | | |
|---|---|---|---|---|---|---|
| **Bandwidth Around State Borders** | **15 km** | **25 km** | **50 km** | **15 km** | **25 km** | **50 km** |
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| ***Panel A: RDD Polynomials in Distance to Boundary*** | | | | | | |
| **Linear** | 0.0388** | 0.0493*** | 0.0609*** | 0.0091 | 0.0222** | 0.0155* |
| | (0.0192) | (0.0175) | (0.0163) | (0.0115) | (0.0096) | (0.0092) |
| **Quadratic** | 0.0822*** | 0.0786*** | 0.0495*** | 0.0317*** | 0.0355*** | -0.0019 |
| | (0.0140) | (0.0170) | (0.0123) | (0.0079) | (0.0099) | (0.0081) |
| **Linear Interacted** | 0.0363** | 0.0408** | 0.0207 | 0.0094 | 0.0172** | -0.0053 |
| | (0.0181) | (0.0175) | (0.0160) | (0.0089) | (0.0086) | (0.0088) |
| ***Panel B: RDD Polynomials in Longitude and Latitude*** | | | | | | |
| **Linear** | 0.0859*** | 0.0810*** | 0.0460*** | 0.0339*** | 0.0378*** | -0.0012 |
| | (0.0139) | (0.0154) | (0.0124) | (0.0078) | (0.0083) | (0.0079) |
| **Quadratic** | 0.0924*** | 0.0943*** | 0.0610*** | 0.0394*** | 0.0436*** | 0.0098 |
| | (0.0139) | (0.0153) | (0.0119) | (0.0083) | (0.0086) | (0.0071) |
| **Cubic** | 0.0874*** | 0.0973*** | 0.0768*** | 0.0376*** | 0.0414*** | 0.0138* |
| | (0.0143) | (0.0153) | (0.0138) | (0.0080) | (0.0083) | (0.0074) |
| **Quartic** | 0.0696*** | 0.0812*** | 0.0815*** | 0.0147** | 0.0299*** | 0.0136 |
| | (0.0139) | (0.0163) | (0.0161) | (0.0067) | (0.0089) | (0.0086) |
| **Boundary Region by Year FE** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Individual Property Controls** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **State Policy Controls** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Municipality Policy Controls** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Local Economic Controls** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Observations** | 466,560 | 723,881 | 1,299,127 | 241,635 | 369,335 | 662,592 |
| **Municipalities** | 2,664 | 4,035 | 6,141 | 2,395 | 3,628 | 5,575 |
| **Data Availability Period** | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 |

*Note:* Shown are the coefficients and standard errors for "high broadband state" under different specifications of the RDD polynomials, with each cell in the table reporting the result of a separate regression. Panel A displays estimates for linear, quadratic, and linear interacted RDD polynomials in distance to the state boundary, whereas Panel B presents the results for linear, quadratic, cubic, and quartic RDD specifications in longitude and latitude. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. *$p<0.1$; **$p<0.05$; ***$p<0.01$.

**Table A.10:** Sensitivity of Spatial RDD Results to Observations Near State Borders ("Donut Hole Approach")

| Spatial RDD Estimates | Sale Prices | | | Rents | | |
|---|---|---|---|---|---|---|
| "Donut Hole" Size | 2 km | 5 km | 10 km | 2 km | 5 km | 10 km |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: RDD Polynomials in Distance to Boundary* | | | | | | |
| **Linear** Linear | 0.0510*** | 0.0797*** | 0.0686** | 0.0264*** | 0.0566*** | 0.0259 |
| | (0.0181) | (0.0227) | (0.0339) | (0.0093) | (0.0156) | (0.0219) |
| **Quadratic** | 0.0826*** | 0.0879*** | 0.0898*** | 0.0414*** | 0.0484*** | 0.0485*** |
| | (0.0173) | (0.0183) | (0.0198) | (0.0100) | (0.0118) | (0.0143) |
| **Linear Interacted** | 0.0408** | 0.0537*** | 0.0710** | 0.0225*** | 0.0396*** | 0.0360** |
| | (0.0174) | (0.0201) | (0.0306) | (0.0079) | (0.0131) | (0.0163) |
| *Panel B: RDD Polynomials in Longitude and Latitude* | | | | | | |
| **Linear** | 0.0860*** | 0.0891*** | 0.0875*** | 0.0440*** | 0.0500*** | 0.0475*** |
| | (0.0156) | (0.0163) | (0.0171) | (0.0086) | (0.0099) | (0.0111) |
| **Quadratic** | 0.0999*** | 0.1061*** | 0.1081*** | 0.0494*** | 0.0570*** | 0.0554*** |
| | (0.0153) | (0.0163) | (0.0176) | (0.0088) | (0.0103) | (0.0116) |
| **Cubic** | 0.1036*** | 0.1151*** | 0.1194*** | 0.0475*** | 0.0585*** | 0.0543*** |
| | (0.0154) | (0.0159) | (0.0172) | (0.0085) | (0.0100) | (0.0107) |
| **Quartic** | 0.0871*** | 0.1053*** | 0.1066*** | 0.0344*** | 0.0514*** | 0.0460*** |
| | (0.0163) | (0.0178) | (0.0205) | (0.0087) | (0.0116) | (0.0141) |
| **Boundary Region by Year FE** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Individual Property Controls** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **State Policy Controls** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Municipality Policy Controls** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Local Economic Controls** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Observations** | 673,445 | 562,963 | 397,683 | 344,925 | 288,305 | 205,371 |
| **Municipalities** | 3,829 | 3,293 | 2,334 | 3,432 | 2,944 | 2,096 |
| **Data Availability Period** | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 |

*Note:* Shown are the coefficients and standard errors for "high broadband state" under different specifications of the RDD polynomials, with each cell in the table reporting the result of a separate regression. Panel A displays estimates for linear, quadratic, and linear interacted RDD polynomials in distance to the state boundary, whereas Panel B presents the results for linear, quadratic, cubic, and quartic RDD specifications in longitude and latitude. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. *p<0.1; **p<0.05; ***p<0.01.

## Sensitivity of Spatial RDD Results to Estimations in Levels

**Table A.11:** Sensitivity of Spatial RDD Results to Estimations in Levels (Total Prices and Prices per Square Meter)

| **Spatial RDD Estimates** | **Sale Prices** | | **Rents** | |
|---|---|---|---|---|
| | **Total** | **Per sqm** | **Total** | **Per sqm** |
| | (1) | (2) | (3) | (4) |
| ***Panel A: RDD Polynomials in Distance to Boundary*** | | | | |
| **Linear** | 7,096.1190** | 62.7443*** | 10.5060* | 0.1742*** |
| | (3,154.6028) | (22.1291) | (5.6605) | (0.0619) |
| **Quadratic** | 14,801.8921*** | 103.1682*** | 19.9307*** | 0.2516*** |
| | (3,493.2355) | (24.0175) | (5.5306) | (0.0665) |
| **Linear Interacted** | 7,175.8117** | 61.1233*** | 9.5201** | 0.1409*** |
| | (3,032.6033) | (20.8117) | (3.9528) | (0.0498) |
| ***Panel B: RDD Polynomials in Longitude and Latitude*** | | | | |
| **Linear** | 14,935.2847*** | 106.5146*** | 21.0093*** | 0.2662*** |
| | (3,026.7221) | (20.7082) | (4.4063) | (0.0558) |
| **Quadratic** | 16,888.0011*** | 127.9448*** | 24.4822*** | 0.3063*** |
| | (2,949.7367) | (20.8545) | (4.6001) | (0.0584) |
| **Cubic** | 16,639.3790*** | 128.6799*** | 22.5143*** | 0.2859*** |
| | (2,876.2996) | (20.2915) | (4.4776) | (0.0556) |
| **Quartic** | 13,244.4593*** | 100.1892*** | 15.5439*** | 0.2134*** |
| | (3,162.1126) | (20.9734) | (4.7907) | (0.0585) |
| **Boundary Region by Year FE** | ✓ | ✓ | ✓ | ✓ |
| **Individual Property Controls** | ✓ | ✓ | ✓ | ✓ |
| **State Policy Controls** | ✓ | ✓ | ✓ | ✓ |
| **Municipality Policy Controls** | ✓ | ✓ | ✓ | ✓ |
| **Local Economic Controls** | ✓ | ✓ | ✓ | ✓ |
| **Observations** | 723,881 | 723,881 | 369,335 | 369,335 |
| **Municipalities** | 3,983 | 3,983 | 3,579 | 3,579 |
| **Data Availability Period** | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 |

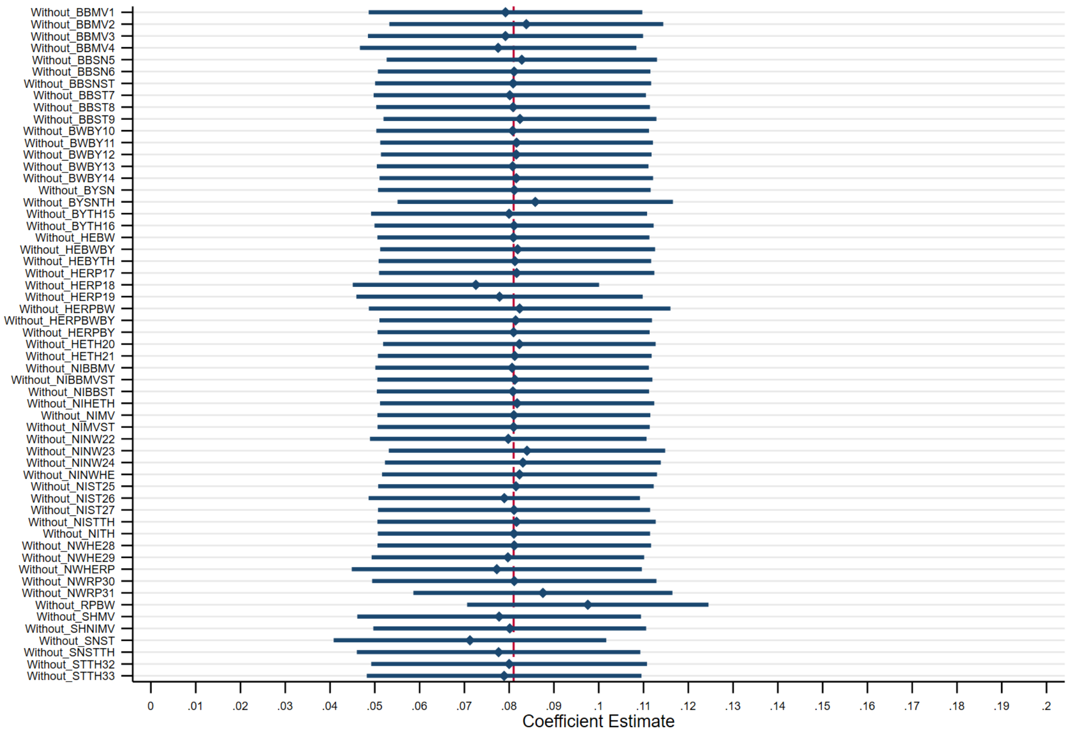
*Note:* Shown are the coefficients and standard errors for "high broadband state" under different specifications of the RDD polynomials, with each cell in the table reporting the result of a separate regression. Panel A displays estimates for linear, quadratic, and linear interacted RDD polynomials in distance to the state boundary, whereas Panel B presents the results for linear, quadratic, cubic, and quartic RDD specifications in longitude and latitude. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. *p<0.1; **p<0.05; ***p<0.01.

## A.5 Robustness Checks

### A.5.1 Robustness Checks on Sample

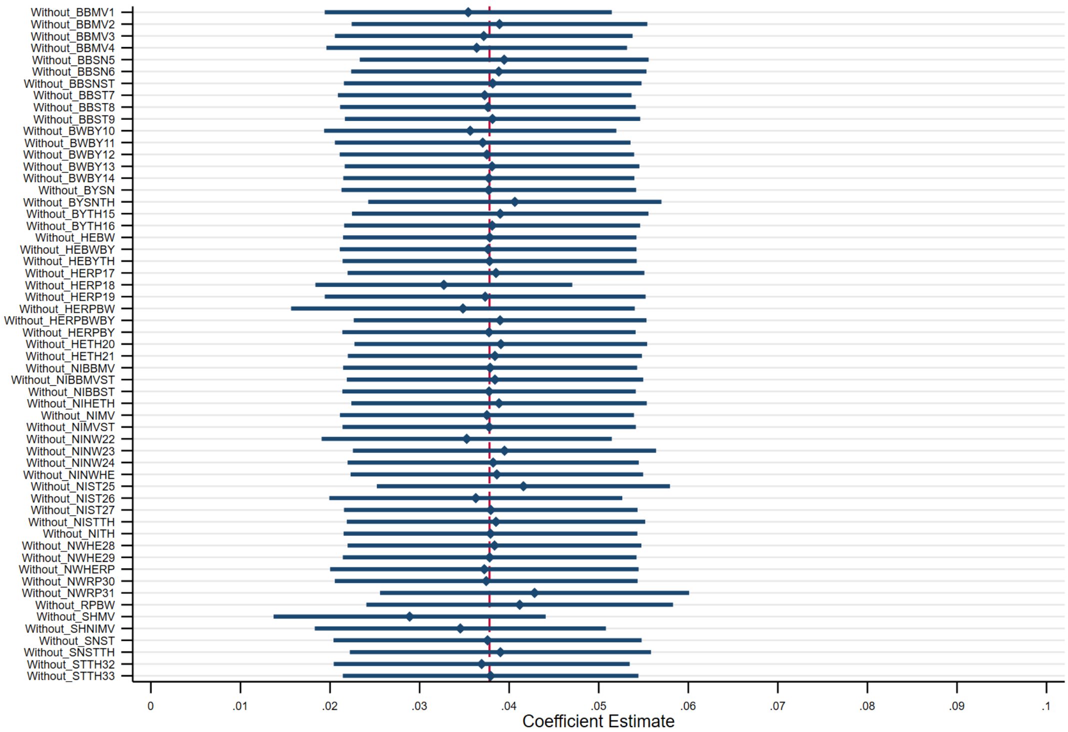
#### Sample Robustness Checks of Leaving One Boundary Region Out

**Figure A.17:** Leaving One Border Region Out: Property Sale Prices




*Note:* This coefficient plot presents the coefficients and standard errors for regressions of "high broadband state" on property sale prices using the preferred RDD specification with linear polynomials in longitude and latitude. Each row reports the result of a separate regression that leaves out one distinct boundary region at a time. The dotted red line shows the baseline coefficient estimate of the entire sample. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level.

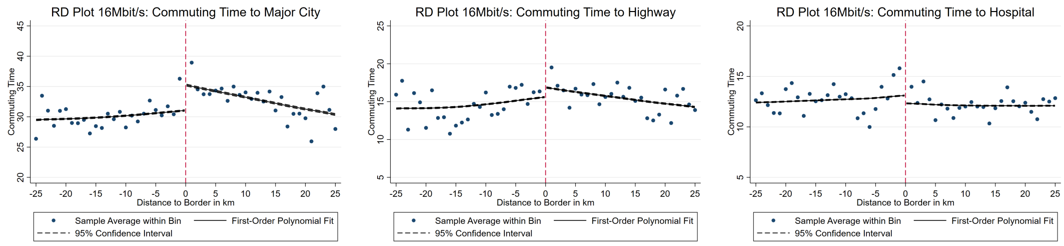
**Figure A.18:** Leaving One Border Region Out: Property Rents




*Note:* This coefficient plot presents the coefficients and standard errors for regressions of "high broadband state" on property rents using the preferred RDD specification with linear polynomials in longitude and latitude. Each row reports the result of a separate regression that leaves out one distinct boundary region at a time. The dotted red line shows the baseline coefficient estimate of the entire sample. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level.

## Sample Robustness Check of Additional Control Variables

**Figure A.19:** Spatial RD Plots for Additional Controls Around State Boundaries




*Note:* This combined figure of RD plots shows additional regional socioeconomic characteristics around the state boundary discontinuity. These variables are the share of age group 18-64; the share of age group 65+; the share of female population; the population density; the commuting time to the nearest major city; the commuting time to the nearest highway. The outcomes are plotted on the y-axis. "Distance to border in km" on the x-axis refers to the distance in kilometers between the observation and the closest state boundary, with negative values of distance indicating "high" broadband states. The RD plots are generated by an evenly spaced number of bins, representing the sample average within each bin, net of boundary-region-by-year fixed effects. The solid lines represent the predicted values from a regression of the outcome variable on a first-order polynomial in distance to the boundary. The corresponding 95 percent confidence intervals are displayed as dotted lines.

**Table A.12:** Sample Robustness Checks for Real Estate Sale Prices

| **Spatial RDD Estimates** | **Real Estate Sale Prices** | | | | |
|---|---|---|---|---|---|
| | **West Germany** | **East Germany** | **Without RLP** | **With Larger Municipalities** | **With Add. Controls** |
| | (1) | (2) | (3) | (4) | (5) |
| *Panel A: RDD Polynomials in Distance to Boundary* | | | | | |
| **Linear** | 0.0341 | 0.1234** | 0.0309** | 0.0436*** | 0.0402** |
| | (0.0245) | (0.0527) | (0.0148) | (0.0164) | (0.0163) |
| **Quadratic** | 0.0690*** | 0.1305*** | 0.0666*** | 0.0857*** | 0.0614*** |
| | (0.0246) | (0.0471) | (0.0141) | (0.0123) | (0.0165) |
| **Linear Interacted** | 0.0324 | 0.1035** | 0.0198 | 0.0393** | 0.0364** |
| | (0.0247) | (0.0499) | (0.0156) | (0.0159) | (0.0158) |
| *Panel B: RDD Polynomials in Longitude-Latitude* | | | | | |
| **Linear** | 0.0747*** | 0.1600*** | 0.0753*** | 0.0843*** | 0.0620*** |
| | (0.0216) | (0.0572) | (0.0141) | (0.0111) | (0.0149) |
| **Quadratic** | 0.0723*** | 0.1732*** | 0.0829*** | 0.0967*** | 0.0748*** |
| | (0.0212) | (0.0558) | (0.0144) | (0.0116) | (0.0149) |
| **Cubic** | 0.0619*** | 0.0966* | 0.0842*** | 0.0995*** | 0.0741*** |
| | (0.0195) | (0.0544) | (0.0171) | (0.0120) | (0.0150) |
| **Quartic** | 0.0453** | 0.0805 | 0.0613*** | 0.0849*** | 0.0752*** |
| | (0.0207) | (0.0534) | (0.0157) | (0.0125) | (0.0149) |
| **Boundary Region by Year FE** | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Individual Property Controls** | ✓ | ✓ | ✓ | ✓ | ✓ |
| **State Policy Controls** | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Municipality Policy Controls** | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Local Economic Controls** | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Observations** | 619,094 | 104,787 | 577,907 | 1,282,186 | 723,881 |
| **Municipalities** | 2,731 | 1,304 | 2,816 | 4,340 | 4,035 |
| **Data Availability Period** | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 |

*Note:* Shown are the coefficients and standard errors for "high broadband state" under different specifications of the RDD polynomials, with each cell in the table reporting the result of a separate regression. Panel A displays estimates for linear, quadratic, and linear interacted RDD polynomials in distance to the state boundary, whereas Panel B presents the results for linear, quadratic, cubic, and quartic RDD specifications in longitude and latitude. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. *$p<0.1$; **$p<0.05$; ***$p<0.01$.

**Table A.13:** Sample Robustness Checks for Real Estate Rents

| Spatial RDD Estimates | Real Estate Rents | | | | |
|---|---|---|---|---|---|
| | West Germany | East Germany | Without RLP | With Larger Municipalities | With Add. Controls |
| *Panel A: RDD Polynomials in Distance to Boundary* | | | | | |
| **Linear** | 0.0424*** | 0.0487* | 0.0050 | 0.0366*** | 0.0144* |
| | (0.0131) | (0.0256) | (0.0105) | (0.0088) | (0.0082) |
| **Quadratic** | 0.0584*** | 0.0277 | 0.0127 | 0.0529*** | 0.0221** |
| | (0.0158) | (0.0224) | (0.0085) | (0.0074) | (0.0093) |
| **Linear Interacted** | 0.0405*** | 0.0328 | -0.0079 | 0.0393*** | 0.0110 |
| | (0.0136) | (0.0294) | (0.0087) | (0.0083) | (0.0068) |
| *Panel B: RDD Polynomials in Longitude-Latitude* | | | | | |
| **Linear** | 0.0591*** | 0.0531** | 0.0197** | 0.0497*** | 0.0238*** |
| | (0.0123) | (0.0236) | (0.0097) | (0.0060) | (0.0078) |
| **Quadratic** | 0.0569*** | 0.0587** | 0.0255** | 0.0541*** | 0.0296*** |
| | (0.0111) | (0.0239) | (0.0100) | (0.0065) | (0.0083) |
| **Cubic** | 0.0453*** | 0.0284 | 0.0218** | 0.0524*** | 0.0285*** |
| | (0.0093) | (0.0194) | (0.0107) | (0.0069) | (0.0076) |
| **Quartic** | 0.0392*** | 0.0368** | 0.0159* | 0.0345*** | 0.0277*** |
| | (0.0095) | (0.0184) | (0.0095) | (0.0074) | (0.0080) |
| **Boundary Region by Year FE** | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Individual Property Controls** | ✓ | ✓ | ✓ | ✓ | ✓ |
| **State Policy Controls** | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Municipality Policy Controls** | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Local Economic Controls** | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Observations** | 296,243 | 73,092 | 313,384 | 1,006,586 | 369,335 |
| **Municipalities** | 2,563 | 1,065 | 2,532 | 3,932 | 3,628 |
| **Data Availability Period** | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 | 2010-2017 |

*Note:* Shown are the coefficients and standard errors for "high broadband state" under different specifications of the RDD polynomials, with each cell in the table reporting the result of a separate regression. Panel A displays estimates for linear, quadratic, and linear interacted RDD polynomials in distance to the state boundary, whereas Panel B presents the results for linear, quadratic, cubic, and quartic RDD specifications in longitude and latitude. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. *p<0.1; **p<0.05; ***p<0.01.

### A.5.2 Robustness Checks of "High Broadband State" Threshold

**Table A.14:** Robustness Checks for Alternative "High Broadband State" Thresholds

| Spatial RDD Estimates | Sale Prices | | Rents | |
|---|---|---|---|---|
| | 65% Threshold | 85% Threshold | 65% Threshold | 85% Threshold |
| | (1) | (2) | (3) | (4) |
| *Panel A: RDD Polynomials in Distance to Boundary* | | | | |
| **Linear** | 0.0629** | 0.0151 | 0.0374*** | 0.0122 |
| | (0.0265) | (0.0287) | (0.0141) | (0.0175) |
| **Quadratic** | 0.0500** | 0.0199 | 0.0331*** | 0.0132 |
| | (0.0238) | (0.0285) | (0.0119) | (0.0175) |
| **Linear Interacted** | 0.0464* | 0.0148 | 0.0312** | 0.0112 |
| | (0.0258) | (0.0282) | (0.0130) | (0.0174) |
| *Panel B: RDD Polynomials in Longitude and Latitude* | | | | |
| **Linear** | 0.0466** | 0.0336 | 0.0291*** | 0.0219 |
| | (0.0180) | (0.0285) | (0.0074) | (0.0210) |
| **Quadratic** | 0.0556*** | 0.0239 | 0.0356*** | 0.0234 |
| | (0.0205) | (0.0327) | (0.0092) | (0.0204) |
| **Cubic** | 0.0704*** | 0.0652* | 0.0419*** | 0.0387** |
| | (0.0203) | (0.0363) | (0.0091) | (0.0193) |
| **Quartic** | 0.0411* | 0.0656** | 0.0295** | 0.0473*** |
| | (0.0242) | (0.0319) | (0.0119) | (0.0167) |
| **Boundary Region by Year FE** | ✓ | ✓ | ✓ | ✓ |
| **Individual Property Controls** | ✓ | ✓ | ✓ | ✓ |
| **State Policy Controls** | ✓ | ✓ | ✓ | ✓ |
| **Municipality Policy Controls** | ✓ | ✓ | ✓ | ✓ |
| **Local Economic Controls** | ✓ | ✓ | ✓ | ✓ |
| **Observations** | 512,899 | 305,497 | 255,878 | 165,203 |
| **Municipalities** | 4,168 | 3,603 | 3,640 | 3,038 |
| **Data Availability Period** | 2010-2015 | 2015-2019 | 2010-2015 | 2015-2019 |

*Note:* Shown are the coefficients and standard errors for "high broadband state" under different specifications of the RDD polynomials, with each cell in the table reporting the result of a separate regression. Panel A displays estimates for linear, quadratic, and linear interacted RDD polynomials in distance to the state boundary, whereas Panel B presents the results for linear, quadratic, cubic, and quartic RDD specifications in longitude and latitude. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. *$p<0.1$; **$p<0.05$; ***$p<0.01$.

## A.6 Placebo Checks

**Table A.15:** Placebo Checks for Property Sale Prices and Rents After Expansion

| | Sale Prices | Rents |
|---|---|---|
| | (1) | (2) |
| *Panel A: RDD Polynomials in Distance to Boundary* | | |
| **Linear** | 0.0072 | 0.0212 |
| | (0.0480) | (0.0235) |
| **Quadratic** | 0.0067 | 0.0208 |
| | (0.0477) | (0.0235) |
| **Linear Interacted** | 0.0072 | 0.0212 |
| | (0.0480) | (0.0235) |
| *Panel B: RDD Polynomials in Longitude and Latitude* | | |
| **Linear** | 0.0096 | 0.0290 |
| | (0.0510) | (0.0257) |
| **Quadratic** | 0.0002 | 0.0330 |
| | (0.0600) | (0.0284) |
| **Cubic** | -0.0114 | 0.0225 |
| | (0.0598) | (0.0274) |
| **Quartic** | 0.0076 | 0.0450 |
| | (0.0584) | (0.0273) |
| **Boundary Region by Year FE** | ✓ | ✓ |
| **Individual Property Controls** | ✓ | ✓ |
| **State Policy Controls** | ✓ | ✓ |
| **Municipality Policy Controls** | ✓ | ✓ |
| **Local Economic Controls** | ✓ | ✓ |
| **Observations** | 489,817 | 242,306 |
| **Municipalities** | 4,219 | 3,570 |
| **Data Availability Period** | 2018-2019 | 2018-2019 |

*Note:* Shown are the coefficients and standard errors for "early high broadband states" under different specifications of the RDD polynomials, with each cell in the table reporting the result of a separate regression. Panel A displays estimates for linear, quadratic, and linear interacted RDD polynomials in distance to the state boundary, whereas Panel B presents the results for linear, quadratic, cubic, and quartic RDD specifications in longitude and latitude. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

## A.7 Alternative Identification Strategies

### A.7.1 Coarsened Exact Matching

In this section, we present a robustness check aimed at addressing concerns regarding the similarity of neighboring municipalities in our main specification. To enhance comparability between the two groups - "high" and "low" broadband states - we employ a coarsened exact matching (CEM) approach as proposed by Iacus et al. (2012). The selection of matching variables and the extent to which variables are coarsened is a trade-off between getting treatment and control group to be as similar as possible on the one hand and leaving enough observations for the estimation in the sample on the other hand.

The CEM approach facilitates the matching of "treatment" observations, where in our context, treatment status is based on a municipality being located in a "high" broadband state for 16 Mbit/s in 2015. The matching uses coarsened variables and assigns weights to observations to improve balance between the groups. For this purpose, we utilize the unemployment rate, school quality, and crime rate from 2013 as the matching variables. To ensure "exact" matches, these variables are coarsened into terciles, thereby requiring that treatment and control municipalities fall within the same tercile for matching variables.

The matching results are summarized in Table A.16. As the first column shows, more than two thirds of the control ("low" broadband state) group have been matched to treated ("high" broadband state) group municipalities. The second column shows that from the "treated" group, nearly 60 percent of observations have been matched. Note that we do not apply one-to-one matching. Observations are weighted to increase balance. These weights are also used in the following regressions.

Table A.17 shows the same regressions as in our main analyses for sale prices and rents using the CEM sample. The estimates are very similar to the main results. For sale prices, the linear estimate in longitude-latitude is 10.0 percent. The respective estimate for rents is 7.9 percent. As in the main specification, this effect is lower than for sale prices. Overall, the fact that results remain qualitatively unchanged supports the comparability of the two groups in our main analysis.

**Table A.16:** Matching Summary

| | **Control: "Low" Broadband States** | **Treatment: "High" Broadband States** |
|---|---|---|
| **All Municipalities** | 1,554 | 4,930 |
| **Matched** | 1,042 | 2,932 |
| **Unmatched** | 512 | 1,998 |

*Note:* The table summarizes the coarsened exact matching on school quality, crime rate, and unemployment rate in 2013, each with tercile bins. Treatment status is assigned based on whether the municipality was a high broadband state (16 Mbit/s) in 2015.

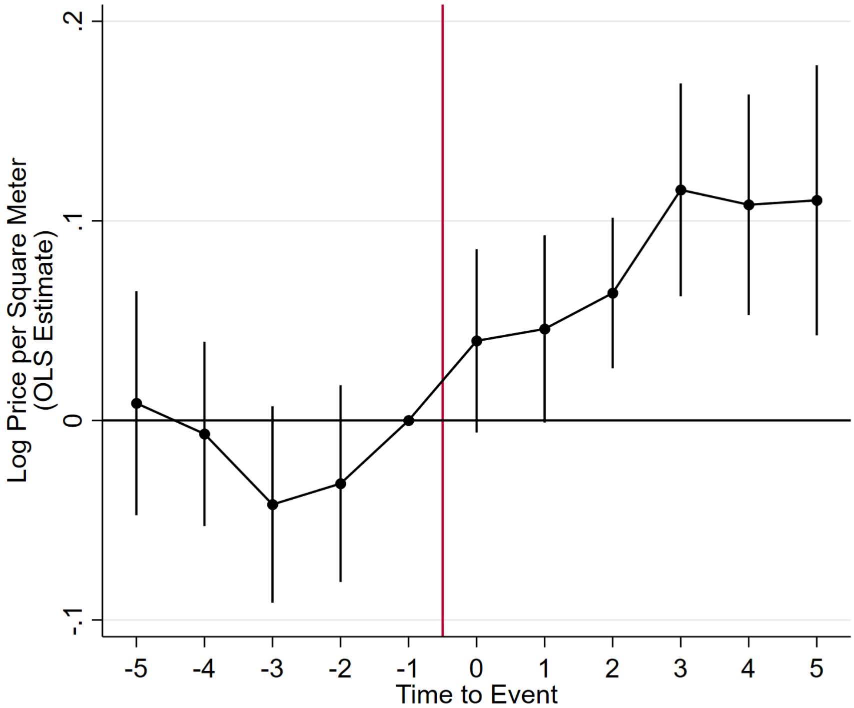
**Table A.17:** Alternative Identification Strategy: Coarsened Exact Matching Results

| **Spatial RDD Estimates** | **Coarsened Exact Matching** | |
|---|---|---|
| | **Sale Prices** | **Rents** |
| | **(1)** | **(2)** |
| ***Panel A: RDD Polynomials Distance to Border*** | | |
| **Linear** | 0.0412*** | 0.0725** |
| | (0.0171) | (0.0329) |
| **Quadratic** | 0.0904*** | 0.0609*** |
| | (0.0172) | (0.0197) |
| **Linear Interacted** | 0.0385** | 0.0518** |
| | (0.0167) | (0.0232) |
| ***Panel B: RDD Polynomials in Longitude-Latitude*** | | |
| **Linear** | 0.1005*** | 0.0787*** |
| | (0.0199) | (0.0242) |
| **Quadratic** | 0.1061*** | 0.0777*** |
| | (0.0189) | (0.0242) |
| **Cubic** | 0.1039*** | 0.0733** |
| | (0.0219) | (0.0324) |
| **Quartic** | 0.0820*** | 0.0560* |
| | (0.0210) | (0.0305) |
| **Boundary Region by Year FE** | ✓ | ✓ |
| **Individual Property Controls** | ✓ | ✓ |
| **State Policy Controls** | ✓ | ✓ |
| **Municipality Policy Controls** | ✓ | ✓ |
| **Local Economic Controls** | ✓ | ✓ |
| **Observations** | 469,538 | 135,758 |
| **Municipalities** | 2,168 | 1,080 |
| **Data Availability Period** | 2010-2017 | 2010-2017 |

*Note:* Shown are the coefficients and standard errors for "high broadband state" under different specifications of the RDD polynomials, with each cell in the table reporting the result of a separate regression, using the matched sample. In addition to the selection of the sample, coarsened exact matching is used to weight observations. Panel A displays estimates for linear, quadratic, and linear interacted RDD polynomials in distance to the state boundary, whereas Panel B presents the results for linear, quadratic, cubic, and quartic RDD specifications in longitude and latitude. Real estate prices are log values to facilitate better comparability of the estimates. Standard errors are clustered at the boundary-region-by-year level. *p<0.1; **p<0.05; ***p<0.01.

### A.7.2 Event Study

**Figure A.20:** Alternative Identification Strategy II: Event Study Results




*Note:* This figure plots event study estimates of property sale prices on the event of states surpassing the "high" broadband threshold. The dependent variable is the log property sale price to facilitate comparability with the main RDD estimates. Confidence intervals are drawn at the 95 percent level and standard errors are clustered at the boundary-region-by-year level. The regression specification is similar to the main RDD analyses and includes all property and socioeconomic controls as well as boundary-region-by-year fixed effects. Contrary to the main analysis, in which the sample is comprised of municipalities around state borders, where one state is considered a "high" and the other one "low", the event study sample consists of all municipalities located at state borders over time. Therefore the event study sample is larger than the main RDD sample sample (3.9 million compared to 0.7 million observations). For the event study, the reference period is normalized to the year -1, i.e. the first year in which a municipality surpassed the threshold of providing 75 percent of households with at least 16 Mbit/s broadband Internet, accounting for the dynamic nature of the "event."

**Table A.18:** Mechanism: Households' Subscriptions and Working From Home Based on German Micro-Census

| | High Broadband States 16 Mbit/s | | | High Broadband States 30 Mbit/s | | | High Broadband States 50 Mbit/s | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Early** | **Late** | **Diff** | **Early** | **Late** | **Diff** | **Early** | **Late** | **Diff** |
| | (1) | (2) | | (3) | (4) | | (5) | (6) | |
| ***Panel A: Speed of Households' Purchased Internet Subscriptions*** | | | | | | | | | |
| **>6 Mbit/s** | 75.73 | 71.37 | 4.36 | 73.98 | 71.97 | 2.01 | 75.94 | 71.60 | 4.34 |
| **>16 Mbit/s** | 52.30 | 45.54 | 6.76 | 53.00 | 43.20 | 9.80 | 52.75 | 45.61 | 7.14 |
| **>50 Mbit/s** | 21.96 | 13.71 | 8.26 | 17.15 | 14.05 | 3.10 | 21.80 | 14.15 | 7.66 |
| ***Panel B: Working from Home*** | | | | | | | | | |
| **Homeoffice (any)** | 10.68 | 9.52 | 1.16 | 10.57 | 8.75 | 1.82 | 10.94 | 9.10 | 1.85 |
| **Homeoffice (share)** | 6.06 | 5.42 | 0.64 | 6.17 | 4.95 | 1.22 | 6.22 | 5.18 | 1.04 |
| **Municipalities** | 770 | 3,250 | 4,020 | 1,272 | 2,053 | 3,325 | 663 | 2,711 | 3,374 |

*Notes:* This table shows the share of households in the micro-census reporting that they have a subscription with their Internet provider offering a speed above 6, 16 and 50 Mbit/s, respectively, as well as the share of households working from home at least sometimes and the average share of the workweek worked from home. The first pair of columns uses the sample of municipalities used for the main analyses with 16 Mbit/s. Municipalities are split based on whether their state has been an early adopter or a late adopter, i.e. whether they are among the earlier half of states to be classified as a high broadband state for this speed. The second pair of columns is divides the municipalities from the 30 Mbit/s sample from the main analyses based on whether their state is a high broadband state for 30 Mbit/s in 2018. The third pair of columns uses the 50 Mbit/s sample and also splits according to 50 Mbit/s availability in 2018.

## A.9 Policy Evaluation

**Table A.19:** Marginal Value of Public Funds

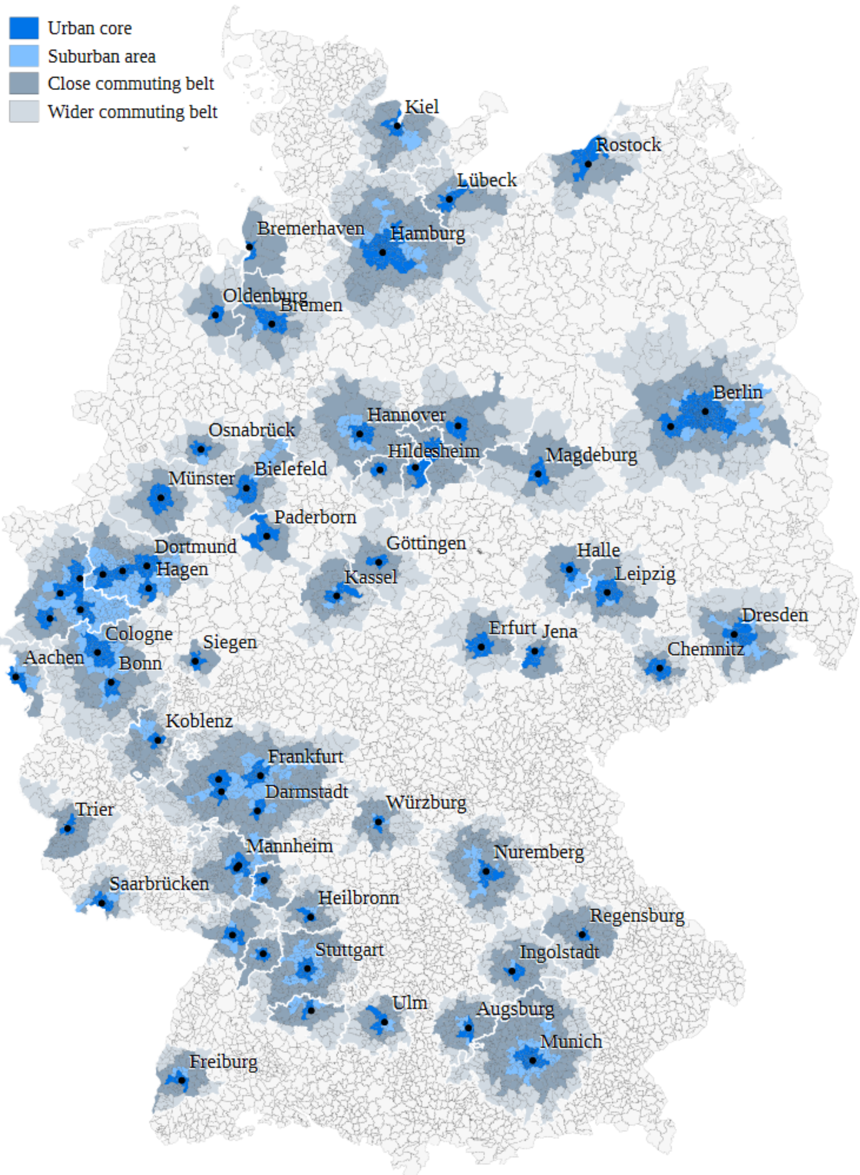
| Disc. rate | Transaction tax | Cost | % Projects | Cost (lb) | % (lb) | Cost (ub) | % (ub) |
|---|---|---|---|---|---|---|---|
| | | 9154 | 92 | 5485 | 73 | 12822 | 97 |
| 0 | 3.5 | 9486 | 93 | 5684 | 73 | 13287 | 98 |
| 2 | 3.5 | 9454 | 93 | 5665 | 73 | 13242 | 98 |
| 4 | 3.5 | 9425 | 93 | 5647 | 73 | 13202 | 98 |
| 2 | 5 | 9588 | 93 | 5745 | 74 | 13430 | 98 |
| 2 | 6.5 | 9727 | 93 | 5828 | 74 | 13624 | 98 |
| 2 | 6.5 | 9790 | 93 | 5866 | 75 | 13713 | 98 |

*Note:* The table shows costs per connected household up to which the marginal value of public funds (MVPF) is larger than one for various scenarios of different discount rates and property transaction tax rates. The table also shows the lower and upper bound costs from the confidence interval as well as the share of projects that has costs up to the shown level.

# B

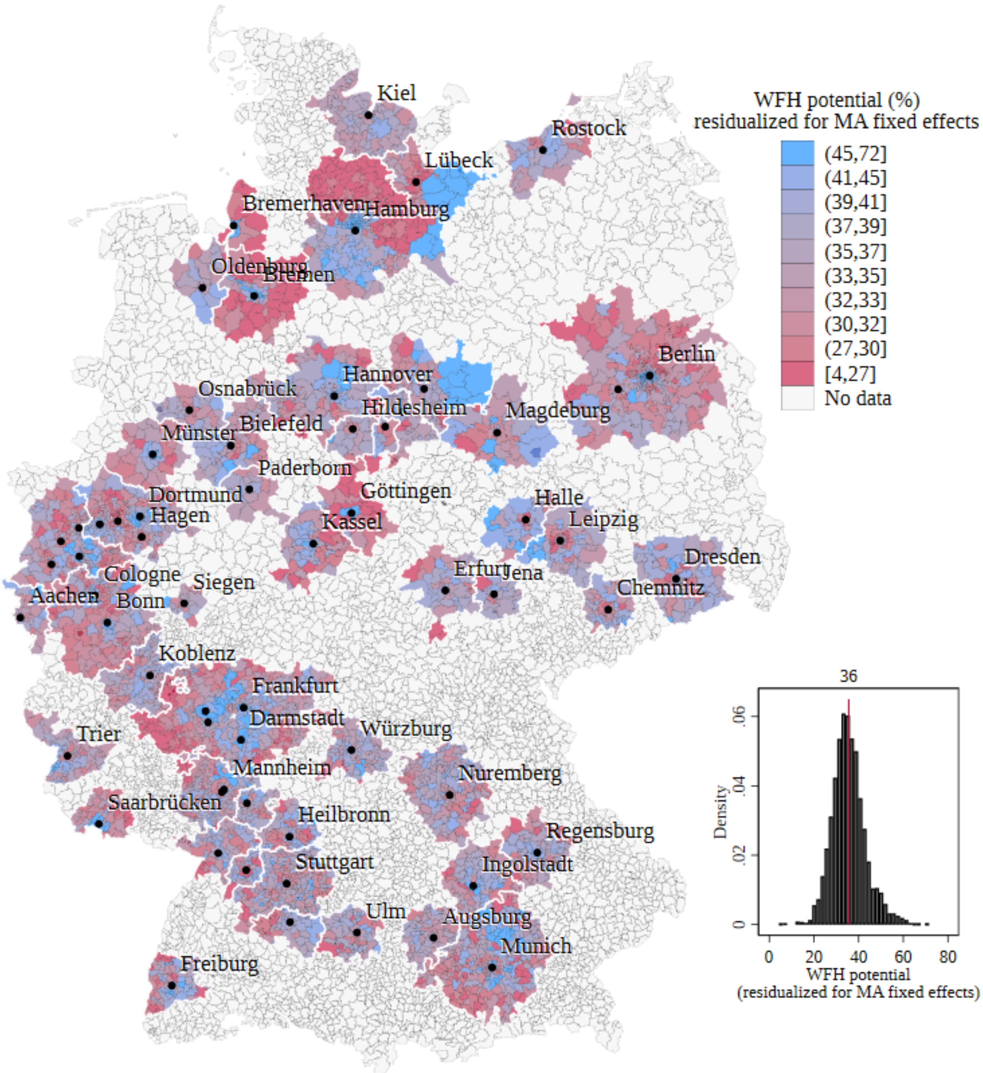
# Appendix to Chapter 2

**Figure B.1:** German Metropolitan Areas




*Notes:* The map highlights postcodes that are part of a metropolitan area (MA) and thus included in our sample. The Federal Office for Building and Regional Planning (BBSR) defines 50 MAs (as of 2019). An MA is centred around at least one urban core (i.e., a municipality with a population above 100,000) and extends to boundaries determined by commuting linkages. MAs can have multiple cores if they are close to each other and interconnected.

**Figure B.2:** Spatial distribution of WFH potential within metro areas




*Notes:* The map shows the spatial distribution of WFH potential, defined as the percentage of residents whose job can be done at home at least one day per week in a postcode. WFH potential is residualized for metro area fixed effects to illustrate the identifying variation. Colours correspond to deciles. The vertical line highlights the mean of the distribution (36%).

## B.2 WFH and Firm Turnover

This section examines the impact of WFH on the supply side. Specifically, we test whether greater exposure to the WFH shock predicts differential trends in firm entry and exit. Theoretical work anticipates that supply follows the WFH-induced relocation of demand (Delventhal and Parkhomenko, 2023). This hypothesis is corroborated by Duguid et al. (2023), who use card terminal data to trace establishment turnover within 16 large US cities. Their findings show that areas with greater residential WFH potential saw a relative *decline* in retail establishments between 2019 and 2021, likely driven by outmigration after the realisation of remote work opportunities. Given that we find no evidence that WFH accelerated internal migration in Germany (see B.6), we do not expect that a higher local WFH potential is associated with declining purchase opportunities. On the other hand, if remote workers shift their spending to their home neighbourhood, this may attract new firms (or slow exits) in these areas. Finally, mandatory business closures, despite being temporary, may cause heterogeneous rates of firm exits across areas.

We draw on two datasets to trace firm turnover in relevant non-tradable industries, Bureau van Dijk's Orbis database, and the Statistics of Business Notifications (*Gewerbeanzeigenstatistik*) from the Federal Statistical Office (Destatis).[1]

Orbis data In the Orbis database, firms are geo-coded at the postcode level and report a date of incorporation, which we use as the period of entry into the local market. We define firm exits as status updates indicating the firm defaulting, subject to insolvency proceedings, in liquidation, or dissolving.

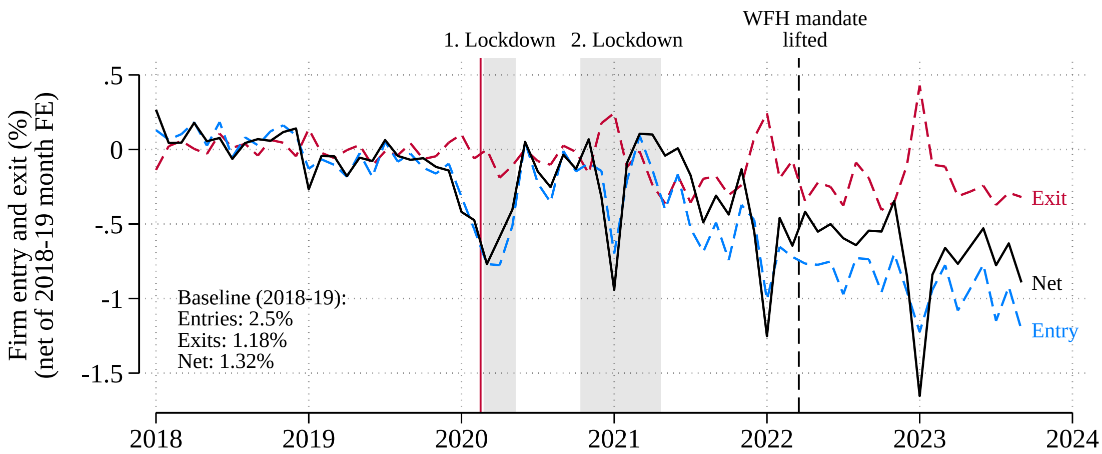
Figure B.3 plots the monthly aggregates of firm entries, exits, and net entries, expressed as a percentage of the stock of active firms, respectively. To make the trends comparable and remove seasonality, we partial out 2018–19 month fixed effects. Thus, a deviation from zero indicates that the value differs from its pre-Covid average of the same month. The trends suggest a noticeable slowdown following the Covid outbreak. The net entry rate remains below its pre-crisis levels in 2023, mainly due to fewer entries rather than accelerating exits. The German government supported businesses affected by the crisis via loans, grants, and recapitalisations worth about 130 billion Euros, in addition to the short-time work scheme

[1] Specifically, we restrict the sample to the following NACE Rev. 2 two-digit industries: 47 (Retail trade, excl. auto), 56 (Food & beverage services), 55 (Accommodation), 96 (Personal service activities).

(BMWK, 2022). These interventions have demonstrably prevented a surge in firm defaults (Grimm et al., 2021).

To explore differential trends by exposure to the WFH shock, we adopt the DiD framework introduced in section 2.3. Figure B.4 plot the results from estimating Equation 2.1 by OLS with firm entry and exit rates as the dependent variable, respectively. For robustness, we also report PPML results using the number of entries and exits as dependent variables (Figure B.5). For all outcomes, nearly all point estimates are statistically indistinguishable from zero throughout the observation period. This result suggests that firm dynamics did not systematically change across high versus low WFH areas within MAs after February 2020.[2]

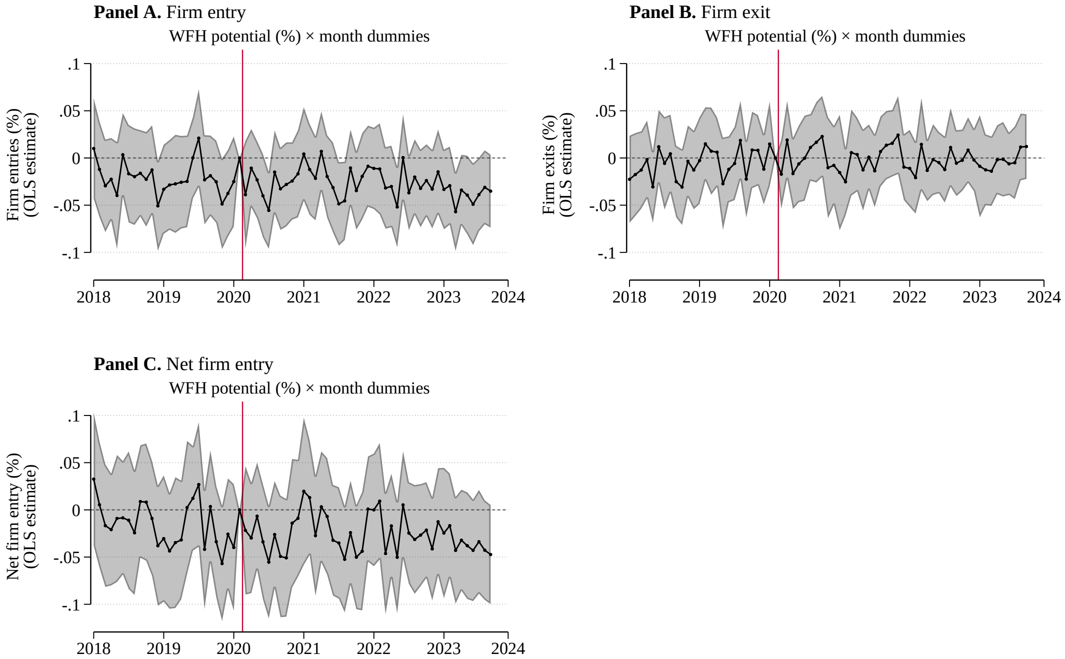
**Figure B.3:** Firm turnover in non-tradable industries




*Notes:* The figure plots aggregate monthly firm entry and exit rates (in percent of active firms) for non-tradable industries. Values equal the month-specific deviation from the corresponding 2018-19 average. The sample is restricted to the following NACE Rev. 2 two-digit industries: 47 (Retail trade, excl. motor), 56 (Food & beverage services), 55 (Accommodation), 96 (Personal care services). Data are from Bureau van Dijk's Orbis database.

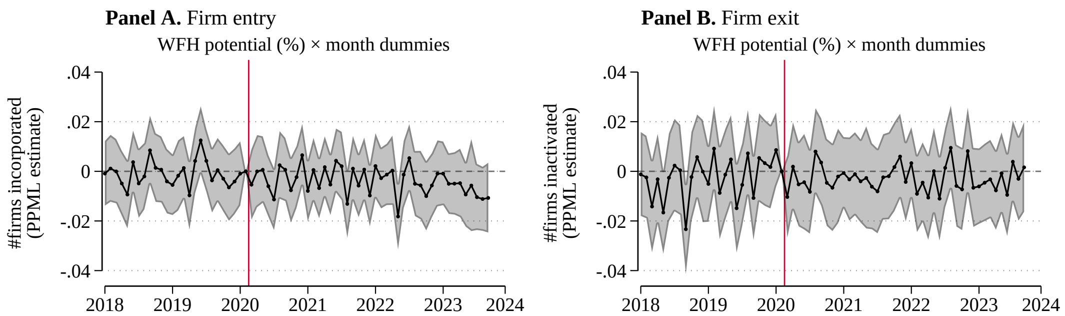
[2]We also estimate DiD specifications that omit the interaction between distance to the city centre and period fixed effects. The results corroborate the conclusion of common trends in firm turnover across different levels of WFH potential.

**Figure B.4:** DiD estimates of WFH potential on firm turnover, Postcode level (OLS results)




*Notes:* The figure shows DiD results based on Equation 2.1 estimated by OLS. Confidence bands are drawn at the 95% level based on standard errors clustered by postcode. Firm turnover data are from Bureau van Dijk's Orbis Database.

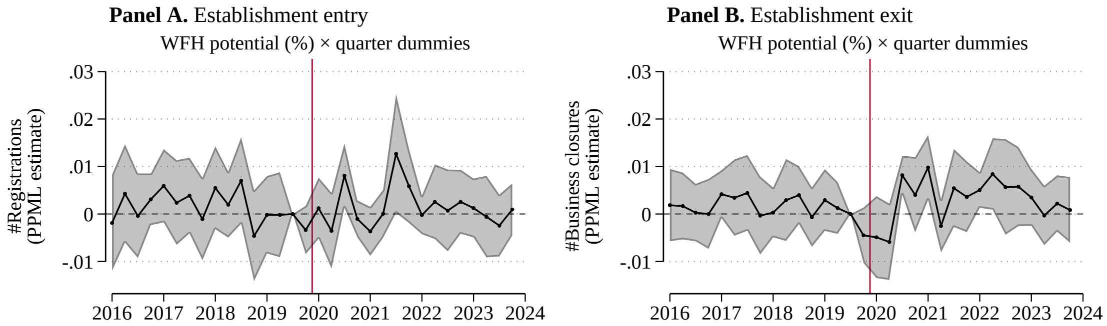
**Figure B.5:** DiD estimates of WFH potential on firm turnover, Postcode level (PPML results)




*Notes:* The figure shows DiD results based on Equation 2.1 estimated by PPML. Estimates are transformed by $\exp(\hat{\beta}^k) - 1$ to reflect proportional changes. Confidence bands are drawn at the 95% level based on standard errors clustered by postcode. Firm turnover data are from Bureau van Dijk's Orbis Database.

Business notifications data The Trade Regulation Code (*Gewerbeanzeigeordnung*) requires businesses[3] to register with local authorities and notify them in case the business is discontinued.[4] Notifications are geo-coded at the municipality level and collected by the Federal Statistical Office (Destatis) in the Statistics of Business Notifications. We focus on notifications due to new registrations (*Neugründungen*) and complete business closures (*vollständige Aufgabe*) to measure quarterly establishment entry and exit at the municipality level between 2016 and 2023. New registrations and business closures account for about 80% of all notifications.

**Figure B.6:** DiD estimates of WFH potential on establishment turnover, Municipality level (PPML results)




*Notes:* The figure shows DiD results based on a version of Equation 2.1 adapted to the municipality-level panel and estimated by PPML. Estimates are transformed by $\exp(\hat{\beta}^k) - 1$ to reflect proportional changes. Confidence bands are drawn at the 95% level based on standard errors clustered by municipality. Establishment turnover data are from the Statistics of Business Notifications (*Gewerbeanzeigenstatistik*) by the German Federal Statistical Office (Destatis).

We estimate a DiD specification (Equation 2.1) adapted to a panel of 4695 municipalities that are part of an MA, and report PPML results in Figure B.6. The dependent variable in Panel A is the quarterly number of new business registrations; Panel B reports results for the number of business closures. PPML coefficients are transformed to reflect proportional effects. The estimates corroborate the results based on the Orbis dataset: The impact estimates are very

[3] Exemptions include freelancers, businesses in the primary sector, and managers of own assets (Sec. 14, Trade Regulation Code, *Gewerbeanzeigeordnung*).

[4] Registration is required for the establishment of a new business, relocation from another jurisdiction, a merger or demerger, a change in legal form, the admission of new partners, or the acquisition of the business. Reasons for de-registration include business closure, relocation to another district, closure in connection with a merger or demerger, withdrawal of partners, a change in legal form, or the transfer of the business to successors.

close to zero and nearly all insignificant, indicating common trends in establishment exits and entries across different levels of WFH potential within MAs.

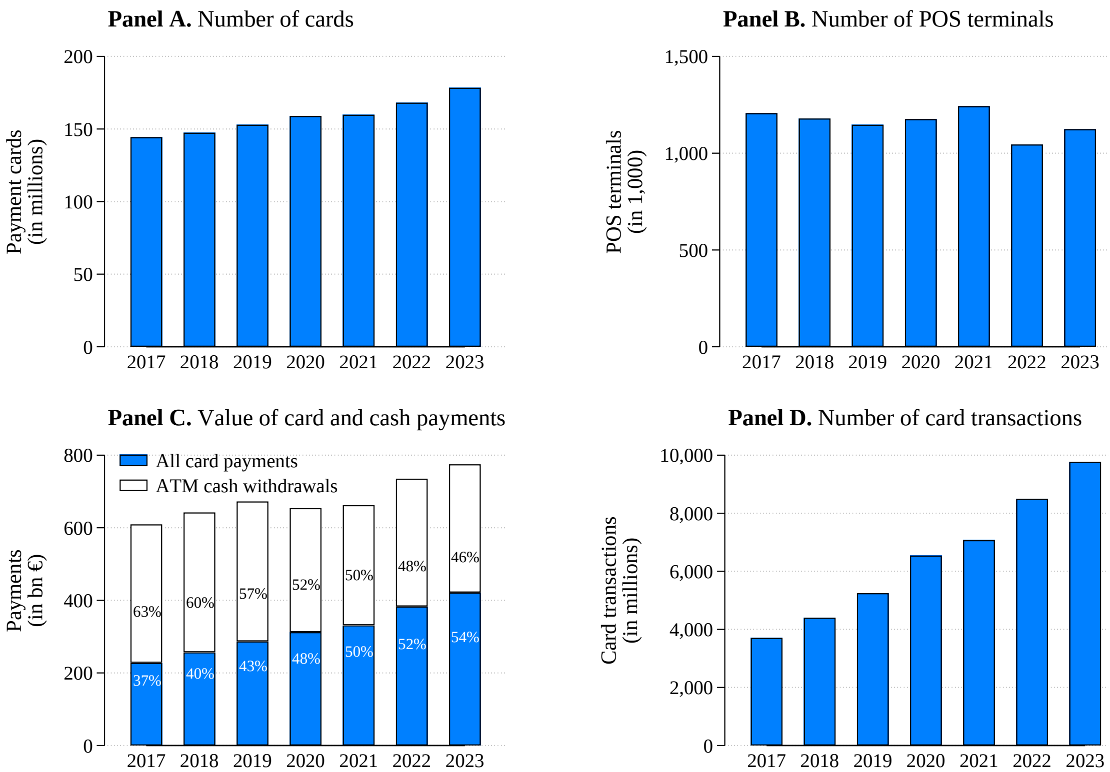
Overall, the analysis suggests that differential business turnover does not govern our WFH impact estimates.

## B.3 Aggregate Trends in Card and Cash Payments

A shortcoming of the geo-referenced Mastercard payment data is the lack of information on cash payments. As noted in section 2.3, heterogenous shifts in the payment technology from cash to card within metro areas constitute a potential threat to identification in our DiD framework if these are correlated with WFH potential. Unfortunately, spatially fine-grained information on the adoption of cash versus card payments is unavailable.

In Figure B.7, we present aggregate data on cash and card payments from the European Central Bank (ECB) Payment Statistics. Reassuringly, the data suggest no discernable trend breaks since the pandemic. Panel A illustrates the consistent growth in the number of domestic payment cards issued (comprising debit, delayed debit, and credit cards) since 2017, reflecting the rising demand for card-based transactions. Panel B shows a relatively flat trend in the number of point-of-sale (POS) terminals, indicating a stable supply of card acceptance infrastructure. Although we cannot rule out any regional disparities based on the aggregate data, the stable number of POS terminals does not suggest major spatial differences in card acceptance by merchants following the pandemic. Panels C and D depict the continued rise in both the value and volume of card payment transactions, respectively. According to Bundesbank (2024) (German Central Bank), the volume of card payments in 2023 is split into 89% for in-store purchases and 10% for online transactions. The share of card payments in all consumer payments increased from 37% to 54% between 2017 and 2023, with an average annual growth rate of about 3 percentage points. There is no evidence of a trend break caused by the pandemic. This may seem unexpected, as authorities encouraged the use of card payments for hygiene reasons; however, this has had no noticeable impact on the long-term trend of payment behaviour.

**Figure B.7:** Trends in Card Payments in Germany



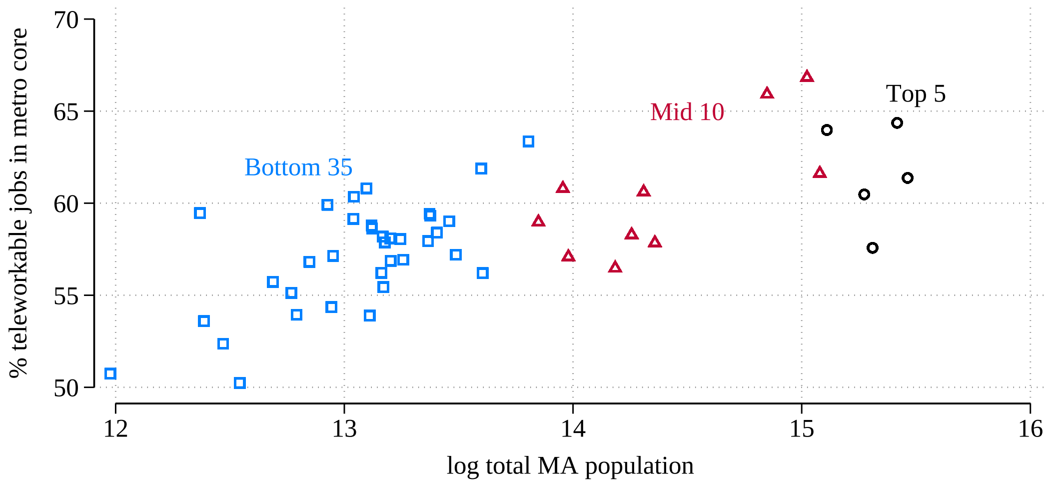

*Notes:* The figure presents trends in the adoption of consumer card payments in Germany. Card payments comprise all types of consumer payment cards (debit, delayed credit, and credit cards) that were issued by resident payment service providers (PSP) and used for offline and online card payments in Germany, excluding cards with an e-money function only. Panel A shows the annual number of cards. Panel B presents the number of POS terminals that accept card payments. Panel C reports the annual volume of card and cash payments and highlights the annual share of each payment technology. Panel D depicts the annual number of card payment transactions. Data are from the European Central Bank (ECB) Payment Statistics.

## B.4 Heterogeneity Analysis

### B.4.1 Heterogeneity by metro area size

We explore the effect heterogeneity of WFH on spending by metro area size. Effect size may differ because of different capabilities or incentives to realise WFH opportunities. For instance, Monte et al. (2023) argue that in the presence of productivity spillovers among individuals when working in person, a coordinated shock to the mode of work, like the one generated by the pandemic, can shift cities to a new equilibrium with high levels of remote work. They find that this is more likely in larger cities, whereas smaller cities tend to revert to their pre-Covid commuter equilibrium. One factor influencing the incentives to realise WFH potential is the concentration of teleworkable jobs in the urban core. Figure B.8 illustrates the fraction of jobs that can be worked from home (at least partly) in the MA core(s), calculated by Alipour et al. (2023), plotted against log MA population. The positive correlation shows that larger cities specialise in industries with higher WFH potential, such as IT and financial services.

**Figure B.8:** MA size and concentration of teleworkable jobs in MA core




*Notes:* The figure plots the percent of jobs that can at least partly be done from home in the MA core(s) against the log of MA population. The measure of WFH jobs concentration comes from Alipour et al. (2023) and is based on the 2018 BIBB-BAuA Employment Survey and 2019 employment statistics by county from the Federal Employment Agency. For MAs with multiple cores, the measure corresponds to a population-weighted average.

We divide our sample into three based on MA size and separately estimate the reduced-form effects of WFH potential on spending and the IV effects of mobility on spending (analogous to subsection 2.4.3). The results in Table B.1 reveal that the reduced-form effects are significant only among the largest 5 MA (Column 1) and the 10 mid-sized MAs (Column 3). By contrast, the reduced-form estimate is near zero and barely significant among the smallest 35 MAs (Column 5). Likewise, the first-stage effect of WFH potential on mobility is weak ($F < 10$), indicating that differences in WFH opportunities do not translate into different adoption rates in small MAs, consistent with the argument by Monte et al. (2023) (Column 6). The estimated mobility elasticity of spending is greater in the largest 5 MAs compared to the mid-sized MAs (-3.66 versus -3.14). This disparity could again be explained by stronger incentives for individuals higher up in the wage distribution to adopt WFH.

We report results from a linear model that excludes all postcodes with zero-valued spending for robustness in Table B.2. The conclusions are the same. However, the gap between the estimated elasticities in large versus mid-sized MAs is somewhat larger (-4.88 versus -2.46).

**Table B.1:** Heterogeneity by metro area size (non-linear model)

| | *Spending (Mo-Fr)* | | | | | |
|---|---|---|---|---|---|---|
| | Top 5 MAs | | Mid 10 MAs | | Bottom 35 MAs | |
| | RF (PPML) | IV-CFA | RF (PPML) | IV-CFA | RF (PPML) | IV-CFA |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| WFH potential (%) | 0.007*** | | 0.007*** | | 0.003* | |
| | (0.002) | | (0.002) | | (0.002) | |
| Log departures 6-9h | | -3.730*** | | -3.186*** | | -2.508 |
| | | (1.149) | | (0.987) | | (1.505) |
| Control function | | 2.886*** | | 2.815*** | | 2.119 |
| | | (1.119) | | (1.007) | | (1.513) |
| Log distance to city centre | -0.004 | 0.025 | -0.082*** | 0.011 | -0.016 | -0.052** |
| | (0.026) | (0.025) | (0.027) | (0.040) | (0.017) | (0.024) |
| 2019 log departures 6-9h | -0.334*** | -0.411*** | -0.425*** | -0.481*** | -0.469*** | -0.502*** |
| | (0.030) | (0.041) | (0.041) | (0.047) | (0.023) | (0.028) |
| Net migration (2019-23) | -0.275 | 0.268 | 0.590** | 0.465 | 0.175 | -0.117 |
| | (0.393) | (0.402) | (0.289) | (0.321) | (0.321) | (0.361) |
| 2019 log departures (6-9h) of neighbours | -0.599*** | 0.010 | -0.308 | -0.524** | -0.155 | -0.315* |
| | (0.191) | (0.247) | (0.197) | (0.207) | (0.127) | (0.164) |
| 2019 log spending p.c. | -0.281*** | -0.308*** | -0.356*** | -0.360*** | -0.418*** | -0.418*** |
| | (0.025) | (0.026) | (0.038) | (0.040) | (0.017) | (0.018) |
| 2019 spending share Food Services | 0.093*** | 0.026 | 0.045 | 0.004 | -0.019 | -0.055 |
| | (0.025) | (0.035) | (0.035) | (0.044) | (0.036) | (0.048) |
| 2019 spending share Grocery and Food Stores | -0.011 | 0.024 | -0.029* | -0.021 | -0.020 | -0.027* |
| | (0.014) | (0.017) | (0.017) | (0.018) | (0.014) | (0.015) |
| 2019 spending share Apparel | 0.142*** | 0.065 | 0.146* | 0.157* | 0.176*** | 0.182*** |
| | (0.043) | (0.051) | (0.083) | (0.087) | (0.048) | (0.055) |
| First stage coef. | | -0.0019 | | -0.0021 | | -0.0010 |
| | | $F = 18.46$ | | $F = 26.95$ | | $F = 5.34$ |
| Implied prop. effect (%) | 0.71 | -3.66 | 0.67 | -3.14 | 0.28 | -2.48 |
| Tot. obs. | 2,496 | 2,496 | 2,726 | 2,726 | 2,902 | 2,902 |
| #Postcodes | 1,248 | 1,248 | 1,363 | 1,363 | 1,451 | 1,451 |

*Notes:* The table presents results based on Equations 2.2 and 2.3. The sample is split into three by metro area population. All columns include postcode and metro area×post-dummy fixed effects. The implied proportional effect (IPE) corresponds to the percentage change in spending associated with a percentage-point change in WFH potential or a percent change in departures 6-9h, respectively, and is calculated as $100 \times [\exp(\cdot) - 1]$. Standard errors are reported in parentheses and clustered by postcode in odd columns. Even columns use cluster-bootstrapped standard errors (1,000 repetitions). $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

**Table B.2:** Heterogeneity by metro area size (linear model)

| | *Log Spending (Mo-Fr)* | | | | | |
|---|---|---|---|---|---|---|
| | Top 5 MAs | | Mid 10 MAs | | Bottom 35 MAs | |
| | RF (OLS) | 2SLS | RF (OLS) | 2SLS | RF (OLS) | 2SLS |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| WFH potential (%) | 0.010*** | | 0.006*** | | 0.000 | |
| | (0.002) | | (0.002) | | (0.002) | |
| log departures 6-9h | | -4.878*** | | -2.461*** | | -0.577 |
| | | (1.221) | | (0.865) | | (2.616) |
| | | [-7.52,-2.63] | | [-4.11,-0.87] | | [.,.] |
| Log distance to city centre | 0.003 | 0.017 | -0.032 | 0.039 | -0.023 | -0.030 |
| | (0.021) | (0.029) | (0.028) | (0.043) | (0.021) | (0.032) |
| 2019 log departures 6-9h | -0.528*** | -0.624*** | -0.681*** | -0.720*** | -0.657*** | -0.662*** |
| | (0.045) | (0.067) | (0.031) | (0.035) | (0.029) | (0.034) |
| Net migration (2019-23) | -0.703** | 0.098 | 0.141 | 0.012 | 0.187 | 0.136 |
| | (0.275) | (0.461) | (0.433) | (0.441) | (0.267) | (0.349) |
| 2019 log departures (6-9h) of neighbours | -0.361** | 0.409 | -0.032 | -0.183 | 0.114 | 0.081 |
| | (0.182) | (0.308) | (0.192) | (0.208) | (0.163) | (0.218) |
| 2019 log spending p.c. | -0.614*** | -0.658*** | -0.676*** | -0.686*** | -0.681*** | -0.679*** |
| | (0.030) | (0.036) | (0.020) | (0.021) | (0.020) | (0.021) |
| 2019 spending share Food Services | 0.062*** | -0.027 | 0.047 | 0.018 | -0.013 | -0.019 |
| | (0.024) | (0.046) | (0.029) | (0.036) | (0.041) | (0.053) |
| 2019 spending share Grocery and Food Stores | -0.046*** | -0.005 | -0.030 | -0.028 | -0.029* | -0.031 |
| | (0.014) | (0.024) | (0.019) | (0.021) | (0.017) | (0.019) |
| 2019 spending share Apparel | 0.349*** | 0.264*** | 0.359*** | 0.371*** | 0.302*** | 0.302*** |
| | (0.048) | (0.070) | (0.059) | (0.058) | (0.074) | (0.073) |
| First stage coef. | | -0.0021 | | -0.0023 | | -0.0008 |
| | | $F$=24.64 | | $F$=30.36 | | $F$=2.73 |
| Implied prop. effect (%) | 1.04 | -4.88 | 0.56 | -2.46 | 0.04 | -0.58 |
| Tot. obs. | 2,410 | 2,410 | 2,398 | 2,398 | 2,466 | 2,466 |
| #Postcodes | 1,205 | 1,205 | 1,199 | 1,199 | 1,233 | 1,233 |

*Notes:* The table presents results based on Equations 2.2 and 2.3. The sample is split into three by metro area population and excludes postcodes with zero-valued spending. All columns include postcode and metro area×post-dummy fixed effects. The implied proportional effect (IPE) corresponds to the percentage change in spending associated with a percentage-point change in WFH potential or a percent change in departures 6-9h, respectively. Standard errors are reported in parentheses and clustered by postcode. *VtF*-95% confidence intervals due to Lee et al. (2022, 2023) are reported in brackets in even columns. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

### B.4.2 Heterogeneity by spending category

We assess whether WFH impacts industries differently by estimating reduced-form and IV effects separately for the three largest spending categories: food services, grocery stores, and apparel stores. Table B.3 presents the results based on the non-linear model (see section 2.3 for details). Postcodes without or with fewer than four merchants in a given category drop out of the sample due to data privacy restrictions. Thus, we have fewer observations than in our main analysis of total spending. Focusing on the largest industries, which are prevalent in many postcodes, ensures enough power.

Despite the smaller sample, the first-stage effects of WFH potential on mobility remain strong across all categories (Columns 2, 4, and 6). The reduced-form effects of WFH potential on spending are only significant for food services and grocery stores (Columns 1 and 3). The impact on apparel stores is zero and insignificant, suggesting that remote workers do not shift spending on clothing and accessory products to the vicinity of their homes (Column 5). The elasticity estimates show that spending on food services reacts more strongly to WFH than grocery spending: A percent decline in morning mobility increases restaurant spending by 3.92% compared to 2.65% in grocery stores. This is unsurprising, given that eating out for lunch is a common feature of working at the office. Transactions are not time-stamped in our data. But it is plausible that some of the saved lunch money is redirected towards restaurant visits during the evenings or even spent on groceries near workers' homes instead. Thus, the positive elasticity estimate for grocery stores may also reflect some substitution among spending categories after workers transition to remote work. The results based on the linear model in Table B.4 corroborate the results of the non-linear model. The elasticity estimates are virtually identical.

**Table B.3:** Heterogeneity by spending category (non-linear model)

| | *Spending (Mo-Fr)* | | | | | |
|---|---|---|---|---|---|---|
| | Food services | | Grocery stores | | Apparel stores | |
| | RF (PPML) | IV-CFA | RF (PPML) | IV-CFA | RF (PPML) | IV-CFA |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| WFH potential (%) | 0.007*** | | 0.005*** | | -0.001 | |
| | (0.002) | | (0.001) | | (0.004) | |
| log departures 6-9h | | -3.995*** | | -2.690*** | | 0.527 |
| | | (1.425) | | (0.669) | | (2.182) |
| Control function | | 3.108** | | 2.320*** | | -0.618 |
| | | (1.487) | | (0.662) | | (2.152) |
| Log distance to city centre | -0.064*** | -0.021 | -0.003 | 0.017 | -0.063* | -0.066 |
| | (0.020) | (0.029) | (0.016) | (0.020) | (0.034) | (0.053) |
| 2019 log departures 6-9h | -0.439*** | -0.495*** | -0.448*** | -0.482*** | -0.206*** | -0.202*** |
| | (0.036) | (0.045) | (0.022) | (0.025) | (0.065) | (0.077) |
| 2019-23 Population change (%) | 0.635 | 0.798** | -0.535* | -0.448 | -1.091* | -1.107 |
| | (0.400) | (0.345) | (0.306) | (0.310) | (0.636) | (0.698) |
| 2019 log departures (6-9h) of neighbours | -0.444** | -0.622*** | 0.139 | 0.033 | -0.180 | -0.154 |
| | (0.174) | (0.180) | (0.118) | (0.126) | (0.323) | (0.364) |
| 2019 log spending p.c. | -0.421*** | -0.443*** | -0.519*** | -0.524*** | -0.280*** | -0.281*** |
| | (0.020) | (0.021) | (0.013) | (0.013) | (0.030) | (0.034) |
| 2019 spending share Food Services | -0.218*** | -0.246*** | -0.068*** | -0.120*** | -0.283*** | -0.273** |
| | (0.038) | (0.043) | (0.019) | (0.025) | (0.093) | (0.115) |
| 2019 spending share Grocery and Food Stores | -0.099*** | -0.082*** | -0.104*** | -0.089*** | -0.151*** | -0.155*** |
| | (0.016) | (0.019) | (0.019) | (0.021) | (0.049) | (0.057) |
| 2019 spending share Apparel | -0.020 | -0.016 | -0.151*** | -0.161*** | -0.287** | -0.284** |
| | (0.037) | (0.040) | (0.039) | (0.041) | (0.129) | (0.142) |
| First stage coef. | | -0.0017 | | -0.0020 | | -0.0022 |
| | | $F$=36.56 | | $F$=59.17 | | $F$=45.18 |
| Implied prop. effect (%) | 0.73 | -3.92 | 0.54 | -2.65 | -0.11 | 0.53 |
| Tot. obs. | 5,240 | 5,240 | 6,700 | 6,700 | 3,460 | 3,460 |
| #Postcodes | 2,620 | 2,620 | 3,350 | 3,350 | 1,730 | 1,730 |

*Notes:* The table presents results based on Equations 2.2 and 2.3. All columns include postcode and metro area×post-dummy fixed effects. The implied proportional effect (IPE) corresponds to the percentage change in spending associated with a percentage-point change in WFH potential or a percent change in departures 6-9h, respectively, and is calculated as $100 \times [\exp(\cdot) - 1]$. Standard errors are reported in parentheses and clustered by postcode in odd columns. Even columns use cluster-bootstrapped standard errors (1,000 repetitions). $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

**Table B.4:** Heterogeneity by spending category (linear model)

| | *Log Spending (Mo-Fr)* | | | | | |
|---|---|---|---|---|---|---|
| | Food services | | Grocery stores | | Apparel stores | |
| | RF (OLS) | 2SLS | RF (OLS) | 2SLS | RF (OLS) | 2SLS |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| WFH potential (%) | 0.009*** | | 0.005*** | | 0.004 | |
| | (0.002) | | (0.002) | | (0.004) | |
| log departures 6-9h | | -3.678*** | | -2.558*** | | -1.359 |
| | | (1.060) | | (0.761) | | (1.464) |
| | | [-5.66,-1.70] | | [-4.02,-1.12] | | [-4.09,1.36] |
| Log distance to city centre | -0.106*** | -0.078** | -0.008 | 0.009 | -0.104** | -0.098** |
| | (0.026) | (0.033) | (0.016) | (0.019) | (0.042) | (0.045) |
| 2019 log departures 6-9h | -0.566*** | -0.628*** | -0.617*** | -0.648*** | -0.327*** | -0.344*** |
| | (0.033) | (0.040) | (0.029) | (0.031) | (0.052) | (0.057) |
| 2019-23 Population change (%) | 0.434 | 0.590 | -0.587* | -0.440 | -1.282 | -1.242 |
| | (0.415) | (0.477) | (0.326) | (0.287) | (0.807) | (0.804) |
| 2019 log departures (6-9h) of neighbours | -0.588*** | -0.769*** | 0.096 | -0.068 | -0.245 | -0.355 |
| | (0.190) | (0.204) | (0.128) | (0.142) | (0.324) | (0.333) |
| 2019 log spending p.c. | -0.711*** | -0.740*** | -0.816*** | -0.835*** | -0.531*** | -0.537*** |
| | (0.016) | (0.019) | (0.014) | (0.016) | (0.022) | (0.023) |
| 2019 spending share Food Services | -0.006 | -0.001 | -0.069*** | -0.113*** | -0.131** | -0.150** |
| | (0.037) | (0.038) | (0.021) | (0.028) | (0.063) | (0.069) |
| 2019 spending share Grocery and Food Stores | -0.030 | -0.020 | -0.012 | 0.014 | -0.049 | -0.035 |
| | (0.021) | (0.023) | (0.020) | (0.023) | (0.037) | (0.041) |
| 2019 spending share Apparel | 0.153*** | 0.175*** | -0.081** | -0.074* | 0.321*** | 0.345*** |
| | (0.040) | (0.047) | (0.036) | (0.040) | (0.110) | (0.113) |
| First stage coef. | | -0.0024 | | -0.0020 | | -0.0027 |
| | | $F$=43.41 | | $F$=56.59 | | $F$=43.79 |
| Implied prop. effect (%) | 0.88 | -3.68 | 0.52 | -2.56 | 0.36 | -1.36 |
| Tot. obs. | 3,548 | 3,548 | 4,826 | 4,826 | 2,580 | 2,580 |
| #Postcodes | 1,774 | 1,774 | 2,413 | 2,413 | 1,290 | 1,290 |

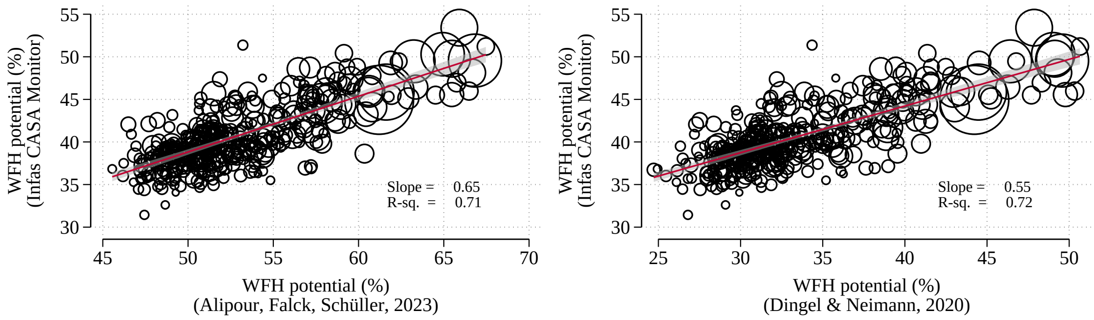
*Notes:* The table presents results based on Equations 2.2 and 2.3. All columns include postcode and metro area×post-dummy fixed effects. The implied proportional effect (IPE) corresponds to the percentage change in spending associated with a percentage-point change in WFH potential or a percent change in departures 6-9h, respectively. Standard errors are reported in parentheses and clustered by postcode. *VtF*-95% confidence intervals due to Lee et al. (2022, 2023) are reported in brackets in even columns. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

## B.5 Robustness

### B.5.1 Validating WFH Potential

We check the plausibility of the WFH potential measure calculated from the infas360 Casa Monitor by comparing it to two other measures proposed by Alipour et al. (2023) (henceforth, AFS) and Dingel and Neiman (2020) (henceforth, DN), respectively. DN use information on the importance of various tasks from O*NET to classify US occupations as fully teleworkable or not. AFS draw on the BIBB-BAuA Employment Survey 2018, which asks about 17,000 employed persons in Germany whether their job could be done from home. If the respondent deems even occasional WFH "impossible", their job is classified as incompatible with WFH. In the Casa Monitor, respondents are asked whether their job could be done from home at least one day per week. Thus, the three measures capture slightly different notions of WFH feasibility.

**Figure B.9:** Comparison of WFH potential measures at the county level




*Notes:* The figure shows scatterplots and linear fits of county-level WFH potential calculated from survey results of the infas360 Casa Monitor (see section 2.2) against WFH potential computed by Alipour et al. (2023) based on the 2018 BIBB-BAuA Employment Survey (left) and Dingel and Neiman (2020) based on US O*NET data (right), respectively.

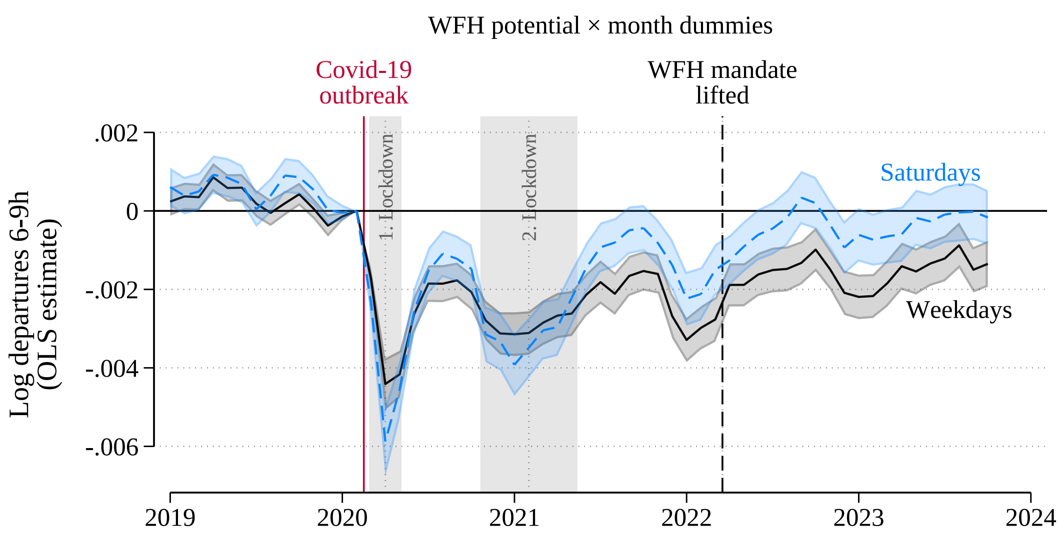
We compare the distribution of these measures across counties in Figure B.9. The extrapolation of occupation-level WFH potential to regions is based on local 2019 occupation compositions. Specifically, a county's WFH potential equals the weighted average of occupational WFH potentials, with weights equal to local employment shares. We plot the infas360 measure against the AKS and the DN measures, respectively. The linear fitted lines reveal that spatial differences in WFH potential are similar overall. The $R^2$ are high and virtually identical (0.7). The slopes are positive but below one, indicating that a marginal increase in either of the two alternative measures are matched by a less-than-proportionate increase in the infas360 measure.

### B.5.2 Robustness to alternative model assumptions

We test the robustness of the results delivered by the PPML estimator to estimating a linear model by OLS. Here, the dependent variables are log-transformed, and the sample excludes postcodes with zero-valued outcomes in any period. Recall that the log transformation means that the proportional effects of the explanatory variables implied by the OLS estimator are unit-specific. By contrast, the PPML estimates deliver proportional effects corresponding to an average level effect rescaled by the outcome mean. Thus, OLS effectively places higher weight on effects for postcodes with lower initial outcome level (Chen and Roth, 2024).

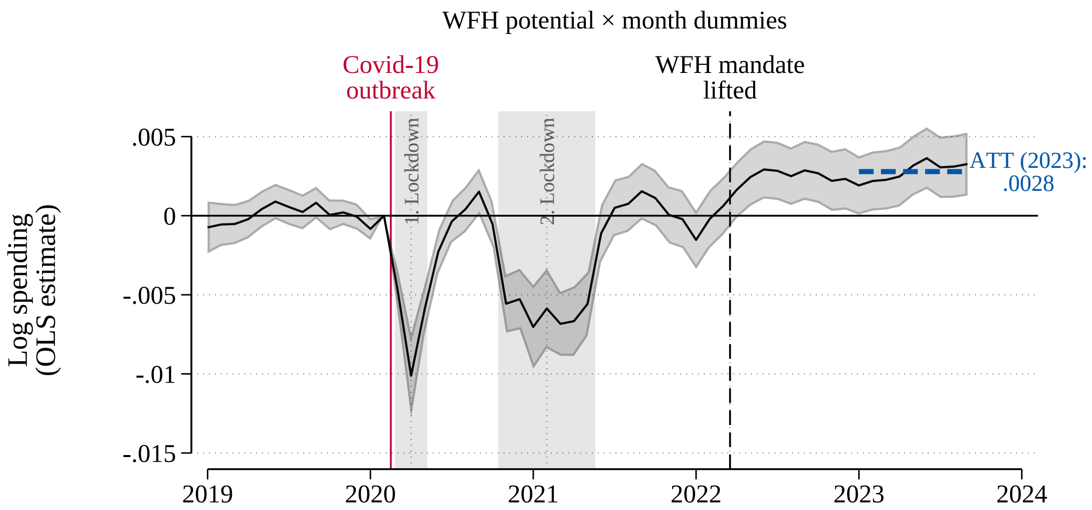
Dynamic DiD First, we report the OLS results of the dynamic DiD specifications (Equation 2.1). Figure B.10 reports the first-stage estimates of WFH potential on log departures between 6 and 9 am. Figure B.11 plots the reduced-form estimates of WFH potential on log spending. In both cases, the patterns are virtually identical to the PPML results presented in Figure 2.2 and Figure 2.3, respectively.

**Figure B.10:** First-stage DiD estimated by OLS




*Notes:* The figure shows DiD results based on Equation 2.1 estimated by OLS. The dependent variable is the log number of outbound trips between 6-9 am at the postcode level. Confidence bands are drawn at the 95% level based on standard errors clustered by postcode.

**Figure B.11:** Reduced-form DiD estimated by OLS




*Notes:* The figure shows DiD results based on Equation 2.1 estimated by OLS. The dependent variable is log spending on weekdays (Mo-Fr) at the postcode level. Confidence bands are drawn at the 95% level based on standard errors clustered by postcode.

IV MODEL In Table B.5, we probe the robustness of the results from the non-linear model (Table 2.1) to estimating a linear model by OLS and 2SLS. Again, the dependent variables are log-transformed, and the sample excludes postcodes with zero-valued spending in 2019 or 2023. Nevertheless, the different models deliver virtually identical estimates of the ITT effects of WFH potential on spending (columns 1 and 2) and the elasticity of spending with respect to WFH-induced mobility changes (columns 5 and 6). Lee et al. (2022, 2023) show that confidence intervals of the 2SLS estimate need to be adjusted in case the first-stage $F$-statistic is below 104.67.[5] Thus, square brackets report $VtF$-95% confidence intervals, which smoothly translate the value of the $F$-statistic into appropriate interval length. The IV estimates remain significant.

[5] More precisely, Lee et al. (2022) demonstrate that $F > 104.67$ ensures that the standard two-sided 5% $t$-test has a rejection rate of at most 5%.

**Table B.5:** Main results (linear model)

| | *Log Spending (Mo-Fr)* | | | | | |
|---|---|---|---|---|---|---|
| | Reduced form (OLS) | | Main equation (OLS) | | IV (2SLS) | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| WFH potential (%) | 0.008*** | 0.006*** | | | | |
| | (0.002) | (0.001) | | | | |
| Log departures 6-9h | | | -0.006 | -0.616*** | -3.791*** | -3.412*** |
| | | | (0.187) | (0.089) | (1.052) | (0.679) |
| | | | | | [-5.82,-1.79] | [-4.69,-2.13] |
| Log distance to city centre | 0.304*** | -0.017 | 0.269*** | -0.034*** | 0.361*** | 0.005 |
| | (0.020) | (0.013) | (0.018) | (0.012) | (0.033) | (0.016) |
| 2019 log departures 6-9h | | -0.634*** | | -0.644*** | | -0.676*** |
| | | (0.020) | | (0.020) | | (0.024) |
| Net migration (2019-23) | | -0.169 | | -0.144 | | -0.087 |
| | | (0.190) | | (0.186) | | (0.231) |
| 2019 log departures (6-9h) of neighbours | | -0.075 | | -0.115 | | -0.174 |
| | | (0.101) | | (0.101) | | (0.116) |
| 2019 log spending p.c. | | -0.662*** | | -0.664*** | | -0.674*** |
| | | (0.013) | | (0.013) | | (0.013) |
| 2019 spending share Food Services | | 0.060*** | | 0.067*** | | -0.012 |
| | | (0.017) | | (0.017) | | (0.028) |
| 2019 spending share Grocery and Food Stores | | -0.037*** | | -0.038*** | | -0.024** |
| | | (0.010) | | (0.010) | | (0.012) |
| 2019 spending share Apparel | | 0.333*** | | 0.333*** | | 0.325*** |
| | | (0.035) | | (0.035) | | (0.037) |
| First stage coef. | | | | | -0.0021 | -0.0019 |
| | | | | | $F=72.08$ | $F=56.62$ |
| Implied prop. effect (%) | 0.80 | 0.65 | -0.01 | -0.62 | -3.79 | -3.41 |
| Tot. obs. | 7,274 | 7,274 | 7,274 | 7,274 | 7,274 | 7,274 |
| #Postcodes | 3,637 | 3,637 | 3,637 | 3,637 | 3,637 | 3,637 |

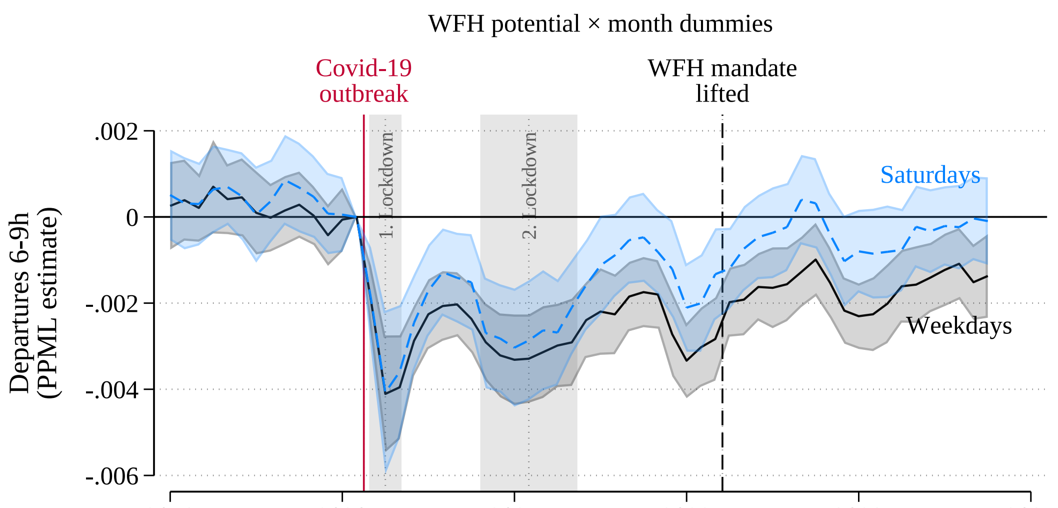
*Notes:* The table presents results based on Equations 2.2 and 2.3. The sample excludes all postcodes with zero-valued spending. All columns include postcode and metro area×post-dummy fixed effects. The implied proportional effect (IPE) corresponds to the percentage change in spending associated with a percentage-point change in WFH potential or a percent change in departures 6-9h, respectively. Standard errors are clustered by postcode and reported in parentheses. *VtF*-95% confidence intervals due to Lee et al. (2022, 2023) are reported in brackets in columns 5 and 6. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

### B.5.3 Correction for spatial correlation

This section addresses the potential concern that model errors are spatially correlated, delivering biased standard errors (SEs).

**Dynamic DiD** To account for potential spatial correlation in the dynamic DiD specifications estimated by PPML, we use two-way clustering at the level of postcodes (to account for serial correlation) and at the level of MA×month-year, allowing for arbitrary correlation across postcodes in the same MA in each period (Cameron et al., 2011). Figure B.12 reports the first-stage results of WFH potential on departures between 6 and 9 am. Figure B.13 plots the reduced-form results of WFH potential on spending. In both cases, the 95% confidence intervals are slightly larger compared to Figure 2.2 and Figure 2.3, respectively. Importantly, effects for weekdays remain significant and the same conclusions hold.

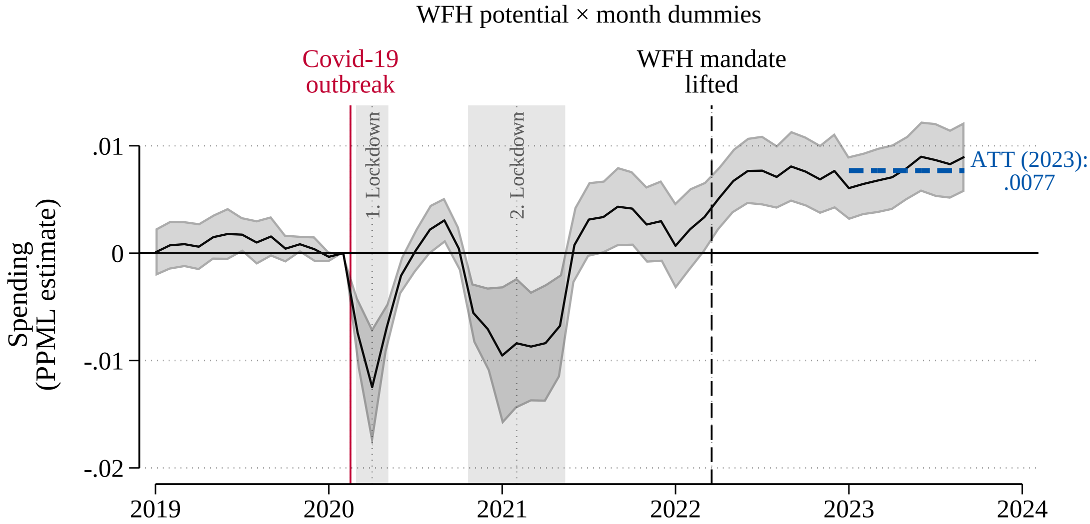
**Figure B.12:** First-stage DiD with two-way clustering of SE




*Notes:* The figure shows DiD results based on Equation 2.1 estimated by PPML. The dependent variable is the number of outbound trips between 6-9 am at the postcode level. Estimates are transformed by $\exp(\hat{\beta}^k) - 1$ to reflect proportional changes. Confidence bands are drawn at the 95% level based on standard errors clustered two-way by postcode and MA×month-year.

**IV model** We test sensitivity of the IV results to correcting standard errors for spatial correlation in the model errors and alternative clustering in Table B.6. The first row reproduces

**Figure B.13:** Reduced-form DiD with two-way clustering of SE




*Notes:* The figure shows DiD results based on Equation 2.1 estimated by PPML. The dependent variable is average spending on weekdays (Mo-Fr) at the postcode level. Estimates are transformed by $\exp(\hat{\beta}^k) - 1$ to reflect proportional changes. Confidence bands are drawn at the 95% level based on standard errors clustered two-way by postcode and MA×month-year.

the reduced-form and IV estimates from the linear model (columns 2 and 6 of Table B.5). Standard errors are clustered by postcode in the baseline. The corresponding 95% confidence intervals are reported in the second row for reference. First, we calculate Conley (1999) SEs to allow for spatial correlation of errors across neighbouring postcodes up to a given threshold (in addition to serial correlation). We set the threshold to 140km, which corresponds to twice the longest distance between a postcode and the city centre in our data, and assume a linear decay in the correlation structure (Bartlett kernel).[6] The confidence intervals are slightly larger than the baseline, but the estimates remain significant. Second, we cluster SEs by metro area to allow for serial correlation and arbitrary spatial correlation across postcodes in the same MA. This reduces the number of clusters to 50. To account for the small number of clusters, we use wild-cluster bootstrap SEs (5,000 repetitions) (MacKinnon et al., 2022). The estimates remain significant at the 5% level. Finally, we adjust confidence intervals using the "spatial correlation principal components" (SCPC) method proposed by Müller and Watson

[6]We compute Conley SEs using the `acreg` STATA command by Colella et al. (2020).

(2022), which assumes a "worst-case" spatial correlation model.[7] Again, the 95% confidence intervals exclude zero, and our results are robust to all adjustments.

**Table B.6:** Spatial-correlation robust inference

| | Reduced form (OLS) | IV-2SLS |
|---|---|---|
| | (1) | (2) |
| Estimate | 0.006 | -3.412 |
| 95%-confidence interval | | |
| Cluster by postcode (baseline) | [0.0042, 0.0087] | [-4.7474, -2.0772] |
| Conley (1999) correction | [0.0030,0.0099] | [-5.1604, -1.6641] |
| Wild cluster-bootstrap by MA | [0.00125, 0.01169] | [-6.369, -1.119] |
| Müller and Watson (2022) SCPC method | [0.0009, 0.0121] | [-6.1640, -0.6606] |

*Notes:* The table presents 95% confidence intervals constructed using different clustering of SEs and corrections for spatial error correlation. The first row reproduces the reduced-form and IV estimates from the linear model (columns 2 and 6 of Table B.5). The baseline uses clustered SEs by postcode. The subsequent rows use Conley SEs with a distance threshold of 140km and a Bartlett kernel, Wild cluster-bootstrapped SEs by metro area (5,000 repetitions), and the SCPC method by Müller and Watson (2022), respectively.

[7] We implement the SCPC correction using the scpc Stata package.

### B.6 WFH and Domestic Migration

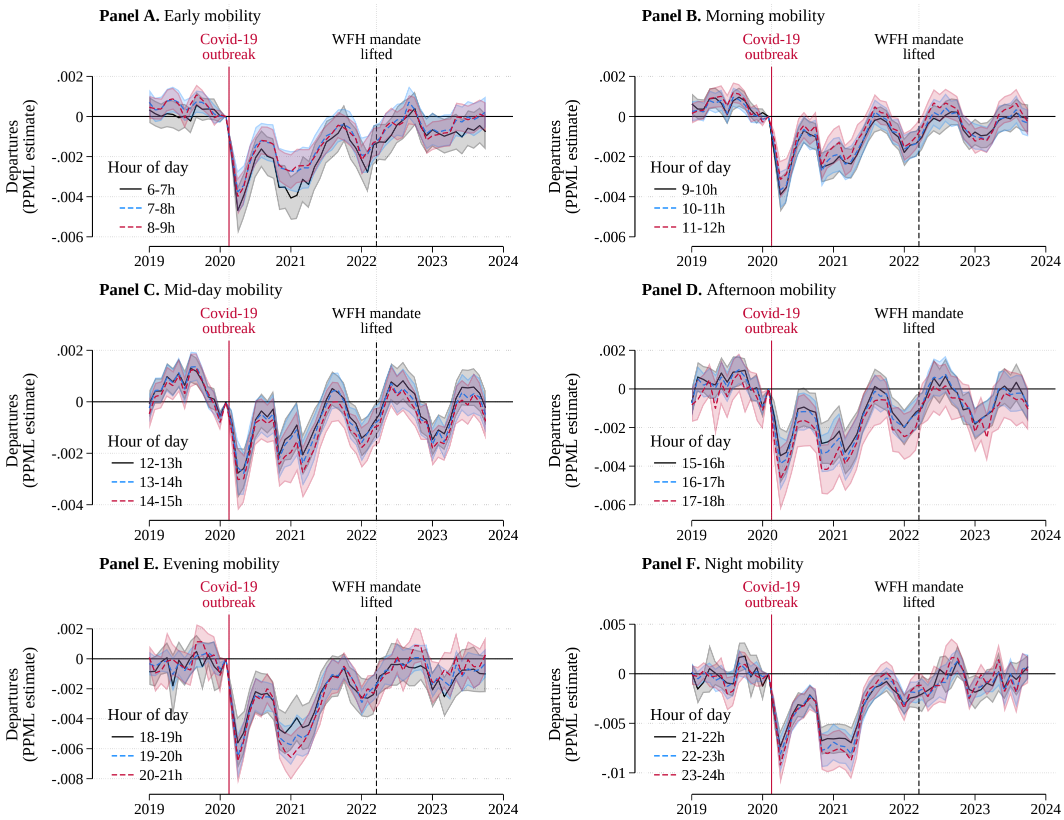
This section explores whether the realisation of WFH opportunities after the onset of Covid-19 spurred domestic migration, particularly away from dense, urban areas.

Saturday mobility gaps We extend the DiD results on mobility differences by WFH potential reported in Figure 2.2, Panel B. We estimate DiD specifications for Saturday mobility, separately by the hour. The DiD plots presented in Figure B.14 reveal that by 2023, average mobility differences across different levels of WFH potentials reverted to their pre-Covid levels throughout the day. These results do not support the hypothesis of systematic population loss driven by WFH-induced outmigration. Had this been the case, we would expect persistent mobility drops in areas subject to population outflows.

Cross-county internal migration We explore trends in internal migration in Germany using administrative data from the German Federal Statistical Office (Destatis). The data include annual origin-destination matrices of moves across the 401 counties from 2013–2022. One limitation is that only net flows are reported for each county pair; consequently, we cannot disentangle gross inflows from outflows.

Panel A of Figure B.15 depicts the annual net internal migration of Germans versus foreigners. Net migration equals the sum of population gains over counties experiencing net gains, which, by definition, equals the aggregate loss in net-losing counties. A value of zero implies either that no migration occurred or that every population outflow was matched by an equal inflow, leaving the spatial distribution of the population unchanged. Net internal migration of foreigners spiked in 2015 due to the large influx of refugees. The data do not directly capture migration from abroad but reflect moves from the initial county of registration to another county in the same year. To avoid influences from such cross-country moves, we subsequently focus on the migration patterns of German citizens. From 2013 to 2019, German net migration across all counties remained steady at approximately 85,000 per year and accelerated in 2020. Note that an increase does not necessarily imply *more* moves; rather, it indicates that the migration that occurred resulted in a more pronounced change in the population distribution across counties.

**Figure B.14:** WFH potential and Saturday mobility

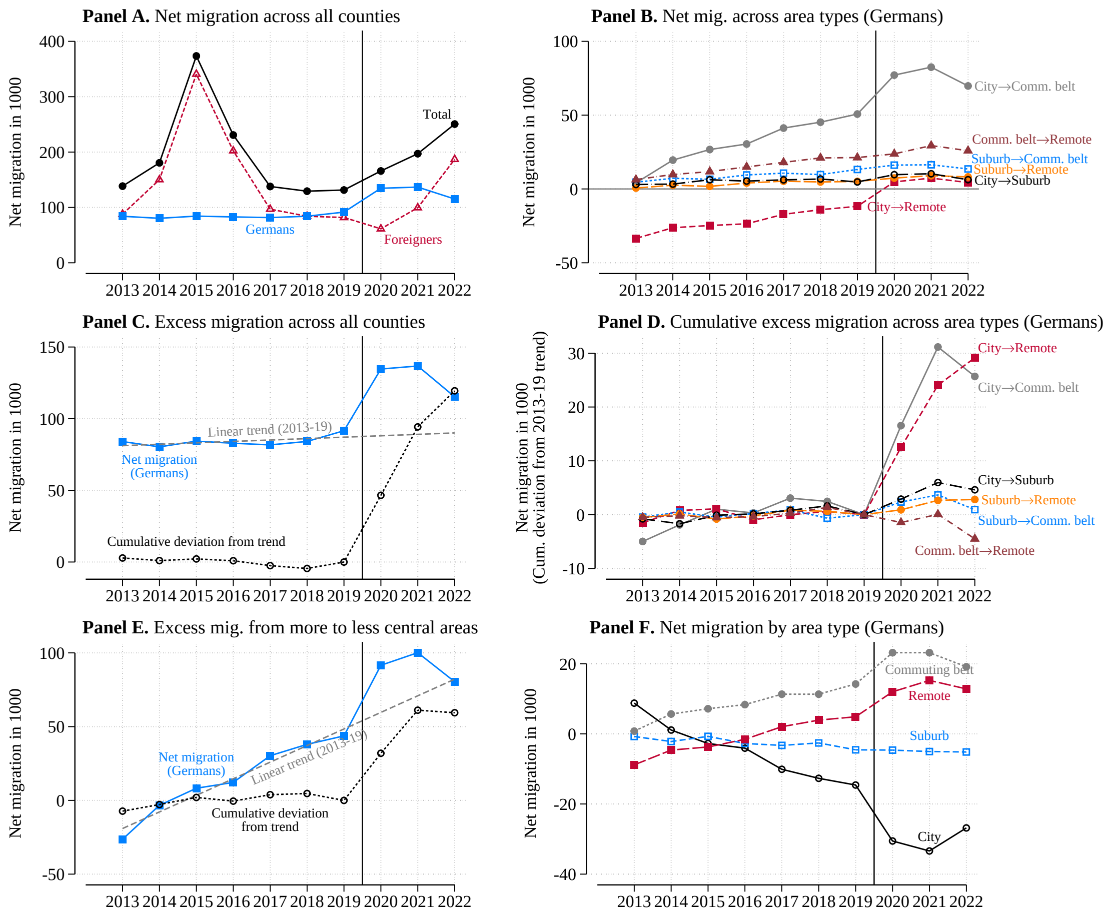



*Notes:* Panels A–F show DiD results based on Equation 2.1 estimated by PPML. The dependent variables are the number of outbound trips by different hours of day at the postcode level. Estimates are transformed by $\exp(\hat{\beta}^k) - 1$ to reflect proportional changes. Confidence bands are drawn at the 95% level based on standard errors clustered by postcode.

Panel B breaks down migration flows by area type. We map counties into one of five categories following the MA catch area definitions (see Figure B.1): *City*, if the county is an urban core of an MA, *Suburb*, for counties primarily within the suburban areas of an MA, *Commuting belt*, for counties that are part of an MA but located further away, and *Remote*, if the county predominantly does not belong to a MA.[8] The chart shows that commuting belts have persistently gained population from cities. The trend accelerated in 2020 and 2021. By contrast, there has been net migration from remote counties into cities until 2019. This changed in 2020–22 when Germans moved from cities to remote counties on balance.

[8] Ambiguous classifications are resolved based on a county's population majority.

**Figure B.15:** Cross-county migration in Germany (origin-destination Matrix)




*Notes:* Panels A–F plot trends in internal migration across county boundaries (excluding flows to or from abroad) based on origin-destination matrices from the German Federal Statistical Office (*Destatis*). Panel A shows annual net migration across all 401 counties by citizenship. Net migration equals the sum of net population gains over counties with net gains (which is equivalent to the aggregate net loss across net-losing counties). Panel B plots the annual net migration of German citizens between different area types. Panel C shows the excess net migration of Germans across all counties, calculated as the cumulative deviation from the 2013-19 linear trend. Panel D reports excess migration for moves between area types, and Panel E shows this for moves from more to less central counties. Panel F plots the net migration of Germans by area type, where negative (positive) values correspond to a net loss (gain).

Panel C quantifies the excess net migration of Germans from 2020 to 2022. The linear trend line over the pre-Covid years (2013–19) shows that annual net migration remained stable until 2019. The dashed line traces cumulative deviations from the linear trend. Over 2020–22, excess migration totalled 119 thousand. For comparison, the extensive-margin increase in WFH among employed persons between 2019 and 2013 alone amounted to roughly 6 million.[9] Panel D plots excess migration among county types. The results indicate that excess migration was primarily driven by net flows from cities to remote counties and cities to commuting belts. Panel E calculates excess migration from more to less central counties. We observe an additional 59 thousand moves between 2020–22 above the pre-Covid trend. Even if we attribute all of these to WFH, this represents less than one percent of new remote workers. Hence, the consequences of WFH-induced migration for spatial changes in economic activity appear negligible at best.

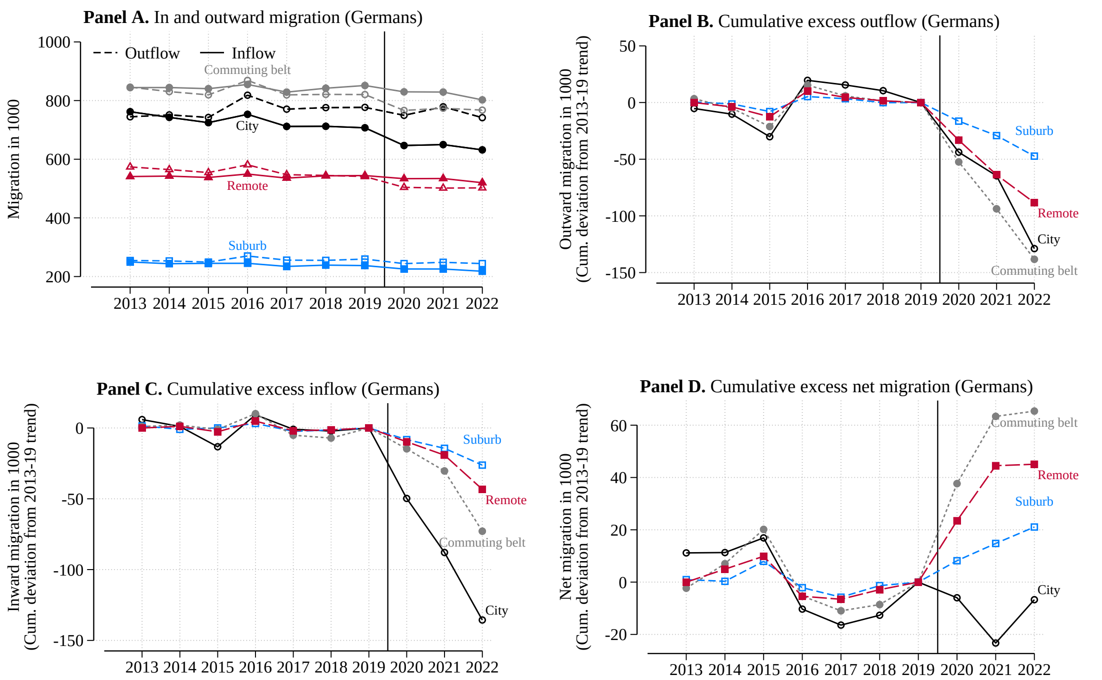
Panel F documents that cities lost (German) population every year before 2020. But the urban population loss accelerated during the crisis. By contrast, commuting belts and remote counties saw even stronger population gains from other counties during the pandemic years.

Inward versus outward migration   Figure B.16 adds nuance to the net internal migration patterns by distinguishing between inflows and outflows. The data register annual flows by county but do not include information on origin or destination. Panel A plots the annual sum of outflows (dashed lines) and inflows (solid lines) by county type. In the years before Covid, cities saw greater outflows than inflows, while the opposite was true for commuting belts. Remarkably, both outflows from and inflows into cities dropped between 2019 and 2020. Thus, the accelerated urban population loss during the crisis is explained by the sharper drop in inflows. This finding contrasts with the narrative that workers transitioning to WFH were the source of a city exodus. Instead, the pattern is predictable by models of internal migration responses to local economic shocks and similar to previous crises (Monras, 2020). Panels B–C compute cumulative excess flows by county type for inward, outward, and net migration, respectively. 2020–22 excess migration is calculated as the sum of deviations from the linear 2013–19 trend. The charts confirm that migration in and out of all county types slowed during the crisis. Importantly, excess population gains in less central areas were driven by a stronger decline in moves to more central counties.

Municipality-level population changes   Next, we examine whether WFH potential is associated with diverging population trends using municipality-level data. To this end, we build a panel of 4,777 municipalities belonging to an MA, including information on each municipality's distance to the MA city centre, its WFH potential (aggregate the postcode

[9] The value is based on WFH rates reported in Figure 2.1 and 33.5 million employed persons in 2019.

**Figure B.16:** Cross-county migration in Germany



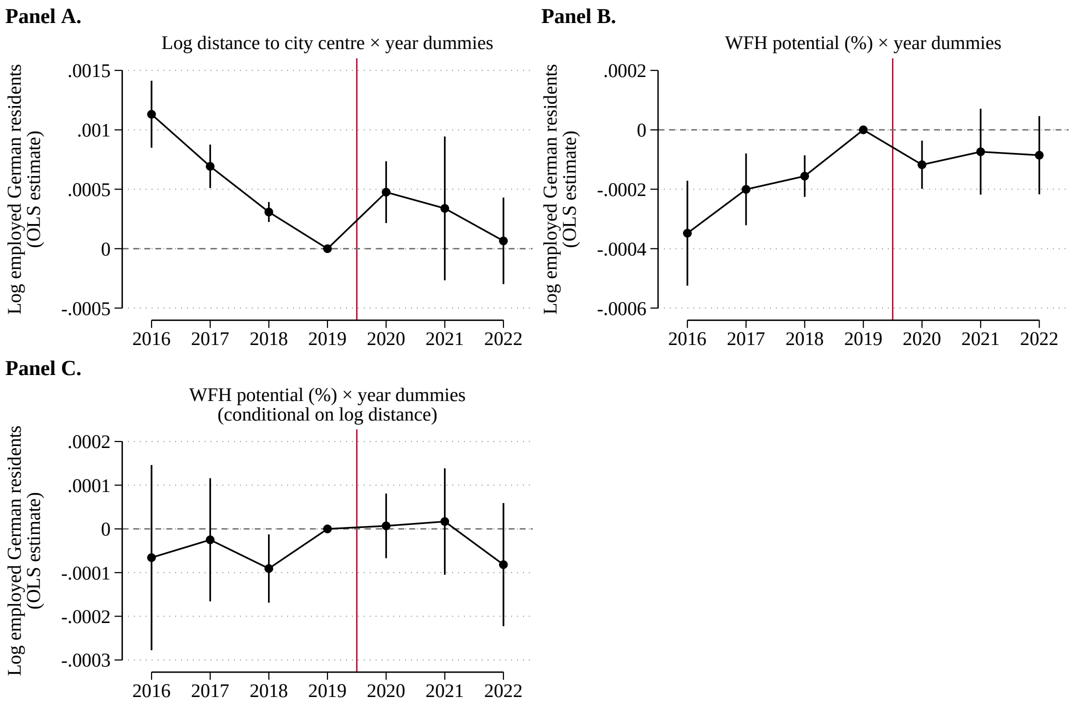

*Notes:* Panels A–D plot trends in internal migration of German citizens across county boundaries (including flows to or from abroad) based on data from the German Federal Statistical Office (*Destatis*). Panel A shows the annual sums of population inflows and outflows by area type. Panels B–D plot excess outflow, inflow, and net migration by area type, respectively, calculated as the cumulative deviation from the respective 2013-19 linear trend.

level), and the annual number of employed German residents.[10] We adapt our DiD specification from Equation 2.1 to the municipality panel. The dependent variable is the annual log number of employed German residents. Again, we include year-MA fixed effects to ensure comparisons within metro areas.

Panel A of Figure B.17 plots the DiD interaction terms with log distance to the city centre. The estimates suggest that more peripheral municipalities consistently grew more slowly than more central municipalities between 2016 and 2019. The trend reversed with the pandemic outbreak. Between 2019 and 2022, population growth was not different across more and less central municipalities. Panel B plots DiD estimates for WFH potential. The pat-

[10]We focus on employed persons and German citizens to capture work-related population changes and avoid influences from the refugee waves of 2015 and 2022.

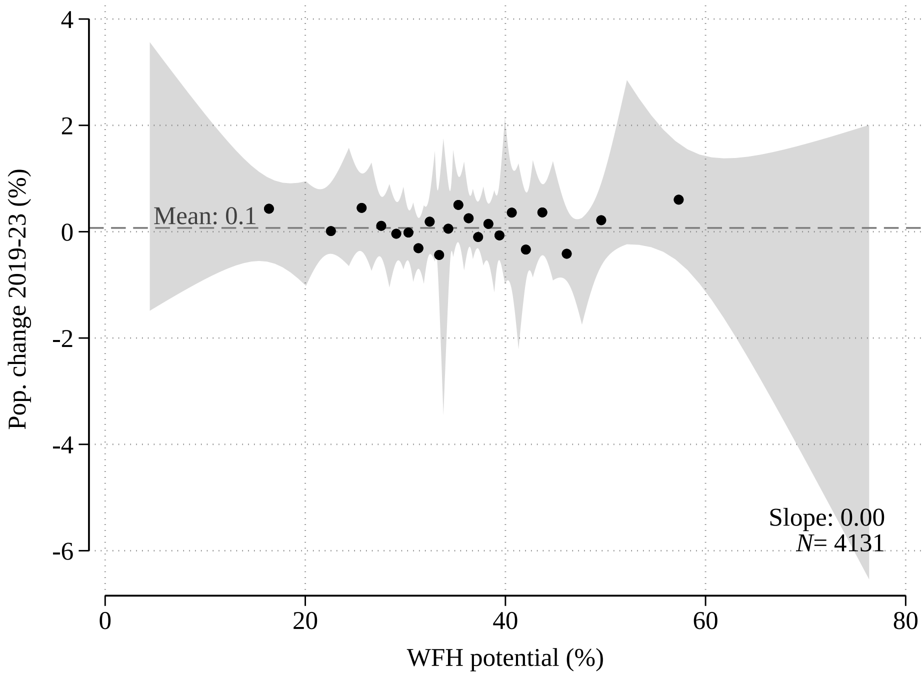
**Figure B.17:** DiD Results on changes in employed population (municipality-level)




*Notes:* Panels A–C report DiD estimates from OLS regressions of the log number of employed German residents on DiD interaction terms, year×MA fixed effects, and municipality fixed effects. DiD interactions equal year-dummies×log distance to the city centre in Panel A and year-dummies×WFH potential in Panel B. Panel C reports the DiD coefficients from WFH potential×year dummy interactions, conditional on log distance×year fixed effects. Confidence intervals are drawn at the 95% level using standard errors clustered by municipality. Employment data are from the Federal Employment Agency (*Bundesagentur für Arbeit*).

tern reveals that higher-WFH-potential areas saw stronger population growth before Covid induced a trend break. Again, log employed population evolved roughly in parallel between 2019 and 2022 across areas with different WFH exposure. Finally, Panel C plots DiD estimates for WFH potential controlling for interaction terms of log distance with year dummies (matching our preferred specification in the main analysis). The results show that partialling out trend differences by distance renders population growth in high versus low WFH areas roughly parallel throughout the observation period. In particular, higher-WFH-potential areas did not experience a stronger population decline after 2019. Again, these findings challenge the view that realising WFH opportunities induced outmigration. More central areas missed out on population growth anticipated by the pre-crisis trends. This may be due to a newfound aversion to density stemming from contagion risks or a decreased appreciation for urban amenities, possibly subjective or influenced by Covid restrictions.

**Figure B.18:** WFH potential and 2019-23 population change (postcode-Level)




*Notes:* The figure shows a binned scatterplot of population changes between 2019 and 2023 in percent against WFH potential, conditional on MA fixed effects using the methodology by Cattaneo et al. (2024). Bins are of equal size using postcode-level observations. The shaded area highlights the 95% confidence band of the conditional mean function using standard errors clustered by postcode.

## B.7 Other Results

### B.7.1 Estimating the wage premium on WFH feasibility

We quantify the wage premium on having a WFH feasible job using pre-Covid data from the 2018 BIBB-BAuA Employment Survey of the German workforce. We restrict the sample to employed persons aged 16–64. Following Alipour et al. (2023), we create a WFH feasibility dummy equal to one if the respondent does *not* indicate that (occasional) WFH is "impossible" with their job.

Figure B.19 collapses the data into 50 hourly wage quantiles. The plot reveals that WFH potential increases nearly monotonically with wage. Employees at the top of the distribution are twice as likely to hold a teleworkable job compared to those at the bottom.

We quantify the average wage premium on WFH feasibility in Table B.7. Column 1 reports the OLS estimate from regressing log hourly wage on a WFH feasibility dummy. The coefficient suggests that having a job that can be done from home comes with a 25.5% wage premium, on average. Column 2 adds broad occupation and sector fixed effects, reducing the estimate to 12.7%. Column 3 conditions on narrow occupation and industry fixed effects instead. This further reduces the premium to 9.9%. Finally, we add controls for demographic characteristics (gender, age, marital status, children, education, migrant background), firm size categories, and firm tenure. Accounting for these factors reduces the estimated premium to 7.6% (Column 4).

**Figure B.19:** WFH potential across the wage distribution

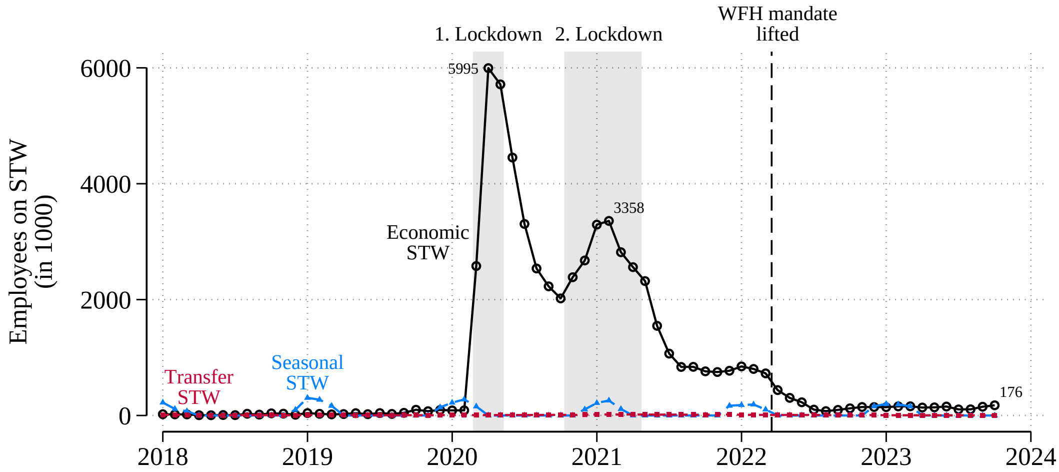

*Notes:* The figure plots WFH potential by hourly wage quantile. WFH potential corresponds to the share of respondents in a wage quantile who do not rule out that their job could be done at least partly from home (see Alipour et al. (2023) for details). Data are from the 2018 BIBB-BAuA Employment Survey.

**Table B.7:** Estimating the wage premium on WFH feasibility

| | *Log hourly wage* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| WFH feasible job (0/1) | 0.255*** | 0.127*** | 0.099*** | 0.076*** |
| | (0.010) | (0.011) | (0.011) | (0.010) |
| Female (0/1) | | | | -0.135*** |
| | | | | (0.010) |
| Migration background (0/1) | | | | -0.011 |
| | | | | (0.012) |
| Log age | | | | 0.093*** |
| | | | | (0.019) |
| Married (0/1) | | | | 0.044*** |
| | | | | (0.009) |
| Children under 18 (0/1) | | | | 0.040*** |
| | | | | (0.009) |
| Academic degree (0/1) | | | | 0.217*** |
| | | | | (0.010) |
| Log firm tenure | | | | 0.098*** |
| | | | | (0.005) |
| Firm size category | | | | |
| $<$10 workers (omitted) | | | | |
| 10-19 workers | | | | 0.068*** |
| | | | | (0.018) |
| 20-49 workers | | | | 0.065*** |
| | | | | (0.016) |
| 50-99 workers | | | | 0.093*** |
| | | | | (0.017) |
| 100-249 workers | | | | 0.111*** |
| | | | | (0.016) |
| 250-499 workers | | | | 0.160*** |
| | | | | (0.017) |
| 500-999 workers | | | | 0.173*** |
| | | | | (0.019) |
| 1000+ workers | | | | 0.241*** |
| | | | | (0.017) |
| $R^2$ | 0.08 | 0.24 | 0.32 | 0.47 |
| Observations | 16,595 | 16,595 | 16,592 | 16,096 |
| 2-digit occupation fixed effects (36 cat.) | | × | | |
| Sector fixed effects (21 cat.) | | × | | |
| 3-digit occupation fixed effects (139 cat.) | | | × | × |
| Industry fixed effects (84 cat.) | | | × | × |

*Notes:* The table reports OLS regressions of log hourly wage on WFH feasibility and other characteristics at the employee level. WFH feasibility is a dummy equal to one if the respondent does not rule out that their job could be done at least partly from home (see Alipour et al. (2023) for details). Heteroskedasticity-robust standard errors are reported in parentheses. Data are from the 2018 BIBB-BAuA Employment Survey. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

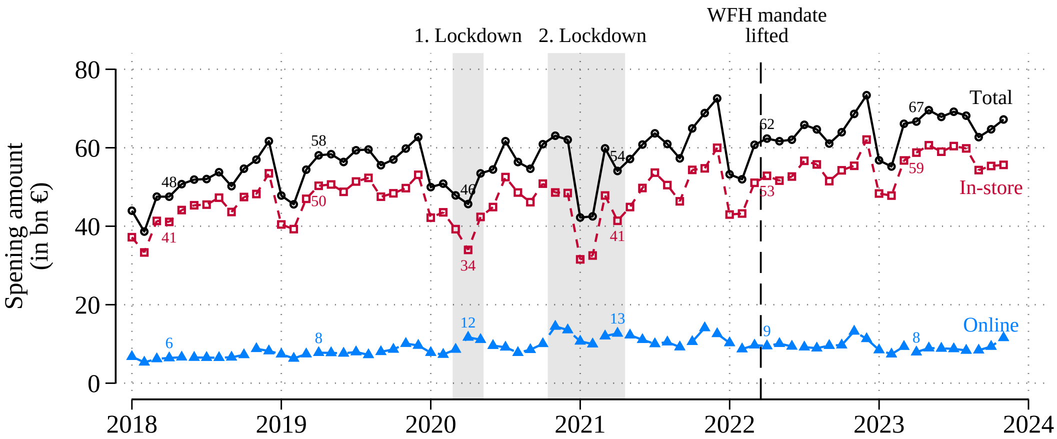
**Figure B.20:** Short-time work in Germany



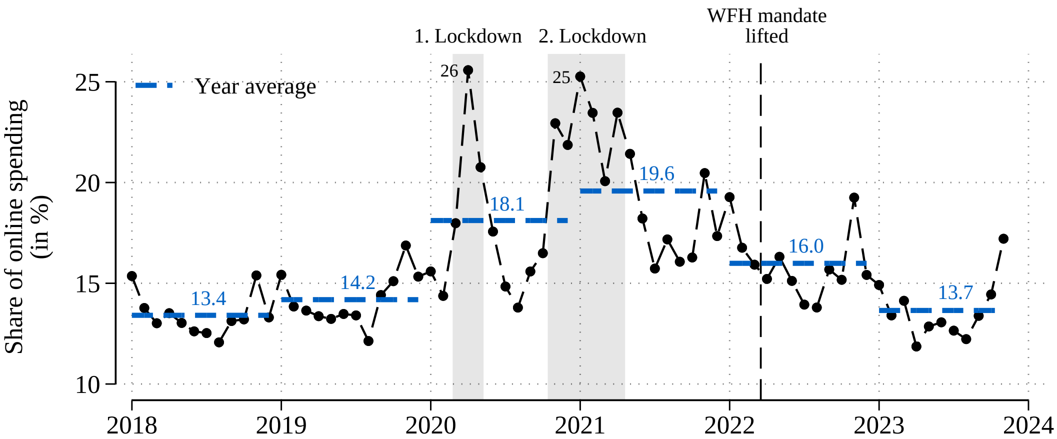

*Notes:* The figure shows the number of employees on short-time work (STW) by month and STW type. Economic STW aims to mitigate unforeseen economic downturns such as the Covid-19 crisis. Seasonal STW addresses predictable demand fluctuations in sectors such as agriculture or construction. Transfer STW aims to support employees transitioning to new roles during employer restructuring. Data are from the Federal Employment Agency (*Bundesagentur für Arbeit*).

**Figure B.21:** Online and offline spending in Germany

**Panel A.** Offline and online spending

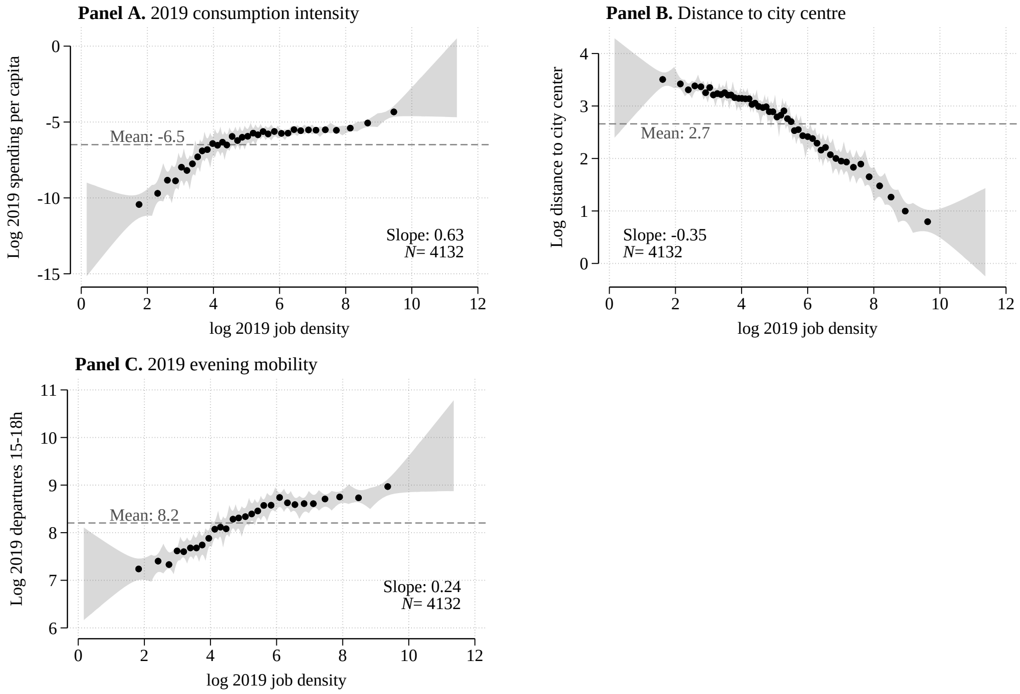



**Panel B.** Share of online spending



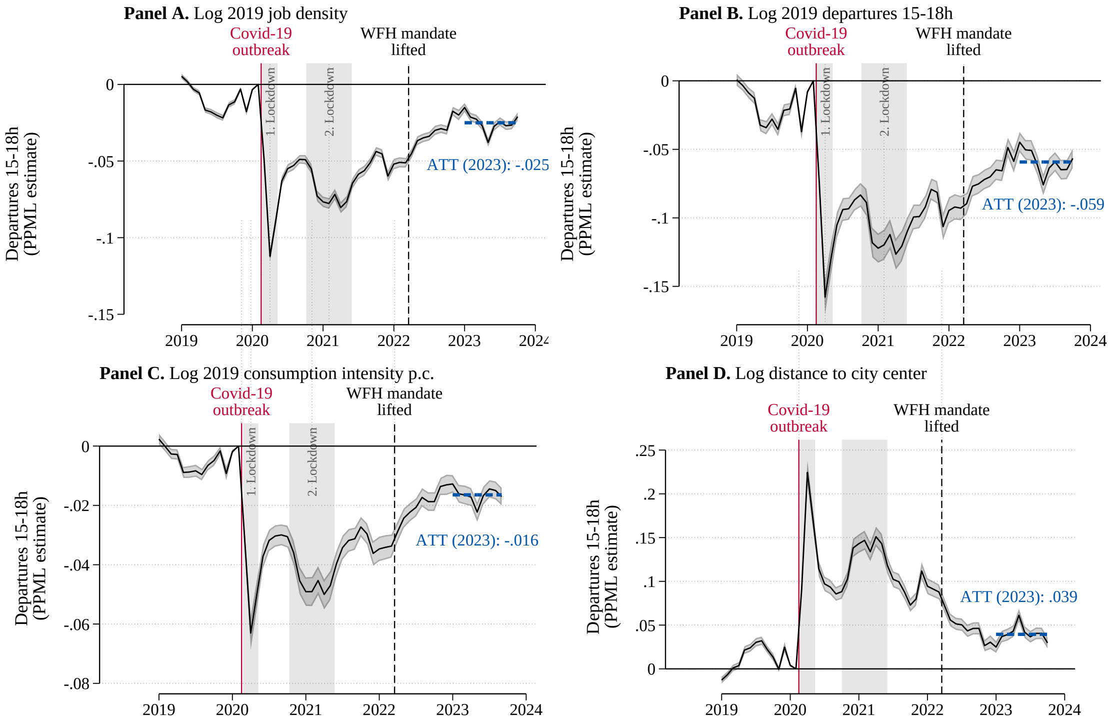

*Notes:* Panel A plots the monthly nominal Euro amounts spent in offline, online and total transactions in Germany. Panel B shows the fraction of the total amount spent online. Data are from Mastercard Spending Pulse.

**Figure B.22:** Correlates of 2019 job density




*Notes:* Panels A–C show binned scatterplots conditional on MA fixed effects using the methodology by Cattaneo et al. (2024). Bins are of equal size using postcode-level observations. The shaded areas highlight 95% confidence bands of the conditional mean functions using standard errors clustered by postcode. Job density is defined as employment per square kilometre.

**Figure B.23:** Consequences for workplace areas




*Notes:* Panels A–D report DiD estimates from a PPML regression of monthly weekday evening departures on DiD interaction terms of month dummies with a time-invariant variable $Z$, month×MA fixed effects, and postcode fixed effects. $Z$ corresponds to log 2019 job density in Panel A, log 2019 departures between 3 and 6 pm (Panel B), log 2019 spending per capita (Panel C), and log distance to the city centre (Panel D). Shaded areas highlight 95% confidence bands using standard errors clustered at the postcode level.

**Table B.8:** Workplace effects by industry (PPML estimates, 2019–23 changes)

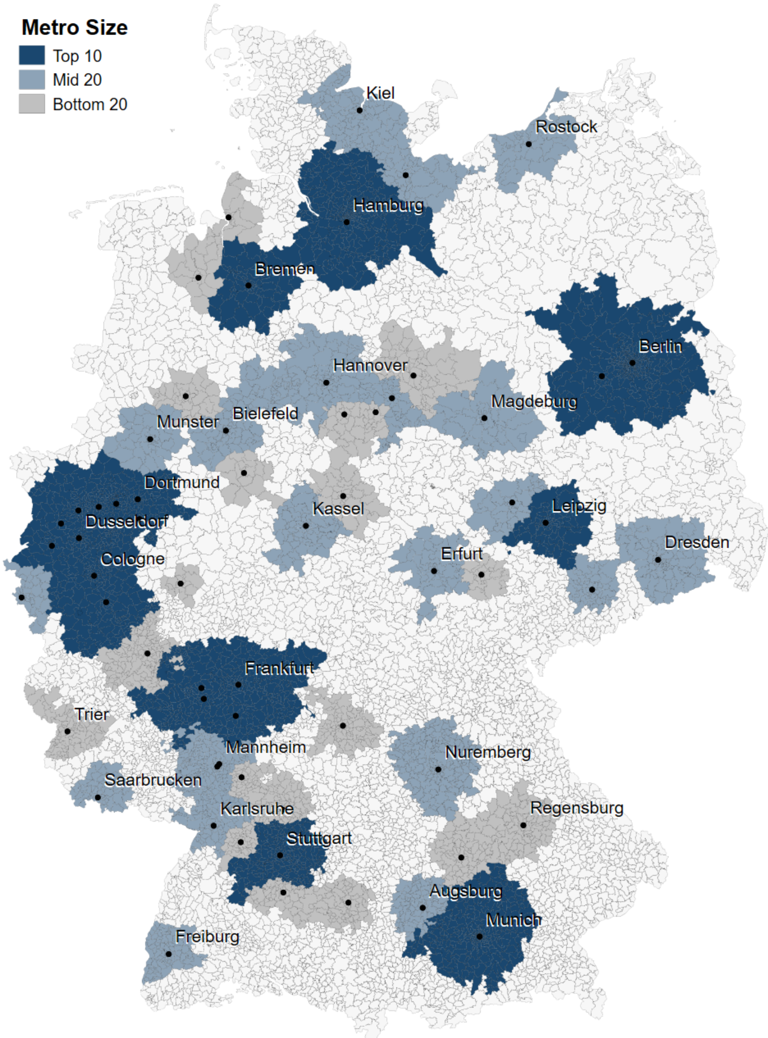
| | *Spending (Mo-Fr)* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Total spending | | | | Grocery stores | | | |
| Log 2019 job density | -0.061*** | | | | -0.191*** | | | |
| | (0.006) | | | | (0.011) | | | |
| 2019 log departures 15-18h | | -0.226*** | | | | -0.609*** | | |
| | | (0.016) | | | | (0.030) | | |
| 2019 log spending p.c. | | | -0.224*** | | | | -0.535*** | |
| | | | (0.021) | | | | (0.010) | |
| Log distance to city centre | | | | 0.077*** | | | | 0.228*** |
| | | | | (0.010) | | | | (0.022) |
| Implied prop. effect (%) | -0.06 | -0.23 | -0.22 | 0.08 | -0.19 | -0.61 | -0.53 | 0.23 |
| Tot. obs. | 8,124 | 8,124 | 8,124 | 8,124 | 6,700 | 6,700 | 6,700 | 6,700 |
| #Postcodes | 4,062 | 4,062 | 4,062 | 4,062 | 3,350 | 3,350 | 3,350 | 3,350 |
| | Food services | | | | Apparel stores | | | |
| Log 2019 job density | -0.171*** | | | | -0.123*** | | | |
| | (0.012) | | | | (0.040) | | | |
| 2019 log departures 15-18h | | -0.281*** | | | | -0.302*** | | |
| | | (0.034) | | | | (0.107) | | |
| 2019 log spending p.c. | | | -0.337*** | | | | -0.277*** | |
| | | | (0.018) | | | | (0.027) | |
| Log distance to city centre | | | | 0.221*** | | | | 0.136*** |
| | | | | (0.019) | | | | (0.047) |
| Implied prop. effect (%) | -0.17 | -0.28 | -0.34 | 0.22 | -0.12 | -0.30 | -0.28 | 0.14 |
| Tot. obs. | 5,240 | 5,240 | 5,240 | 5,240 | 3,460 | 3,460 | 3,460 | 3,460 |
| #Postcodes | 2,620 | 2,620 | 2,620 | 2,620 | 1,730 | 1,730 | 1,730 | 1,730 |

*Notes:* The table presents results based on a variation of Equation 2.2, where average weekday spending is regressed on an interaction of post-dummy× explanatory variable of interest using the PPML estimator. All columns include postcode and metro area×post-dummy fixed effects. The implied proportional effect (IPE) corresponds to the percentage change in spending associated with percent change in the explanatory variable of interest, respectively, and is calculated as $100 \times [\exp(\cdot) - 1]$. Standard errors are clustered by postcode and reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

# C
# Appendix to Chapter 3

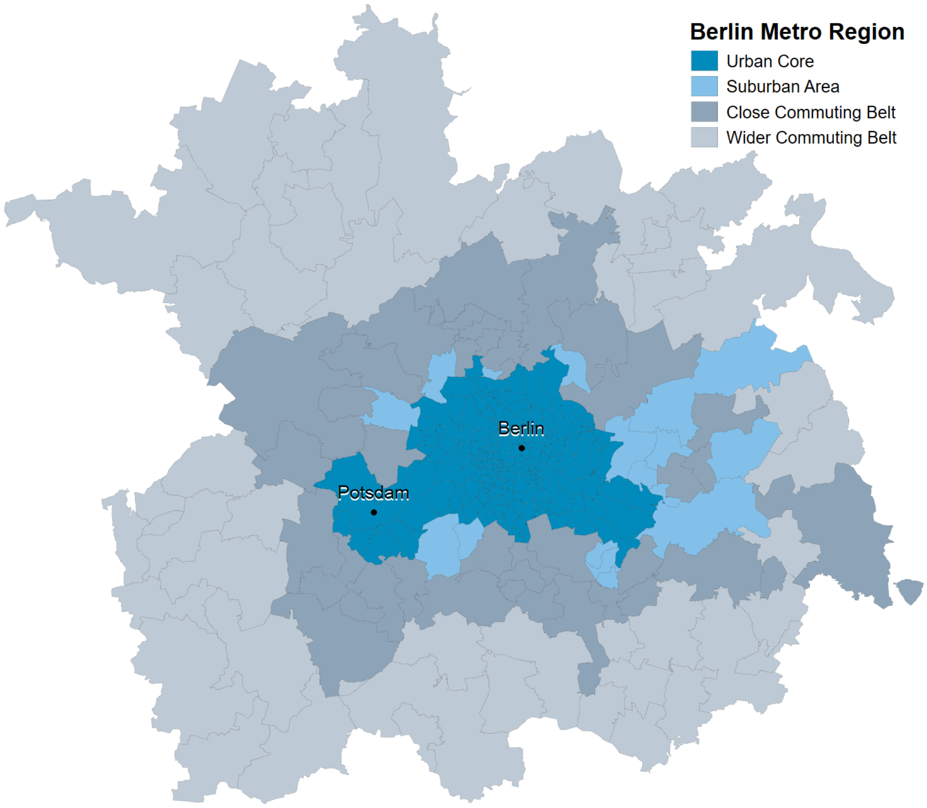
## C.1 Sample and Summary Statistics

**Figure C.1:** Sample Illustration of 50 German Metro Regions by Population Size



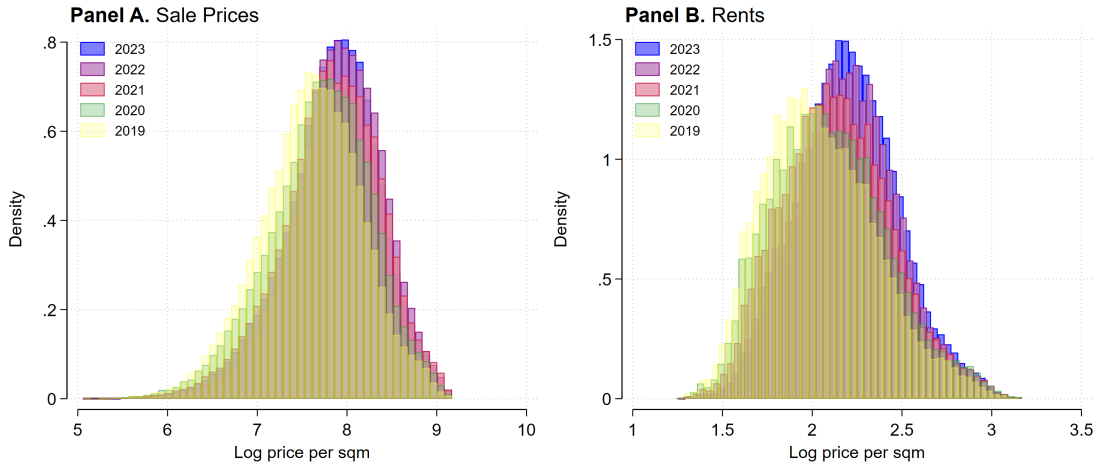

*Notes:* This figure displays our sample comprised of the 50 largest metro regions in Germany by population size. The top 10 metro areas are shown in dark blue, the mid 20 metro regions in light blue, and the bottom 20 metro regions in gray. The administrative classification of the metro areas is provided by the German Federal Office for Building and Regional Planning (BBSR).

**Figure C.2:** Illustration of Catchment Areas Within Berlin-Potsdam Metro Region




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

**Figure C.3:** Histogram of Log Sale Prices and Rents 2019-2023 in Sample




*Notes:* This figure displays the annual distribution of log property sale prices (Panel A) and rents (Panel B) from 2019 to 2023. The two histograms show the density per bin.

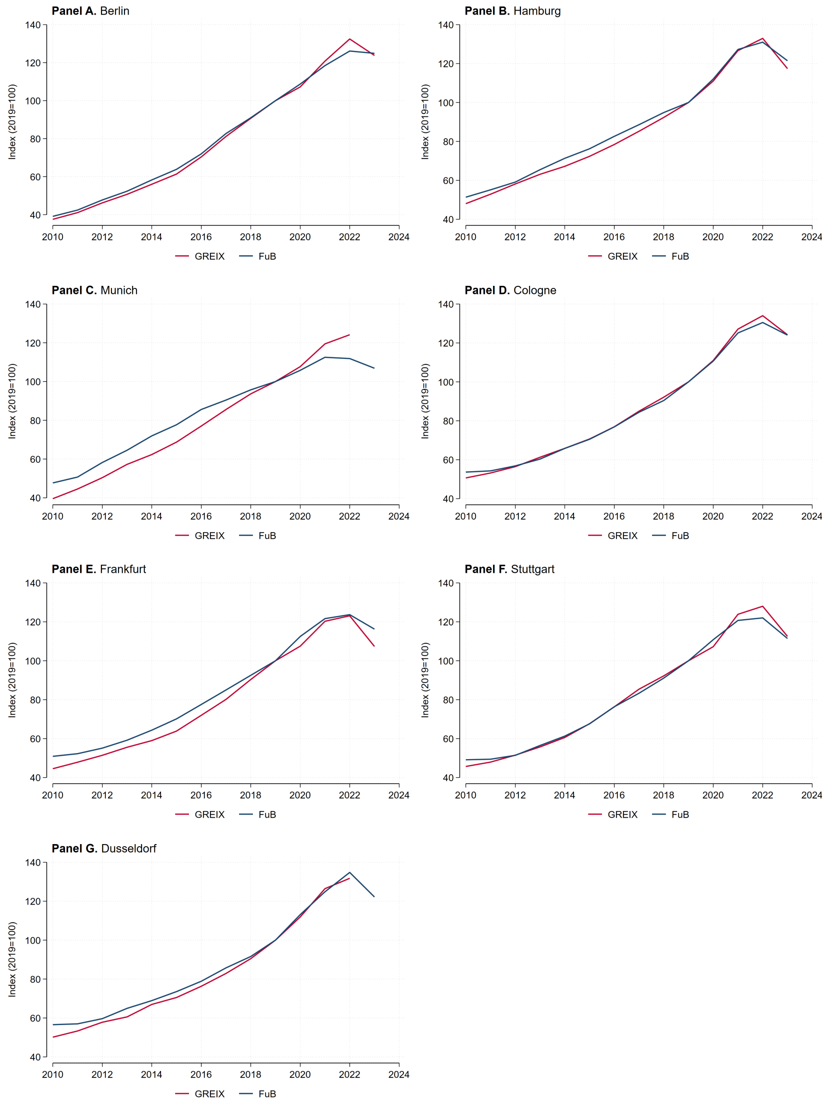
**Table C.1:** Summary Statistics: Real Estate and Postcode Characteristics

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| **Panel A. Residential Real Estate Sale Prices** | | | | |
| Average Property Price per Square Meter | 2429.49 | 1367.05 | 156.25 | 9520.55 |
| Median Property Price per Square Meter | 2397.24 | 1402.15 | 156.25 | 9520.55 |
| Sum of Property Offers per Postcode and Month | 17.01 | 18.75 | 1.00 | 562.00 |
| Average Space in Square Meters | 138.13 | 46.67 | 28.00 | 1304.00 |
| Average Number of Rooms | 4.53 | 1.57 | 0.00 | 57.00 |
| Share New Buildings | 0.20 | 0.23 | 0.00 | 1.00 |
| **Panel B. Residential Real Estate Rents** | | | | |
| Average Property Price per Square Meter | 8.22 | 2.87 | 3.45 | 23.21 |
| Median Property Price per Square Meter | 8.08 | 2.88 | 3.45 | 23.21 |
| Sum of Property Offers per Postcode and Month | 19.63 | 28.53 | 1.00 | 1473.00 |
| Average Space in Square Meters | 83.02 | 21.86 | 23.00 | 290.00 |
| Average Number of Rooms | 2.84 | 0.78 | 0.00 | 18.00 |
| Share New Buildings | 0.13 | 0.19 | 0.00 | 1.00 |
| **Panel C. Working From Home** | | | | |
| WFH Potential Residence (Percent) | 35.57 | 9.22 | 0.00 | 77.56 |
| WFH Potential Workplace (Percent) | 41.98 | 7.54 | 12.23 | 92.49 |
| WFH Prior to Covid (Percent) | 14.22 | 7.40 | 0.00 | 52.66 |
| WFH Untapped Potential (Percent) | 60.99 | 15.20 | 10.58 | 100.00 |
| WFH During Covid (Percent) | 21.11 | 8.68 | 0.00 | 54.68 |
| WFH Growth | 0.72 | 0.95 | -0.66 | 22.74 |
| WFH Employee Desires After Covid (Percent) | 29.01 | 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 | 13246.27 | 9289.41 | 0.00 | 58826.00 |
| Area per Postcode (sqkm) | 35.35 | 45.84 | 0.00 | 567.73 |
| Population Density (Inhabitants per sqkm) | 1580.41 | 2873.00 | 0.00 | 26718.58 |
| Distance to City Center (km) | 18.03 | 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 Maintanance 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 G), sociodemographic structure (Panel H) and industry composition (Panel I) are collected and provided by infas360 based on survey and administrative data.

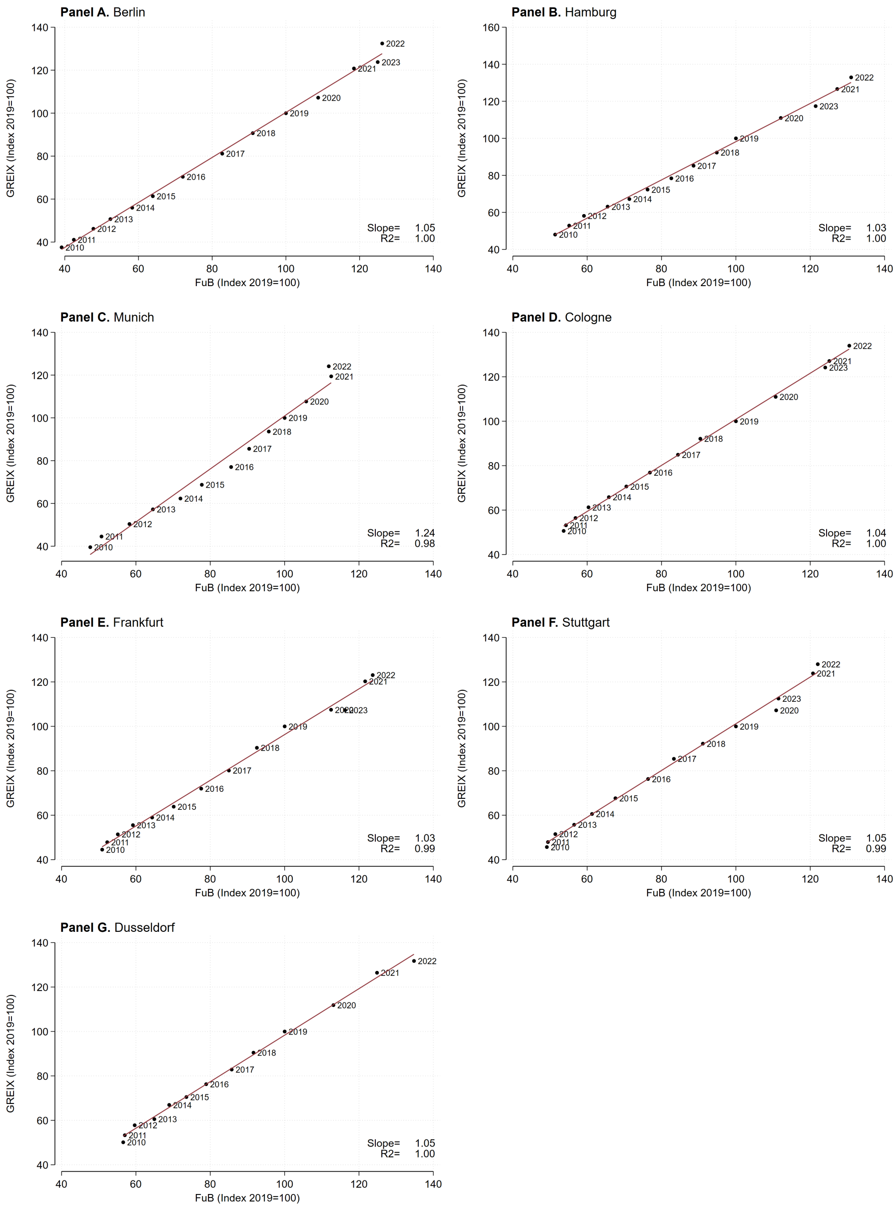
## C.2 Data Validation

**Figure C.4:** Data Validation of Property Offering Prices: Evolution of FuB Property Offerings Price Index and German Real Estate Index (GREIX) 2010-2023



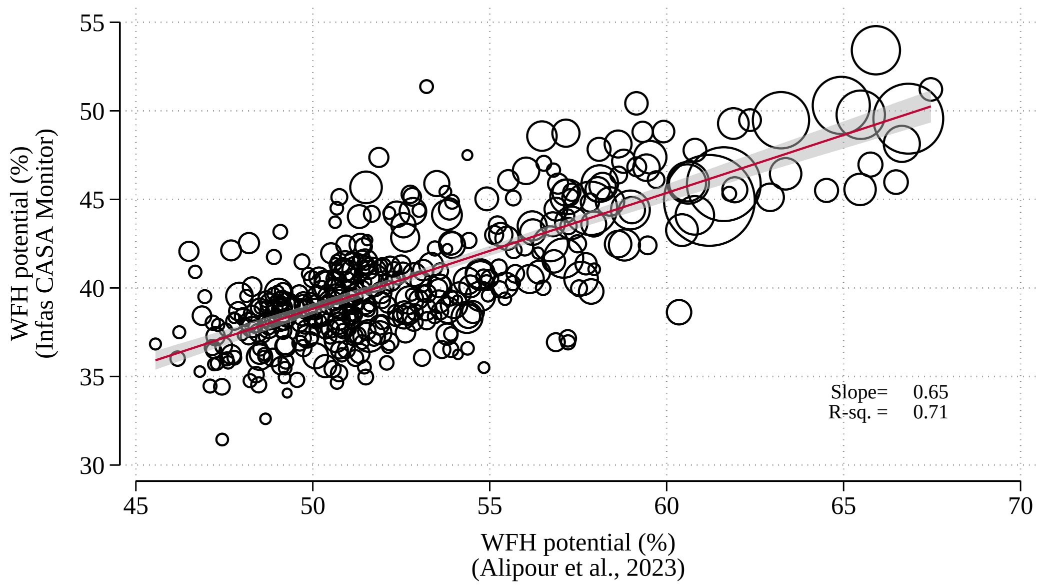

*Notes:* This figure illustrates the evolution of real estate price indices in Germany's seven largest cities (Berlin, Hamburg, Munich, Cologne, Frankfurt, Stuttgart, and Dusseldorf) from 2010 to 2023. The blue lines represent the FuB property offering price indices, which are used in the analyses of this paper. The red lines depict 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 C.5:** Data Validation of Property Offering Prices: Correlation of FuB Property Offerings Price Index and German Real Estate Index (GREIX) 2010-2023




*Notes:* This figure illustrates the correlation of real estate price indices in Germany's seven largest cities (Berlin, Hamburg, Munich, Cologne, Frankfurt, Stuttgart, and Dusseldorf) from 2010 to 2023. The x-axis displays the FuB 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).

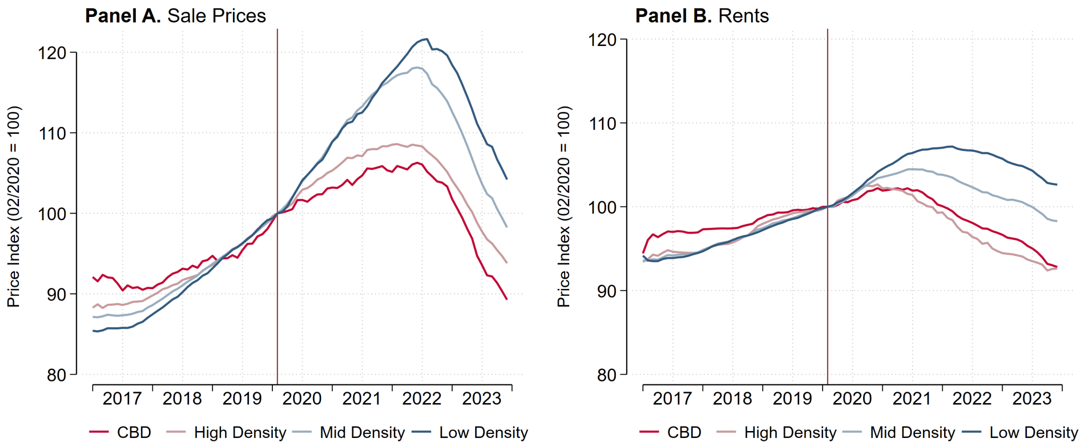
**Figure C.6:** Validation of WFH Data: Correlation of infas Postcode-Level Survey Data and County-Level Admin Data from Alipour et al. (2023)




*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 for this data validation exercise.

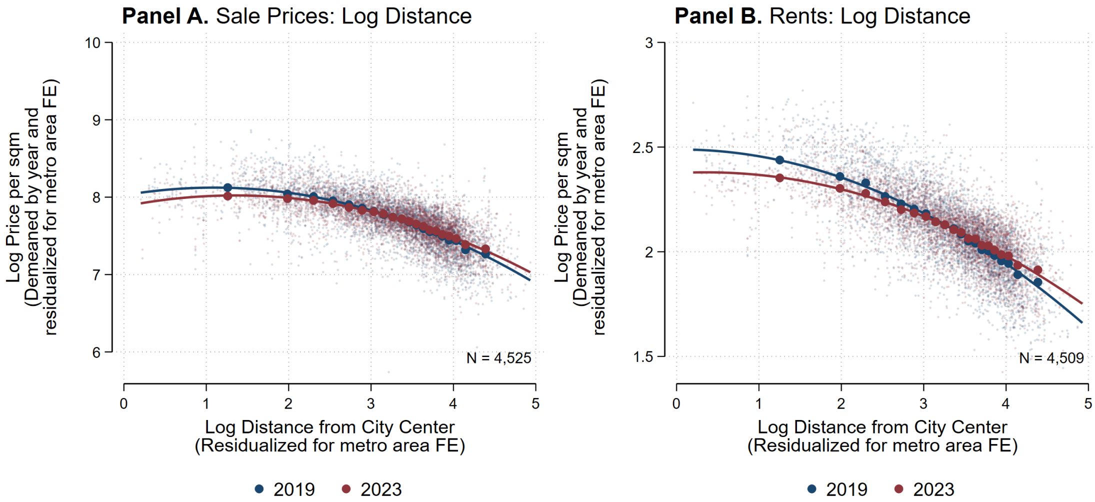
## C.3 Descriptive Evidence

**Figure C.7:** Donut Effect of Urban Housing Prices



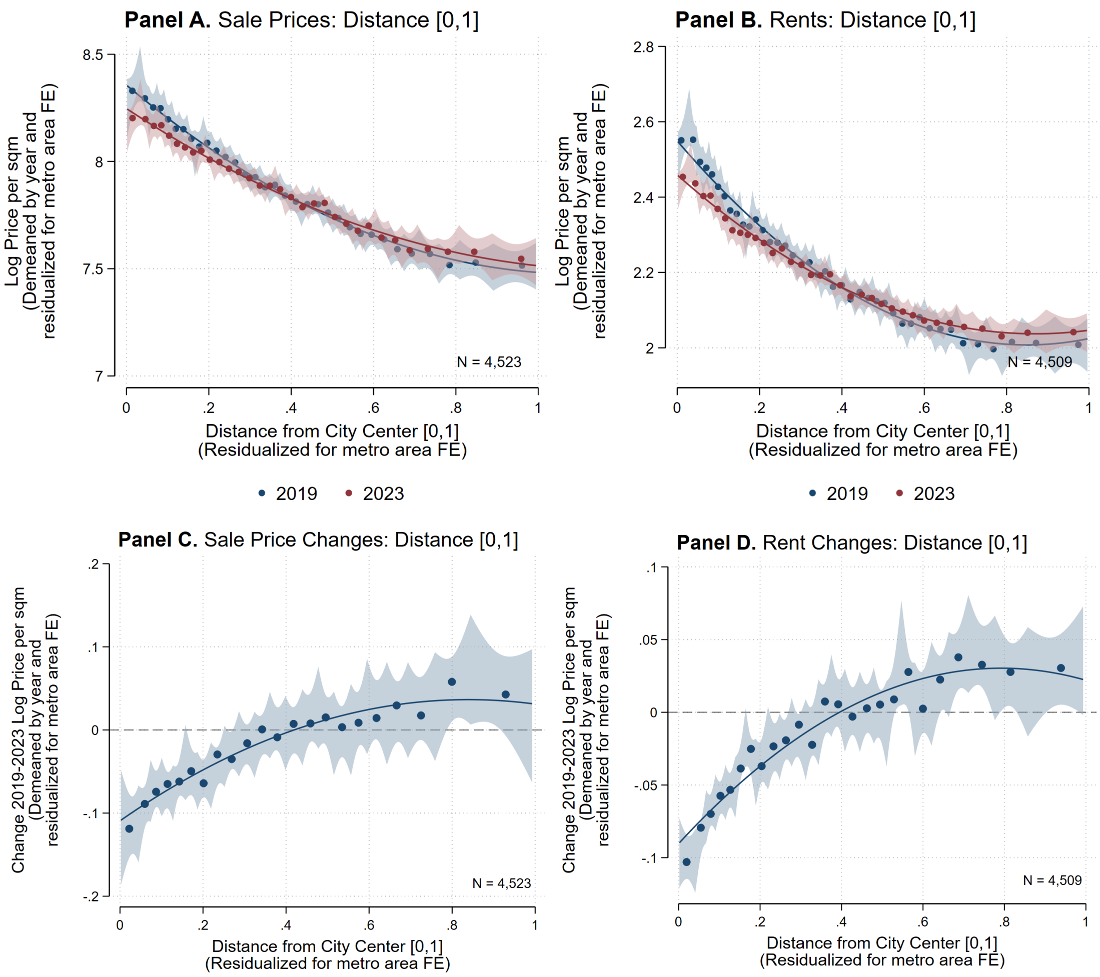

*Notes:* This figure displays the development of real estate prices in German metropolitan areas between 2017 and 2023. The two panels plot the evolution of sale prices and rents. Postcodes are grouped into four categories: low, medium, high density, and central business district. Average monthly inflation-corrected real estate prices are transformed into an index that takes the value of 100 in February 2020. The vertical red line marks the outbreak of the Covid-19 pandemic between February and March 2020.

**Figure C.8:** Flattening of Urban Housing Price Gradient: Scatter Plots Relative to Log Distance from Urban Centers



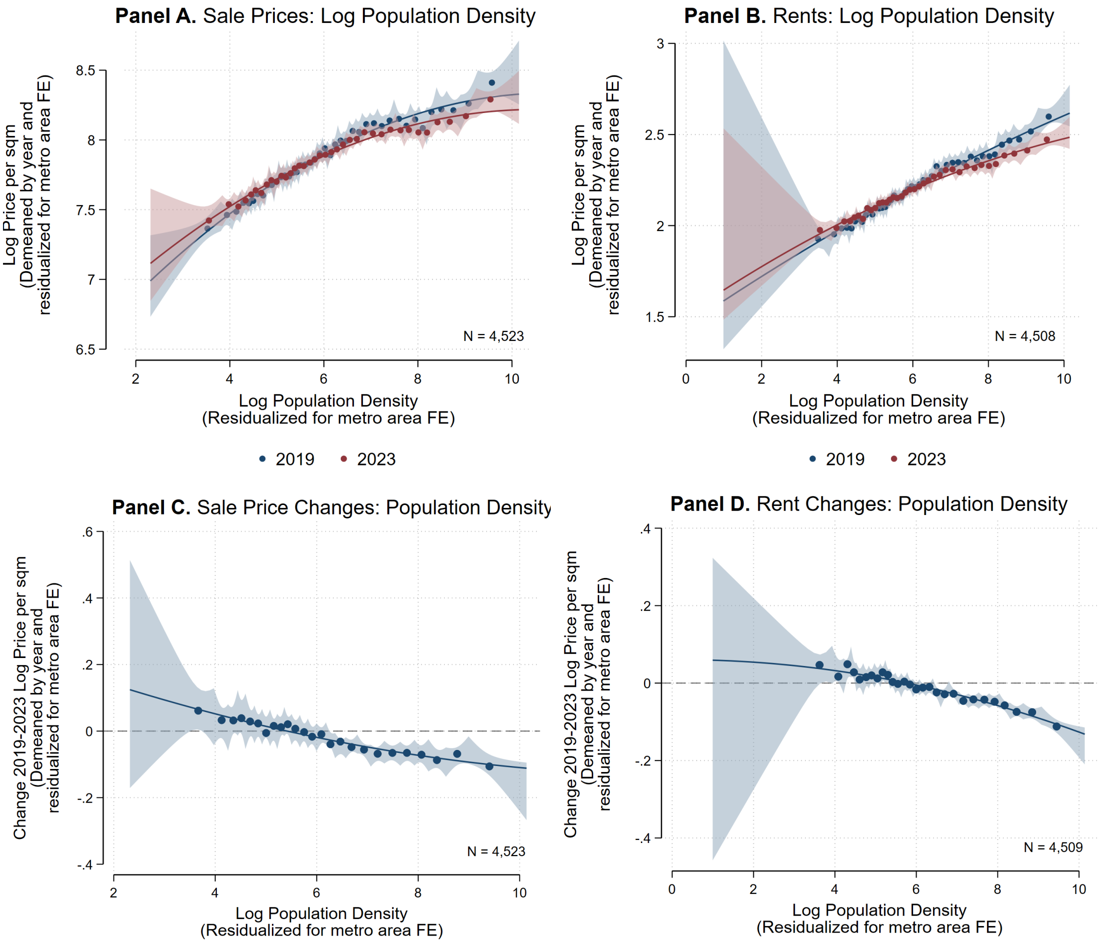

*Notes:* This figure displays the relationship between distance from the city center (log of 1 + the distance in kilometers from city center) and the log of residential sale prices (Panel A) and residential rents (Panel B) in 2019 (blue) and 2023 (red). Lighter points indicate postcodes, while darker points are the averages of 5% distance bins (binscatter).

**Figure C.9:** Flattening of Urban Housing Price Gradient: Normalized Distance [0,1]



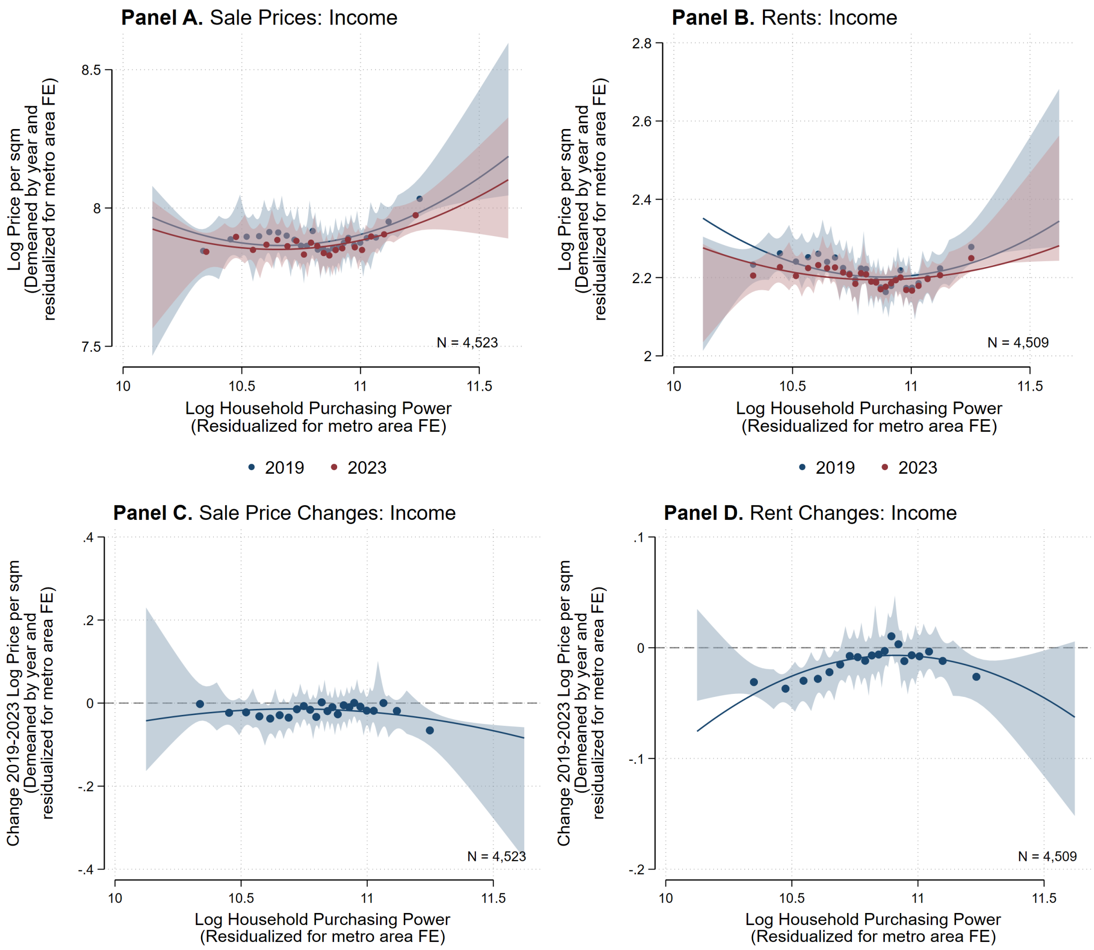

*Notes:* This figure displays binned scatter plots following the methodology proposed by Cattaneo et al. (2024) on the postcode-level relationship between the normalized distance from the city center [0,1] and the log sale prices (Panel A) and rents (Panel B) of residential properties in 2019 (blue) and 2023 (red). Panels C and D show the relationship between the normalized distance and the change in log sale prices and rents from 2019 to 2023, respectively. The shaded areas highlight 95% confidence bands of the conditional mean functions. Log property prices are demeaned by year fixed effects and residualized for metro area fixed effects. Normalized distance is residualized for metro area fixed effects.

**Figure C.10:** Flattening of Urban Housing Price Gradient: Log Population Density



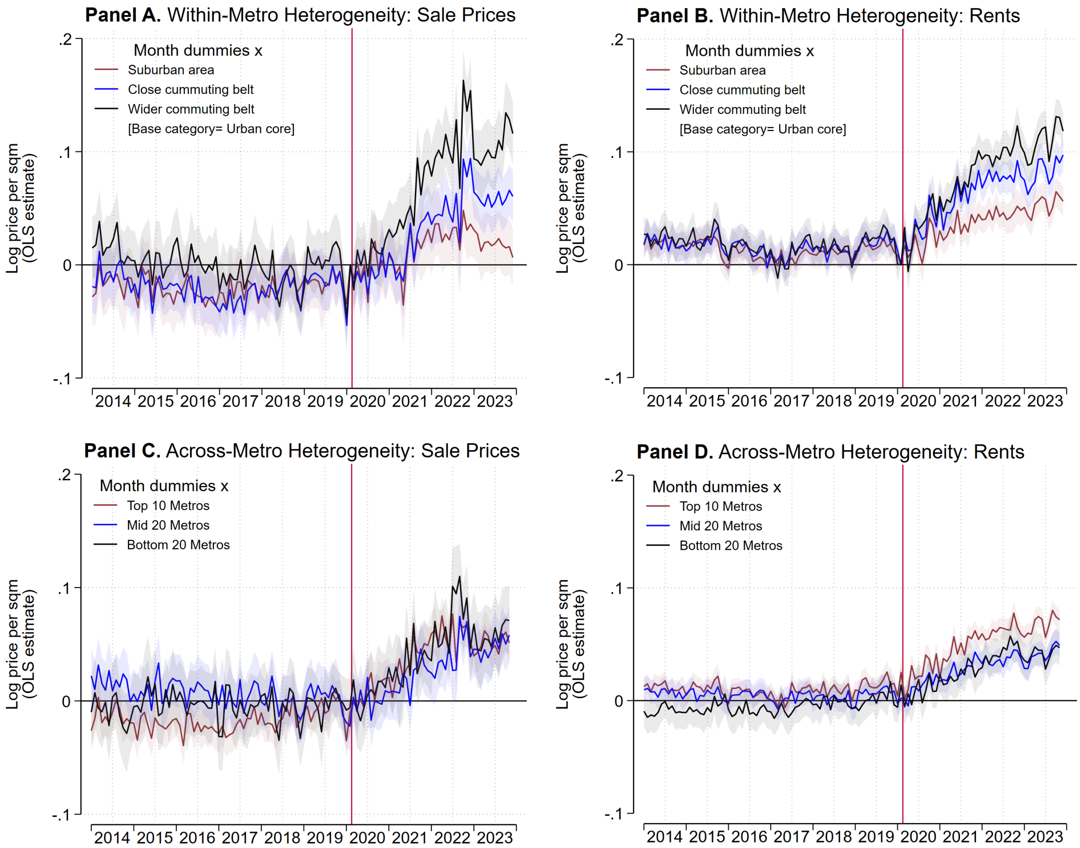

*Notes:* This figure displays binned scatter plots following the methodology proposed by Cattaneo et al. (2024) on the postcode-level relationship between the log population density and the log sale prices (Panel A) and rents (Panel B) of residential properties in 2019 (blue) and 2023 (red). Panels C and D show the relationship between log population density and the change in log sale prices and rents from 2019 to 2023, respectively. The shaded areas highlight 95% confidence bands of the conditional mean functions. Log property prices are demeaned by year fixed effects and residualized for metro area fixed effects. Log population density is residualized for metro area fixed effects.

**Figure C.11:** Flattening of Urban Housing Price Gradient: Household Purchasing Power



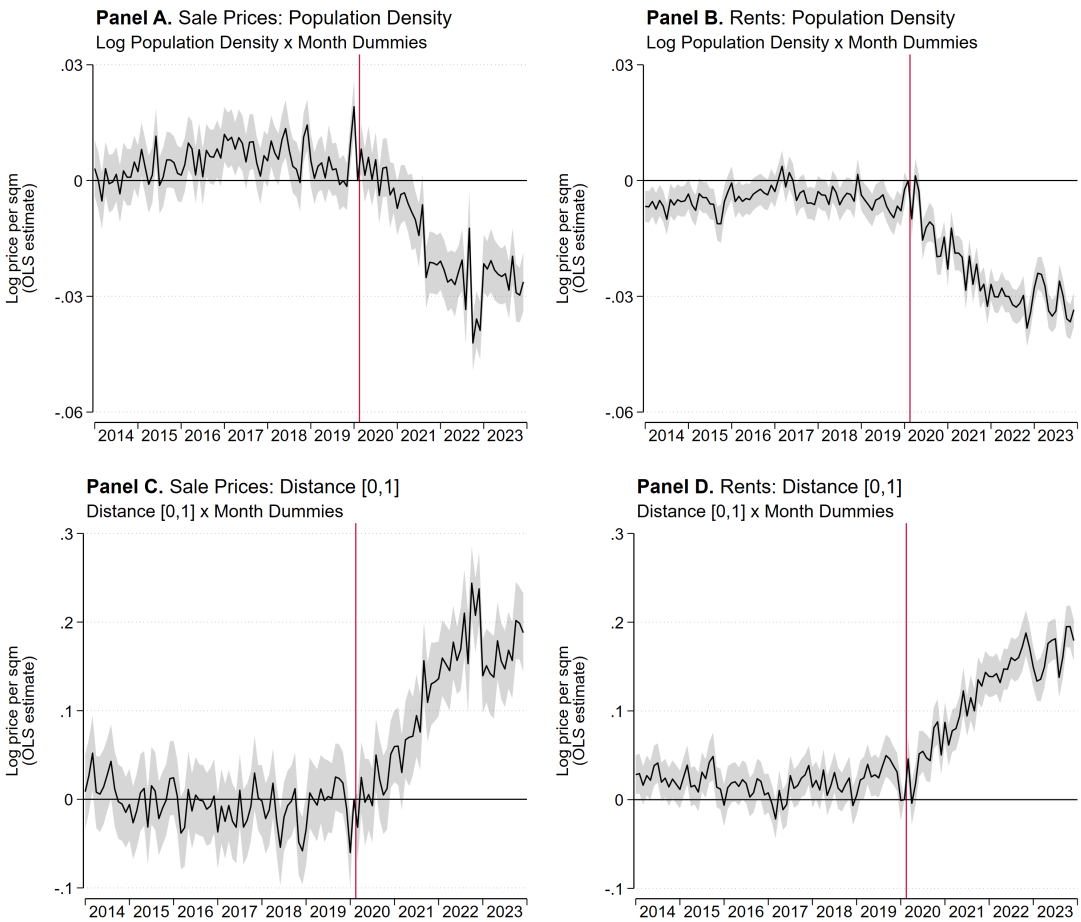

*Notes:* This figure displays binned scatter plots following the methodology proposed by Cattaneo et al. (2024) on the postcode-level relationship between the log household purchasing power and the log sale prices (Panel A) and rents (Panel B) of residential properties in 2019 (blue) and 2023 (red). Panels C and D show the relationship between log household purchasing power and the change in log sale prices and rents from 2019 to 2023. The shaded areas highlight 95% confidence bands of the conditional mean functions. Log property prices are demeaned by year fixed effects and residualized for metro area fixed effects. Log household purchasing power is residualized for metro area fixed effects.

**Figure C.12:** Heterogeneity of DiD Results Within and Across Metro Regions Relative to Log Distance from City Center



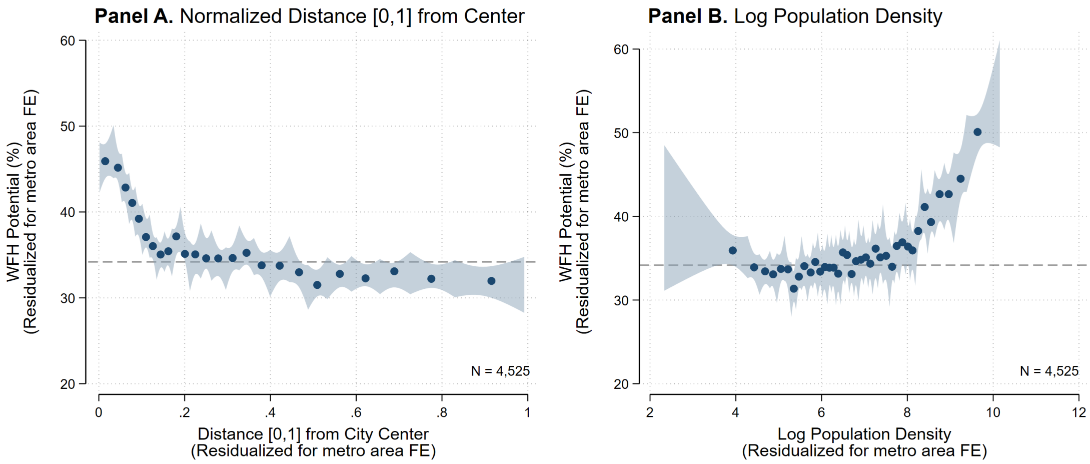

*Notes:* This figure presents DiD estimates $\hat{\beta}_k$ from separate regressions of Equation 3.1, in which the interaction terms are between monthly dummies from January 2014 until December 2023 and the catch areas within metro regions in Panels A and B as well as between monthly dummies and the log distance from the city center by size of the metro region in Panels C and D. The dependent variable is the postcode-level average log sale price per square meter in Panels A and C as well as 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.

**Figure C.13:** DiD Analysis of Housing Price Changes Relative to Population Density and Normalized Distance from City Center [0,1]



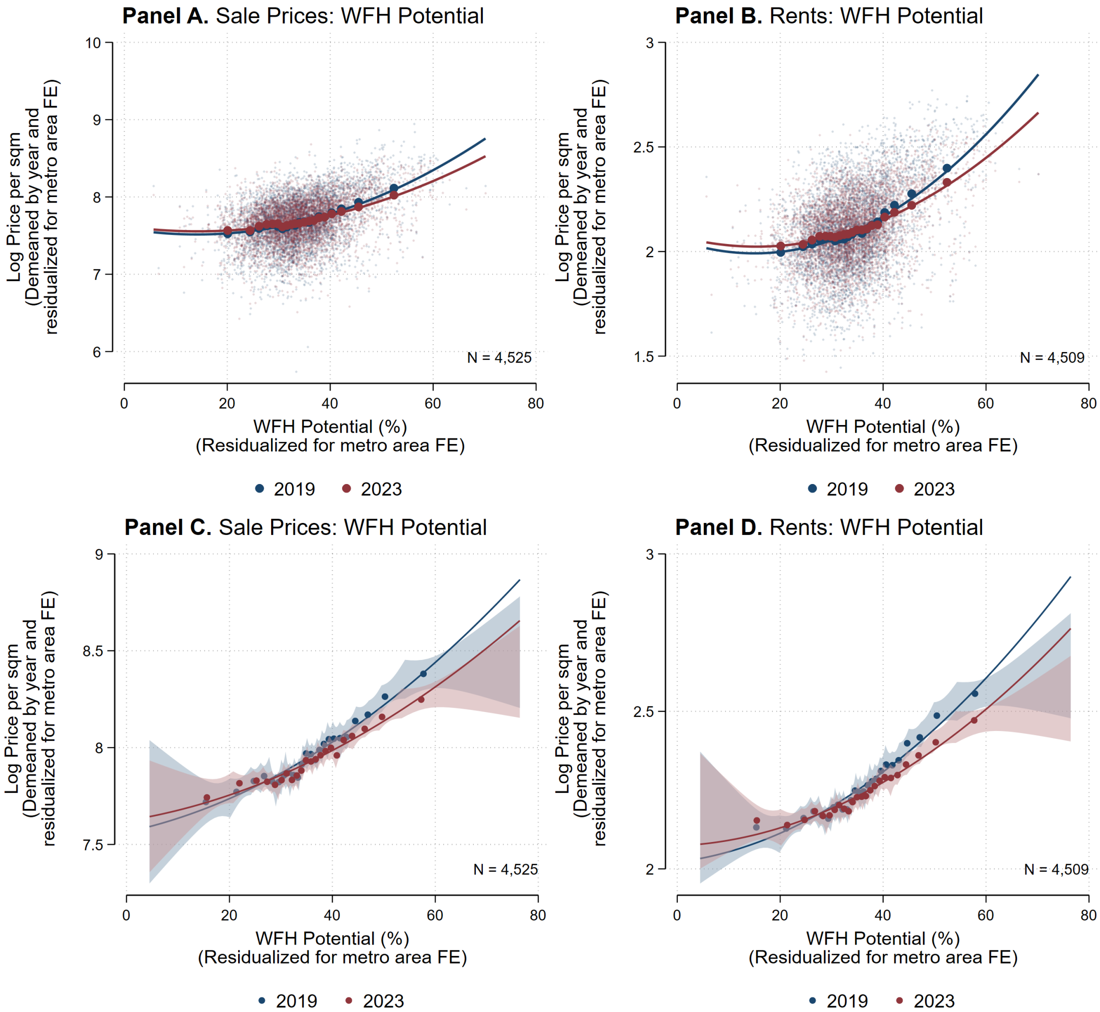

*Notes:* This figure presents DiD estimates $\hat{\beta}_k$ from separate regressions of Equation 3.1, in which the interaction terms are between monthly dummies from January 2014 until December 2023 and log population density in Panels A and B as well as between monthly dummies and the normalized measure of distance from the city center [0,1] in Panels C and D. The dependent variable is the postcode-level average log sale price per square meter in Panels A and C as well as 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.

**Figure C.14:** Association of WFH Potential with Normalized Distance from City Center [0,1] and Log Population Density




*Notes:* This figure displays binned scatter plots following the methodology proposed by Cattaneo et al. (2024) on the postcode-level relationship between the WFH potential at the place of residence with the normalized distance from the city center [0,1] in Panel A as well as with the log population density in 2019 in Panel B. The shaded areas highlight 95% confidence bands of the conditional mean functions. 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 dashed line in Panels A and B marks the average WFH Potential at the place of residence of 34.18 %. Normalized distance, log population density and WFH potential are residualized for metro area fixed effects.

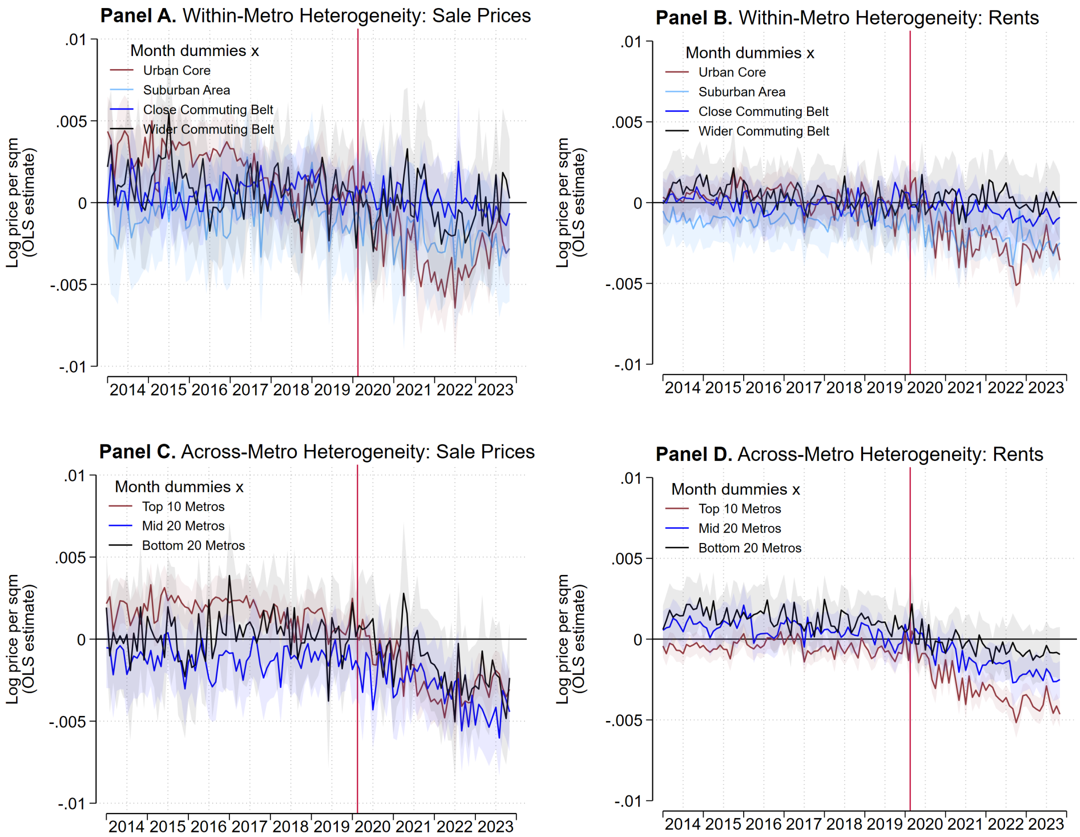
**Figure C.15:** Flattening of Urban Housing Price Gradient Relative to WFH Potential




*Notes:* This figure displays binned scatter plots on the postcode-level relationship between the WFH potential at the place of residence and the log of sale prices (Panel A) and rents (Panel B) of residential properties in 2019 (blue) and 2023 (red). Lighter points indicate postcodes, while darker points are the averages of 5% distance bins (binscatter). Panels C and D display binned scatter plots following the methodology proposed by Cattaneo et al. (2024) on the postcode-level relationship between the WFH potential at the place of residence with the log sale prices (Panel C) and rents (Panel D) of residential properties in 2019 (blue) and 2023 (red). The shaded areas highlight 95% confidence bands of the conditional mean functions. Log property prices are demeaned by year fixed effects and residualized for metro area fixed effects. WFH potential is residualized for metro area fixed effects.

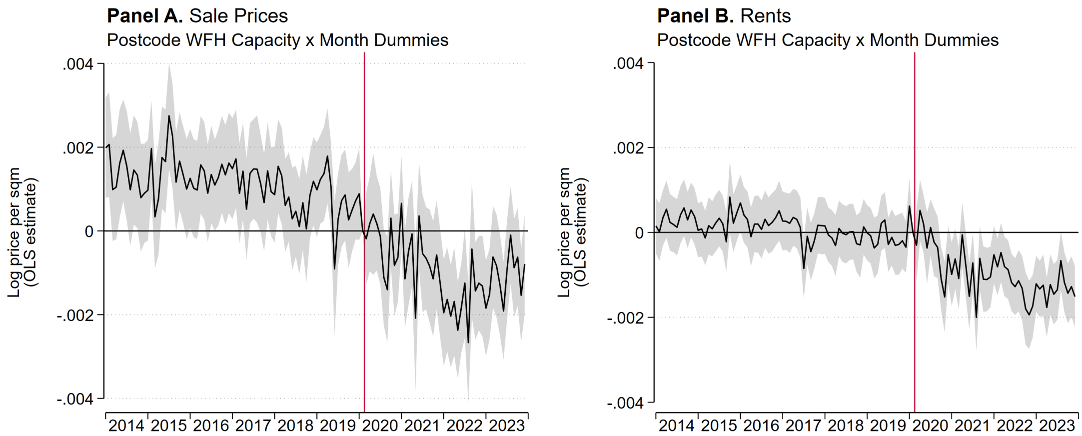
## C.4 WFH Impact on Urban Housing Prices

**Figure C.16:** Heterogeneity of DiD Results on WFH Effect Within and Across Metro Areas



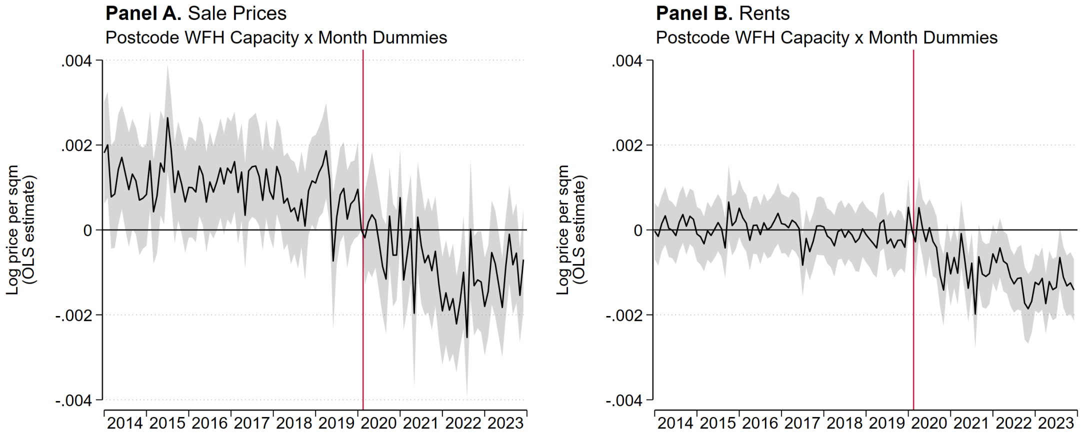

*Notes:* This figure presents DiD estimates $\hat{\beta}_k$ from separate regressions of Equation 3.3, in which the interaction terms are between monthly dummies from January 2014 until December 2023 and postcode-level WFH potential of residents by catch areas within metro regions in Panels A and B and 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.

**Figure C.17:** Robustness of DiD Results on the Impact of WFH Potential on Urban Housing Prices (Controlling for Log Distance from City Center and Log Population Density)



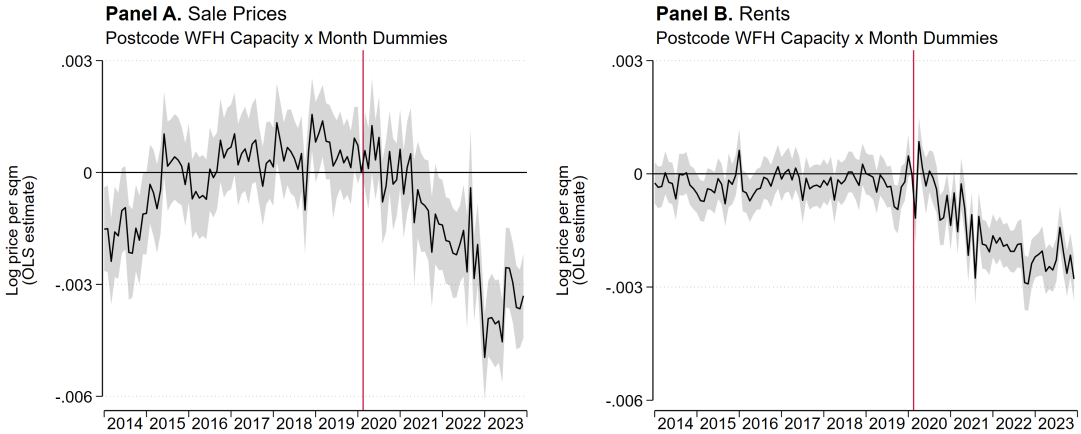

*Notes:* This figure presents DiD estimates $\hat{\beta}_k$ from separate regressions of Equation 3.3, in which the interaction terms are between monthly dummies from January 2014 until December 2023 and postcode-level WFH potential of residents with additional controls for log distance from city center and log population density. 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 Panel A and the average log rent per square meter 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 C.18:** Robustness of DiD Results on the Impact of WFH Potential on Urban Housing Prices (Controlling for Log Distance from City Center, Log Population Density, Industry Composition, and Sociodemographic Structure)




*Notes:* This figure presents DiD estimates $\hat{\beta}_k$ from separate regressions of Equation 3.3, in which the interaction terms are between monthly dummies from January 2014 until December 2023 and postcode-level WFH potential of residents with additional controls for log distance from city center, log population density, industry composition and sociodemographic structure. 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 Panel A and the average log rent per square meter 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 C.19:** Robustness of DiD Results on the Impact of WFH Potential on Urban Housing Prices (Using Residualized Prices as Outcome)




*Notes:* This figure presents DiD estimates $\hat{\beta}_k$ from separate regressions of Equation 3.3, in which the interaction terms are between monthly dummies from January 2014 until December 2023 and postcode-level WFH potential of residents. 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 residualized postcode-level average log sale price per square meter in Panel A and the average log rent per square meter 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.

**Table C.2:** DiD Results on Impact of WFH Potential on Urban Housing Prices

| | Log Sale Prices | | | | Log Rents | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ***Residential WFH Potential*** | | | | | | | | |
| × April - December 2020 | -0.0016*** | -0.0013*** | -0.0012*** | -0.0011*** | -0.0008*** | -0.0003** | -0.0002* | -0.0002 |
| | (0.0002) | (0.0003) | (0.0003) | (0.0003) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| × Year 2021 | -0.0027*** | -0.0015*** | -0.0013*** | -0.0013*** | -0.0021*** | -0.0008*** | -0.0006*** | -0.0006*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| × Year 2022 | -0.0045*** | -0.0026*** | -0.0023*** | -0.0023*** | -0.0029*** | -0.0009*** | -0.0007*** | -0.0007** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0001) | (0.0002) | (0.0001) | (0.0001) |
| × Year 2023 | -0.0041*** | -0.0023*** | -0.0020*** | | -0.0032*** | -0.0012*** | -0.0010*** | |
| | (0.0002) | (0.0003) | (0.0003) | | (0.0001) | (0.0001) | (0.0001) | |
| $R^2$ | 0.89 | 0.89 | 0.89 | 0.89 | 0.92 | 0.92 | 0.92 | 0.92 |
| $N$ | 499,142 | 499,142 | 499,088 | 447,791 | 475,957 | 475,957 | 475,944 | 423,265 |
| Postcode FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Metro Area × Month FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Population Density × Month Controls | | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ |
| Distance to Center × Month Controls | | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ |
| Industry Composition × Month Controls | | | ✓ | ✓ | | | ✓ | ✓ |
| Sociodemographics × Month Controls | | | ✓ | ✓ | | | ✓ | ✓ |
| Migration × Month Controls | | | | ✓ | | | | ✓ |

*Notes:* The table reports DiD estimates $\hat{\mu}^k$ of WFH potential on residential real estate prices based on Equation 3.3. 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 columns (1) to (4), and the estimates for residential rents are shown in columns (5) to (8). Baseline estimates conditional on metropolitan area and month-year fixed effects are displayed in columns (1) and (4). Columns (2) and (5) introduce the variables log population density and log distance from city center, each interacted with the post dummy. Columns (3) and (6) additionally control for industry composition and sociodemographic structure, each interacted with the post dummy. Standard errors are clustered at the postcode-level. *p<0.1; **p<0.05; ***p<0.01.

**Table C.3:** Heterogeneity Within Metro Regions of Impact of WFH Potential

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| ***Panel A Dependent Variable: 2019-2023 Change in Log Property Sale Prices*** | | | | | | |
| WFH Potential | -0.0035*** | -0.0018*** | -0.0022*** | -0.0030*** | -0.0021*** | -0.0034*** |
| | (0.0003) | (0.0003) | (0.003) | (0.0005) | (0.0003) | (0.0005) |
| Log Distance | | 0.0369*** | 0.0222*** | 0.0145*** | -0.0270** | -0.0343** |
| | | (0.0029) | (0.0050) | (0.0054) | (0.0127) | (0.0140) |
| WFH Pot. × Suburban Area | | | 0.0001 | 0.0015* | 0.0001 | 0.0022*** |
| | | | (0.0002) | (0.0009) | (0.0002) | (0.0009) |
| WFH Pot. × Close Commuting Belt | | | 0.0007*** | 0.0020*** | 0.0005*** | 0.0027*** |
| | | | (0.0002) | (0.0007) | (0.0002) | (0.0007) |
| WFH Pot. × Wider Commuting Belt | | | 0.0011*** | 0.0023** | 0.0006** | 0.0028*** |
| | | | (0.0003) | (0.0010) | (0.0003) | (0.0010) |
| Log Distance Squared | | | | | 0.0121*** | 0.0122*** |
| | | | | | (0.0026) | (0.0030) |
| *Number Postcodes* | 4,523 | 4,523 | 4,523 | 4,518 | 4,523 | 4,518 |
| ***Panel B Dependent Variable: 2019-2023 Change in Log Property Rents*** | | | | | | |
| WFH Potential | -0.0028*** | -0.0011*** | -0.0015*** | -0.0017*** | -0.0014*** | -0.0018*** |
| | (0.0001) | (0.0001) | (0.0002) | (0.0003) | (0.0002) | (0.0003) |
| Log Distance | | 0.0360*** | 0.0244*** | 0.0210*** | -0.0079 | 0.0049 |
| | | (0.0015) | (0.0027) | (0.0030) | (0.0058) | (0.0068) |
| WFH Pot. × Suburban Area | | | 0.0002** | 0.0005 | 0.0002** | 0.0008* |
| | | | (0.0001) | (0.0004) | (0.0001) | (0.0005) |
| WFH Pot. × Close Commuting Belt | | | 0.0006*** | 0.0009** | 0.0005*** | 0.0011*** |
| | | | (0.0001) | (0.0004) | (0.0001) | (0.0004) |
| WFH Pot. × Wider Commuting Belt | | | 0.0008*** | 0.0018*** | 0.0004*** | 0.0020*** |
| | | | (0.0001) | (0.0005) | (0.0001) | (0.0005) |
| Log Distance Squared | | | | | 0.0080*** | 0.0040*** |
| | | | | | (0.0012) | (0.0014) |
| *Number Postcodes* | 4,507 | 4,507 | 4,507 | 4,502 | 4,507 | 4,502 |
| 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 3.4. Panel A displays the results for the 2019-2023 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 3.3 portrayed in Figure 3.7. Column (2) adds the log distance from the city center. Columns (3) and (4) additionally include an interaction term of WFH potential and the catch areas within metro regions, 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 3.4. 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 C.4:** Heterogeneity Across Metro Regions of Impact of WFH Potential

| | **Top 10 Metros** | | **Mid 20 Metros** | | **Bottom 20 Metros** | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| ***Panel A Dependent Variable: 2019-2023 Change in Log Property Sale Prices*** | | | | | | |
| WFH Potential | -0.0061*** | -0.0065*** | -0.0012 | -0.0055*** | -0.0020 | -0.0068*** |
| | (0.0010) | (0.0011) | (0.0013) | (0.0021) | (0.0018) | (0.0025) |
| Log Distance | -0.1546*** | -0.1485*** | -0.0005 | -0.0880* | -0.0519 | -0.1013** |
| | (0.0308) | (0.0351) | (0.0330) | (0.0456) | (0.0429) | (0.0478) |
| WFH Potential × Log Distance | 0.0263*** | 0.0208*** | 0.0105** | 0.0153*** | 0.0190*** | 0.0140** |
| | (0.0041) | (0.0049) | (0.0048) | (0.0057) | (0.0060) | (0.0069) |
| Log Distance Squared | 0.0016*** | 0.0018*** | -0.0003 | 0.0015** | 0.0007 | 0.0019** |
| | (0.0004) | (0.0004) | (0.0005) | (0.0007) | (0.0008) | (0.0009) |
| *Number Postcodes* | 2,248 | 2,248 | 1,390 | 1,388 | 885 | 882 |
| ***Panel B Dependent Variable: 2019-2023 Change in Log Property Rents*** | | | | | | |
| WFH Potential | -0.0030*** | -0.0037*** | -0.0013*** | -0.0027*** | -0.0011 | -0.0033*** |
| | (0.0006) | (0.0007) | (0.0005) | (0.0007) | (0.0009) | (0.0012) |
| Log Distance | -0.0552*** | -0.0541** | 0.0018 | -0.0270 | -0.0054 | -0.0193 |
| | (0.0186) | (0.0232) | (0.0131) | (0.0168) | (0.0205) | (0.0205) |
| WFH Potential × Log Distance | 0.0142*** | 0.0089*** | 0.0051*** | 0.0027 | 0.0069*** | 0.0060** |
| | (0.0023) | (0.0028) | (0.0019) | (0.0023) | (0.0025) | (0.0027) |
| Log Distance Squared | 0.0007*** | 0.0010*** | 0.0001 | 0.0008*** | 0.0004 | 0.0007* |
| | (0.0002) | (0.0003) | (0.0002) | (0.0003) | (0.0004) | (0.0004) |
| *Number Postcodes* | 2,247 | 2,247 | 1,378 | 1,376 | 882 | 879 |
| 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 3.4. Panel A displays the results for the 2019-2023 postcode-level changes in log sale prices and Panel B the changes in log rents. Columns (1) and (2) report estimates for the top 10 metro regions for the effect of WFH potential, log distance from center, an interaction term of WFH potential and distance from the urban center, and a quadratic term of distance from center, conditional on metro area fixed effects in column (1) and conditional on metro area times catchment area fixed effects in column (2). Columns (3) and (4) report estimates for the mid 20 metro regions, Columns (5) and (6) for the bottom 20 metro regions. In columns (3) and (5), the estimates are conditional on metro area fixed effects, while in column (4) and (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.

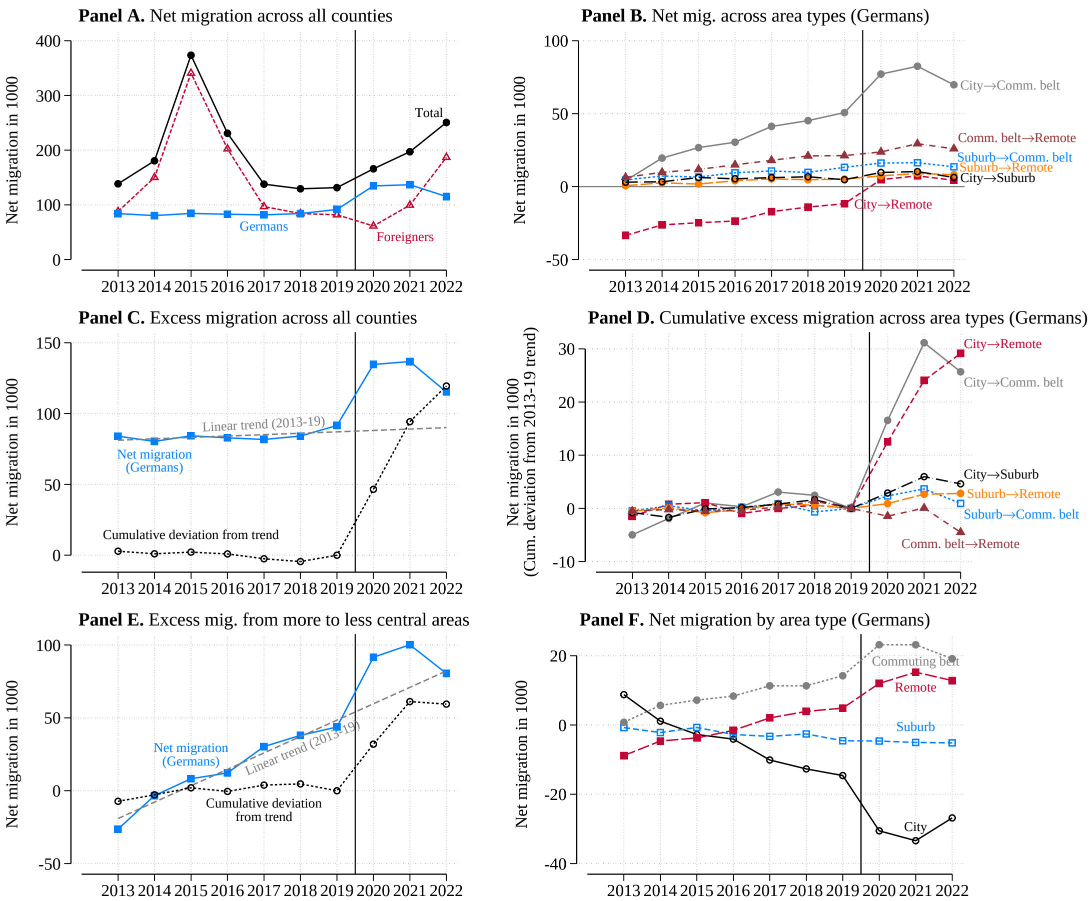
**Table C.5:** Robustness of the Long DiD Results on Effect of WFH Potential and Log Distance on Housing Price Changes

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| ***Panel A Dependent Variable: 2019-2023 Change in Log Property Sale Prices*** | | | | | | |
| WFH Potential Residence | -0.0030*** | -0.0055*** | -0.0007 | -0.0022** | -0.0006 | -0.0023** |
| | (0.0007) | (0.0009) | (0.0007) | (0.0009) | (0.0007) | (0.0010) |
| Log Distance from Center | -0.0538*** | -0.1009*** | -0.0475*** | -0.0751*** | -0.0306* | -0.0632*** |
| | (0.0187) | (0.0220) | (0.0180) | (0.0216) | (0.0181) | (0.0211) |
| WFH Potential × Log Distance | 0.0158*** | 0.0152*** | 0.0153*** | 0.0148*** | 0.0116*** | 0.0120*** |
| | (0.0026) | (0.0030) | (0.0026) | (0.0031) | (0.0027) | (0.0031) |
| Log Distance Squared | 0.0005** | 0.0015*** | -0.0001 | 0.0006* | -0.0001 | 0.0007** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| *Number Postcodes* | 4,523 | 4,518 | 4,523 | 4,518 | 4,522 | 4,517 |
| ***Panel B Dependent Variable: 2019-2023 Change in Log Property Rents*** | | | | | | |
| WFH Potential Residence | -0.0022*** | -0.0032*** | -0.0008*** | -0.0015*** | -0.0003 | -0.0011** |
| | (0.0003) | (0.0004) | (0.0003) | (0.0004) | (0.0003) | (0.0005) |
| Log Distance from Center | -0.0261*** | -0.0360*** | -0.0223** | -0.0219* | -0.0142 | -0.0182 |
| | (0.0093) | (0.0119) | (0.0092) | (0.0121) | (0.0097) | (0.0120) |
| WFH Potential × Log Distance | 0.0100*** | 0.0061*** | 0.0082*** | 0.0053*** | 0.0070*** | 0.0045*** |
| | (0.0013) | (0.0015) | (0.0013) | (0.0016) | (0.0014) | (0.0016) |
| Log Distance Squared | 0.0004*** | 0.0009*** | 0.0001 | 0.0004** | -0.0001 | 0.0003* |
| | (0.0001) | (0.0002) | (0.0001) | (0.0002) | (0.0001) | (0.0002) |
| *Number Postcodes* | 4,507 | 4,502 | 4,507 | 4,502 | 4,507 | 4,502 |
| Metro Area FE | ✓ | | ✓ | | ✓ | |
| Metro × Catchment Area FE | | ✓ | | ✓ | | ✓ |
| Population Density Control | | | ✓ | ✓ | ✓ | ✓ |
| Industry Composition Controls | | | ✓ | ✓ | ✓ | ✓ |
| Sociodemographic Structure Controls | | | | | ✓ | ✓ |

*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 3.4. Panel A displays the results for the 2019-2023 postcode-level changes in log sale prices and Panel B the changes in log rents. Columns (1) and (2) report baseline estimates for the effect of WFH potential, log distance from center, an interaction term of WFH potential and distance from the urban center, and a quadratic term of distance from center, conditional on metro area fixed effects in column (1) and conditional on metro area times catchment area fixed effects in column (2). Columns (3) and (4) additionally include a control for log population density and the industry composition, 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) add a control for the sociodemographic structure. 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. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

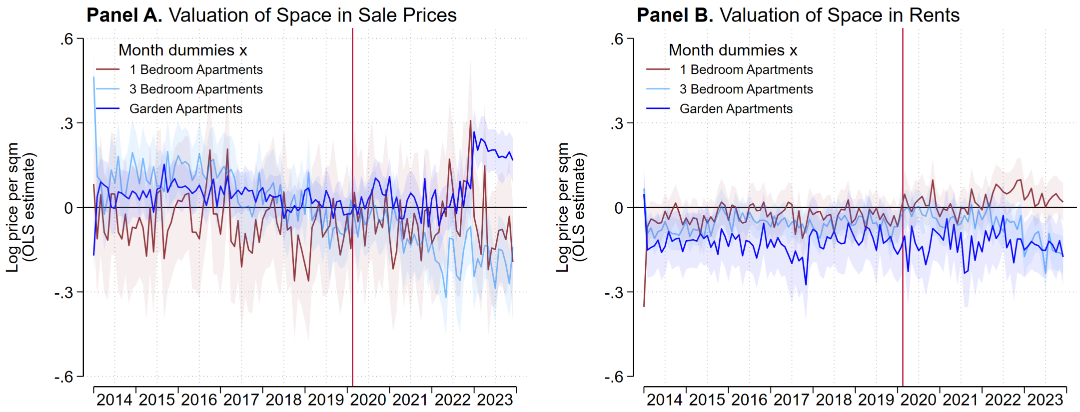
## C.5 Mechanisms

**Figure C.20:** Changes in Urban Net Migration Flows (Origin-Destination Matrix)



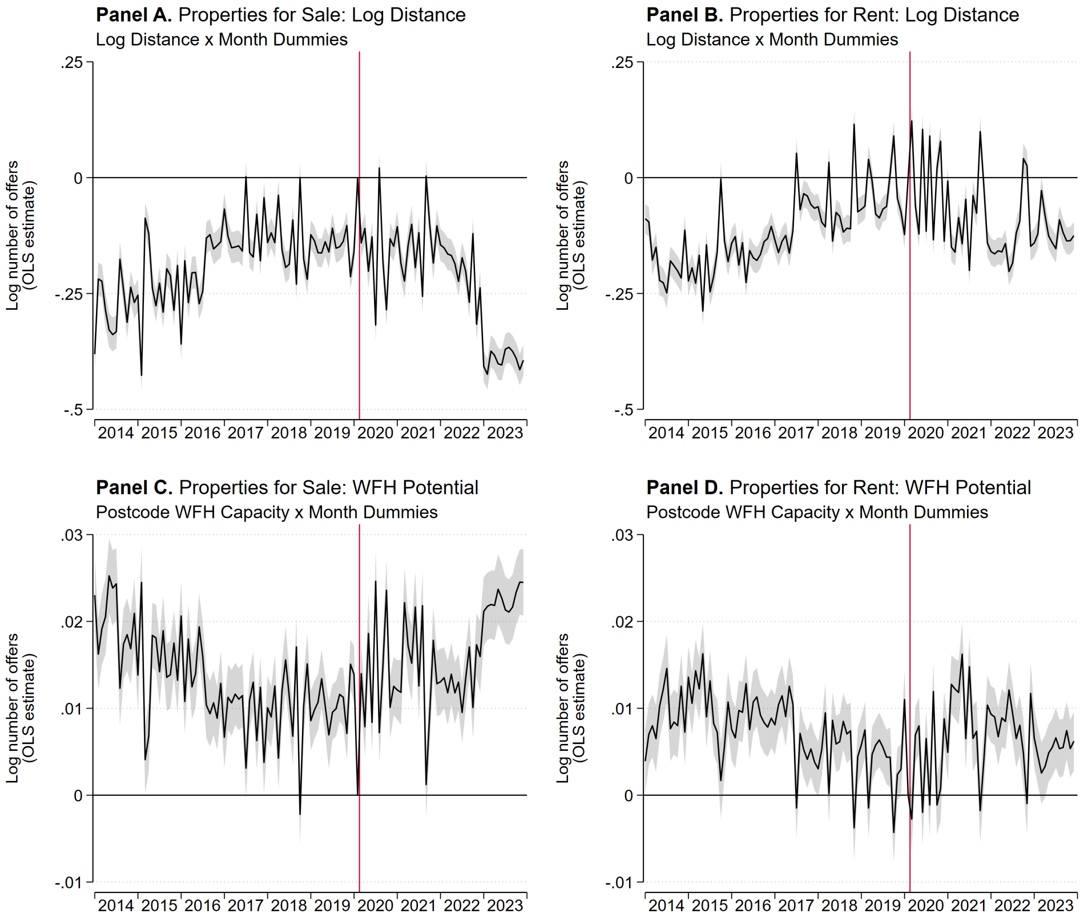

*Notes:* This figure displays pairwise net domestic migration flows across county borders in Germany between 2013 and 2022 based on origin-destination matrices. Panel A shows annual net migration across all 401 counties by citizenship. Net migration equals the sum of net population gains over counties with net gains (which is equivalent to the aggregate net loss across net-losing counties). Panel B plots the annual net migration of German citizens between different area types. Panel C shows the excess net migration of Germans across all counties, calculated as the cumulative deviation from the 2013-19 linear trend. Panel D reports excess migration for moves between area types. Panel E shows this for moves from more to less central counties. Panel F plots the net migration of Germans by area type, where negative (positive) values correspond to a net loss (gain). Administrative data on migration statics are provided by the German Federal Statistical Office.

**Figure C.21:** Heterogeneity of Increased Valuation of Space by Property Types



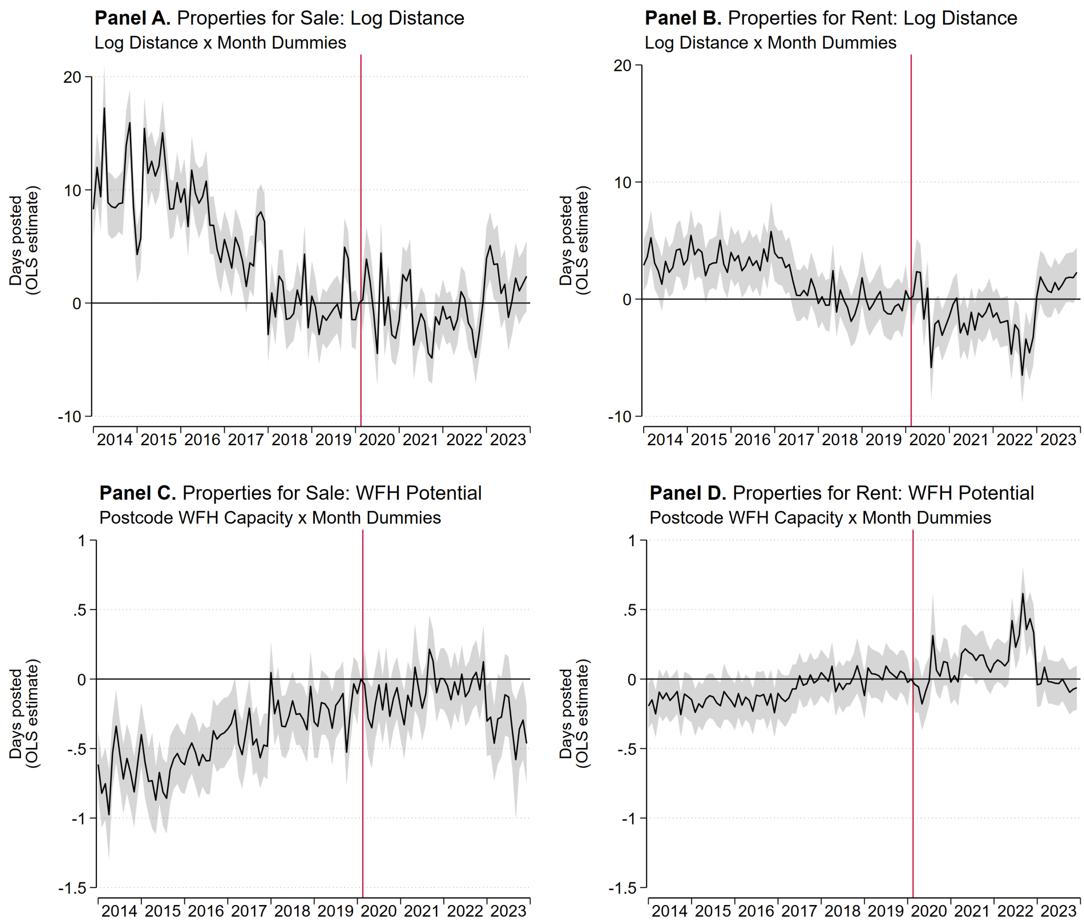

*Notes:* This figure presents DiD estimates $\hat{\beta}_k$ from separate regressions in the form of Equation 3.1 and Equation 3.3, in which the interaction terms are between monthly dummies from January 2014 until December 2023 and postcode-level average log floor space per property for 1 Bedroom, 2 Bedroom and Garden Apartments. The dependent variable is the postcode-level average log sale price per square meter in Panel A as well as the average log rent per square meter 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 C.22:** Supply-Side Mechanism Housing Quantity: Changes in Log Number of Property Offers Relative to Log Distance and WFH Potential




*Notes:* This figure presents DiD estimates $\hat{\beta}_k$ from separate regressions in the form of Equation 3.1 and Equation 3.3, in which the interaction terms are between monthly dummies from January 2014 until December 2023 and log distance from city center in Panels A and B as well as between monthly dummies and postcode-level WFH potential of residents in Panels C and D. The dependent variable is the postcode-level log number of offers of properties for sale in Panels A and C as well as the log number of offers of properties for rent 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.

**Figure C.23:** Supply-Side Mechanism Housing Liquidity: Changes in Days-on-the-Market of Property Postings Relative to Log Distance and WFH Potential




*Notes:* This figure presents DiD estimates $\hat{\beta}_k$ from separate regressions in the form of Equation 3.1 and Equation 3.3, in which the interaction terms are between monthly dummies from January 2014 until December 2023 and log distance from city center in Panels A and B as well as between monthly dummies and postcode-level WFH potential of residents in Panels C and D. The dependent variable is the postcode-level average number of days a property for sale is posted in Panels A and C as well as the average number of days a property for rent is posted 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.

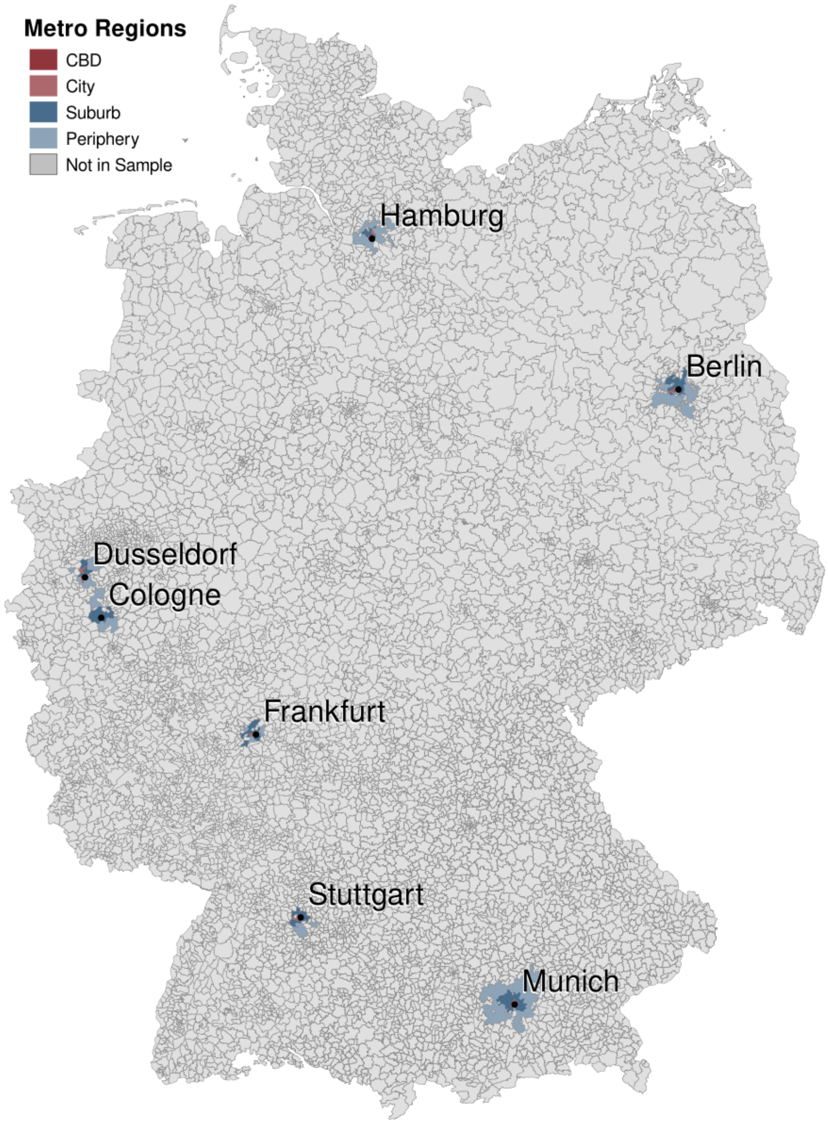
# D

# Appendix to Chapter 4

## D.1 Sample and Summary Statistics

### D.1.1 Sample Illustration

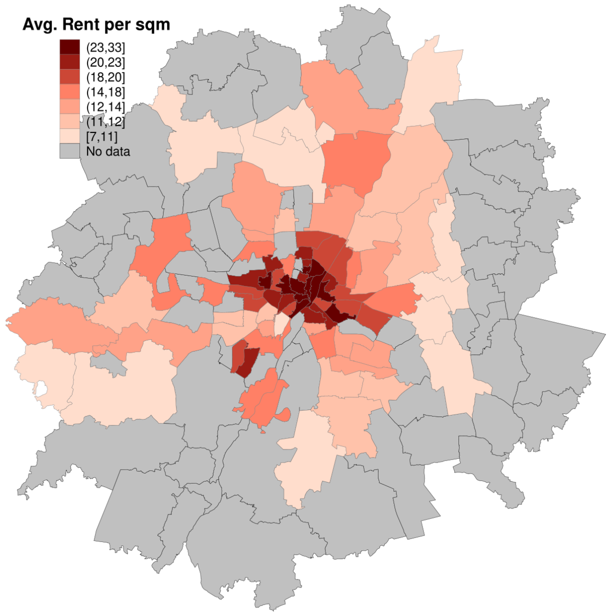
**Figure D.1:** Sample Illustration of the Top 7 German Office Markets (Metro Region Submarkets)



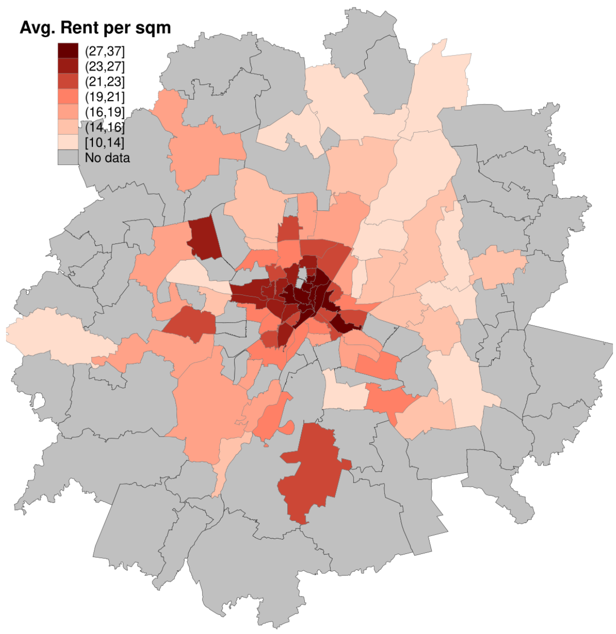

*Notes:* This postcode-level map of Germany displays the sample comprised of the 7 largest German metropolitan areas. The office submarkets are highlighted as follows: central business district (CBD) in dark red, city in light red, suburbs in dark blue, and periphery in light blue. Gray areas are excluded from the sample.

**Figure D.2:** Smaple Illustration: Average Office Rents in Munich Postcode Areas

**(a)** 2019




**(b)** 2023




*Note:* This postcode-level map of the Munich metropolitan area displays the average rent for office spaces, reported in euros per square meter in different postcode areas of Munich in 2019 (Panel A) and 2023 (Panel B). Darker shades of red indicate higher rents. Gray areas are excluded from sample data. Data are from Colliers (2024).

### D.1.2 Summary Statistics

**Table D.1:** Summary Statistics: WFH and Lease Agreement Characteristics

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| **Panel A: Working from Home (WFH)** | | | | |
| Industry-Level WFH Share 2019 (Percent) | 13.87 | 5.84 | 1.60 | 21.33 |
| Industry-Level WFH Share 04/2023 (Percent) | 32.85 | 13.65 | 1.60 | 53.04 |
| Industry-Level WFH Growth 2019-2023 (Percentage Points) | 18.99 | 8.60 | 0.00 | 33.03 |
| WFH Capacity by Industry (Alipour et al. 2023) | 73.32 | 24.42 | 24.17 | 97.18 |
| **Panel B: Office Leasing** | | | | |
| Lease Area in Square Meters | 916.53 | 2,287.99 | 10.00 | 84,314.00 |
| Log Lease Area in Square Meters | 6.09 | 1.03 | 2.30 | 11.34 |
| Total Rent per Month | 18,522.50 | 56,796.91 | 42.00 | 2,933,250.00 |
| Net Effective Rent per Month | 18,390.70 | 56,311.87 | -15,272.63 | 2,933,250.00 |
| Rent per Square Meter | 17.79 | 7.33 | 2.07 | 155.00 |
| Net Effective Rent per Square Meter | 17.74 | 7.31 | -69.42 | 155.00 |
| Prime Rent per Square Meter | 33.37 | 7.65 | 9.00 | 54.25 |
| Log Total Rent per Month | 8.93 | 1.16 | 3.74 | 14.89 |
| Log Net Effective Rent per Square Meter | 2.80 | 0.40 | 0.73 | 5.04 |
| Log Rent per Square Meter | 2.80 | 0.40 | 0.73 | 5.04 |
| Log Prime Rent per Square Meter | 3.48 | 0.23 | 2.20 | 3.99 |
| Incentives: Months of Free Rent | 6.89 | 13.02 | 0.05 | 310.02 |
| Sublease Indicator | 0.03 | 0.16 | 0.00 | 1.00 |
| Construction / Modernization Year | 1,995.81 | 30.83 | 1,541.00 | 2,029.00 |
| Current Building Age | 22.86 | 30.64 | 0.00 | 480.00 |
| Numeric Object Quality Indicator | 75.71 | 19.63 | 33.00 | 100.00 |
| Numeric Object Type Indicator | 1.16 | 0.37 | 1.00 | 2.00 |
| **Panel C: Industry Characteristics** | | | | |
| Industry Number of Office Lease Takers (Colliers) | 8.69 | 4.76 | 1.00 | 18.00 |
| Industry-Level Employment December 2019 | 783,001.40 | 716,414.82 | 166,635.00 | 2,766,734.00 |
| Industry-Level Employment December 2023 | 742,863.35 | 672,774.32 | 165,680.00 | 2,575,974.00 |
| Industry-Level Employment Share | 0.05 | 0.03 | 0.01 | 0.12 |
| Number of Economic Sectors | 2.42 | 1.11 | 1.00 | 5.00 |
| Sector Employment | 523,868.07 | 322,926.96 | 13,969.00 | 1,134,140.00 |
| Sector Employment Share | 0.50 | 0.20 | 0.03 | 0.65 |
| **Panel D: Municipality Characteristics** | | | | |
| City Population (2022) | 1,700,848.87 | 1,142,847.54 | 629,047.00 | 3,755,251.00 |
| City Employment (2023) | 956,185.96 | 434,409.99 | 443,730.00 | 1,689,260.00 |
| Gross Domestic Product per Worker (2017) | 92.17 | 11.68 | 63.80 | 103.30 |
| Gross Value Added per Worker (2017) | 83.13 | 10.54 | 57.50 | 93.20 |
| Municipality-Level Property Tax Rate | 549.79 | 144.35 | 140.00 | 995.00 |
| Municipality-Level Business Tax Rate | 444.29 | 43.74 | 240.00 | 490.00 |
| **Panel E: Postcode Variables** | | | | |
| Postcode Population (2022) | 14,108.46 | 7,859.41 | 0.00 | 56,833.00 |
| Postcode Area | 5.31 | 7.73 | 0.00 | 81.75 |
| Distance from City Center (km) | 4.24 | 3.78 | 0.00 | 31.58 |
| Postcode Population Density | 5,631.62 | 4,269.52 | 0.00 | 26,718.58 |
| Log (1 + Postcode Distance to City Center) | 1.42 | 0.71 | 0.00 | 3.48 |
| Log (1 + Postcode Population Density) | 8.22 | 1.22 | 0.00 | 10.19 |

*Notes:* This table reports summary statistics of the sample comprising Germany's seven largest metropolitan areas and office markets. For each variable, the mean, standard deviation, minimum, and maximum are displayed. Panel A reports the variables on WFH, Panel B on office leasing, Panel C on industry characteristics, Panel D on municipality, and Panel E on postcode characteristics.

### D.1.3 Matching of Industry-Level Data

**Table D.2:** Mapping of Industries Across Administrative, ifo, and Colliers Data

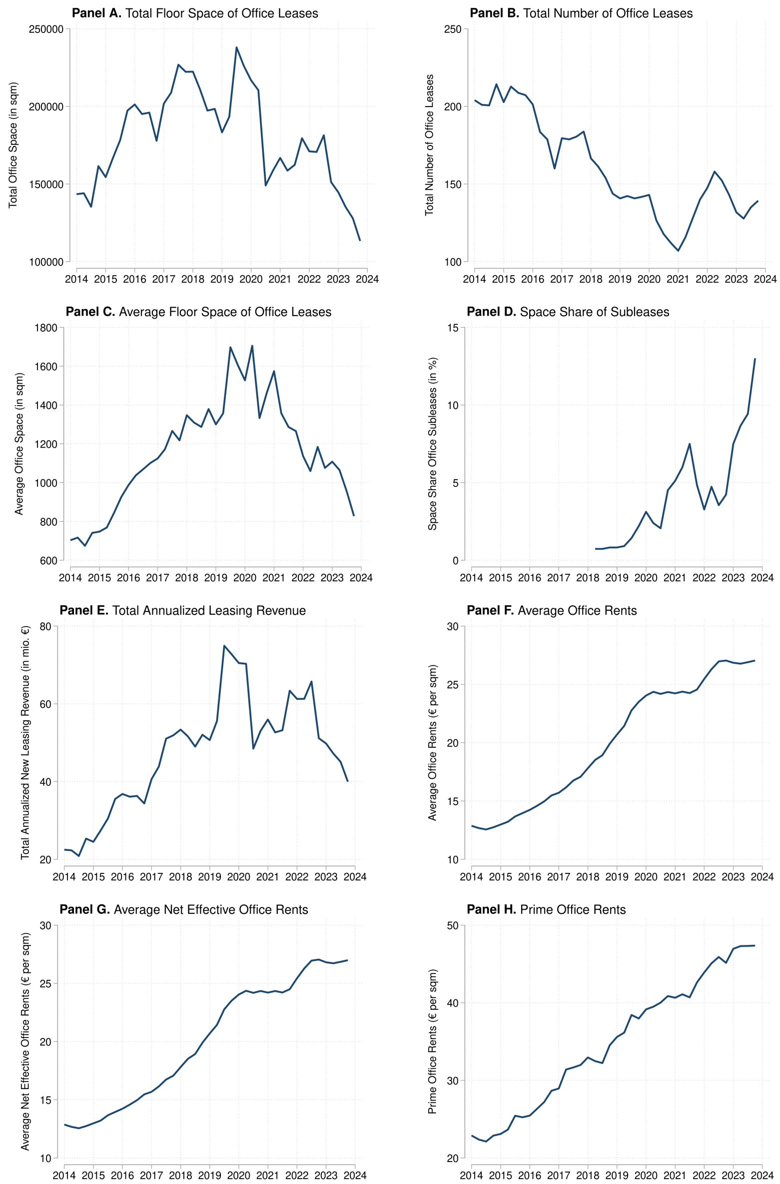
| WZ 2008 Classification (German) | ifo Industry Classification | Colliers Industry Classification |
|---|---|---|
| 29 Hst. Kraftwagen und Teile | Automotive Industry | Automotive Industry |
| 14 Hst. Bekleidung | Clothing Manufacturing | Manufacturing Industry |
| 20 Hst. chemische Erzeugnisse | Chemical Industry | Manufacturing Industry |
| 18 Hst. Druckerz.; Vervielf. Ton-, Bild- | Printing Production | Manufacturing Industry |
| 27 Hst. elektr. Ausrüstungen | Electronics Industry | Manufacturing Industry |
| 11 Getränkeherstellung | Beverage Manufacturing | Manufacturing Industry |
| 23 Hst. Glas, Keramik, Steine | Glass Industry | Manufacturing Industry |
| 32 Hst. sonstige Waren | Manufacture of Other Goods | Manufacturing Industry |
| 26 Hst. DV-Geräte, elektr. | Manufacture of Reproduction Electronics | Manufacturing Industry |
| 16 Hst. Holz-, Flecht-, Korb- | Wood Industry | Manufacturing Industry |
| 22 Hst. Gummi- und Kunststoffw. | Plastic Processing | Manufacturing Industry |
| 15 Hst. Leder, Lederwaren, Schuhe | Leather Processing | Manufacturing Industry |
| 28 Maschinenbau | Mechanical Engineering | Manufacturing Industry |
| 24 Metallerzeugung, -bearbeitung | Metal Industry | Manufacturing Industry |
| 25 Hst. Metallerzeugnisse | Metal Processing | Manufacturing Industry |
| 31 Hst. Möbel | Furniture Industry | Manufacturing Industry |
| 10 Hst. Nahrungs-, Futtermittel | Food Industry | Manufacturing Industry |
| 17 Hst. Papier, Pappe | Paper Industry | Manufacturing Industry |
| 21 Hst. pharmazeut. Erzeugnisse | Pharmaceutical Industry | Manufacturing Industry |
| 13 Hst. Textilien | Textile Manufacturing | Manufacturing Industry |
| 78 Arbeitskräftevermittlung | Employment Services | Consulting Firms |
| 71 Architektur-, Ingenieurbüros | Architectural and Engineering Services | Real Estate |
| 55 Beherbergung | Accommodation | Tourism and Transport |
| 59 Filmproduktion, Verlag | Film and Television | Information and Telecommunications |
| 72 Forschung, Entwicklung | Research and Development | Research and Development |
| 74 Sonst. freiberufl. Tätigkeiten | Freelance Activities | Other Companies |
| 56 Gastronomie | Catering | Gastronomy and Hospitality |
| 68 Grundstücks-, Wohnungswesen | Real Estate | Real Estate |
| 81 Gebäudebetreuung | Property Management | Real Estate |
| 63 Informationsdienstl. | Information Services | Information and Telecommunications |
| 62 IT-Dienstleistungen | Technical Information Services | Information and Telecommunications |
| 52 Lagerei, Transport-DL | Warehousing | Other Companies |
| 49 Landverkehr, Transport | Land Transport | Tourism and Transport |
| 53 Post-, Kurierdienste | Postal and Courier Services | Tourism and Transport |
| 69 Rechts-, Steuerberatung | Legal and Economic Consulting | Consulting Firms |
| 79 Reisebüros, Veranstalter | Travel Agencies | Tourism and Transport |
| 60 Rundfunkveranstalter | Broadcasting Companies | Information and Telecommunications |
| 80 Sicherheitsdienste | Security Services | Other Companies |
| 61 Telekommunikation | Telecommunications | Information and Telecommunications |
| 70 Unternehmensberatung | Business Consulting | Consulting Firms |
| 93 Sport-, Event-Dienstl. | Event Industry | Leisure and Sports |
| 58 Verlagswesen | Publishing | Information and Telecommunications |
| 77 Vermietung beweglicher Sachen | Rental | Other Companies |
| 73 Werbung, Marktforschung | Advertising and Market Research | Information and Telecommunications |
| 64 Finanzdienstleistungen | Economic Services | Banking and Finance |
| 82 Unternehmens-Dienstl. | Economic Services | Business Centers |
| 65 Versicherungen, Pensionen | Economic Services | Insurance |
| 47 Einzelhandel (exkl. KFZ) | Retail | Retail and Wholesale |
| 46 Großhandel (exkl. KFZ) | Wholesale | Retail and Wholesale |
| 41 Hochbau | Construction Industry | Construction Industry |
| 85 Erziehung, Unterricht | Public Sector | Educational Institutions |
| 84 Öffentl. Verwaltung, Sozialvers. | Public Sector | Public Administration and Associations |
| 86 Gesundheitswesen | Public Sector | Health and Social Services |

*Note:* This table provides a detailed overview of the mapping of German industry classifications across the administrative WZ 2008 definition in the left column, the ifo industry classification in the middle column, and the Colliers industry classification in the right column.

## D.2 Descriptive Evidence

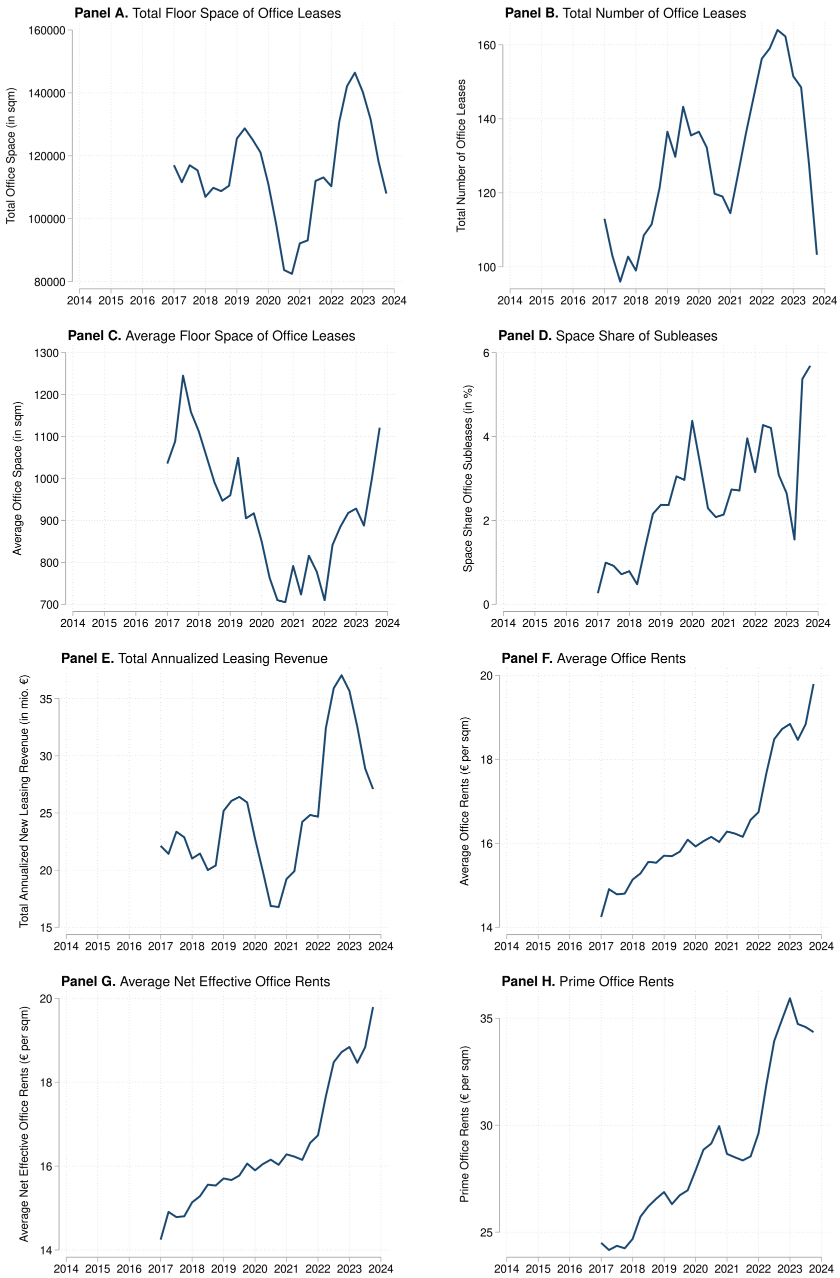
### D.2.1 Trends in Office Leases

**Figure D.3:** Trends in Office Space Take-up and Rents in Berlin 2014-2023



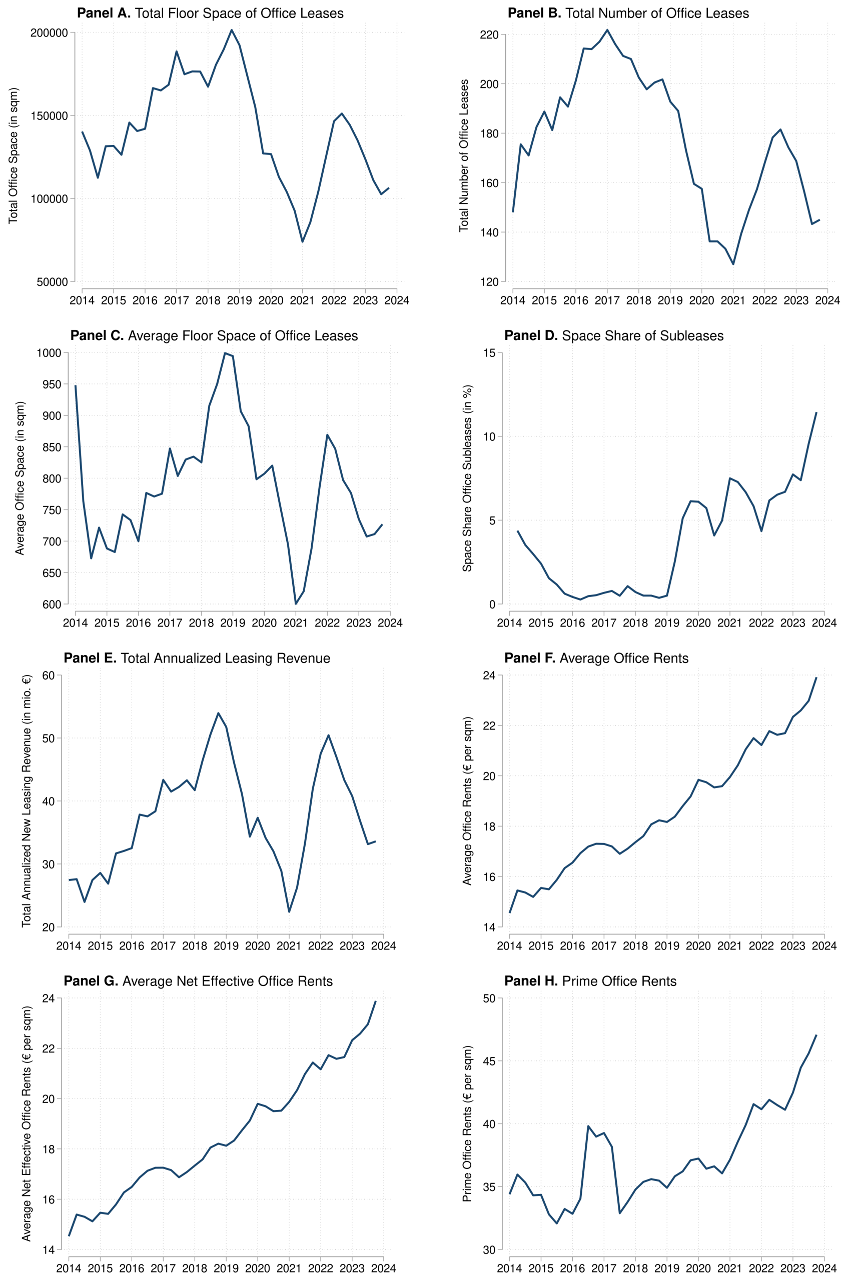

*Notes:* This figure presents descriptive evidence on office leases between 2014 and 2023 in Berlin. Panel A reports the total office space in square meters (sqm), Panel B the total number of lease agreements, Panel C the average space in sqm, Panel D the share of subleasing agreements, Panel E the total leasing revenue p.a. in mio. euros, Panel F the average office rent in euros per sqm, Panel G the average net effective office rent in euros per sqm, and Panel H the prime office rent in euros per sqm. Data are from Colliers (2024).

**Figure D.4:** Trends in Office Space Take-up and Rents in Hamburg 2017-2023



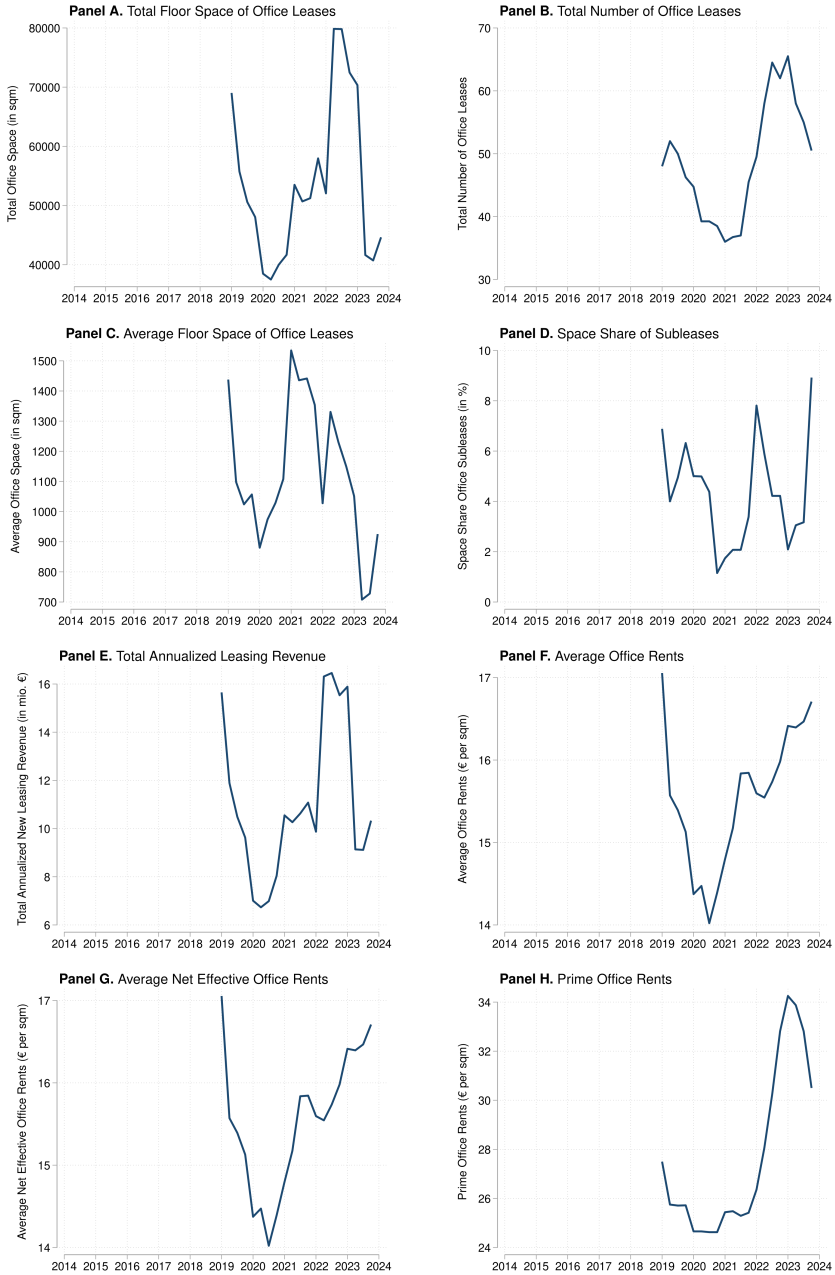

*Notes:* This figure presents descriptive evidence on office leases between 2017 and 2023 in Hamburg. Panel A reports the total office space in square meters. Panel B reports the total number of lease agreements. Panel C gives the average space of individual leases in square meters, Panel D the percentage share of lease agreements that are subleases. Panel E reports the total leasing revenue per annum in millions of euros. Panel F reports average office rents in euros per square meter. Panel G shows average net effective office rents in euros per square meter. Panel H reports rents in euros per square meter for prime office spaces. Data are from Colliers (2024).

**Figure D.5:** Trends in Office Space Take-up and Rents in Munich 2014-2023



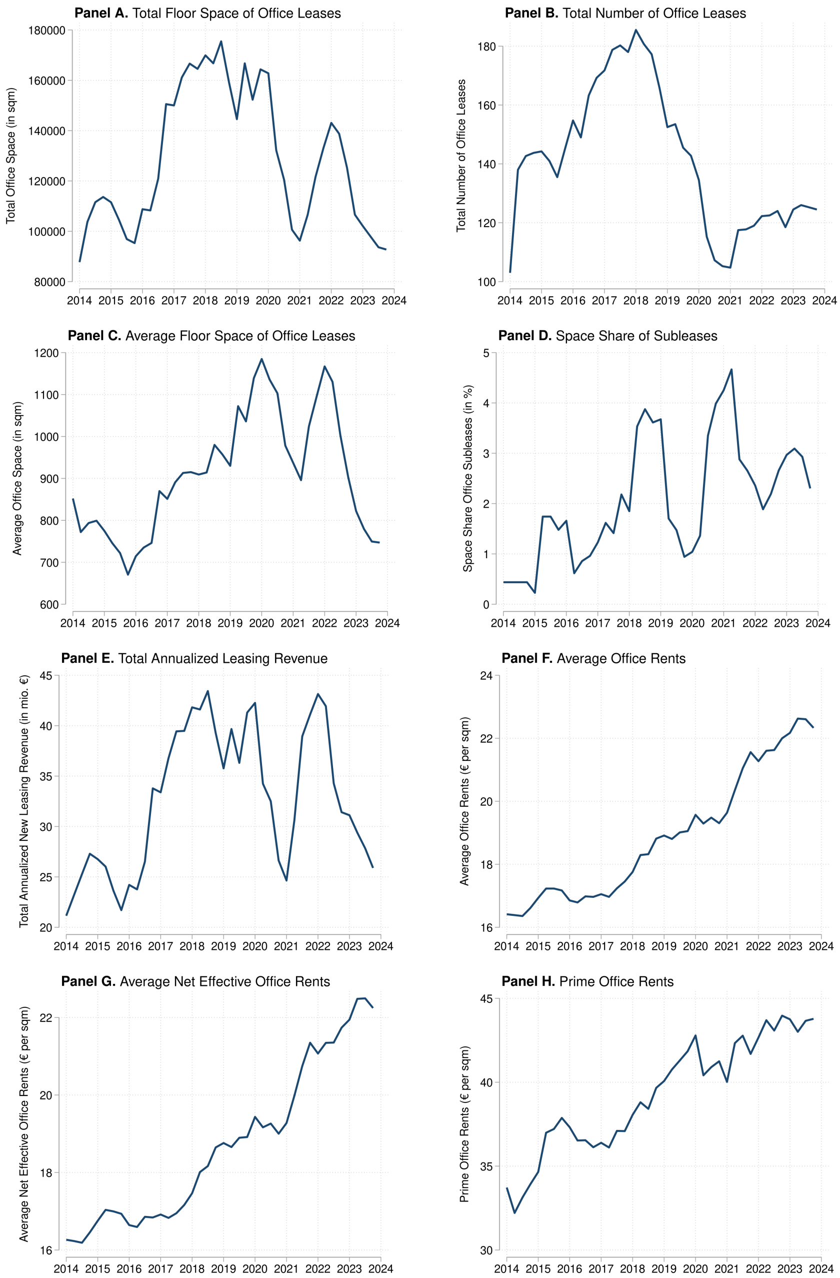

*Notes:* This figure presents descriptive evidence on office leases between 2014 and 2023 in Munich. Panel A reports the total office space in square meters. Panel B reports the total number of lease agreements. Panel C gives the average space of individual leases in square meters, Panel D the percentage share of lease agreements that are subleases. Panel E reports the total leasing revenue per annum in millions of euros. Panel F reports average office rents in euros per square meter. Panel G shows average net effective office rents in euros per square meter. Panel H reports rents in euros per square meter for prime office spaces. Data are from Colliers (2024).

**Figure D.6:** Trends in Office Space Take-up and Rents in Cologne 2019-2023



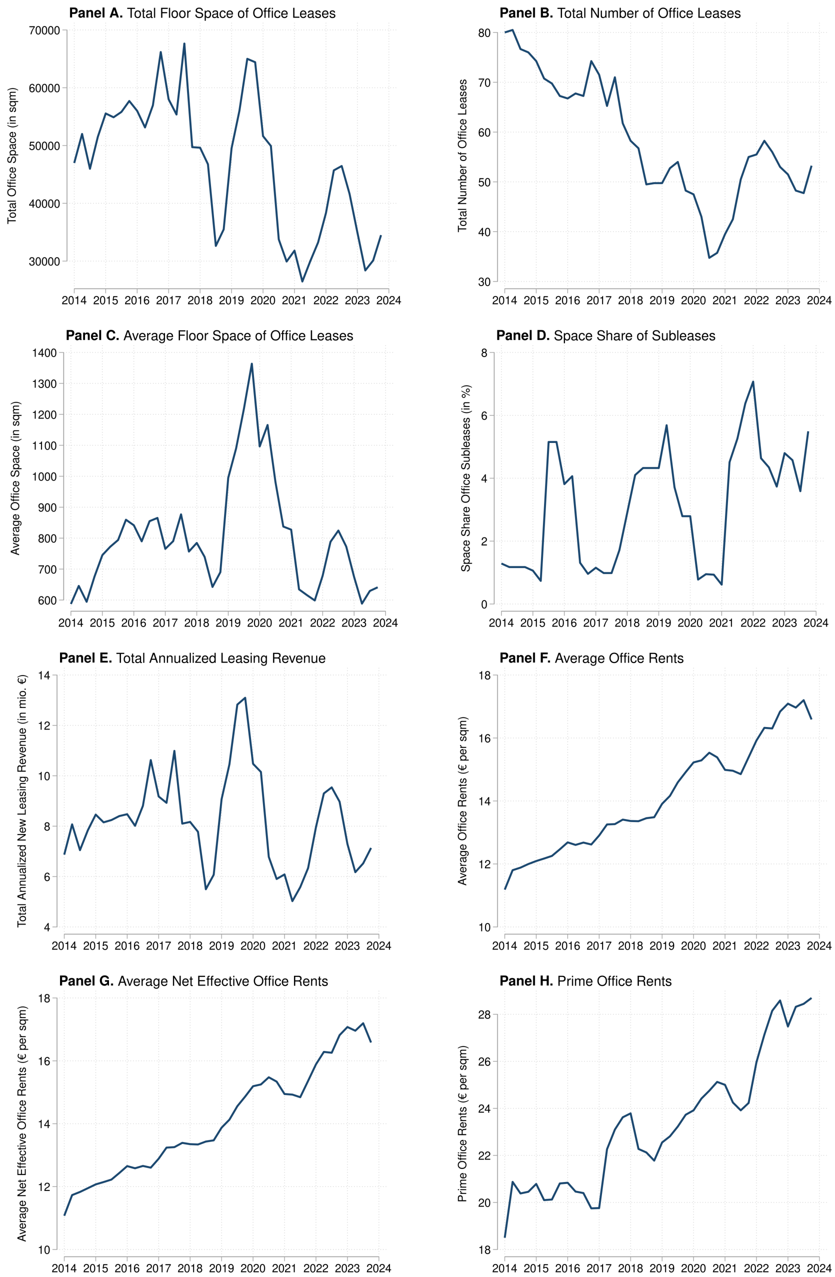

*Notes:* This figure presents descriptive evidence on office leases between 2019 and 2023 in Cologne. Panel A reports the total office space in square meters. Panel B reports the total number of lease agreements. Panel C gives the average space of individual leases in square meters, Panel D the percentage share of lease agreements that are subleases. Panel E reports the total leasing revenue per annum in millions of euros. Panel F reports average office rents in euros per square meter. Panel G shows average net effective office rents in euros per square meter. Panel H reports rents in euros per square meter for prime office spaces. Data are from Colliers (2024).

**Figure D.7:** Trends in Office Space Take-up and Rents in Frankfurt 2014-2023



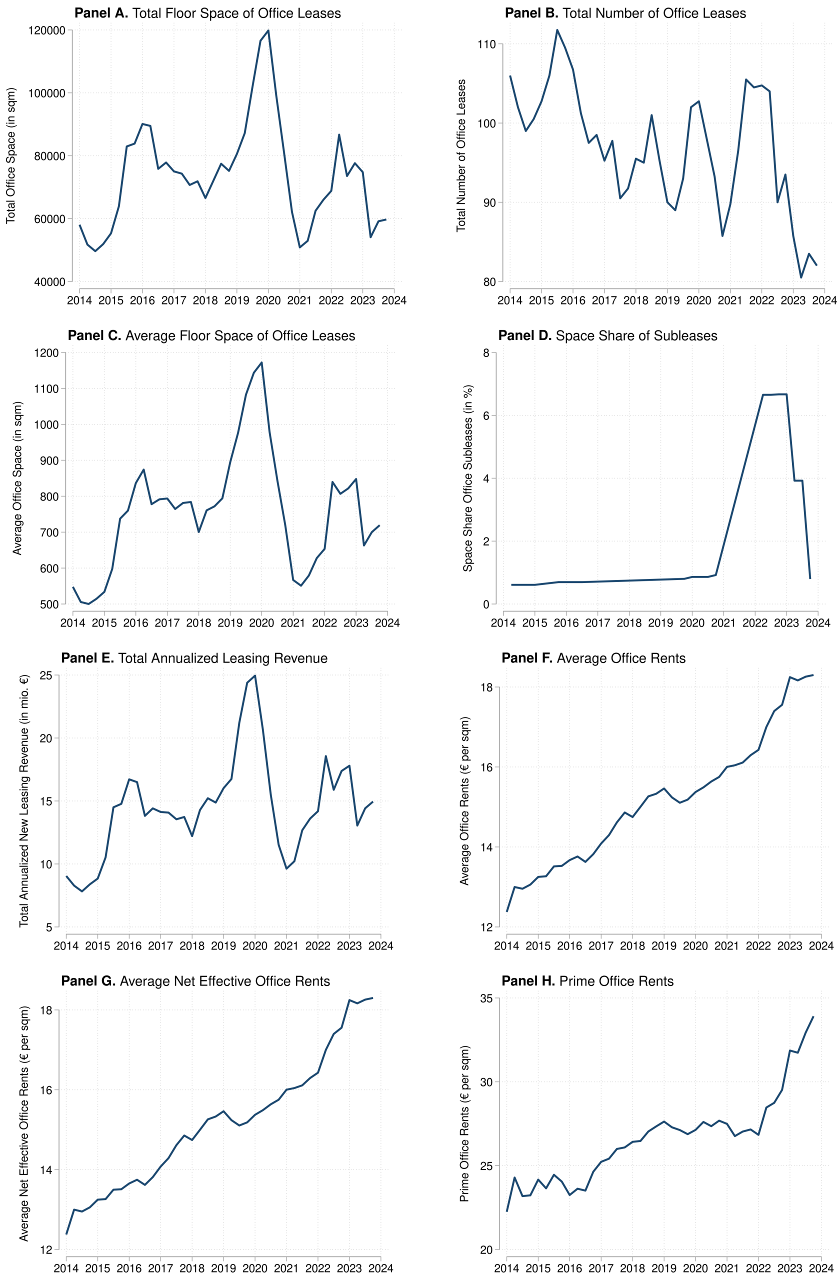

*Notes:* This figure presents descriptive evidence on office leases between 2014 and 2023 in Frankfurt. Panel A reports the total office space in square meters. Panel B reports the total number of lease agreements. Panel C gives the average space of individual leases in square meters, Panel D the percentage share of lease agreements that are subleases. Panel E reports the total leasing revenue per annum in millions of euros. Panel F reports average office rents in euros per square meter. Panel G shows average net effective office rents in euros per square meter. Panel H reports rents in euros per square meter for prime office spaces. Data are from Colliers (2024).

**Figure D.8:** Trends in Office Space Take-up and Rents in Stuttgart 2014-2023




*Notes:* This figure presents descriptive evidence on office leases between 2014 and 2023 in Stuttgart. Panel A reports the total office space in square meters. Panel B reports the total number of lease agreements. Panel C gives the average space of individual leases in square meters, Panel D the percentage share of lease agreements that are subleases. Panel E reports the total leasing revenue per annum in millions of euros. Panel F reports average office rents in euros per square meter. Panel G shows average net effective office rents in euros per square meter. Panel H reports rents in euros per square meter for prime office spaces. Data are from Colliers (2024).

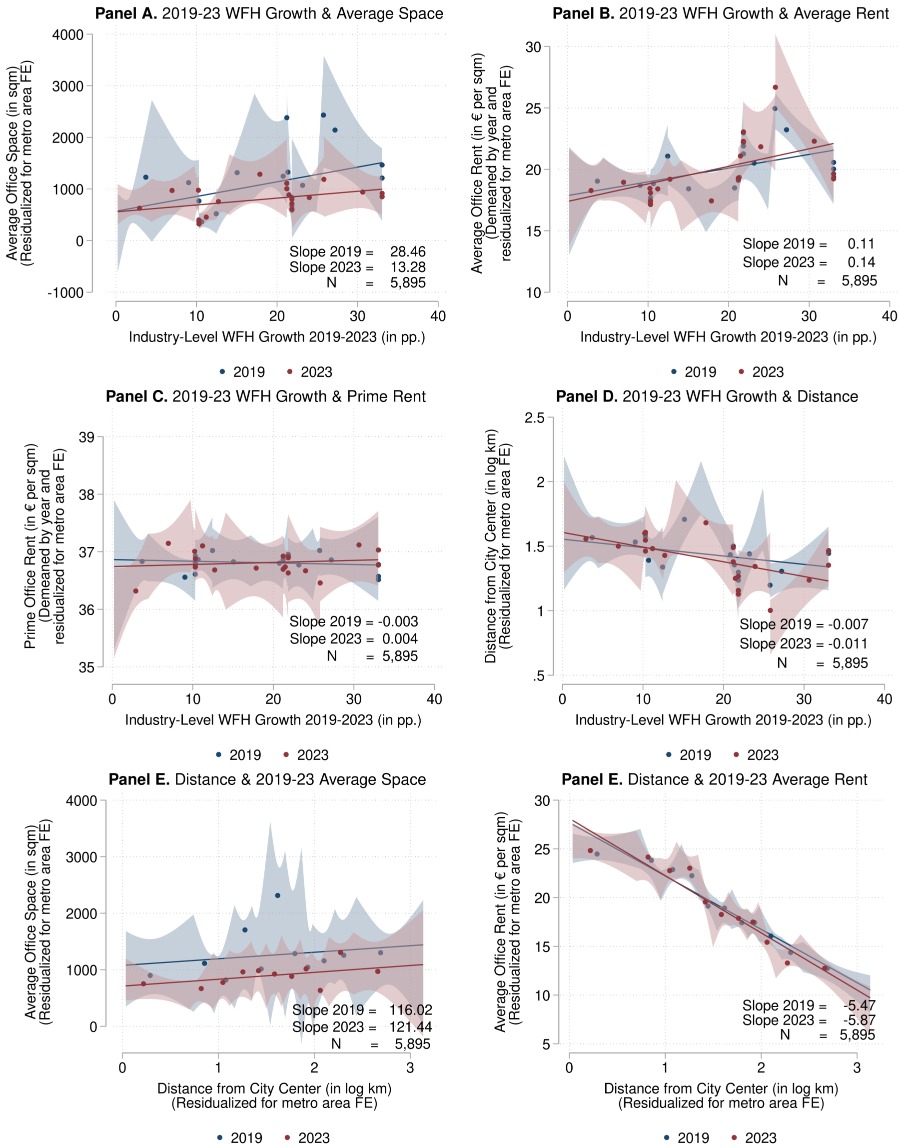
**Figure D.9:** Trends in Office Space Take-up and Rents in Dusseldorf 2014-2023




*Notes:* This figure presents descriptive evidence on office leases between 2014 and 2023 in Dusseldorf. Panel A reports the total office space in square meters. Panel B reports the total number of lease agreements. Panel C gives the average space of individual leases in square meters, Panel D the percentage share of lease agreements that are subleases. Panel E reports the total leasing revenue per annum in millions of euros. Panel F reports average office rents in euros per square meter. Panel G shows average net effective office rents in euros per square meter. Panel H reports rents in euros per square meter for prime office spaces. Data are from Colliers (2024).

### D.2.2 Connecting WFH Growth and Urban Office Leases

**Figure D.10:** Firm-Level Link Between WFH and Distance with Office Space and Rents




*Notes:* This figure shows changes in the relationship between WFH growth, distance, and office outcomes (2019–2023) at the individual office lease level. Binscatter regression estimates are residualized for metro area fixed effects, using evenly spaced bins (quantiles), fitted lines, and 95 percent confidence intervals (Cattaneo et al., 2024). Estimates for 2019 are in blue, and for 2023 in red. Panel A presents the relationship between industry-level WFH growth and average office space in sqm. Panel B follows the same approach for average office rents (euros per sqm), while Panel C focuses on prime office rents. Panel D shows industry-level WFH growth and firms' distance from the city center (log km). Panels E and F relate distance to average office space and rents, respectively. Data are from the ifo Business Survey (EBDC-BEP, 2023) and Colliers (2024).

## D.3 Stylized Model: WFH Impact on Urban Office Leases

### Step 1: Firms and Employees Choose WFH Arrangements

The first stage models the decision-making process of firms and employees in choosing work arrangements under the maximization of profits (firms) and utility (employees). Firms balance the benefits of in-office work (productivity, agglomeration effects) against the costs of leasing office space. Employees trade off the benefits of working in a central office (networking, urban amenities) against commuting costs and remote work flexibility. Given Cobb-Douglas preferences, there is positive demand for both in-office and remote work, which implies hybrid work as the optimal work arrangement. This aligns with the real economy, where hybrid currently is the predominant WFH model.

### Employees' Optimization

Employees have a Cobb-Douglas utility function. They choose $L_j$ (office work) and $W_j$ (remote work):

$$U_j = (L_j - C_j(d))^{1-\alpha} W_j^{\alpha} \nu(d),$$

subject to the time constraint (normalized to 1):

$$L_j + W_j = 1.$$

Where:

- $L_j$ is the quantity of working in the office,
- $C_j(d)$ represents commuting costs, increasing with distance $d$,
- $W_j$ is the quantity of WFH,
- $\alpha \in (0, 1)$ represents the weight employees assign to WFH,
- $\nu(d)$ captures the agglomeration spillovers of being in a central office location, e.g. networking and access to urban amenities.

#### FOC w.r.t. $L_j$ (Office Work)

$$\frac{\partial U_j}{\partial L_j} = (1-\alpha)(L_j - C_j(d))^{-\alpha} W_j^{\alpha} \nu(d) = 0.$$

Since $W_j^{\alpha}\nu(d) > 0$, I obtain the condition:

$$L_j - C_j(d) > 0.$$

#### FOC w.r.t. $W_j$ (Remote Work)

$$\frac{\partial U_j}{\partial W_j} = \alpha(L_j - C_j(d))^{1-\alpha} W_j^{\alpha-1} \nu(d) = 0.$$

Since $(L_j - C_j(d))^{1-\alpha}\nu(d) > 0$, I obtain the condition:

$$W_j > 0.$$

#### Solving for $L_j^*$ and $W_j^*$

Setting the FOCs equal to each other:

$$\frac{1-\alpha}{L_j - C_j(d)} = \frac{\alpha}{W_j}.$$

Using the time constraint $L_j + W_j = N_j$, I solve for the optimal values:

$$L_j^* = (1-\alpha)N_j + \alpha C_j(d),$$

$$W_j^* = \alpha(N_j - C_j(d)).$$

#### Interpretation of Employees' Optimization

- Due to homothetic preferences in the Cobb-Douglas utility function, there is positive demand for both $L_j^* > 0$ and $W_j^* > 0$. This makes hybrid work the optimal choice.

- Commuting costs matter: If commuting costs $C_j(d)$ increase, employees reduce office work ($L_j^*$) and shift toward remote work ($W_j^*$).
- WFH preference ($\alpha$) determines balance between office work and WFH.
- Agglomeration benefits $\nu(d)$ suggest that central locations retain some appeal, even for employees who prefer WFH.

### Firms' Optimization

Firms maximize profits by choosing the optimal balance between office ($L_j$) and remote work ($W_j$):

$$\Pi_i = p_i \cdot Q_i - C_i(A, d).$$

Output is produced using both in-office and remote work:

$$Q_i = L_i \cdot \theta_i(A) \cdot \mu(d) + W_i \cdot \psi.$$

The cost function of office space is:

$$C_i(A, d) = \frac{c_0 A}{d}.$$

Firms' total labor supply is normalized to 1:

$$L_i + W_i = 1.$$

Where:

- $L_i$ is in-office work, and $W_i$ is remote work,
- $\theta_i(A)$ captures the productivity benefit of in-office work, which depends on office size $A$,

- $\mu(d)$ represents agglomeration benefits from locating in an urban center, which enhances in-office productivity,
- $\psi$ is the productivity term for remote work, assumed constant and independent of location,
- $C_i(A, d)$ represents the cost of office space, increasing in office size $A$ and and unit costs $c_0$, while decreasing in distance $d$ from the city center.

### FOC w.r.t. $L_i$ (Office Work)

$$\frac{\partial \Pi_i}{\partial L_i} = p_i \cdot \theta_i(A) \cdot \mu(d) = 0.$$

### FOC w.r.t. $W_i$ (Remote Work)

$$\frac{\partial \Pi_i}{\partial W_i} = p_i \cdot \psi = 0.$$

Since firms optimize by equalizing the marginal benefits of in-office and remote work, setting these FOCs equal to each other gives:

$$\theta_i(A) \cdot \mu(d) = \psi.$$

### Solving for $L_i^*$ and $W_i^*$

Setting the FOCs equal to each other:

$$p_i \cdot \theta_i(A) \cdot \mu(d) = p_i \cdot \psi.$$

Since the firm's total labor supply is constrained by:

$$L_i + W_i = 1,$$

I solve for $L_i^*$ and $W_i^*$:

$$L_i^* = \frac{\psi}{\theta_i(A) \cdot \mu(d) + \psi},$$

$$W_i^* = \frac{\theta_i(A) \cdot \mu(d)}{\theta_i(A) \cdot \mu(d) + \psi}.$$

### Interpretation of Firms' Optimization

- If in-office productivity and agglomeration benefits are high (($\theta_i(A)$ and $\mu(d)$), firms allocate more labor to in-office work ($L_i^*$) and reduce remote work ($W_i^*$).
- If remote productivity ($\psi$) is high, firms allocate more labor to remote work ($W_i^*$) and reduce in-office work ($L_i^*$).
- If in-office and remote work productivity are equal ($\theta_i(A) \cdot \mu(d) = \psi$), firms split labor equally: $L_i^* = W_i^* = \frac{N_i}{2}$.

### Equilibrium Hybrid Work Policy ($\lambda^*$)

Firms and employees jointly determine the optimal fraction of time employees work in the office. To reach this equilibrium hybrid work arrangement, I impose two conditions:

1. Employees' marginal utility of office and remote work have to be equal:

$$\frac{\partial U_j}{\partial L_j} = \frac{\partial U_j}{\partial W_j}.$$

2. Firms' marginal profits of office and remote work have to be equal:

$$\frac{\partial \Pi_i}{\partial L_i} = \frac{\partial \Pi_i}{\partial W_i}.$$

I express the share of work in the office with $\lambda$:

$$L_i = \lambda N_i, \quad W_i = (1 - \lambda) N_i.$$

### Solving for the Optimal $\lambda^*$

Using the conditions above, I solve for the equilibrium fraction of office work:

$$\lambda^* = \frac{\psi}{\theta_i(A) \cdot \mu(d) + \psi}.$$

### Interpretation of Optimal Hybrid Work Policy

- Higher office productivity benefits ($\theta_i(A) \cdot \mu(d)$) increase office attendance ($\lambda^*$).
- Higher remote productivity ($\psi$) increases WFH ($1 - \lambda^*$), leading to lower office attendance.
- Commuting costs affect employee preferences but do not directly impact firms' optimal hybrid policy, as firms set $\lambda^*$ based on productivity considerations.
- If in-office and remote productivity are equal ($\theta_i(A) \cdot \mu(d) = \psi$), then $\lambda^* = \frac{1}{2}$, meaning an equal split between office and remote work.

### Step 2: Firms Determine Office Space Adjustments

Based on the hybrid work arrangement $\lambda^*$, firms adjust their office space accordingly. Since $\lambda^*$ differs across organizations, I am not using its definition through other parameters from the previous step, but instead focus on how the share of work in the office affects firm decisions about office space. Firms optimize their office size ($A$) and location ($d$) to maximize profits.

### Firm Optimization: Choosing Optimal $A^*$ and $d^*$

Firms maximize their profit function:

$$\Pi_i = p_i Q_i - C_i(A, d).$$

where output depends on both in-office and remote work:

$$Q_i = L_i \cdot \theta_i(A) \cdot \mu(d) + W_i \cdot \psi = \lambda\theta_i(A)\mu(d) + (1-\lambda)\psi.$$

The firm's office cost function is:

$$C_i(A, d) = \frac{c_0 A}{d}.$$

Thus, firms' profit maximization problem is:

$$\max_{A,d} \Pi_i = p_i \left[\lambda\theta_i(A)\mu(d) + (1-\lambda)\psi\right] - \frac{c_0 A}{d}.$$

### FOC w.r.t. $A$ (Office Size)

$$\frac{\partial \Pi_i}{\partial A} = p_i\lambda\mu(d)\frac{\partial\theta_i(A)}{\partial A} - \frac{c_0}{d} = 0.$$

Solving for $d^*$:

$$d^* = \frac{c_0}{p_i\lambda\mu(d)\frac{\partial\theta_i(A)}{\partial A}}.$$

### Interpretation of Optimal Office Distance from Center $d^*$

Firms locate farther from the city center ($d^* \uparrow$) if:

- Office costs are high ($c_0 \uparrow$).
- The productivity gain from office size is small ($\frac{\partial\theta_i(A)}{\partial A} \downarrow$).
- The agglomeration benefit ($\mu(d)$) is weak.
- The fraction of in-office work is low ($\lambda \downarrow$).

#### FOC w.r.t. $d$ (Office Location)

$$\frac{\partial \Pi_i}{\partial d} = p_i \lambda \theta_i(A) \frac{\partial \mu(d)}{\partial d} + \frac{c_0 A}{d^2} = 0.$$

Solving for $A^*$:

$$A^* = -\frac{p_i \lambda \theta_i(A) d^2 \frac{\partial \mu(d)}{\partial d}}{c_0}.$$

Since agglomeration benefits $\mu(d)$ typically decline with distance, $\frac{\partial \mu(d)}{\partial d} < 0$, the negative sign cancels out:

$$A^* = \frac{p_i \lambda \theta_i(A) d^2 |\frac{\partial \mu(d)}{\partial d}|}{c_0}.$$

#### Interpretation of Optimal Office Space ($A^*$)

Firms demand larger office space ($A^* \uparrow$) if:

- Firm productivity is high ($p_i \uparrow$).
- The fraction of in-office work is high ($\lambda \uparrow$).
- Office productivity increases with space ($\theta_i(A) \uparrow$).
- Agglomeration benefits decline steeply with distance ($|\frac{\partial \mu(d)}{\partial d}| \uparrow$).
- The firm is located farther from the city center ($d^2 \uparrow$).

#### Interpretation of $\lambda$ in Firms' Optimization

The equilibrium office size and location choices depend directly on the fraction of time employees spend in the office ($\lambda$).

- When firms require more in-office work ($\lambda$ is high), they demand larger office spaces in more central locations.

- Conversely, when remote work is more prevalent ($\lambda$ is low), firms reduce office footprints and may relocate to lower-cost peripheral areas.

### Hypothesis 1: Office Downsizing

Firms reduce total office space in response to WFH if the cost savings from downsizing outweigh the productivity and agglomeration benefits of office space. From the FOC for $A^*$, firms reduce office size if the marginal productivity gain from increasing office space is lower than the marginal cost increase:

$$A^* = \frac{p_i \lambda \theta_i(A) d^2 |\frac{\partial \mu(d)}{\partial d}|}{c_0}.$$

A larger reduction in office space is expected if:

- The marginal productivity of office space ($\frac{\partial \theta_i(A)}{\partial A}$) is low.
- Agglomeration benefits ($\mu(d)$) are weak or decline slowly with distance ($|\frac{\partial \mu(d)}{\partial d}|$ is small).
- The firm requires less in-office work ($\lambda \downarrow$).
- Office costs ($c_0$) are high.

### Hypothesis 2: Flight to Quality

Firms shifting to hybrid work may upgrade to higher-quality offices that offer better amenities, modern infrastructure, and flexible layouts, increasing productivity per unit of space. From the FOC for $A^*$ and $d^*$, firms upgrade office quality if the marginal productivity benefits outweigh higher costs:

$$A^* = \frac{p_i \lambda \theta_i(A) d^2 |\frac{\partial \mu(d)}{\partial d}|}{c_0}, \quad d^* = \frac{c_0}{p_i \lambda \mu(d) \frac{\partial \theta_i(A)}{\partial A}}.$$

A shift toward high-quality office space is more likely if:

- The marginal productivity of office quality ($\frac{\partial \theta_i(A)}{\partial A}$) is high.

- Agglomeration benefits ($\mu(d)$) are strong.
- Cost savings from downsizing ($A^* \downarrow$) free up budget to invest in higher-quality office environments.
- The firm still requires substantial in-office work ($\lambda$ remains moderate to high).

### Hypothesis 3: Centralization Effect

Firms relocate closer to the city center if the agglomeration benefits and in-office productivity outweigh the cost of office space in the CBD. From the FOC for $d^*$, firms relocate centrally if the marginal productivity gains from central office locations exceed the rent cost differential:

$$d^* = \frac{c_0}{p_i \lambda \mu(d) \frac{\partial \theta_i(A)}{\partial A}}.$$

A shift toward more central locations is more likely if:

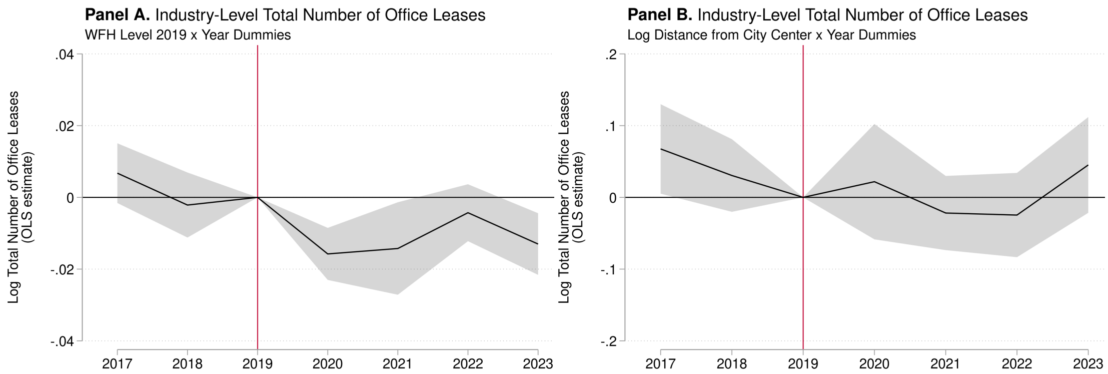
- Agglomeration benefits ($\mu(d)$) are strong.
- The marginal productivity of office work and size ($\frac{\partial \theta_i(A)}{\partial A}$) is high.
- The fraction of in-office work ($\lambda$) is high.
- Office space unit costs ($c_0$) do not rise disproportionately in the CBD.

### Model Summary

This model provides a stylized framework to analyze how WFH affects firms' office leasing decisions. The three hypotheses are office space downsizing, quality upgrading, and relocation toward the urban center. The empirical analysis tests these predictions by examining office leasing outcomes in response to industry-level WFH growth.

## D.4 Detailed Results

**Figure D.11:** DiD Estimates on Quantity Changes of Office Leases 2017–2023




*Notes:* This figure presents dynamic DiD estimates $\hat{\beta}_k$ from separate regressions of Equation 4.1 on the association between WFH growth, distance from the city center, and the number of office leases. In Panel A, the log number of office leases is regressed onto an interaction term of WFH growth and year dummies from 2017 to 2023. In Panel B, the log number of office leases is regressed onto an interaction term of log postcode-level distance from the city center and year dummies. 95 percent confidence intervals are displayed in gray. In Panel A, standard errors clustered are at the industry-by-submarket-type level, and in Panel B at the metro-area-by-submarket-type level. The vertical red line marks 2019, the reference year before the Covid-19 pandemic. Data are from the ifo Business Survey (EBDC-BEP, 2023) and Colliers (2024).

## D.5 Heterogeneity Analysis

**Table D.3:** Heterogeneity Analysis of Long DiD Outcomes: WFH Growth

| | Industry-Level | | Firm-Level | | | |
|---|---|---|---|---|---|---|
| | **Log Total Office Space Demand** | **Log Total Office Rent Revenue** | **Log Average Office Space** | **Log Average Office Rent** | **Log Prime Office Rent** | **Log Distance from City Center** |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ***Panel A: Above-Average WFH Growth*** | | | | | | |
| **WFH Growth × Post** ***(2023)*** | -0.0188*** | -0.0166*** | -0.0078 | -0.0030* | 0.0015* | -0.0054 |
| | (0.0060) | (0.0048) | (0.0072) | (0.0016) | (0.0008) | (0.0039) |
| $N$ | 3,594 | 3,594 | 3,584 | 3,584 | 3,584 | 3,584 |
| $R^2$ | 0.21 | 0.31 | 0.03 | 0.48 | 0.92 | 0.19 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |
| ***Panel B: Below-Average WFH Growth*** | | | | | | |
| **WFH Growth × Post** ***(2023)*** | -0.0120 | -0.0184 | -0.0039 | -0.0058 | -0.0014 | 0.0044 |
| | (0.0206) | (0.0147) | (0.0155) | (0.0037) | (0.0012) | (0.0121) |
| $N$ | 2,301 | 2,301 | 2,291 | 2,291 | 2,291 | 2,291 |
| $R^2$ | 0.18 | 0.21 | 0.03 | 0.49 | 0.93 | 0.16 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |

*Notes:* This table reports heterogeneity results of long DiD estimates $\hat{\beta}$ of WFH growth on office characteristics based on Equation 4.2. Time dummies are grouped into two bins: the year 2019 as the pre-Covid reference period and the year 2023 as the only post-period. Panel A shows the results for industries with above-average WFH growth (exceeding 15 percentage points), while Panel B reports them for industries with below-average WFH growth. Columns (1) and (2) display industry-level estimates of the WFH growth effect on log total office space demand and log total office leasing revenue. The firm-level results in columns (3) to (6) report the results for log average office space, log average office rent, log prime office rent, and log distance from city center, respectively. The estimates are conditional on metropolitan area fixed effects, municipality tax controls, postcode controls, and employment controls. Standard errors are clustered at the industry-by-submarket-type level. *p<0.1; **p<0.05; ***p<0.01.

**Table D.4:** Heterogeneity Analysis of Long DiD Outcomes: Building Quality

| | Industry-Level | | Firm-Level | | | |
|---|---|---|---|---|---|---|
| | **Log Total Office Space Demand** | **Log Total Office Rent Revenue** | **Log Average Office Space** | **Log Average Office Rent** | **Log Prime Office Rent** | **Log Distance from City Center** |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ***Panel A: Building Quality Category A*** | | | | | | |
| **WFH Growth × Post** ***(2023)*** | -0.0064 | 0.0002 | 0.0006 | 0.0005 | -0.0001 | -0.0047 |
| | (0.0080) | (0.0045) | (0.0061) | (0.0014) | (0.0007) | (0.0037) |
| $N$ | 1,673 | 1,673 | 1,666 | 1,666 | 1,666 | 1,666 |
| $R^2$ | 0.20 | 0.34 | 0.05 | 0.55 | 0.92 | 0.24 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |
| ***Panel B: Building Quality Category B or C*** | | | | | | |
| **WFH Growth × Post** ***(2023)*** | -0.0187*** | 0.0003 | -0.0155*** | -0.0026** | 0.0012** | -0.0044 |
| | (0.0053) | (0.0049) | (0.0034) | (0.0011) | (0.0005) | (0.0030) |
| $N$ | 3,473 | 3,473 | 3,460 | 3,460 | 3,460 | 3,460 |
| $R^2$ | 0.09 | 0.14 | 0.06 | 0.54 | 0.93 | 0.21 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |

*Notes:* This table reports heterogeneity results of long DiD estimates $\hat{\beta}$ of WFH growth on office characteristics based on Equation 4.2. Time dummies are grouped into two bins: the year 2019 as the pre-Covid reference period and the year 2023 as the only post-period. Panel A shows the results for office buildings with the highest quality grade A, while Panel B reports them for buildings with quality categories B and C. Columns (1) and (2) display industry-level estimates of the WFH growth effect on log total office space demand and log total office leasing revenue. The firm-level results in columns (3) to (6) report the results for log average office space, log average office rent, log prime office rent, and log distance from city center, respectively. The estimates are conditional on metropolitan area fixed effects, municipality tax controls, postcode controls, and employment controls. Standard errors are clustered at the industry-by-submarket-type level. *p<0.1; **p<0.05; ***p<0.01.

**Table D.5:** Heterogeneity Analysis of Long DiD Outcomes: Building Age

| | Industry-Level | | Firm-Level | | | |
|---|---|---|---|---|---|---|
| | **Log Total Office Space Demand** | **Log Total Office Rent Revenue** | **Log Average Office Space** | **Log Average Office Rent** | **Log Prime Office Rent** | **Log Distance from City Center** |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ***Panel A: Building Year Since 2020*** | | | | | | |
| **WFH Growth × Post** *(2023)* | -0.0153 | -0.0104 | -0.0006 | -0.0028 | 0.0002 | -0.0144** |
| | (0.0146) | (0.0098) | (0.0100) | (0.0030) | (0.0007) | (0.0066) |
| *N* | 720 | 720 | 716 | 716 | 716 | 716 |
| $R^2$ | 0.30 | 0.46 | 0.15 | 0.56 | 0.91 | 0.25 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |
| ***Panel B: Building Year 1990–2019*** | | | | | | |
| **WFH Growth × Post** *(2023)* | -0.0241*** | -0.0073* | -0.0113*** | -0.0014 | 0.0006 | -0.0062** |
| | (0.0051) | (0.0039) | (0.0035) | (0.0010) | (0.0006) | (0.0025) |
| *N* | 3,448 | 3,448 | 3,447 | 3,447 | 3,447 | 3,447 |
| $R^2$ | 0.22 | 0.21 | 0.05 | 0.53 | 0.92 | 0.21 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |
| ***Panel C: Building Year Before 1990*** | | | | | | |
| **WFH Growth × Post** *(2023)* | -0.0292*** | -0.0215*** | -0.0078 | -0.0001 | 0.0012** | 0.0045 |
| | (0.0089) | (0.0061) | (0.0084) | (0.0022) | (0.0006) | (0.0054) |
| *N* | 866 | 866 | 866 | 866 | 866 | 866 |
| $R^2$ | 0.08 | 0.14 | 0.04 | 0.51 | 0.93 | 0.14 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |

*Notes:* This table reports heterogeneity results of long DiD estimates $\hat{\beta}$ of WFH growth on office characteristics based on Equation 4.2. Time dummies are grouped into two bins: the year 2019 as the pre-Covid reference period and the year 2023 as the only post-period. The building year stands for the year of completion or the year of the last major renovation, whichever is applicable. Panel A shows the results for the newest office buildings (building year since 2020), while Panel B reports them for buildings from 1990 to 2019, and Panel C focuses on the oldest buildings (building year before 1990). Columns (1) and (2) display industry-level estimates of the WFH growth effect on log total office space demand and log total office leasing revenue. The firm-level results in columns (3) to (6) report the results for log average office space, log average office rent, log prime office rent, and log distance from city center, respectively. The estimates are conditional on metropolitan area fixed effects, municipality tax controls, postcode controls, and employment controls. Standard errors are clustered at the industry-by-submarket-type level. *p<0.1; **p<0.05; ***p<0.01.

**Table D.6:** Heterogeneity Analysis of Long DiD Outcomes: Within Metro Areas

| | **Industry-Level** | | **Firm-Level** | | | |
|---|---|---|---|---|---|---|
| | **Log Total Office Space Demand** | **Log Total Office Rent Revenue** | **Log Average Office Space** | **Log Average Office Rent** | **Log Prime Office Rent** | **Log Distance from City Center** |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ***Panel A: Central Business District (CBD)*** | | | | | | |
| **WFH Growth × Post *(2023)*** | 0.0308*** | 0.0185** | 0.0055 | -0.0017 | 0.0002 | -0.0066* |
| | (0.0077) | (0.0074) | (0.0046) | (0.0019) | (0.0012) | (0.0035) |
| $N$ | 1,465 | 1,465 | 1,457 | 1,457 | 1,457 | 1,457 |
| $R^2$ | 0.20 | 0.26 | 0.04 | 0.39 | 0.92 | 0.27 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |
| ***Panel B: City*** | | | | | | |
| **WFH Growth × Post *(2023)*** | -0.0255** | -0.0012 | -0.0150** | 0.0002 | 0.0003 | 0.0002 |
| | (0.0099) | (0.0081) | (0.0061) | (0.0009) | (0.0005) | (0.0023) |
| $N$ | 1,381 | 1,381 | 1,375 | 1,375 | 1,375 | 1,375 |
| $R^2$ | 0.16 | 0.33 | 0.06 | 0.43 | 0.93 | 0.20 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |
| ***Panel C: Suburb*** | | | | | | |
| **WFH Growth × Post *(2023)*** | -0.0352*** | -0.0260*** | -0.0087 | -0.0008 | 0.0008 | 0.0012 |
| | (0.0099) | (0.0067) | (0.0054) | (0.0012) | (0.0005) | (0.0015) |
| $N$ | 1,963 | 1,963 | 1,960 | 1,960 | 1,960 | 1,960 |
| $R^2$ | 0.20 | 0.28 | 0.06 | 0.50 | 0.92 | 0.18 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |
| ***Panel D: Periphery*** | | | | | | |
| **WFH Growth × Post *(2023)*** | -0.0107 | 0.0125*** | -0.0175** | -0.0017 | 0.0012** | -0.0058** |
| | (0.0104) | (0.0030) | (0.0071) | (0.0020) | (0.0005) | (0.0026) |
| $N$ | 1,086 | 1,086 | 1,083 | 1,083 | 1,083 | 1,083 |
| $R^2$ | 0.12 | 0.21 | 0.06 | 0.47 | 0.93 | 0.38 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |

*Notes:* This table reports heterogeneity results of long DiD estimates $\hat{\beta}$ of WFH growth on office characteristics based on Equation 4.2. Time dummies are grouped into two bins: the year 2019 as the pre-Covid reference period and the year 2023 as the only post-period. Panel A shows the results for the central business district (CBD), Panel B for the city, Panel C for suburbs, and Panel D for the periphery. Columns (1) and (2) display industry-level estimates of the WFH growth effect on log total office space demand and log total office leasing revenue. The firm-level results in columns (3) to (6) report the results for log average office space, log average office rent, log prime office rent, and log distance from city center, respectively. The estimates are conditional on metropolitan area fixed effects, municipality tax controls, postcode controls, and employment controls. Standard errors are clustered at the industry-by-submarket-type level. *p<0.1; **p<0.05; ***p<0.01.

**Table D.7:** Heterogeneity Analysis of Long DiD Outcomes: Across Metro Areas

| | Industry-Level | | Firm-Level | | | |
|---|---|---|---|---|---|---|
| | Log Total Office Space Demand | Log Total Office Rent Revenue | Log Average Office Space | Log Average Office Rent | Log Prime Office Rent | Log Distance from City Center |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ***Panel A: Top 3 Metro Regions*** | | | | | | |
| **WFH Growth × Post** ***(2023)*** | -0.0100* | -0.0024 | -0.0014 | 0.0002 | 0.0002 | -0.0028 |
| | (0.0051) | (0.0048) | (0.0037) | (0.0012) | (0.0002) | (0.0026) |
| $N$ | 3,297 | 3,297 | 3,296 | 3,296 | 3,296 | 3,296 |
| $R^2$ | 0.19 | 0.13 | 0.02 | 0.55 | 0.94 | 0.20 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |
| ***Panel B: Bottom 4 Metro Regions*** | | | | | | |
| **WFH Growth × Post** ***(2023)*** | -0.0388*** | -0.0077 | -0.0208*** | -0.0031** | 0.0000 | -0.0093*** |
| | (0.0049) | (0.0049) | (0.0049) | (0.0013) | (0.0008) | (0.0029) |
| $N$ | 2,598 | 2,598 | 2,579 | 2,579 | 2,579 | 2,579 |
| $R^2$ | 0.20 | 0.20 | 0.08 | 0.40 | 0.92 | 0.13 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |

*Notes:* This table reports heterogeneity results of long DiD estimates $\hat{\beta}$ of WFH growth on office characteristics based on Equation 4.2. Time dummies are grouped into two bins: the year 2019 as the pre-Covid reference period and the year 2023 as the only post-period. Panel A shows the results for the three largest metropolitan areas: Berlin, Hamburg and Munich. Panel B reports the estimates for the bottom four of the seven largest metropolitan areas: Cologne, Frankfurt, Stuttgart and Dusseldorf. Columns (1) and (2) display industry-level estimates of the WFH growth effect on log total office space demand and log total office leasing revenue. The firm-level results in columns (3) to (6) report the results for log average office space, log average office rent, log prime office rent, and log distance from city center, respectively. The estimates are conditional on metropolitan area fixed effects, municipality tax controls, postcode controls, and employment controls. Standard errors are clustered at the industry-by-submarket-type level. *p<0.1; **p<0.05; ***p<0.01.

## D.6 Robustness Checks

**Table D.8:** Robustness Check of Long DiD Results: Alternative Employment Control

| | Industry-Level | | Firm-Level | | | |
|---|---|---|---|---|---|---|
| | **Log Total Office Space Demand** | **Log Total Office Rent Revenue** | **Log Average Office Space** | **Log Average Office Rent** | **Log Prime Office Rent** | **Log Distance from City Center** |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **WFH Growth × Post *(2023)*** | -0.0216*** | -0.0050 | -0.0091*** | -0.0010 | 0.0006 | -0.0058*** |
| | (0.0033) | (0.0040) | (0.0033) | (0.0008) | (0.0005) | (0.0020) |
| $N$ | 5,895 | 5,895 | 5,875 | 5,875 | 5,875 | 5,875 |
| $R^2$ | 0.22 | 0.21 | 0.04 | 0.50 | 0.92 | 0.18 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| 2019 Employment Controls | | | ✓ | ✓ | ✓ | ✓ |

*Notes:* This table reports robustness checks of long DiD estimates $\hat{\beta}$ of WFH growth on office characteristics based on Equation 4.2. Specifically, this robustness check tests the differences in outcomes when using log employment at the industry level in 2019 as a control instead of the yearly log employment controls in the main specification. Time dummies are grouped into two bins: the year 2019 as the pre-Covid reference period and the year 2023 as the only post-period. Columns (1) and (2) display industry-level estimates of the WFH growth effect on log total office space demand and log total office leasing revenue. The firm-level results in columns (3) to (6) report the results for log average office space, log average office rent, log prime office rent, and log distance from city center, respectively. The estimates are conditional on metropolitan area fixed effects, municipality tax controls, postcode controls, and employment controls. Standard errors are clustered at the industry-by-submarket-type level. *p<0.1; **p<0.05; ***p<0.01.

**Table D.9:** Robustness Check of Long DiD Results: Clustering Standard Errors at Different Levels

| | Industry-Level | | Firm-Level | | | |
|---|---|---|---|---|---|---|
| | **Log Total Office Space Demand** | **Log Total Office Rent Revenue** | **Log Average Office Space** | **Log Average Office Rent** | **Log Prime Office Rent** | **Log Distance from City Center** |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ***Panel A: SE Clustering at Industry x Submarket Type Level (Baseline)*** | | | | | | |
| **WFH Growth × Post *(2023)*** | -0.0216*** | -0.0050 | -0.0095*** | -0.0011 | 0.0006 | -0.0056*** |
| | (0.0033) | (0.0039) | (0.0034) | (0.0007) | (0.0005) | (0.0021) |
| ***Panel B: SE Clustering at Industry x Year Level*** | | | | | | |
| **WFH Growth × Post *(2023)*** | -0.0216*** | -0.0050 | -0.0095*** | -0.0011 | 0.0006 | -0.0056*** |
| | (0.0031) | (0.0052) | (0.0028) | (0.0007) | (0.0006) | (0.0017) |
| ***Panel C: SE Clustering at Metro Area x Submarket Type Level*** | | | | | | |
| **WFH Growth × Post *(2023)*** | -0.0216*** | -0.0050 | -0.0095** | -0.0011 | 0.0006 | -0.0056** |
| | (0.0052) | (0.0051) | (0.0040) | (0.0010) | (0.0004) | (0.0026) |
| ***Panel D: SE Clustering at Individual Metro Submarket Level*** | | | | | | |
| **WFH Growth × Post *(2023)*** | -0.0216*** | -0.0050 | -0.0095** | -0.0011 | 0.0006 | -0.0056** |
| | (0.0040) | (0.0038) | (0.0036) | (0.0010) | (0.0003) | (0.0024) |
| ***Panel E: SE Clustering at Postcode Level*** | | | | | | |
| **WFH Growth × Post *(2023)*** | -0.0216*** | -0.0050 | -0.0095*** | -0.0011 | 0.0006* | -0.0056** |
| | (0.0033) | (0.0032) | (0.0033) | (0.0009) | (0.0003) | (0.0023) |
| **Regression Specifications** | | | | | | |
| $N$ | 5,895 | 5,895 | 5,875 | 5,875 | 5,758 | 5,875 |
| $R^2$ | 0.22 | 0.21 | 0.04 | 0.50 | 0.92 | 0.18 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |

*Notes:* This table reports robustness checks of long DiD estimates $\hat{\beta}$ of WFH growth on office characteristics based on Equation 4.2. Specifically, this robustness check tests the differences in outcomes when clustering standard errors at alternative levels: Panel A reports the baseline estimates with clustering at the industry-by-submarket-type level (up to 72 clusters). Panel B clusters standard errors at the industry-by-year level (up to 108 clusters), while Panel C clusters at the metro-area-by-submarket-type level (up to 28 clusters). The clustering level in Panel D is the individual submarket level in cities (up to 101 clusters). Finally, Panel E clusters at the postcode level (more than 500 clusters). Time dummies are grouped into two bins: the year 2019 as the pre-Covid reference period and the year 2023 as the only post-period. Columns (1) and (2) display industry-level estimates of the WFH growth effect on log total office space demand and log total office leasing revenue. The firm-level results in columns (3) to (6) report the results for log average office space, log average office rent, log prime office rent, and log distance from city center, respectively. The estimates are conditional on metropolitan area fixed effects, municipality tax controls, postcode controls, and employment controls. *p<0.1; **p<0.05; ***p<0.01.

**Table D.10:** Robustness Check of Long DiD Results: Additional Controls

| | Industry-Level | | Firm-Level | | | |
|---|---|---|---|---|---|---|
| | **Log Total Office Space Demand** | **Log Total Office Rent Revenue** | **Log Average Office Space** | **Log Average Office Rent** | **Log Prime Office Rent** | **Log Distance from City Center** |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **WFH Growth × Post *(2023)*** | -0.0216*** | -0.0050 | -0.0095*** | -0.0011 | 0.0006 | -0.0013* |
| | (0.0033) | (0.0040) | (0.0033) | (0.0008) | (0.0005) | (0.0008) |
| $N$ | 5,895 | 5,895 | 5,870 | 5,870 | 5,870 | 5,870 |
| $R^2$ | 0.22 | 0.21 | 0.05 | 0.51 | 0.92 | 0.89 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | ✓ |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |
| Additional Controls | | | ✓ | ✓ | ✓ | ✓ |

*Notes:* This table reports robustness checks of long DiD estimates $\hat{\beta}$ of WFH growth on office characteristics based on Equation 4.2. Specifically, this robustness check tests the differences in outcomes when using additional controls: subleasing, car distance from the city center, postcode-level employment, metro area GDP, municipality-level property tax and business tax income. Time dummies are grouped into two bins: the year 2019 as the pre-Covid reference period and the year 2023 as the only post-period. Columns (1) and (2) display industry-level estimates of the WFH growth effect on log total office space demand and log total office leasing revenue. The firm-level results in columns (3) to (6) report the results for log average office space, log average office rent, log prime office rent, and log distance from city center, respectively. The estimates are conditional on metropolitan area fixed effects, municipality tax controls, postcode controls, and employment controls. Standard errors are clustered at the industry-by-submarket-type level. *p<0.1; **p<0.05; ***p<0.01.

**Table D.11:** Robustness Check of Long DiD Results: Additional Fixed Effects

| | Industry-Level | | Firm-Level | | | |
|---|---|---|---|---|---|---|
| | **Log Total Office Space Demand** | **Log Total Office Rent Revenue** | **Log Average Office Space** | **Log Average Office Rent** | **Log Prime Office Rent** | **Log Distance from City Center** |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **WFH Growth × Post *(2023)*** | -0.0224*** | -0.0059 | -0.0077** | -0.0006 | 0.0005 | -0.0048** |
| | (0.0034) | (0.0039) | (0.0034) | (0.0008) | (0.0005) | (0.0021) |
| $N$ | 5,895 | 5,895 | 5,808 | 5,808 | 5,808 | 5,875 |
| $R^2$ | 0.25 | 0.24 | 0.19 | 0.71 | 0.93 | 0.20 |
| Metro Area x Quarter FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Postcode FE | | | ✓ | ✓ | ✓ | |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |

*Notes:* This table reports robustness checks of long DiD estimates $\hat{\beta}$ of WFH growth on office characteristics based on Equation 4.2. Specifically, this robustness check tests the differences in outcomes when using alternative and additional fixed effects: In addition to metro-area-by-year fixed effects, I add postcode fixed effects instead of postcode-level controls. Time dummies are grouped into two bins: the year 2019 as the pre-Covid reference period and the year 2023 as the only post-period. Columns (1) and (2) display industry-level estimates of the WFH growth effect on log total office space demand and log total office leasing revenue. The firm-level results in columns (3) to (6) report the results for log average office space, log average office rent, log prime office rent, and log distance from city center, respectively. The estimates are conditional on metropolitan area fixed effects, municipality tax controls, postcode controls, and employment controls. Standard errors are clustered at the industry-by-submarket-type level. *p<0.1; **p<0.05; ***p<0.01.

**Table D.12:** Robustness Check of Long DiD Results: Leaving Out Financial and Public Sectors

| | Industry-Level | | Firm-Level | | | |
|---|---|---|---|---|---|---|
| | **Log Total Office Space Demand** | **Log Total Office Rent Revenue** | **Log Average Office Space** | **Log Average Office Rent** | **Log Prime Office Rent** | **Log Distance from City Center** |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **WFH Growth × Post *(2023)*** | -0.0207*** | -0.0055 | -0.0090*** | -0.0013 | 0.0008** | -0.0043** |
| | (0.0035) | (0.0037) | (0.0033) | (0.0008) | (0.0004) | (0.0019) |
| $N$ | 5,298 | 5,298 | 5,281 | 5,281 | 5,281 | 5,281 |
| $R^2$ | 0.23 | 0.21 | 0.04 | 0.49 | 0.93 | 0.18 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |

*Notes:* This table reports robustness checks of long DiD estimates $\hat{\beta}$ of WFH on office characteristics based on Equation 4.2. Specifically, this robustness check tests the differences in outcomes when estimating the same regressions without observations from the financial and public sectors, which are not included in the WFH survey data and whose values were imputed with the service-sector average. Time dummies are grouped into two bins: the year 2019 as the pre-Covid reference period and the year 2023 as the only post-period. Columns (1) and (2) display industry-level estimates of the WFH growth effect on log total office space demand and log total office leasing revenue. The firm-level results in columns (3) to (6) report the results for log average office space, log average office rent, log prime office rent, and log distance from city center, respectively. The estimates are conditional on metropolitan area fixed effects, municipality tax controls, postcode controls, and employment controls. Standard errors are clustered at the industry-by-submarket-type level. *p<0.1; **p<0.05; ***p<0.01.

**Table D.13:** Robustness Check of Long DiD Results: WFH Rate 2019 Instead of WFH Growth 2019–2023

| | **Industry-Level** | | **Firm-Level** | | | |
|---|---|---|---|---|---|---|
| | **Log Total Office Space Demand** | **Log Total Office Rent Revenue** | **Log Average Office Space** | **Log Average Office Rent** | **Log Prime Office Rent** | **Log Distance from City Center** |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **WFH Rate 2019 × Post *(2023)*** | -0.0235*** | -0.0118*** | -0.0041 | -0.0008 | 0.0005 | -0.0043* |
| | (0.0068) | (0.0044) | (0.0057) | (0.0012) | (0.0007) | (0.0025) |
| $N$ | 5,895 | 5,895 | 5,875 | 5,875 | 5,875 | 5,875 |
| $R^2$ | 0.29 | 0.38 | 0.02 | 0.49 | 0.92 | 0.19 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |

*Notes:* This table reports robustness checks of long DiD estimates $\hat{\beta}$ of WFH on office characteristics based on Equation 4.2. Specifically, this robustness check tests the differences in outcomes when using industries' WFH rate in 2019 from the ifo Business Survey (EBDC-BEP, 2023) as alternative treatment variable instead of WFH growth (2019-2023). Time dummies are grouped into two bins: the year 2019 as the pre-Covid reference period and the year 2023 as the only post-period. Columns (1) and (2) display industry-level estimates of the WFH growth effect on log total office space demand and log total office leasing revenue. The firm-level results in columns (3) to (6) report the results for log average office space, log average office rent, log prime office rent, and log distance from city center, respectively. The estimates are conditional on metropolitan area fixed effects, municipality tax controls, postcode controls, and employment controls. Standard errors are clustered at the industry-by-submarket-type level. *p<0.1; **p<0.05; ***p<0.01.

**Table D.14:** Robustness Check of Long DiD Results: Alternative WFH Potential Measure

| | Industry-Level | | Firm-Level | | | |
|---|---|---|---|---|---|---|
| | **Log Total Office Space Demand** | **Log Total Office Rent Revenue** | **Log Average Office Space** | **Log Average Office Rent** | **Log Prime Office Rent** | **Log Distance from City Center** |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **WFH Potential × Post *(2023)*** | -0.0070*** | -0.0023** | -0.0028** | -0.0005* | -0.0001 | -0.0015** |
| | (0.0014) | (0.0011) | (0.0013) | (0.0003) | (0.0002) | (0.0007) |
| $N$ | 5,895 | 5,895 | 5,875 | 5,875 | 5,875 | 5,875 |
| $R^2$ | 0.32 | 0.34 | 0.03 | 0.50 | 0.92 | 0.19 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | ✓ | ✓ | ✓ | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |

*Notes:* This table reports robustness checks of long DiD estimates $\hat{\beta}$ of WFH on office characteristics based on Equation 4.2. Specifically, this robustness check tests the differences in outcomes when using industries' WFH potential based on Alipour et al. (2023) as alternative treatment variable instead of WFH growth (2019-2023). Time dummies are grouped into two bins: the year 2019 as the pre-Covid reference period and the year 2023 as the only post-period. Columns (1) and (2) display industry-level estimates of the WFH growth effect on log total office space demand and log total office leasing revenue. The firm-level results in columns (3) to (6) report the results for log average office space, log average office rent, log prime office rent, and log distance from city center, respectively. The estimates are conditional on metropolitan area fixed effects, municipality tax controls, postcode controls, and employment controls. Standard errors are clustered at the industry-by-submarket-type level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

## D.7 Urban Results

**Table D.15:** Urban Long DiD Results of WFH Growth Effect on Office Characteristics

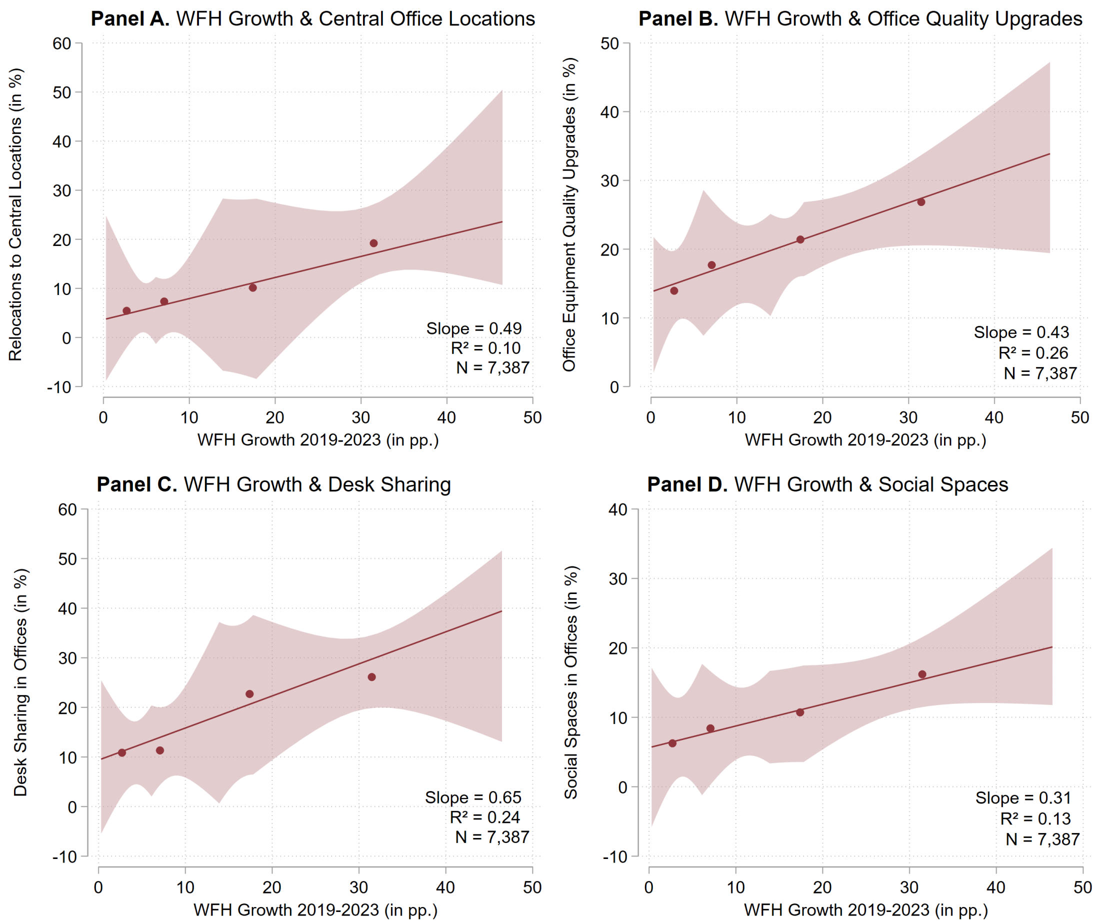
| | Industry-Level | | Firm-Level | | | |
|---|---|---|---|---|---|---|
| | **Log Total Office Space Demand** | **Log Total Office Rent Revenue** | **Log Average Office Space** | **Log Average Office Rent** | **Log Net Effective Office Rent** | **Log Prime Office Rent** |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Distance from City Center** | | | | | | |
| $\times$ **Post** ***(2023)*** | -0.0032 | 0.0271 | -0.0188 | 0.0194 | 0.0191 | 0.0115 |
| | (0.0691) | (0.0288) | (0.0586) | (0.0133) | (0.0135) | (0.0189) |
| $N$ | 5,875 | 5,875 | 5,875 | 5,875 | 5,875 | 5,875 |
| $R^2$ | 0.02 | 0.29 | 0.01 | 0.49 | 0.49 | 0.92 |
| Metro Area FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Municipality Tax Controls | | | ✓ | ✓ | ✓ | ✓ |
| Postcode Controls | | | | | | |
| Employment Controls | | | ✓ | ✓ | ✓ | ✓ |

*Notes:* This table reports long DiD estimates $\hat{\beta}$ of log postcode-level distance from the city center on office characteristics. Time dummies are grouped into two bins: the year 2019 as the pre-Covid reference period and the year 2023 as the only post-period. Columns (1) and (2) display industry-level estimates on the distance effect on log total office space demand and log total office leasing revenue. The firm-level results in columns (3) to (6) report the results for log average office space, log average office rent, log prime office rent, and log distance from city center, respectively. The estimates are conditional on metropolitan area fixed effects, municipality tax controls, postcode controls, and employment controls. Standard errors are clustered at the metro-area-by-submarket-type level. *p<0.1; **p<0.05; ***p<0.01.

## D.8 Mechanism Results

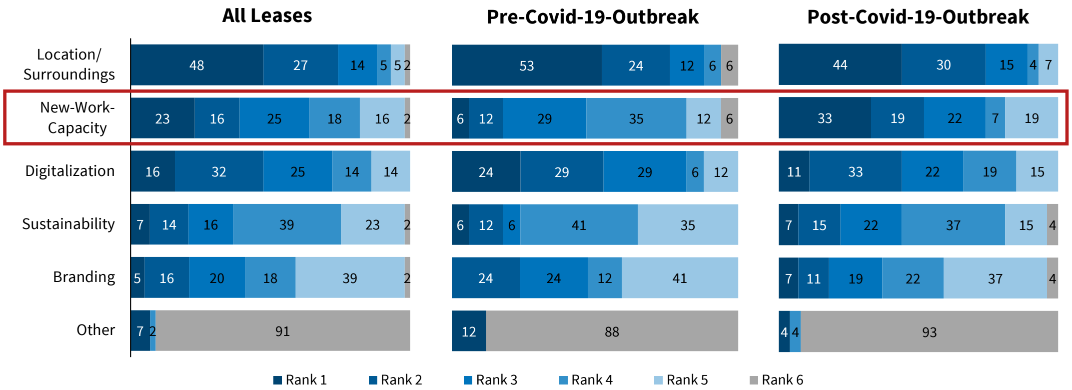
### D.8.1 Shifting Demand: WFH Industries Prioritize Centrality, Quality, and Flexibility

**Figure D.12:** Industry-Level Relationship Between WFH and Office Characteristics




*Notes:* This figure presents binscatter regression plots of the industry-level association of WFH growth with changes in office characteristics. Panel A shows the industry-level relationship between WFH growth and the share of companies that plan to move at least one corporate office towards a more central, more accessible location closer to the city center. Panel B plots the association between WFH growth and the share of companies that have conducted or plan to conduct quality upgrades of their office spaces. Panels C and D relate WFH growth to the share of companies that have expanded or plan to expand desk sharing and social spaces in offices, respectively. In each panel, the linear fitted line and 95 percent confidence intervals are shown in red. Data are from the ifo Business Survey August 2024 (ifo Institute for Economic Research, 2024).

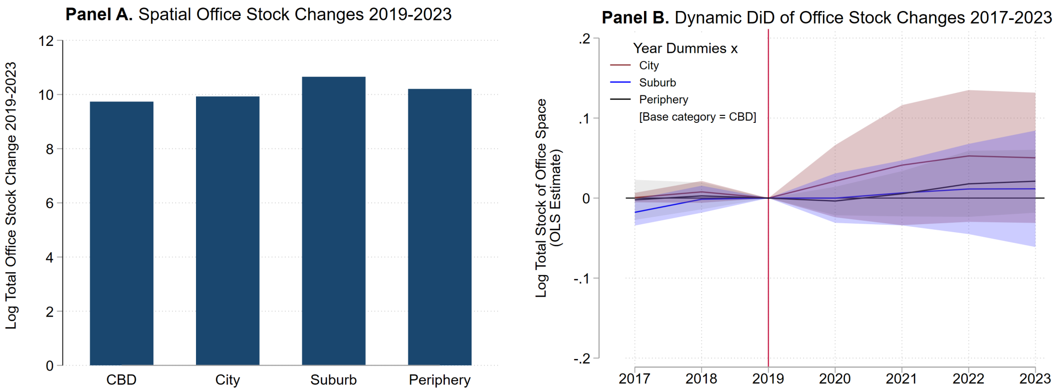
**Figure D.13:** Changing Importance of Criteria in Office Leasing Decisions




*Notes:* This figure displays the changing importance of criteria in office leasing decisions based on a ranking. The left panel reports the results of all leases, whereas the middle and the left panel report the results for the pre-pandemic and post-pandemic outbreak periods separately. The qualitative evidence is based on 44 structured expert interviews with CRE brokers at the German CRE consulting firm Colliers about the office lettings that they supported in major German cities between 2018 and 2023. The interviews were conducted by Colliers in November 2023. Data are from Colliers (2024).

### D.8.2 Supply-Side: Spatial Changes in Office Stock

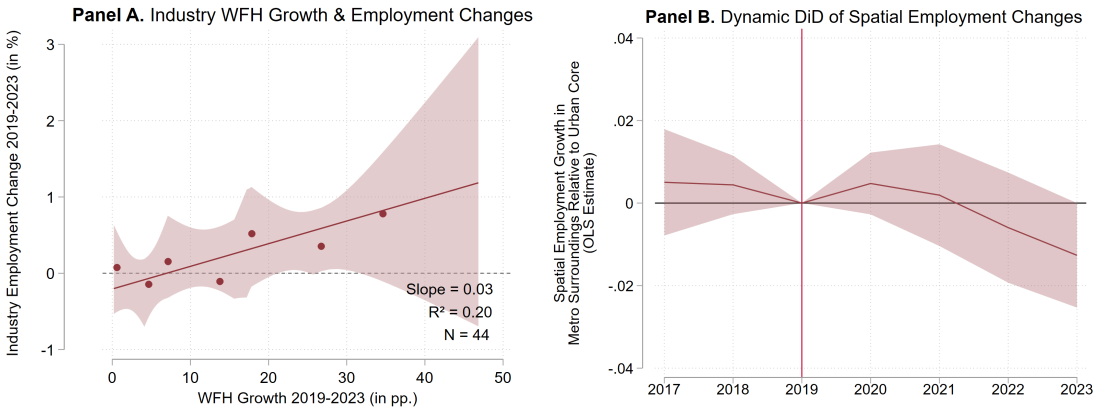
**Figure D.14:** Spatial Changes in Office Stock Within Metros




*Notes:* This figure presents within-metro changes in office stock at the level of submarkets in the seven largest German office real estate markets. Panel A presents the average change in log total office stock between 2019 and 2023 for the central business district (CBD), city, suburb, and periphery. Panel B shows the changes in log total office stock at the submarket level from 2017 to 2023 relative to the CBD in 2019, which is set as the base category. The annual DiD estimates are drawn with 95 percent confidence intervals. Standard errors are clustered at the metro-area-by-submarket-type level. Data on submarket office stock are from Colliers (2024).

### D.8.3 Industry-Level and Spatial Changes in Employment

**Figure D.15:** Industry-Level and Spatial Changes in Employment




*Notes:* This figure examines industry-level and spatial employment changes. Panel A presents binscatter regressions on the relationship between industry-level WFH growth and employment changes from 2019 to 2023. Panel B reports estimates from a dynamic DiD regression comparing employment growth in metro area surroundings (suburbs and periphery) to the urban core (CBD and city) for Germany's seven largest metro areas. The spatial employment data from the Federal Employment Agency follow the administrative classification of labor market regions, which defines the cities and counties included in each metro area. Data on 44 industries come from the ifo Business Survey (EBDC-BEP, 2023) and employment records from the German Federal Employment Agency (2025).

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