Estimating the impact of working from home on urban equilibrium: neighborhood scale effects using mobile data

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Abstract

The COVID-19 pandemic has fundamentally reshaped urban dynamics through the accelerated adoption of remote and hybrid work, in almost all countries of the world, including Israel. The new work schedule allows employees from the IT and financial sector to work from home or from any other location outside the office, at least couple of days a week. This allows them to save time and money on commuting. These shifts challenge long-standing urban equilibrium frameworks, such as the Alonso-Muth-Mills model, which has traditionally guided understanding of residential choice in urban economics and regional science. Previously, proximity to the CBD served as a primary factor influencing residential desirability and house prices. However, with the increase in remote work, this proximity has become less relevant and new spatial equilibrium is currently more explained by housing value and local amenities.

This paper examines the impact of working from home (WFH) on urban equilibrium in the Tel Aviv metropolitan area. To do so, we construct neighborhood-level WFH metrics using GPS-based mobility data and analyze their spatial and temporal variation in relation to rental price changes. Our findings reveal significant spatial heterogeneity in the response to WFH: while central neighborhoods have seen a decline in housing demand, remote neighborhoods exhibit faster rent price growth, which we interpret as a sign of increasing attractiveness.

1. Introduction

The COVID-19 pandemic significantly disrupted traditional urban dynamics, particularly in major cities around the world. During lockdown periods, a substantial portion of the workforce was compelled to work remotely, leading to a sharp decline in both economic activity in central business districts (CBDs) and daily commuting volumes. For instance, in the United States, the share of fully paid remote working days reached 33% during the pandemic (Dey et al., 2021)while in the European Union, approximately 37% of salaried employees worked from home (Eurofound, 2020). Among occupations suitable for remote work (Dingel & Neiman, 2020) this figure was even higher—between 50% and 60%

More critically, working from home (WFH) has persisted beyond the lifting of pandemic restrictions. Highly skilled employees, particularly in sectors with high adoption of digital tools such as information technology and finance, have continued to work from home several days per week. As a result, scholars have begun referring to such hybrid work arrangements as the “new normal” for urban labor markets (Barbosa et al., 2022; Barrero et al., 2021, 2023).

Recent statistical evidence of major cities in Europe and US supports this shift: in 2023, approximately 48% of high-skilled workers in London were working remotely at least two days per week(ONS, 2023). In San Francisco, the figure stood at 33%, and in Paris, around 20%(Jaclyn DeJohn, 2024; OECD, 2023).

This paper contributes to the growing literature on the long-term effects of remote work on urban equilibrium by examining how WFH patterns evolved during the Covid-19 pandemic and in the three years following, using high-resolution mobility data. We aim to address two central questions:

- How can GPS-based mobility data be used to measure WFH dynamics at a fine spatial scale?
- What is the impact of increased remote work on the urban spatial equilibrium, particularly as reflected in rental prices?

To answer these questions, we employ a combination of spatial analysis and panel regression. The paper proceeds as follows. We begin with a review of the theoretical and empirical literature on urban equilibrium and the economic implications of remote work. We then present our theoretical framework, followed by a description of the study area and dataset. Next, we detail our empirical strategy for identifying WFH patterns and estimating their impact on rents. Finally, we present the results and discuss their implications for urban structure and policy.

2. Literature review

From a theoretical perspective, the new behavior of some high skilled workers implies significant changes to the classic Alonso-Muth-Mill monocentric 'closed city' model that economists normally use to explain housing market and population dynamics in the city (Alonso, 1964; Mills, 1967; Muth 1969). This model suggests that residential location choices are driven by individuals seeking to maximize utility by making an optimal trade-off between commuting costs and housing quality, given a fixed income. Individuals aim to live as close as possible to the central business district (CBD), where workplaces are concentrated. Later extensions of the model added a third factor to residential choice: local accessibility of amenities (Brueckner et al., 1999). While the classic monocentric model assumes that neighborhoods located at the same distance from CBD are economically homogenous, introduction of amenities brings more spatial heterogeneity into to the model as it allows residents from different income groups to live at equal proximity to the CBD.

With the rise of remote work however, commuting frequency (Barrero et al., 2021; Bond-Smith et al., 2022; Brueckner et al., 2021; Delventhal et al., 2022; Monte et al., 2023) has been reduced, disrupting the established urban equilibrium. This has motivated a huge wave of research on how WFH affects housing markets, residential behavior and their impact on urban equilibrium.

The papers that explore the impact of remote work on urban structure predict a new spatial equilibrium (Brueckner et al., 2021) where the density of population is better defined by the quality and density of local amenities rather than local employment level (Delventhal et al., 2022; Ramani

& Bloom, 2021). Under these new conditions, remote workers are disconnected from their workplaces, and they value residential places based on their local characteristics such as the availability of natural amenities, safety, school quality and house prices.

As a result of this shift, studies suggest a reduction of the housing and rental -price gradient in the long run. Most papers describe a decrease in housing demand in the central areas of large cities and an increase in suburbia and small metro areas nearby – so called 'donut effect'(Ramani & Bloom, 2021). While some papers present only theoretical evidence, others have empirically confirmed this phenomenon based on empirical evidence from the period 2020-2022. Especially interesting is the fact that the results are mostly consistent for different cities across the world: individuals tend to leave the central area but still stay within the metro area as it provides access to services, flattening intra-city house-price gradients, especially for rents.

As such, in the US several papers report empirically- grounded population shifts (about 10%) in large US cities, from high-density zip codes and city centers towards lower-density and less expensive areas. (Althoff et al., 2022; Barrero et al., 2021; Health et al., 2020; Ramani & Bloom, 2021). This movement is limited to metro boundaries, as only 4% of shifters move to rural areas.

In the UK (De Fraja et al., 2020; Gokan et al., 2022) evidence also supports the "donut effect" with greater growth occurring in the suburbs and hinterlands surrounding large cities. Additionally, there is also an estimated "Zoomshock" (De Fraja et al., 2020) which represents a shift in economic activity due to remote work. This found to be significant and heterogeneous at a granular level, leading to decreased activity in productive city centers and increased activity in residential suburbs.

In Italy, Biagetti et al (2024) find two opposite trends: on the one hand, survey evidence shows people desire to move closer to nature if allowed to work remotely. On the other hand, studies from Milan show that people desire to stay within the city as it provides good quality and a variety of services. In Australia, Lennox (2020) finds that the largest and most productive cities gain both jobs and residents as they accumulate most remote work jobs. But residents prefer to live in outer suburbs causing urban sprawl. Other work shows a significant increase in residents in smaller cities and towns close to large employment centres, especially ones with good access to natural amenities (Guaralda et al., 2020; Zenkteler et al., 2022).

Despite the growing number of empirical studies on remote work, most face significant limitations. Many estimate the indirect impact of remote work based solely on its presence after the Covid-19 outbreak, often without capturing pre-pandemic dynamics. Others rely on low-resolution data—typically at the national or county level which limits their ability to examine dynamics within cities (Barrero et al., 2021; Biagetti et al., 2024; De Fraja et al., 2020).. A further challenge is that these studies are usually based on static snapshots taken at a single point in time, which prevents researchers from capturing temporal trends or behavioral shifts.

These limitations stem from the inherent difficulty of measuring remote work accurately. Most existing approaches depend either on costly surveys, which are subject to human biases (Barrero et al., 2023; Biagetti et al., 2024; De Fraja et al., 2021), or ticket validation records, which only indirectly reflect remote work patterns (Zheng et al., 2024)

A possible solution to these data limitations is to use mobile phone data. Overall, it has proven to be a reliable source for capturing high-resolution, dynamic travel patterns. However, in the context of remote work, studies utilizing such data have rarely examined long-term effects. Instead, they tend to focus primarily on the immediate impact on urban economic activity of mobility restrictions during lockdown periods (Huang et al., 2023; Östh et al., 2023). One of few studies that analyses long-term consequence of WFH is Li et al., 2024. They examine what popular third places in Beijing become frequented by remote workers, using mobile phone signals and app usage data from platforms designed to support remote work. Another study that measures two-years impact with mobile phone data is Monte et al (2023). They use GPS-locations of mobile users to measure changes in commuting frequency between 274 US cities and compare them with changes in housing prices gradients.

This paper addresses the existing gap in the understanding of remote work long-term impact on the intracity equilibrium based on reliable data by leveraging a high-resolution GPS dataset along with rental price data available both for the pre- and post-COVID-19 periods. Using these sources enables the direct estimation of the impact of remote work on rental price dynamics across time and space, capturing both temporal shifts and spatial heterogeneity in urban housing markets.

3. Theoretical model

The theoretical part of the study analyzes the potential outcomes of WFH opportunity on a spatial equilibrium. To do this we use the intercity model of Brueckner et al (2023) which we adapt to be applicable for neighborhoods of similar size within urban agglomeration. In this study we examine four types of neighborhoods:

N1: Close distance to the CBD (x_{N1}) with high amenity level (A_1)

N2: Close distance to the CBD (x_{N2}) with low amenity level (A_2)

N3: Long distance from the CBD (x_{N3}) with low amenity level (A_3)

N4: Long distance from the CBD (x_{N4}) with high amenity level (A_4)

where $x_{N1} = x_{N2} = x_{CBD} < x_{N3} = x_{N4} = x_R$, $A_1 = A_4 > A_2 = A_3$

Brueckner suggests that the resident utility function inside the city can be presented as:

$$u(e_i, q_i, A_i) = A_i + e_i + V(q_i) \tag{1}$$

where A_i denotes the amenity level in city i, e_i denotes other consumption (non-housing) whose price is normalized to 1, and $V(q_i)$ is a function of the utility from housing services q_i.

The budget constraint is as follows:

$$W(p_i, \alpha_i) = r_i q_i + e_i \tag{2}$$

where r_i is housing prices (rental prices in our analysis) and the wage in city i, $W(p_i, \alpha_i)$ is determined by the city's population size p_i, responds negatively to it (w_p< 0), and by the productivity level α_i, to which it responds positively ($w_\alpha > 0$).

Substituting the budget constraint into the utility function yields:

$$u(e_i, q_i, A_i) = A_i + W(p_i, \alpha_i) + H(p_i) \tag{3}$$

where $H(p_i) = V(q_i) - r_i q_i$ is a net utility from housing, which is negatively influenced by population size (h_p < 0), since housing prices r_i rise with population (we assume housing stock is fixed). Because both net housing utility and wages decline with population size, utility in city i also declines as population increases.

Adaptation of utility function to the city neighborhoods

Given that the paper addresses the impact of WFH inside cities, the analytical framework requires adjustments to reflect intracity specifics. To do this, we integrate insights from agglomeration theory as proposed by Koster and Thisse (2024).

First, we assume two discrete levels of productivity within an agglomeration, denoted as: α_{CBD}, α_R, representring the productivity levels in central and suburban neighborhoods, respectively. Following Koster and Thisse (2024), we posit that $\alpha_{CBD} > \alpha_R$, as the higher economic density near the CBD attracts high-skilled, productive workers. Then, given the fact that highly productive workers tend to work longer hours and live closer to their work location, we can associate productivity with residents rather than firms.

Next, we present two levels of neighborhood population: p_{CBD}, p_R, where based on the classic Alonso-Muth-Mill model and the fact that neighborhoods have similar size $p_{CBD} > p_R$.

As such, we replace p_i, α_i in Eq. 3 with neighborhood-specific variables, resulting in two distinct wage levels: W_{CBD}, W_R. However, in contrast to Brueckner's specification of budget constraint (Eq.2), here $W(p_i, \alpha_i)$ also capitalizes the commuting cost to CBD. That is,

$$W(p_i, \alpha_i) = r_i q_i + e_i + t x_i \tag{4}$$

where t is the marginal commuting cost per unit of distance. We assume that for central-area residents $x_{CBD} = 0$. As such, for commuters residing in the neighborhoods 3 and 4, the wage differs from that of the central-area residents by the amount of commuting cost, such that W_{RC}=$W_{CBD} - tx$. However, this also holds for locally employed residents of these neighborhoods. By differentiating Eq. 2 with respect to distance to the CBD and assuming that e_i is independent of distance, we obtain: $\frac{\partial W(p,\alpha)}{dx} = \frac{\partial r}{dx} = -t$. This implies that wages decrease at constant rate – t as distance to CBD increases, so W_{RL}=W_{CBD} – tx. Then, we can denote wages in remote neighborhoods simply as W_R.

Lastly, in the intercity model, net utility from housing is typically determined by how individuals maximize their utility from consuming housing alongside other goods. As such, the utility is not only the function of population but also reflects a neighborhood-specific idiosyncratic taste for housing of its residents. Therefore, we keep net utility from housing unique for each neighborhood - even their populations may be equal – denoted as $H(p_i, N_i)$, or H_{N_i}. The same assumption we apply to amenities based on Koster & Thisse's conclusion that amenities serve as a key source of a neighborhood's heterogeneity. This yields the amenities value: A_{N_i}

Equilibrium Without WFH

The equilibrium condition absent WFH and migration costs requires utility to be equal across different neighborhoods:

$$A^*_{Ni} + W^*_f + H^*_{N_i} = A^*_{N_j} + W^*_g + H^*_{N_1} \tag{5}$$

Where $f, g \in [CBD, R]$. For $f, g = CBD,\ i, j = 1{,}2.$ For $f, g = R,\ i, j = 3{,}4$

Example I: N1 vs N3

In N1 housing prices are high, so $H^*_{N_1}$ is low. In N3 housing prices are low, so $H^*_{N_3}$ is high. This balances the equilibrium equation:

$$A_{N1} + W_{CBD} + H_{N_1} = A_{N3} + W_R + H_{N_3} \tag{6}$$

Which leads to: $H_{N3} - H_{N1} = (A_{N1} - A_{N3}) + (W_{CBD} - W_R)$

The housing prices of N3 should be low enough as well as residents' individual preference for housing over amenities should be high enough to compensate for low real wages and lack of amenities in the neighborhood.

Example II: N1 vs N2

In both neighborhoods house prices are high and wages are high and identical (W_{CBD}). Then, modifying Eq.5 the equilibrium equation:

$$H_{N2} - H_{N1} = A_{N1} - A_{N2} \tag{7}$$

Notably, if we keep H as the function of population, then we would have $H_{N_1} = H_{N_2}$ and to satisfy the equilibrium: $A_{N1} = A_{N2}$. This would contradict the defining heterogeneity of neighborhoods. Therefore, it is crucial for our model to incorporate neighborhood-specific preferences into the net utility from housing.

Equilibrium with WFH

Now, assume WFH is possible, and all people start working from home all the time. However, insufficient time has passed for local services to adapt or for individuals to change their jobs. As such, $\tilde{A}_{N_i} = A_{N_i}$ and $\widetilde{W_{N_i}} = W_{N_i}$. Moreover, individual value of housing also stays: $V(q_i) = \widetilde{V(q_i)}$

That implies an individual can live in a certain neighborhood yet enjoy the productivity level of another neighborhood without paying commuting costs. In such case, wages must equalize across all neighborhood types:

$$W_{CBD} = W_R \tag{8}$$

Consequently, the new equilibrium under WFH is (with the wage term canceled from both sides):

$$A_{N_i} + \widetilde{H}_{Ni} = A_{N_j} + \widetilde{H}_{Nj} \tag{9}$$

where $\widetilde{H}_{N_i}$ denotes the net utility from housing in the neighborhood N_i after WFH becomes possible. The new equilibrium implies that net housing utility under WFH decreases by the wage differential between the two neighborhoods.

We now derive the new net housing utility values for pairs of neighborhoods located at different distances from the CBD. Neighborhood pairs situated at equal distances are excluded from the analysis, as their wage levels were already equal in the pre-WFH equilibrium.

Proposition I. New Equilibrium between N1 and N4 under WFH

Assume that neighborhoods *N1* and *N4* provide the same level of amenities ($A_{N1} = A_{N4}$) but differ in their distance to the CBD, with *N1* being closer. Then, when WFH becomes possible, net housing utility equalizes:

$$H^*_{N1} < \widetilde{H}_{N1} = \widetilde{H}_{N4} < H^*_{N4} \tag{10}$$

Since we don't assume WFH alters individual housing preferences, the equalization of net housing utility between *N1* and *N4* must result from population reallocation. Eq. 10 implies a net migration from *N1* to *N4* in the new equilibrium. As people migrate, rental prices fall in *N1* and increase in *N4*: $r^*_{N1} > \widetilde{r_{N1}}$ and $r^*_{N4} < \widetilde{r_{N4}}$

Proposition II. New Equilibrium between N2 and N4 under WFH

Assume that N4 has higher amenities ($A_{N2} < A_{N4}$) but lower productivity ($\alpha_{N2} > \alpha_{N4}$). Pre-WFH amenity advantage of *N4* is offset by its lower productivity and hence lower wages. After enabling WFH, productivity differences disappear, i.e., $\alpha_{N2} = \alpha_{N4}$ and difference in housing utility is purely explained by amenities differential:

$$\widetilde{H}_{N4} - \widetilde{H}_{N2} = A_{N2} - A_{N4} < 0 \tag{11}$$

Eq. 11 implies that increase in net housing utility in *N2* is even more significant than in *N1.* Then, out-migration from *N2* and the corresponding decline in housing prices is faster than that in the high amenity neighborhood.

Proposition III. New Equilibrium between N1 and N3 under WFH

Assume that *N1* has higher amenities ($A_{N1} > A_{N3}$) but lower productivity ($\alpha_{N1} > \alpha_{N3}$). Then, even that WFH equalizes productivity, i.e., $\alpha_{N1} = \alpha_{N3}$ *N1* still keeps the amenity advantage.

$$\widetilde{H}_{N3} - \widetilde{H}_{N1} = A_{N1} - A_{N3} > 0 \tag{12}$$

Then, the resident's movement from *N1* to *N3* is assumed but in smaller rate than between *N1* and *N4*.

Proposition IV. New Equilibrium between N2 and N3 under WFH

Assume that N2 and N3 has the same level of amenities ($A_{N2} = A_{N3}$) but *N3* is located further from CBD and then is lower in productivity ($\alpha_{N2} > \alpha_{N3}$). Then, the new equilibrium equalizes net housing utility between *N3* and *N2*:

$$H^*_{N2} < \widetilde{H}_{N2} = \widetilde{H}_{N3} < H^*_{N3} \tag{13}$$

If Eq.13 holds, population should be evenly distributed between *N2* and *N3*. This implies residents' migration from *N2* to *N3* until the housing prices converge, i.e., $r_{N2} = r_{N3}$.

Summary of Propositions

Summarizing all propositions, we learn that under a WFH equilibrium—where individuals work entirely from home but maintain unchanged preferences for housing—residential relocation occurs from the central city to more affordable suburban neighborhoods. Among these, neighborhoods offering amenity advantages become particularly attractive. This reallocation of population is expected to exert upward pressure on housing prices in remote neighborhoods and downward pressure on prices in the central business district.

4. Study area

4.1 Remote and hybrid work in Israel

The choice of the Tel Aviv Metropolitan Area (TAM) as the study area is motivated by its' monocentric urban structure and its' significant potential for remote work. During the COVID-19 pandemic, Israel underwent three national lockdowns: March 19–May 4, 2020; September 18–October 18, 2020; and December 27, 2020–February 7, 2021. These lockdowns compelled many employers to adopt remote work practices. According to estimates by Zontag et al (2022), based on Labor Force Surveys by Israel's Central Bureau of Statistics, approximately 20% of all workers worked remotely during the second and third lockdowns.

In sectors dominated by highly skilled professionals, such as IT and communications, finance, and professional, scientific, and technical services, the share of remote workers reached 65–70%, aligning with similar rates observed in the U.S. and Europe. Furthermore, Zontag et al. (2022) found that individuals with longer commutes were more likely to work remotely, suggesting that distance from the workplace plays a significant role in telework adoption. Hence, we expect higher levels of remote work among residents located further from their work locations.

A study by the Bank of Israel found that while telework declined after pandemic restrictions were lifted, it did not disappear (BOI 2022). By late 2021, around 15% of workers continued working from home several days per week. Notably, most of these workers chose to work from home rather than from other locations. This trend may be linked to the high rate of home internet access – over 91% among working-age, non-religious Jews in 2020 (CBS, 2023).

Although, no comprehensive national studies have tracked WFH trends in Israel beyond 2022, official statistics suggest that hybrid work arrangements have persisted, particularly in The Tel Aviv Metropolitan Area (TAM).

Anecdotal evidence of a shift toward a new urban spatial equilibrium can be seen in migration patterns. According to our analysis of annual migration reports of Central Bureau of Statistics (2024), after the Covid-19 pandemic, Tel Aviv Municipality experienced the most significant population loss since 2011 (Fig. 1). While the Tel Aviv Municipality experienced a positive net migration of around 3% between 2018 and 2019, this trend reversed sharply during 2020–2022, with the in-out migration ratio dropping to –25%. A more detailed analysis indicates that the decline was largely driven by the out-migration of young families, with the steepest decreases occurring in the 30–44 age group and among children aged 0–4.

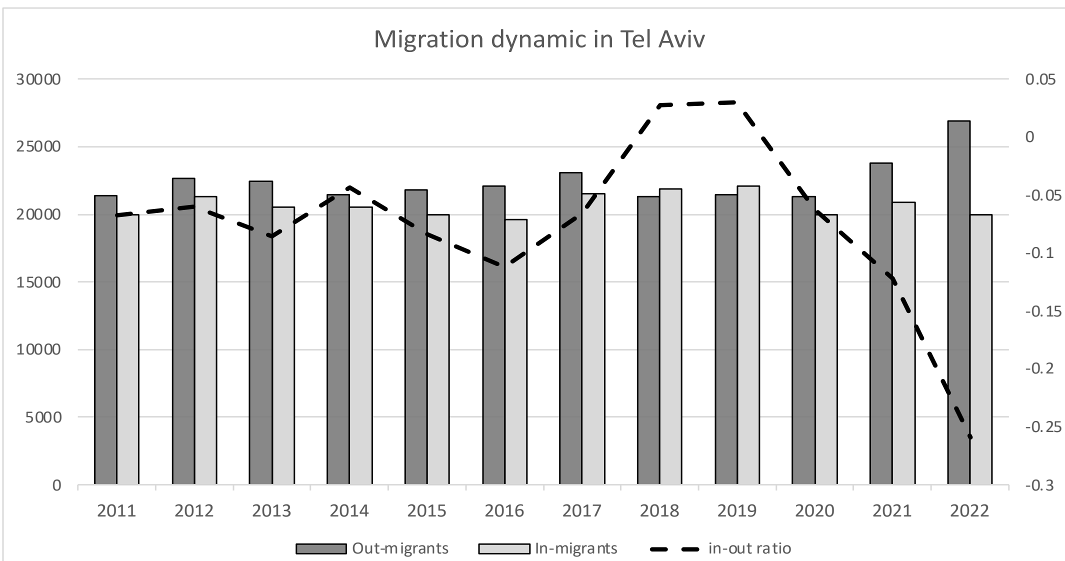

Fig. 1Migration dynamics in the Tel Aviv Municipality

4.2 The Structure of the Tel Aviv Metropolitan Area

The TAM exhibits a monocentric urban structure similar to that of major European cities, which also report remote work rates of approximately 20%. We identify evidence of the TAM's monocentricity through the analysis of three distinct sources.

First, to validate Tel Aviv's monocentricity, we use data from a 2018–2019 cellular-based travel survey conducted by the Israeli Ministry of Transport. This survey tracked daily travel patterns via mobile phone data from major telecom providers (Pelephone and Cellcom), covering approximately 40% of the population—about 3.7 million individuals. Based on the analysis of weekday morning trips in 1270 transport zones in the area we find a clear pattern: commuting distance increases with the distance from central Tel Aviv. In Fig.2, the zones with the lightest commuter outflows are represented by Tel Aviv and its neighboring cities: Ramat Gan, Herzliya, and Petah Tikva that contain the highest concentration of workplaces.

Another factor that makes TAM a good case study for remote work is its high share of employees in sectors well-suited to telecommuting, particularly information and communication technologies (ICT) and finance. According to surveys conducted by the Central Bureau of Statistics, these sectors account for 24.2% of total employment in the region(CBS, 2023). Having established the TAM potential for remote work, we proceed to quantify it and measure its impact using mobile GPS signals.

4.3 Statistical Areas of Israel Central Bureau of Statistics

As the research focuses on spatial heterogeneity, all spatial units presented are aggregated at the level of Israel's Statistical Areas (SAs), defined by the Central Bureau of Statistics. These units offer the finest spatial resolution available for socioeconomic and demographic analysis in Israel. Within the boundaries of the TAM, there are a total of 1,223 residential and 101 commercial or institutional SAs. The average estimated population per residential SA in TAM is approximately 3,137 residents.

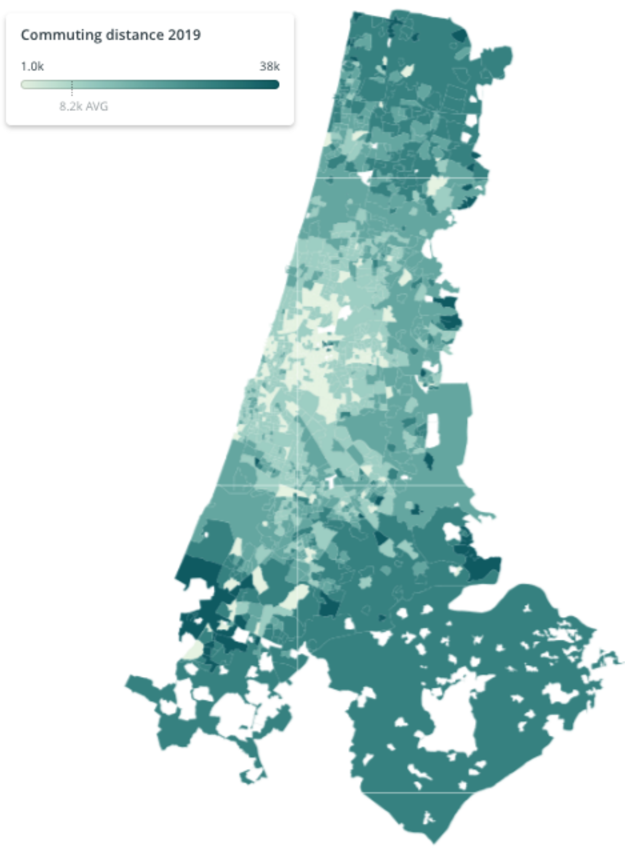

Fig. 2 Outbound Commuting Distances in the TAM (2019)

5. Data

5.1 Mobile signals Data

Empirical testing of the model requires a method for measuring the dynamics of remote work at the neighborhood level before and after the Covid-19 pandemic. To this end, we use a unique dataset of mobile GPS signals collected between January 2019 and December 2023 by a commercial data analytics company Habidatum with coverage of all Israel. For the purpose of the study, we consider only the period until the end of September 2023 as the surge of rocket attacks from Gaza in October 2023 also forced people to work from home, thus distorting the impact of WFH on actual presence at home.

The original dataset includes approximately 400 million anonymized geo-located signal clusters, representing the activity of about 310,000 unique users each month. Each row presents information relating to type of platform (IOS/Android), the beginning and end of the individual's stay, coordinates and number of signals during the stay. An illustration of the original dataset with relevant features is provided in Table 1.

Table 1 . An illustration of the original dataset

Identifier	Identifier type	Timestamp	Local date time	Duration seconds	Centroid latitude	Centroid longitude	Bump count
001b3***115	GAID	01/01/2020 18:27:10	01/01/2020 20:27:10	12036	31.7969337	34.70179411	14
0050c***f20	IDFA	01/01/2020 18:19:06	01/01/2020 20:19:06	11218	31.8041044	34.76149723	19

Data preparation comprises several steps aiming at retaining only users whose records demonstrate high accuracy and consistent stay patterns. We filter the data in the following way to ensure reliable WFH estimations:

1. Remove occasional stops by filtering out stays with a duration of less than 3 minutes and those located outside TAM
2. Remove users with total frequency < 4 stays, frequency of night hours<2 and frequency of work hours<2
3. Remove months with unique users after filtering <50,000 but keep all months with Covid-19 restrictions. We empirically identify the 50,000 threshold by analyzing user distribution across statistical areas and ensuring a minimum of three users per area.

After applying the filters, we arrive at an average of 160,000 unique users per month which represents 4% of TAM population (Fig.3). We limit the period of analysis and start from 01/2020 as in 2019 the dataset has an insufficient number of users. We exclude the following months due to data limitations: December 2020, December 2022, July 2023, and August 2023. The lack of signals in the listed months is primarily attributed to technical configurations on the side of the data provider. Although we do not have direct explanation from the provider, previous studies using similar datasets have observed comparable drops in signal volume during lockdown periods (Z. Li et al., 2024). They explained these declines by the tendency of individuals to disable location sharing in response to government-imposed mobility restrictions.

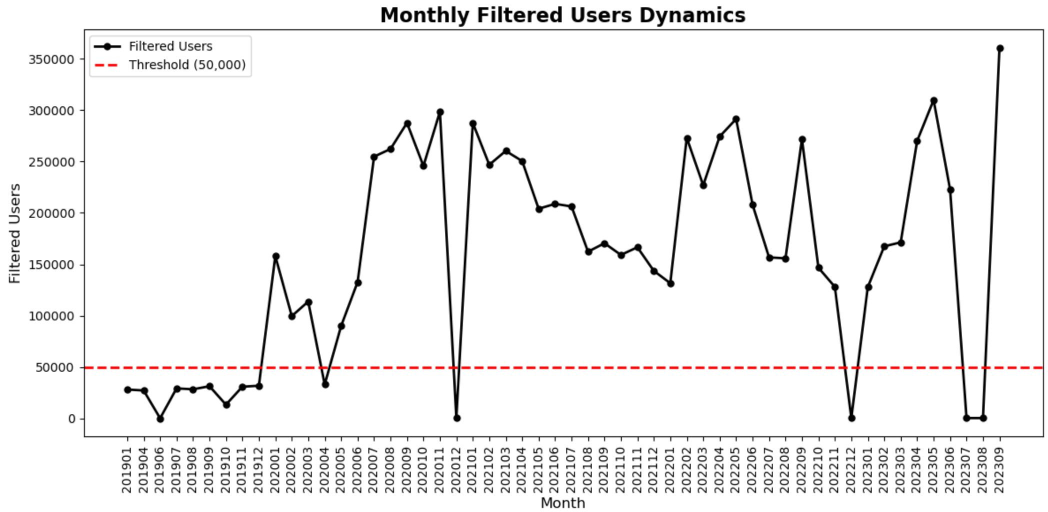

Fig. 3 Monthly volumes of users in mobility dataset

5.2 Rental Price Data

One of the key components required to estimate the impact of remote work on urban equilibrium is rental prices. This study relies on rental listings provided by the Israel Central Bureau of Statistics (CBS). Each listing includes detailed information about the rental unit, such as the asking price, unit size, and geographic location. The dataset contains approximately 1.8 million listings from Q1 2015 to Q4 2024, with 53% of them located in the TAM. Rental prices increased from 56 NIS per square meter in Q1 2015 to 70.6 NIS in Q4 2024, reaching a peak of 72.5 NIS in Q1 2023 (Fig.4). This reflects an overall price growth of 26.2%.

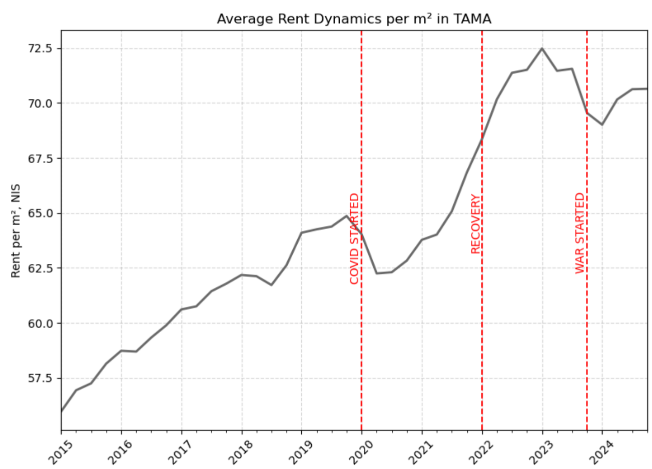

Fig. 4 Rental price dynamic in TAM

The dynamics of the rental price gradient (Fig. 5) reveal patterns consistent with previous research. Following the COVID-19 outbreak, the previously declining gradient trend—reflecting increasing price differences between central and peripheral areas—began to flatten in 2021–2022 and later shifted upward. This shift reflects a relative acceleration of rent growth in peripheral neighborhoods, leading to a shrinking gap between central and outlying areas. Temporary slowdowns occurred in mid-2021 and early 2023. Overall, these trends support our hypothesis that remote work has increased rental demand in more distant neighborhoods.

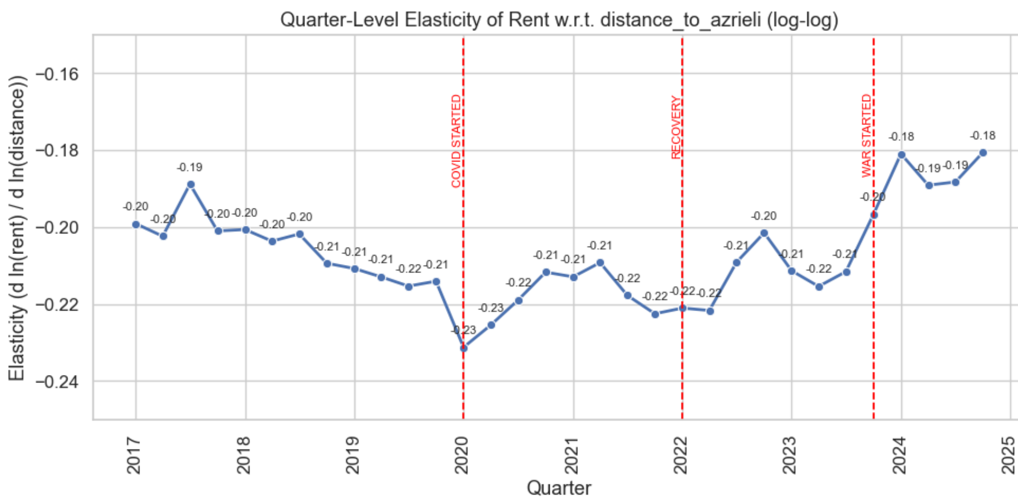

Fig. 5 The dynamics of the rental price per m^2 gradient 2017-2024

5.3 Other sources

Other datasets are used to validate the estimation of WFH and build the data for the panel regression estimation, are presented in Table 2.

Table 2. Data sources

Num	Dataset	Source of data	Variables	Unit
1	Israel Census 2022	Israel Central Bureau of Statistics	Demographic features	Statistical area
2	GIS layer of buildings	MAPI (Survey of Israel)	Building use	Building
3	Employment zones	Israel Open data portal	Number of employers	Employment zone
4	Geography of POIs and public spaces	Open Street Map	POI’s category	POI

6. The Empirical strategy

6.1 Remote work estimations

This study employs two complementary approaches to estimating remote work at the statistical area (SA) level:

- Area-based estimation: measures the change in the difference between daytime and evening signal volumes during workdays across statistical areas.
- Individual-based estimation: tracks the percentage of work hours at home at the user level over time.

The area-based approach offers broader representativeness and enables validation across months and spatial units. The individual-based approach provides higher precision and allows for tracking user-level behavioral changes and profiling remote work patterns.

We expect the aggregated results by statistical area to show consistent temporal and spatial correlations.

Area-based estimation of remote work

In the first approach to estimating remote work dynamics, we construct a normalized indicator (Eq.14) by comparing mobile signal density during weekday daytime and evening hours across 2022 Census statistical areas. To ensure comparability, we apply two adjustments. First, we define equal-length time windows for both day and evening periods, each spanning exactly five hours. Second, we weight evening signals so that the total number of signals in the TAM area remains constant between day and evening. This adjustment assumes that all workers reside within TAM and that all TAM residents work there.

$$I = \frac{day\ signals - evening\ signals}{day\ signals + evening\ signals} \tag{14}$$

Under normal conditions, we expect the indicator I to be negative in residential areas, positive in commercial areas, and near zero in mixed-use zones. Remote work, however, shifts daytime activity from commercial to residential areas which is widely confirmed in previous research (Biagetti et al., 2024; Ramani & Bloom, 2021), driving I toward zero across all area types—particularly during lockdowns. We use this convergence as additional validation of the representativeness of the mobile data. In the post–COVID-19 period, the dynamic trajectory of I reveals the pace and extent of recovery in different neighborhoods: increasing I in commercial zones signals a return to office-based work, while persistently low or decreasing I in residential areas indicates the continued presence of remote work.

Individual-based estimation of remote work

This estimation of remote work consists of 2 steps: the identification of individuals' home and work locations and the estimation of the share of an individual's work days spent at home. Calculations are done at the monthly level. The full workflow is presented in Fig.6.

Home and work locations

In the study the identification of home and work location incorporates a deterministic approach. This is popular for home-work detection based on mobile data (Kung et al., 2014). Home locations are characterized by an individual's stays frequency during night hours (10 PM to 7 AM) and Saturdays. The minimum required frequency is set to two times during night hours and one time during Saturdays. Work locations are defined as the most frequent locations located outside the home neighborhood where signals are recorded only during workdays (from Sunday till Thursday excluding national holidays and weekends).

The validation of detected home and work locations relies on publicly available data sources, including the Israel Census 2022, employment zones, and the GIS layer of buildings. Home locations are aggregated by CBS statistical areas and compared with Census data using the Pearson correlation, while work locations are validated against declared employment figures within Israel's designated work zones, also using the Pearson correlation. Additionally, each home location is linked to a specific building, and the proportion of identified home locations situated in commercial buildings is calculated as an accuracy measure. Lastly, each geohash is labeled as either a home or a work location based on the dominant category of detected points. The results are then intersected with official work zones to measure classification accuracy, including the evaluation of Type I and Type II errors.

Before estimating an individual's remote work hours, we first define their typical hourly activity pattern based on *office days*. An *office day* is defined as a day when at least one signal is detected at the individual's work location, while a *working day* refers to a weekday that is not a weekend or public holiday. Estimating these probabilities is necessary for two main reasons: (1) signal distribution across hours and users is not uniform, meaning that for some users, signals may be observed only during specific times of day, which can bias remote work estimations; (2) individuals may follow different work hour schedules, which vary significantly across the population.

Therefore, for each hour between 8 AM and 7 PM, we estimate the probability that an individual is at one of three types of locations: home, work, or a third place—based on statistics derived from office days. The methodology is identical for all location types; however, we illustrate it here using the example of the work location. To compute these probabilities, we apply Bayesian conditional probability. Specifically, for each hour h on *office days* we estimate the probability of being at that work location as follows:

$$P_i(W|h) = P_i(W) * P_i(h|W)/P_i(h) \quad (15)$$

Where $P_i(W)$ denotes an individual's share of office location hours in a working day during the month, $P_i(h)$ denotes an individual's share of exact hours on *office days*, $P_i(h|W)$ is the individual's share of exact hour at an office location on *office days*. Similarly, we calculate an individual's conditional probability of being at home $P_i(H|h)$ or a third place $P_i(A|h)$ at specific hour of days with signals from work location.

Then, *Work hour flag:*

$$WH = \begin{Bmatrix} 1, \ P_i(W|h) > P_i(H|h) \ \ and \ \ P_i(W|h) > P_i(A|h) \\ 0, otherwise \end{Bmatrix} \ ;$$

Workhours day flag:

$$WHD = \begin{Bmatrix} 1, \sum WH > 0 \\ 0, otherwise \end{Bmatrix} \ ;$$

Remote work hour flag:

$$RWH = \begin{Bmatrix} 1, WH = 1 \ and \ OD = 0 \ and \ HL = 1 \\ 0, otherwise \end{Bmatrix}$$

Where OD=1 indicates an *office day* and HL = 1 indicates that the individual's actual location is at home.

In order to avoid giving high weights to non-typical office hours (e.g. late evening), the *Remote work hour flag* is weighted using a general monthly probability:

$$RWH\_weighted = RWH * 1/n \sum P(W|h)$$

where n is number of users in specific month.

The days where an individual has at least one weighted remote work hour higher than 50%, are called remote work days (RWD). The monthly remote work level for a neighborhood is defined as:

$$Remote\ Work\ level \ = avg(\frac{\sum(1_{RWD})}{\sum(1_{WHD})} \tag{16}$$

As the final target is to provide numbers by statistical area, the remote work level is averaged across users whose home location falls within that statistical area. The accuracy of estimations is validated by correlating the monthly dynamics of the TAM $Remote\ Work\ level$ with the monthly share of remote work hours from Labor Force Surveys conducted by Israel Central Bureau of Statistics.

A limitation of this approach is the difficulty in capturing work activity occurring in ‘third places’ i.e. places that are not predominantly home or work locations. The accuracy of GPS signals is often insufficient to unambiguously link a user's location to a specific point of interest (POI), particularly in urban settings where many POIs are located within mixed-use buildings. This spatial ambiguity complicates the identification of remote work sites beyond home or office.

Fig. 6 Remote work estimation process

6.2 Classifying neighborhoods

Additionally, following the theoretical model, each statistical zone is classified into one of four neighborhood types: CBD (N1), central residential neighborhood (N2), remote residential neighborhood (N3), remote neighborhood with high amenities (N4). The classification is based on a plot comparing amenity accessibility within a 1 km buffer around each statistical area to its distance from the Azrieli commercial center (Fig. 7). Both variables were standardized by subtracting the median and dividing by the standard deviation to ensure comparability. For this study, we apply Brueckner's (1999) definition of amenities, focusing on two categories: *natural amenities* (parks and sea beaches) and *modern amenities* which include cafés, restaurants, shops, schools, and hospitals. We don't include *historical amenities* in the analysis, as the study area lacks a significant historical heritage.

Neighborhoods with a positive scaled distance (y-axis) are classified as remote areas or satellite cities, while those with a negative value are considered part of the central area. The x-axis represents amenities, where negative values indicate low accessibility to amenities and positive values indicate high accessibility to amenities.

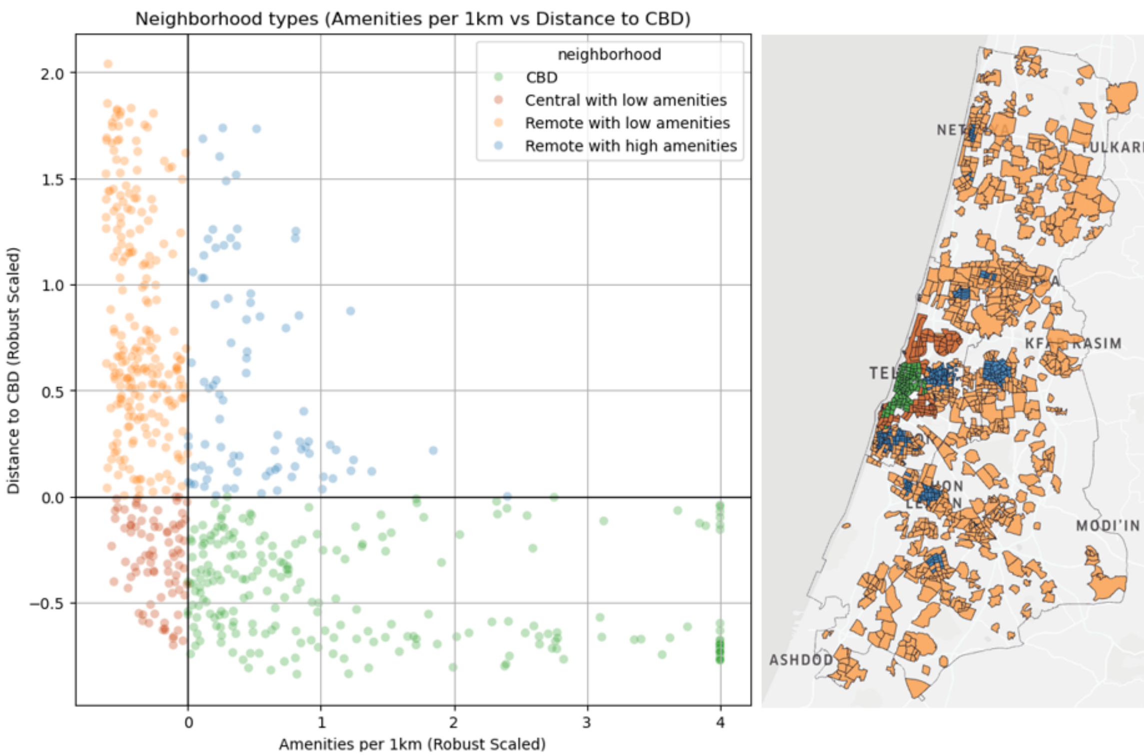

Fig. 7 Neighborhoods Types distribution

6.3 Panel data description

Based on the collected data, we construct a balanced panel that includes only Statistical Areas (SAs) within the TAM where both rental listings and home location estimations from GPS signal data are available for every quarter between Q1 2020 to Q3 2023 ("examined period"). To estimate remote work levels, we use individual-level WFH indicators, which are then averaged by SA according to users' inferred home locations. To convert monthly WFH estimates into quarterly values, we select the month within each quarter that contains the highest average number of users per SA, ensuring consistency and data quality. The final panel covers 15 quarters, 620 SAs, and comprises a total of 9,300 observations.

The neighborhoods are categorized into four types: 44 CBD neighborhoods (N1), 457 residential neighborhoods with low amenities with 60 in Tel Aviv (N2) and 397 outside (N3), and 119 satellite city centers (N4). Fig. 8 presents the average asking rent per square meter by quarter and neighborhood type. The average asking rent per square meter across neighborhoods in the balanced panel ranged from ₪27 to ₪158 over the examined period.

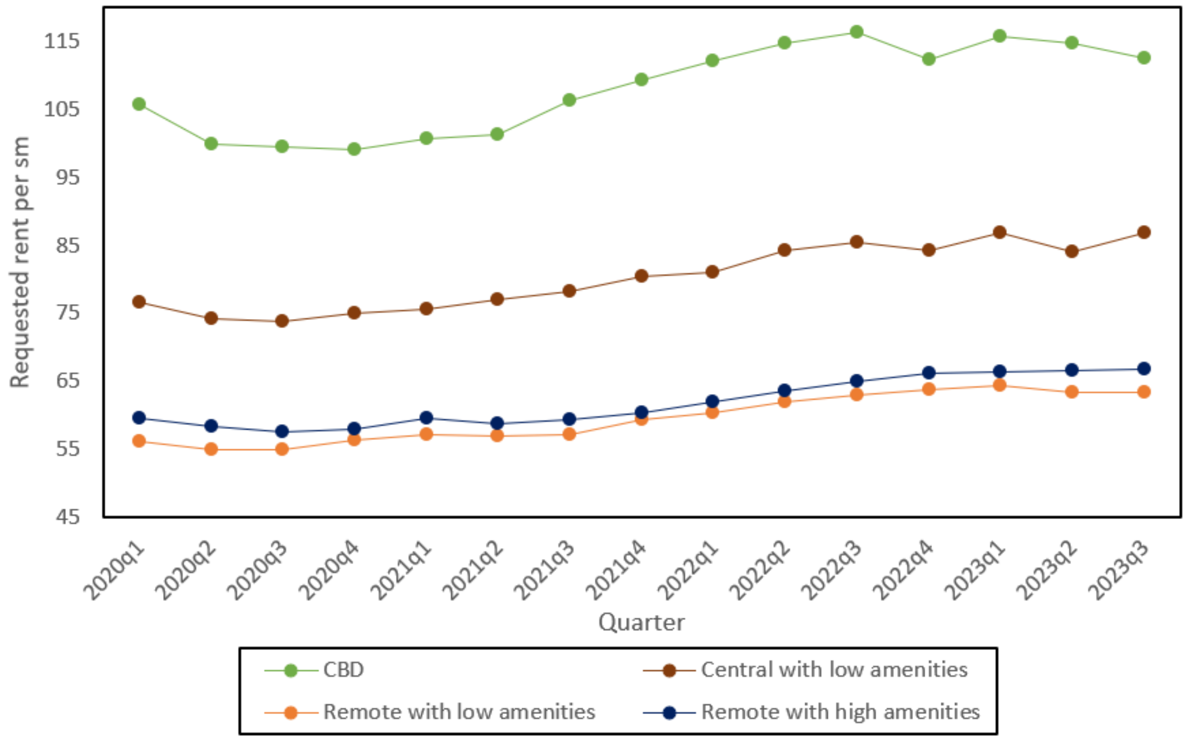

Fig. 8 Rental prices dynamics in 4 groups of neighborhoods

6.4 Empirical testing of WFH impact on rental prices

Following the theoretical model, the goal of the empirical study is to examine how the opportunity to work from home influences the urban equilibrium. Following Ramani and Bloom (2022) and Bruckner et al (2023) we estimate this by measuring the impact of WFH on rental prices across the TAM. Specifically, we specify four equations:

- *Equation (17):* Assesses the direct effect of WFH on rental prices relative to neighborhood distance from the CBD and relative to local accessibility of services.
- *Equation (18):* Based on the empirical methodology proposed in Bruckner (2023) equation 7. That is, an integration of three variables: the share of WFH, a binary indicator for whether the neighborhood's level of amenities is above the median, and the number of amenities as a continuous variable. Accordingly, in the same equation, there will be an integration of three variables with respect to the distance from the CBD—namely, the share of WFH, a binary indicator for whether the neighborhood is located closer than the median distance to the CBD, and the actual distance as a continuous variable.

- *Equation (19):* Examines the differential impact of WFH across neighborhood types, which incorporates both distance and accessibility dimensions.
- *Equation (20):* An Event Study estimation is conducted in which the treatment group is defined as neighborhoods of the fourth type: remote neighborhoods with a high level of amenities. We assume that these neighborhoods, in line with the prediction of the theoretical model, will experience a greater inflow of population and, consequently, an increase in rental prices. This effect will be examined in comparison to all other neighborhood types, which serve as the control group.

Given our assumption that households adjust to changes in work patterns with some lag, our estimation incorporates an interaction term using the log of the previous quarter's WFH rate. Although a longer lag (e.g., two quarters) would be desirable, data constraints and sample size considerations favor a one-quarter lag. Additionally, since many rental agreements in Israel allow for termination every three months, it is reasonable to assume that relocation decisions are often made within that timeframe.

Equation (17) integrates two interaction mechanisms to account for potential heterogeneity in the effect of WFH across urban geography. Specifically, we interact the lagged WFH rate with both the distance to the CBD and the accessibility of amenities. The full specification is as follows:

Equation (17) is specified as follows:

$$R_{n,q} = \alpha + \beta \sum_{i=0}^{k} \mathrm{WFH}_{n,q-i} + \delta_1(\mathrm{WFH}_{n,q-1} \times \mathrm{CBDdis}_n) + \delta_2(\mathrm{WFH}_{n,q-1} \times \mathrm{A}_n) + \gamma \sum_{i=1}^{k} \mathrm{R}_{n,q-i} + \tau_q + \varepsilon_{n,q} \qquad (17)$$

Where $\mathrm{R}_{n,q}$ denotes the log asking rent per square meter in neighborhood *n* during quarter q, $\mathrm{WFH}_{n,q-i}$ is the lagged WFH rate, $CBDdis_n$ is the distance to the CBD, A_n captures the density of local amenities per square kilometer, τ_q is quarter fixed effects, and $\varepsilon_{n,q}$ is the error term.

We expect both interaction terms to reveal meaningful spatial variation in the rental price response to WFH. A negative and statistically significant δ_1 would suggest that the rental impact of WFH increases with distance to the CBD, consistent with the hypothesis that WFH enables households to relocate to peripheral areas. Similarly, a negative and statistically significant δ_2 would imply that higher accessibility to local amenities amplifies the effect of WFH on rental prices, indicating that remote workers may still place value on urban-like conveniences when choosing residential locations.

Equation (18) is based on the empirical methodology proposed in Bruckner (2023), as follows:

$$R_{n,q} = \alpha + \beta \sum_{i=0}^{k} \mathrm{WFH}_{n,q-i} + \delta_1(\mathrm{WFH}_{n,q-1} \times \mathrm{HighA} \times \mathrm{A}_n) + \delta_1(\mathrm{WFH}_{n,q-1} \times \mathrm{CloseCBD} \times \mathrm{CBDdis}_n) + \gamma \sum_{i=1}^{k} \mathrm{R}_{n,q-i} + \tau_q + \varepsilon_{n,q} \qquad (18)$$

The innovation in this specification lies in the inclusion of two additional interaction terms: one with a dummy variable equal to 1 if the neighborhood's amenity level is above the sample median, HighA, and another with a dummy variable equal to 1 if the neighborhood's distance to the CBD is below the sample median, CloseCBD.

Equation (19) introduces a vector of neighborhood-type dummy variables Type_n^j to evaluate heterogeneity in the WFH effect:

$$R_{n,q} = \alpha + \beta \sum_{i=0}^{k} \mathrm{WFH}_{n,q-i} + \delta(\mathrm{WFH}_{n,q-1} \times \sum_{j=2}^{4} \mathrm{Type}_n^j) + \gamma \sum_{i=1}^{k} \mathrm{R}_{n,q-i} + \eta_n + \tau_q + \varepsilon_{n,q} \quad (19)$$

Here, η_n and τ_q are neighborhood and quarter fixed effects, respectively. The base group in this regression is CBD neighborhoods (Type I), so we expect positive coefficients for neighborhoods located in satellite cities (Type III & IV), and negative for central residential neighborhoods (Type II). All regressions cluster standard errors by neighborhood type.

Since our theoretical prediction suggests that the neighborhoods most positively affected by the option to WFH are those that are both remote and characterized by a high level of amenities, we examine the impact on these neighborhoods using an *Event Study* framework. Specifically, we define an interaction variable between a dummy variable—equal to 1 if neighborhood *n* belongs to the group of *remote neighborhoods with high amenity levels*—and a set of quarter indicators.

We exclude the last quarter of 2019—the final quarter before the outbreak of the COVID-19 pandemic—from the regression, allowing it to serve as the benchmark period for estimation. The regression specification includes neighborhood and quarter fixed effects, as presented below:

$$R_{n,q} = \alpha + \gamma^q \sum_{\substack{q=18q1 \\ q\neq -19q4}}^{23q3} Q_q * RH_n + Ad_{n,q} + \eta_n + \tau_q + \varepsilon_{n,q} \quad (20)$$

The variable *RH* is equal to 1 if the neighborhood belongs to the group of remote neighborhoods with high levels of amenities. In order for the parallel trends assumption to hold, we require that the estimated coefficients γ for the quarters prior to the last quarter of 2019 are statistically insignificant. Conversely, we expect the post-treatment (from 2020) γ coefficients to be positive and statistically significant. Such a pattern would indicate that the option to WFH had a positive effect on rental prices in this group of neighborhoods, relative to other neighborhoods.

7. Results

7.1 Results of area-based remote work estimation

The analysis of mobile signal dynamics reveals the clear presence of remote work in the TAM starting in April 2020. The most significant drop in signals during work hours in the central area is observed in September 2020, during the second lockdown (Fig. 9).

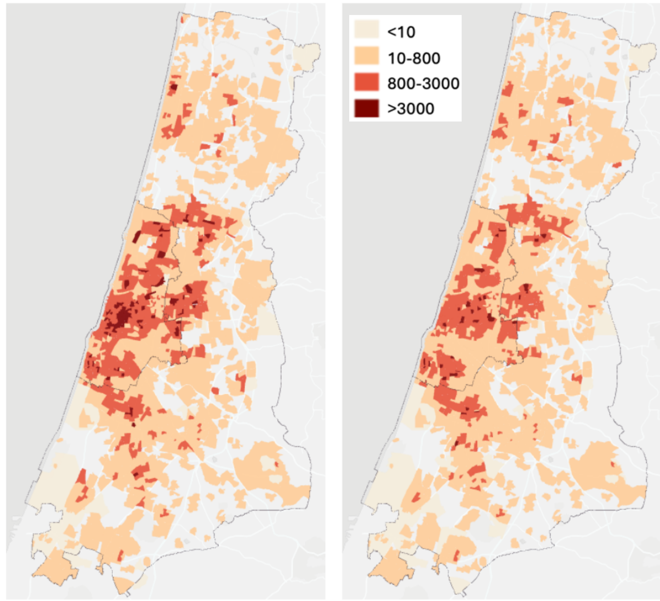

Fig. 9 Mobile signals during work hours in 01/2020 (left) and 09/2020 (right)

In addition, we study changes in the day-to-evening ratio independently for residential and commercial zones. To distinguish between these two areas, we use the sign of the day-to-evening signal ratio from January 2020, rather than relying on Census classifications. Within the residential category, we only focused on areas where, according to the 2022 Census, more than 50% of residents work outside their home. As expected, the indicator moves in opposite directions for commercial (*Fig. 10)* and residential zones (*Fig. 11)*, showing a significant decline in signals in commercial zones and raise in residential ones during the second lockdown in September 2020. Notably, none of these areas return to their pre-pandemic levels—each remains below the baseline of January 2020. Overall, this confirms the ability of mobile signals data to reflect WFH dynamics.

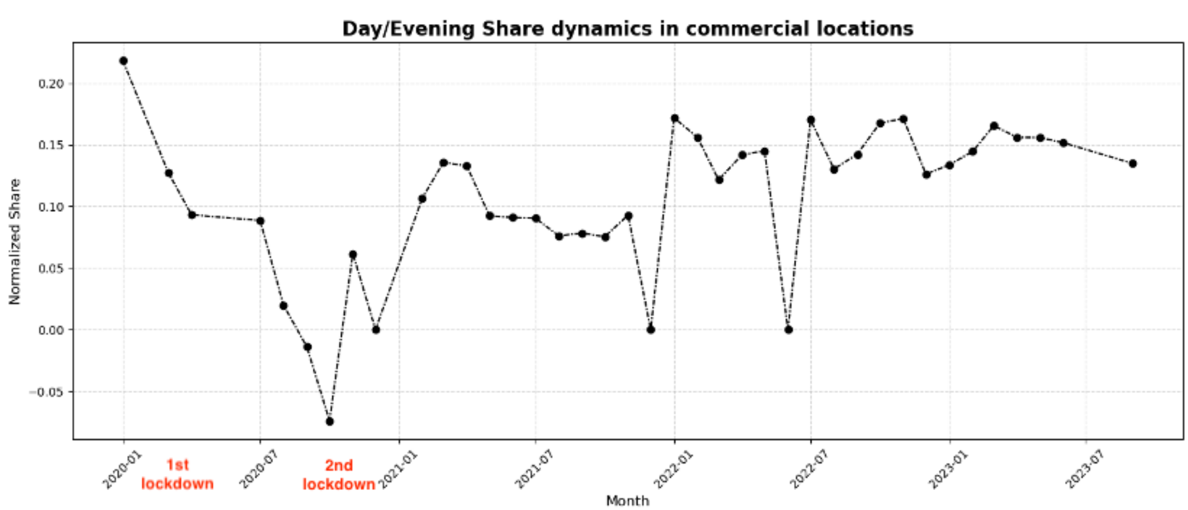

Fig. 10 Day/evening signals ratio dynamic in commercial locations

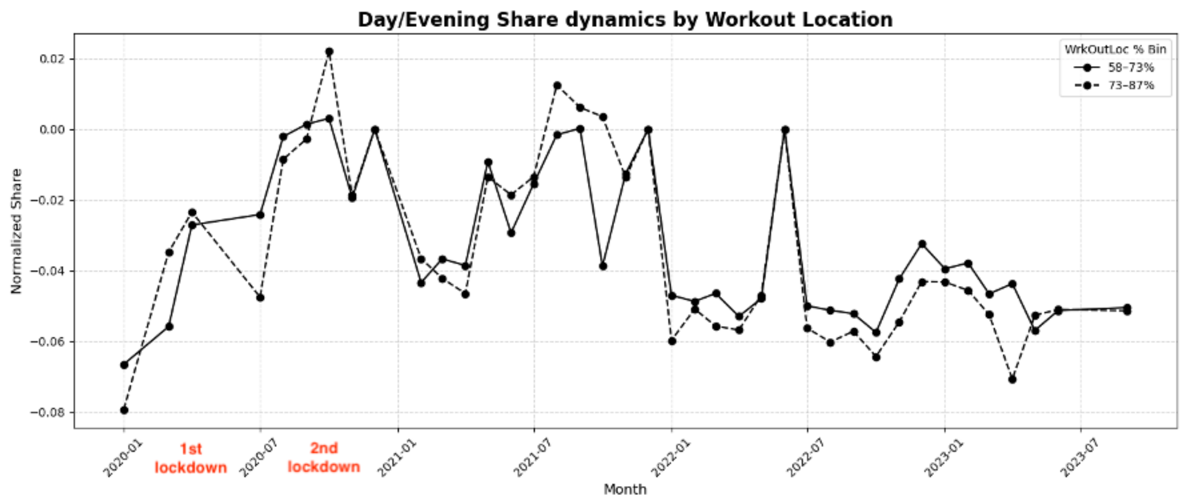

Fig. 11 Day/evening signals ratio dynamic in residential locations with more than 50% of employers working outside their residence location

7.2 Results of individual-based remote work estimations

The validation results for the estimated home and work locations, based on GPS-signal data and compared with the official datasets described in Section 6.2, are presented in Table 3. The table demonstrates a high level of accuracy in identifying both home and work locations.

The estimated number of home locations per CBS statistical area shows a moderate positive Pearson correlation with population counts from the 2022 Israel Population Census (ρ=0.57) at the statistical area level and a high correlation at the municipality level (ρ=0.9). The moderate correlation at the statistical area level is largely explained by low smartphone penetration and the complete non-use of smartphones on Saturdays in religious neighborhoods. When these areas are excluded from the analysis, the correlation increases to ρ =0.68. Moreover, only 2.3% of estimated home locations were identified in commercial buildings, indicating high spatial accuracy.

Similarly, the estimated number of work locations is strongly correlated with the number of declared employers in designated work zones (ρ=0.91). At the geohash level, classification accuracy reached 96%.

Table 3. Validation results for detected home and work locations

Validated measure	Validation source	ρ (Pearson)	Accuracy (%)	Spatial unit
Home locations vs. Census population	2022 Israel Population Census	0.57	-	Statistical area
Home locations vs. Census population	2022 Israel Population Census	0.9	-	Municipality
Home locations in residential buildings	GIS building layer	-	97.7%	Building
Work locations vs. declared employers in work zones	CBS official employment register	0.91	-	Employment zones

Geohash classification (home/work)	Intersection with official work zones	-	96%	Geohash

Remote work estimates for the Tel Aviv Metropolitan Area align closely with data from the Central Bureau of Statistics (CBS) on average weekly work-from-home hours. A sharp increase in remote work share to 35% is observed between March and November 2020, followed by stabilization at approximately 23% from 2021 to 2023, with noticeable dips during vacation months (Fig.12).

Occupational differences in remote work adoption, as identified in prior research (Zontag et al, 2022), are also evident in our findings. Neighborhoods where workers in the top three WFH-suitable occupations account for less than 10% of the workforce consistently show a 6 ppt lower remote work share compared to neighborhoods with a high concentration of such workers (Fig.12). Furthermore, while low-skilled neighborhoods largely return to pre-COVID levels in terms of days spent at home, high-skilled neighborhoods (with more than 30% of high-skilled workers) maintain a 9 ppt increase in work-from-home days through September 2023 compared to January 2020.

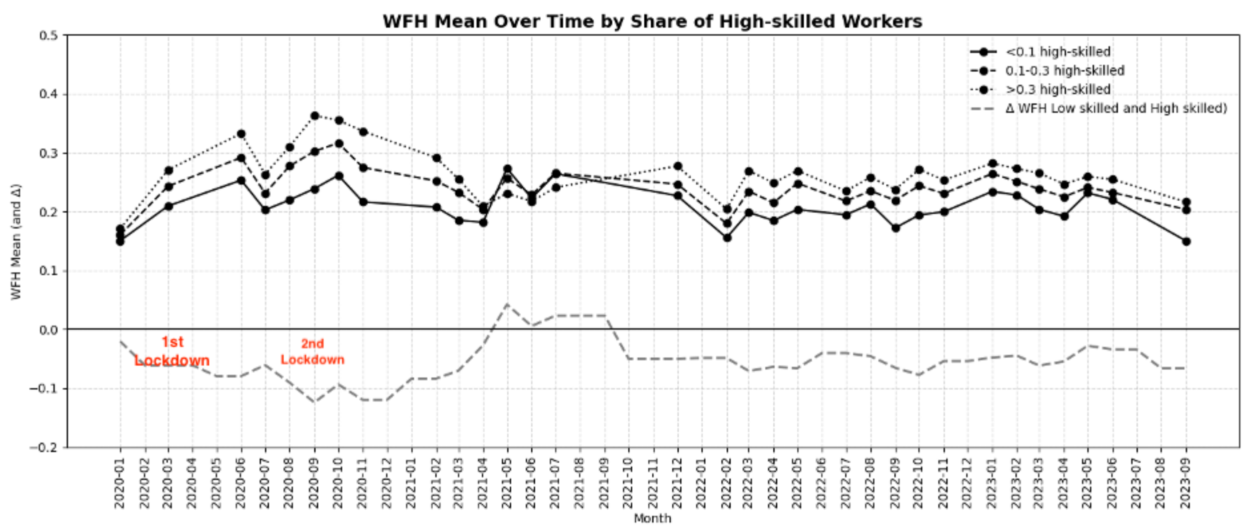

Fig. 12 WFH dynamics by share of high-skilled workers

7.3 Result of empirical testing of WFH impact on rental prices

This section presents the empirical results of the dynamic panel estimations conducted to examine the effect of remote work on residential rent prices. The models incorporate lagged variables at the quarterly level, allowing us to capture not only contemporaneous effects but also delayed responses in the housing market. The estimations control for fixed effects where applicable (time fixed effect in equations 17-18, time and SA (statistical area) fixed effects in equations 19-20).

The results are presented across three tables, each focusing on a different dimension of the housing market's spatial structure. Table 4 examines the interactions between WFH rate and distance from the CBD, WFH rate and degree of local amenities; Table 5 focuses on the methodology based on Bruckner (2023); Table 6 introduces neighborhood types based on both distance and degree of amenities, capturing heterogeneous effects across urban, and suburban areas.

Table 4. Estimated results for Equation 17

VARIABLES	(1)	(2)	(3)	(4)
		ln (Rent per m^2)		
ln(WFH)	0.00396	0.0113***	0.0102***	-0.000545
	(0.00377)	(0.00367)	(0.00373)	(0.0248)
lag1 ln(WFH)	-0.0305	-0.0554**	-0.0582**	-0.0568**
	(0.0249)	(0.0230)	(0.0245)	(0.0273)
lag2 ln(WFH)			0.00669***	0.00656***
			(0.00211)	(0.00204)
ln_diff				0.0627
				(0.162)
ln(amenities)	-0.0165	-0.00773	-0.00744	-0.00747
	(0.0187)	(0.00484)	(0.00505)	(0.00506)
lag1 ln(WFH) × ln(amenities)	**-0.00337**	**-0.00368**	**-0.00353**	**-0.00351**
	(0.00322)	(0.00249)	(0.00262)	(0.00256)
ln(distance to CBD)	-0.191***	-0.0159	-0.0158	-0.0160
	(0.0246)	(0.0100)	(0.0102)	(0.0105)
lag1 ln(WFH) × ln distance to CBD	**0.00334**	**0.00733***	**0.00747***	**0.00730**
	(0.00313)	(0.00262)	(0.00277)	(0.00310)
lag1 ln (Rent per m^2)		0.512***	0.511***	0.511***
		(0.0216)	(0.0217)	(0.0219)
lag2 ln (Rent per m^2)		0.345***	0.345***	0.345***
		(0.0338)	(0.0337)	(0.0340)
ln(number of ads)	-0.0185***	-0.00723***	-0.00718***	-0.00720***
	(0.00198)	(0.00147)	(0.00148)	(0.00147)
Constant	5.878***	0.775**	0.786**	0.771***
	(0.262)	(0.305)	(0.306)	(0.273)
Observations	8,680	8,060	8,060	8,060
Number of Code SAs	620	620	620	620
SA FE	No	No	No	No
Time FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Empirical Findings and Interpretation; remote work, distance from the CBD and amenities.

Table 4 presents the regression estimates aimed at evaluating the relationship between remote work prevalence, spatial proximity to the CBD, the degree of local amenities, and their joint effects on residential rental prices. The results indicate that, controlling lags of rental prices and WFH rate including time fixed effects, neighborhoods located further from the CBD have experienced relatively higher rental price growth in the wake of increased remote work rates. This pattern emerges most clearly through the interaction term *lag1 ln(WFH) × ln distance to CBD* , which is central to the research hypothesis; The coefficient associated with this term ranges from 0.0033 to

0.0073, implies that, compared to other similar neighborhoods, a 1% increase in distance from the CBD and a 1% higher remote work share (in the previous quarter) is associated with an additional increase of up to 0. 0073% in rent prices.

On the other hand, it was found that, once controlling for the distance from the CBD, the degree of amenities has no statistically significant effect on rental prices. A possible explanation is the high collinearity between this variable and the distance to CBD—on average, neighborhoods located closer to the CBD also tend to have a higher level of amenities.

It is important to note that this result does not suggest that peripheral neighborhoods now have higher absolute rents than central areas. Rather, it indicates a convergence in rent levels, such that the gap between central and peripheral areas has narrowed following shifts in work patterns which we also see in Fig.5.

Beyond the central interaction, several additional patterns emerge. In Column (1), the model excludes lagged rent values. The *ln(WFH)* coefficient suggests a positive and statistically significant short-run effect, with a 1% increase in the current remote work rate associated with a rent increase of up to 0.01%. In contrast, the lagged value *lag1 ln(WFH)* is consistently negative and significant, suggesting that remote work adoption in the previous quarter is correlated with lower current rent levels, potentially reflecting delayed household mobility or market adjustment dynamics. Specifically, a 1% increase in lagged remote work is associated with a decline in rents of up to 0.06%.

The coefficient for *ln(distance to CBD)* is negative and significant in the first specification, indicating that, on average, neighborhoods located 1% farther from the center have rents approximately 0.19% lower. However, in Column (2), once rent lags of *ln (Rent per m2)* are included, the explanatory power of distance vanishes. This suggests that rental persistence absorbs much of the spatial gradient. As expected, past rents are strongly predictive of current rents, confirming price inertia in the housing market. The variable *ln(amenities)* is not statistically significant across all the specifications presented, most likely due to the high level of collinearity with the *distance to CBD* variable.

Column (3) introduces *lag2_ln_wfh*, capturing remote work prevalence two quarters prior. This variable exhibits a positive and statistically significant effect, akin to the contemporaneous coefficient and in contrast to the short-run negative lag. This outcome supports the hypothesis that households adjust their housing decisions with a lag, possibly within a typical contract renewal window of one to two quarters.

Finally, Column (4) adds *ln_diff*, measuring the deviation of a neighborhood's remote work rate from the peer-group average. The coefficient on this term is not statistically significant, suggesting no systematic premium or penalty for neighborhoods that deviate from expected remote work levels once other covariates are accounted for.

Table 5. Estimated results for Equation 18

	(1)	(2)	(3)
		ln (Rent per m2)	
VARIABLES			
ln(WFH)	0.148***	0.104	0.101
	(0.0417)	(0.0916)	(0.0886)
lag1 ln(WFH)			0.00953**
			(0.00423)
lag2 ln(WFH)			0.00509
			(0.00322)
High Amenities	-0.0623**	-0.0115**	-0.00989*
	(0.0269)	(0.00520)	(0.00575)
lag1 ln(WFH) × High Amenities	0.00373	-0.000433	0.000502
	(0.00396)	(0.00445)	(0.00477)
ln(amenities)	-0.0243***	-0.0181***	-0.0185***
	(0.00265)	(0.000999)	(0.000919)
High Amenities × ln(amenities)	0.102	0.0405**	0.0428**
	(0.0921)	(0.0170)	(0.0175)
lag1 ln(WFH) × ln(amenities)	**-0.00965*** **	**-0.0102*** **	**-0.0105*** **
	(0.000609)	(0.000685)	(0.000637)
High Amenities × lag1 ln(WFH) × ln(amenities)	**0.0122*** **	**0.0164*** **	**0.0178*** **
	(0.00257)	(0.00323)	(0.00317)
Close to CBD	-0.0399	-0.303***	-0.319***
	(0.219)	(0.0640)	(0.0679)
ln(WFH) × Close to CBD	-0.252***	-0.251***	-0.260***
	(0.0503)	(0.0480)	(0.0488)
ln(distance to CBD)	-0.214***	-0.0409**	-0.0414**
	(0.0214)	(0.0175)	(0.0171)
Close to CBD × ln(distance to CBD)	-0.00362	0.0325***	0.0343***
	(0.0270)	(0.00739)	(0.00834)
lag1 ln(WFH) × ln(distance to CBD)	**-0.0160*** **	**-0.00988**	**-0.0101**
	(0.00416)	(0.00938)	(0.00888)
Close to CBD × lag1 ln(WFH) × ln(distance to CBD)	**0.0273*** **	**0.0277*** **	**0.0287*** **
	(0.00606)	(0.00557)	(0.00598)
ln_lag1_rentperM		0.506***	0.505***
		(0.0197)	(0.0199)
ln_lag2_rentperM		0.339***	0.338***
		(0.0341)	(0.0342)
ln(number of ads)	-0.0185***	-0.00755***	-0.00742***
	(0.00184)	(0.00125)	(0.00129)
Constant	6.107***	1.041***	1.068***
	(0.226)	(0.302)	(0.302)
Observations	8,680	8,060	8,060
Number of CodeSAs	620	620	620
SA FE	No	No	No
Time FE	Yes	Yes	Yes

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

This specification allows us to compare the effect of WFH between amenity-rich and amenity-poor neighborhoods, as well as between neighborhoods located near the CBD and those farther away.

The results presented in the table 5 indicate that, among neighborhoods with a high degree of local amenities, the effect of the share of WFH on rental prices is positive and statistically significant. Moreover, each additional increase in the level of local amenities further amplifies this positive effect on rental prices. Empirically, a 1% increase in the share of WFH, combined with a 1% increase in the degree of amenities, is associated with up to a 0.018% increase in rental prices (Column 3).

In contrast, for neighborhoods with the low level of amenities, the effect is negative and statistically significant (the coefficient of lag1 *ln(WFH)* × *ln(distance to CBD)* is about -0.01.), controlling for the neighborhoods' proximity to the CBD. This specification therefore suggests that, with respect to the level of amenities, when households choose to relocate farther from the CBD, they are more likely to do so to neighborhoods with a high level of local amenities.

Consistent with the theoretical prediction, neighborhoods located closer to the CBD exhibit a negative relationship between the share of working from home and rental prices. This result also holds when focusing exclusively on neighborhoods relatively close to the CBD; even among them, greater distance from the center is associated with a positive effect of the share of WFH on rental prices. Specifically, for neighborhoods relatively close to the CBD, a 1% increase in distance from the CBD combined with a 1% increase in the share of WFH is associated with up to a 0.03% increase in rental prices. In contrast, for neighborhoods located relatively far from the CBD, no statistically significant effect of an additional marginal unit of distance is observed.

Table 6. Estimated Results for Equation 19

	(1)	(2)	(3)	(4)	(5)	(6)
			ln (Rent per m2)			
VARIABLES						
ln(WFH)	0.000105	0.000223	-8.34e-05	0.000238	-0.000561	0.0422*
	(0.00366)	(0.00398)	(0.00354)	(0.00340)	(0.00371)	(0.0145)
lag1 ln(WFH)	-0.00439*	-0.00586	-0.0134**	-0.0132**	-0.0132**	-0.0147***
	(0.00141)	(0.00279)	(0.00250)	(0.00259)	(0.00248)	(0.00211)
lag2 ln(WFH)		-0.0127*			-0.0113	-0.0115
		(0.00524)			(0.00504)	(0.00500)
ln_diff						-0.252*
						(0.0906)
lag1 ln(WFH) × central low A			-0.00698***	-0.0154***	-0.0145***	-0.0131***
			(0.000485)	(0.000557)	(0.000559)	(0.000614)
lag1 ln(WFH) × remote low A			0.0141***	0.0118***	0.0117***	0.0129***
			(0.00102)	(0.000878)	(0.000902)	(0.00108)

lag1 ln(WFH) × remote high A			0.00925***	0.0179***	0.0171***	0.0188***
			(0.00137)	(0.000590)	(0.000878)	(0.00130)
ln_lag1_rentperM				0.141***	0.141***	0.140***
				(0.0165)	(0.0165)	(0.0172)
ln_lag2_rentperM				-0.0180*	-0.0182*	-0.0189*
				(0.00710)	(0.00720)	(0.00702)
ln(number of ads)	-0.0189***	-0.0182***	-0.0185***	-0.0179***	-0.0177***	-0.0175***
	(0.00122)	(0.00135)	(0.00113)	(0.00111)	(0.00106)	(0.000948)
Constant	4.131***	4.109***	4.132***	3.635***	3.612***	3.683***
	(0.00632)	(0.0150)	(0.0113)	(0.0833)	(0.0827)	(0.1000)
Observations	8,680	8,060	8,680	8,060	8,060	8,060
R-squared	0.328	0.314	0.328	0.328	0.329	0.329
Number of CodeSAs	620	620	620	620	620	620
SA FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Empirical Findings and Interpretation: neighborhood types based on distance and accessibility.

Table 6 presents regression estimates that disaggregate the effect of remote work by neighborhood type, where types are defined by both proximity to the CBD and local amenities degree. Unlike previous specifications, this model includes neighborhood fixed effects, since the variable of interest—neighborhood type—varies within the panel and is not omitted due to multicollinearity.

The interaction terms between neighborhood type and lagged remote work (*lag1 ln(WFH) × central low A, lag1 ln(WFH) × remote low A, lag1 ln(WFH) × remote high A*) are central to addressing the research question. The coefficient on *lag1 ln(WFH)* alone remains negative on average, indicating that a 1% increase in remote work in the previous quarter is associated with a decline in current rent prices between 0.015% and 0.004%. However, this negative effect is attenuated in suburban neighborhoods, as reflected in the positive interaction coefficients for *remote low A* and *remote high A*. In aggregate, the effect of lagged remote work on rents is negligible in *remote low A* neighborhoods and even positive in *remote high A* neighborhoods. In contrast, *central low A* neighborhoods experience a sharper negative effect than the base category (*CBD*).

Table 7 summarizes the marginal effects of lagged remote work across neighborhood types, based on the results from Column 4, which includes the richest set of controls and exhibits the highest R^2:

Table 7. Summary of the influence of working from home by neighborhood type

	CBD	Residential Central	Residential Remote	Satellite City
lag1_ln_wfh	–1.96%	–1.96%	–1.96%	–1.96%
Interaction term	—	–1.05%	+1.89%	+2.25%
Total effect	–1.96%	–3.01%	–0.07%	+0.29%

These results are consistent with the theoretical framework proposed in this paper: peripheral neighborhoods benefit from the rise of WFH, while central neighborhoods lose ground in relative rental value. A particularly noteworthy finding is that neighborhoods located in the central area but with lower degree of local amenities—experience the greatest decline, exceeding even that observed in the CBD.

One plausible explanation is that households responding to remote work opportunities opt for more decisive relocation strategies. Instead of shifting slightly out of the urban core, many choose to move farther to suburban locations where rent is significantly lower, thereby maximizing housing consumption per monetary unit. Without sufficient amenities, there is little incentive to remain in the central area and bear its high housing costs. In essence, the value of distancing from the CBD rises when commuting constraints are relaxed, making distant, lower-cost neighborhoods more attractive.

Together, the three tables provide compelling empirical support for the hypothesis that remote work has reshaped the spatial dynamics of urban rental markets. The negative effect of lagged remote work on rental prices—most evident in central and low local level of amenities areas—suggests a weakening of the traditional urban rent premium. Suburban and satellite neighborhoods appear to benefit, as indicated by the attenuated or even positive effects of remote work in those areas.

Finally, Figure 13 presents the results of the Event Study approach specified in Equation (20). This analysis focuses on remote neighborhoods with high amenity levels—the group that, according to the theoretical model, is most affected by the option to work from home. It addresses two questions: (i) whether rental price trends were similar across neighborhood types before the COVID-19 pandemic, and (ii) whether the observed changes are persistent or fade over time.

As can be seen, the coefficients of the interaction term for neighborhoods in the group of remote with high levels of amenities are statistically insignificant prior to the COVID-19 outbreak. However, following the onset of the pandemic, the coefficients become positive and statistically significant for a period of approximately one and a half years. This indicates that rental prices in thes neighborhoods exhibited a relatively stronger upward trend compared to other neighborhoods, but only for a limited period. After the Q42022 the effect has disappeared.

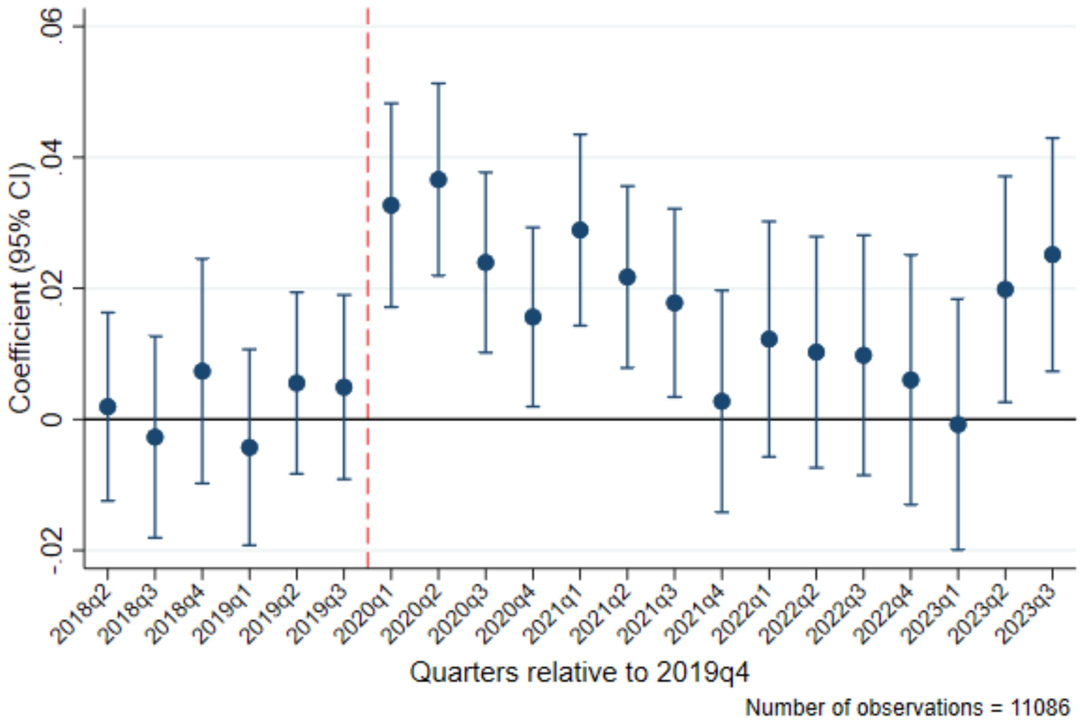

Fig. 13 Evidence from an event study analysis

This provides further evidence of a relative increase in demand for more affordable, remote neighborhoods that still offer a sufficient level of amenities. They are consistent with the theoretical prediction that the option to work from home reduces reliance on CBD proximity, allowing households to choose locations that lower housing costs or provide higher-quality housing without sacrificing local amenities.

8. Conclusions and contribution

This study contributes to our understanding of how the rise of remote work influences spatial equilibrium reflected in housing market inside urban agglomeration. We began with two core research questions:

1. How can GPS-based mobility data be applicable to measure work-from-home (WFH) dynamics at statistical area level?
2. What is the impact of increased remote work on urban spatial equilibrium, particularly as reflected in changes in rental prices?

Both questions are addressed empirically and theoretically in the paper. First, we demonstrate that GPS- signals data can reliably capture spatial and temporal heterogeneity in WFH behavior. While such data demand careful preprocessing to account for biases related to time-of-day or device sampling, they provide valuable insights into real-time shifts in urban activity patterns at high spatial and time granularity.

Second, our empirical results strongly support the theoretical expectation that remote work reshapes the spatial distribution of housing demand. Across multiple specifications, we find that neighborhoods farther from the CBD experience relatively faster rental price growth as remote work prevalence increases. The key interaction term—between lagged WFH rates and distance to the CBD—consistently shows that remote work flattens the traditional rent gradient by reducing the premium placed on centrality.

This effect is most noticeable in remote neighborhoods both with high and low level of accessibility, where remote work is associated with rent increase, compared to decline in more central areas. Notably, the greatest negative effects are observed not in the CBD itself, but in the adjacent residential neighborhoods—locations that combine high rents with lower accessibility benefits. This suggests that remote workers prefer to move farther from the center, where they can attain better living conditions for a lower price, rather than paying high rents in central areas.

While the association with distance from the CBD is consistent across all models, the role of amenities is less straightforward. On the one hand, among central neighborhoods, those lacking access to amenities show slower rental price growth. We associate this with higher out-migration, suggesting that amenities may encourage residents to remain in the central area despite higher housing costs. On the other hand, the fastest rent growth is observed in remote neighborhoods without amenities, which, before the rise of WFH, offered the most affordable housing options. This pattern indicates that, when relocating, households tend to prioritize maximizing housing utility over maintaining access to amenities. Overall, the results suggest that, in the context of remote work, housing affordability has become a more important factor than accessibility. This likely reflects the increased amount of time people spend at home.

Taken together, these results provide compelling evidence that remote work is not just a short-term disruption but a structural force reshaping urban housing markets. It alters both the spatial logic of household location choices and the equilibrium dynamics of rent prices.

These insights have important implications for urban policy and planning. Policymakers should recognize the continued presence of remote and hybrid work and adjust zoning, infrastructure investment, and service provision accordingly. For instance, growing peripheral neighborhoods may require expanded transportation, digital infrastructure, and public services to accommodate the rising demand for housing in these areas.

Finally, this paper contributes to the evolving theory of urban spatial structure by explicitly incorporating the role of remote work. As cities continue to adapt to post-pandemic realities, understanding the spatial implications of work location flexibility will be essential. Our findings underscore the need to rethink traditional models of urban form, commuting behavior, and housing demand in light of a more decentralized, digitally connected workforce.

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