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. At the same time other factors such as housing affordability and access to local amenities gain importance in the residential decision-making process.

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, aka hybrid schedule. As a result, scholars have begun referring to 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. In San Francisco, the figure stood at 33%, and in Paris, around 20%.

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 urban spatial equilibrium, particularly 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 model of 'closed city' 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 (Chay & Greenstone, 2005; Fujita, 1989; Mathur & Stein, 1993) This factor is usually presented in the model through hedonic price modeling (Roback, 1982). In equilibrium, this trade-off leads to a stable spatial pattern where households have no incentive to relocate.

With he 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 of 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, as such flattening of intracity house-price gradients, especially for rents.

As such, in the US several papers report empirically- grounded poulation 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 amenites (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—collected through surveys (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 or travel data, 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 demographic 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 of mobility restrictions during lockdown periods on urban economic activity (Huang et al., 2023; Östh et al., 2023). One exception is the study by Wenzhu Li et al (Li et al., 2024), which examines popular third places in Beijing 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 of impact is the study of Monte et al (2023). They use mobile phone data to measure changes in commute frequency between 274 US cities and compare them with changes in housing prices gradients.

Therefore, this paper addresses the existing gap 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

First, we estimate potential outputs from remote work with a theoretical model. It explains the consequences of remote work on the urban equilibrium, including the emergence of the so-called 'donut effect' by comparing urban equilibrium under normal conditions with urban equilibrium when people work from home. Equilibrium conditions exist when everyone tends to maximize utility:

$$U_i = f(s_i, q_i, t_c, A_i) \quad (1)$$

s_i– *composite good,* q_i *– size of housing, sq. foot,* t_c*–commuting time to CBD,* A_i *– local amenities*

The study formulates the urban equilibrium using three equations:

1. A budget constraint extended with hedonic rent:

$$Y_i = S + q_i * \exp(\alpha + x_1 A_n + x_2 (A_{CBD} * (1-h)^{-k} t_c^{-k})_n + C_n \quad (2)$$

where Y_i = income, C = commuting costs, S = is disposable income, k, α – model coefficients, A_{CBD} - amenities in CBD, A_n- local amenities, h = share of working days per week that a person works from home,h~0;

2. The equilibrium between spare time, spending and disposable income:

$$S = K, K = t_l * \left(\frac{p}{f}\right), \ t_l = T - t_c(1-h) + t_w \quad (3)$$

where K = total amenities spending, T= total active time per week, t_l - leisure time per week, t_w = work time per week, p = price of 1 man-made amenity fixed inside city, f = average time spent by individual on one service

3. The local market equilibrium for amenities:

$$z^n(1-h^n)K_W^n + g^n h K_H^n = A_n * p \quad (4)$$

where z^n = number of workplaces in the neighborhood n, g^n = number of residents in the neighborhood n, K_W- workers spendings in the neighborhood n, K_H − residents spending in the neighborhood n.

Violation of the equilibrium during WFH is assumed to vary across the urban agglomeration. To account for this, we present three archetypal neighborhoods following Elldér et al. (2022): the CBD, the residential neighborhood and the satellite city. Each of them has a unique combination of parameters which define how a neighborhood recovers after a pandemic.

The paper defines the short-term disequilibrium caused by WFH and its consequence over the long-term. This means that disequilbrium appears when people have already started working from home *(h>0)* but haven't made significant changes such as change of residence ($R_{WFH} = R$) or work ($Y_{WFH} = Y$). The consequences vary across neighborhoods.

In the CBD, where commuting time is valued over other factors, residents find that because of WFH they can afford better housing conditions by maintaining low weekly commuting time. To achieve this they move out from expensive downtown to more affordable suburbia as fas as $\frac{dU}{dq} > -\frac{dU}{dt_c^{WFH}}$. In residential neighborhoods, extra spare time (Δt_l) and the decrease in accessibility of central amenities (A_{CBD}) induced by the drop in commuting frequency (-Δh), increase residents' expectations from local accessibility.

As long as the following condition is met: $A_{CBD} * \Delta h * \Delta t_l \leq A_n$ (5)

residents stay in the neighborhood but once this condition no longer exists they are likely to migrate to areas with higher local accessibility.

The urban equilibrium of the satellite city also depends on local accessibility. But in this case condition (5) is more likely to be satisfied as this type of neighborhood has already disconnected from the CBD: $lim(1-h)^{-k}t_c^{-k} = 0$ and provides a sufficient level of local accessibility to compensate for a longer commute. Overall, the satellite city is expected to experience positive change during WFH and to attract residents from the two other types of neighborhoods.

We now proceed to empirically explore the new urban equilibrium in the Tel Aviv Metropolitan Area in Israel.

4. Data and study area

4.1 Remote and hybrid work in Israel

The choice of the Tel Aviv Metropolitan Area (TAMA) 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 (Yaron Amir, 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. However, no comprehensive national studies have tracked WFH trends in Israel beyond 2022. Nevertheless, official statistics suggest that hybrid work arrangements have persisted, particularly in The Tel Aviv Metropolitan Area (TAMA).

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, after the Covid-19 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.

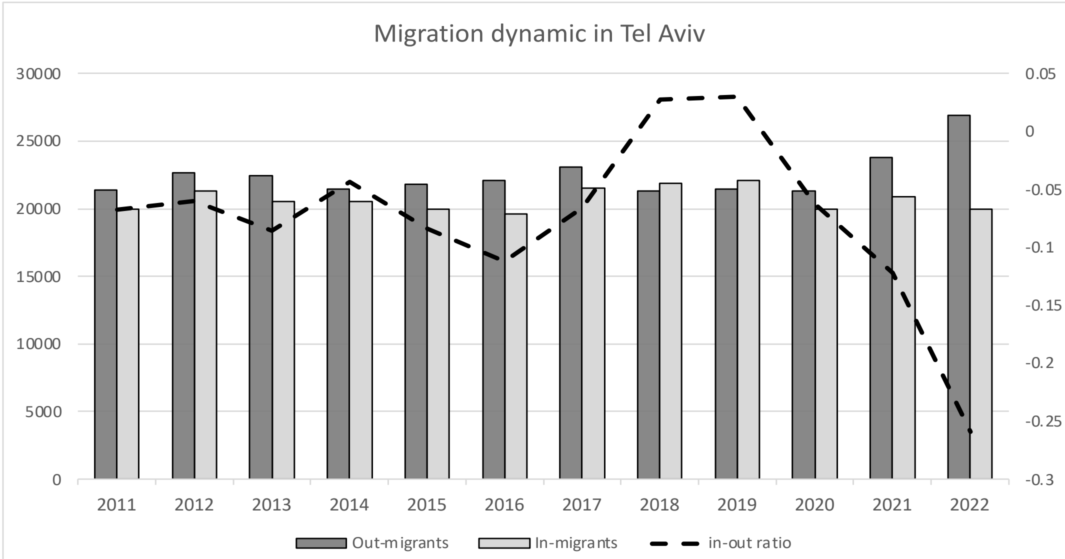

Fig. 1Migration dynamics in the Tel Aviv Municipality

4.2 The Structure of the Tel Aviv Metropolitan Area

The TAMA 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 TAMA'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 commuting 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 50% of the population—about 3.7 million users. 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 Tel Aviv center. In Fig.2, the zones with the lightest commuter outflows represent Tel Aviv with its neighboring cities: Ramat Gan, Herzliya, and Petah Tikva that contain the highest concentration of workplaces.

Another factor that makes the Tel Aviv Metropolitan Area 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. Having established the TAMA potential for remote work, we proceed to quantify it and measure its impact using mobile GPS signals.

4.2 Statistical Areas of Israel Central Bureau of Statistics

As this 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 TAMA (Tel Aviv Metropolitan Area), there are a total of 1,223 residential and 101 commercial or institutional SAs. The average estimated population per residential SA in TAMA is approximately 3,137 residents.

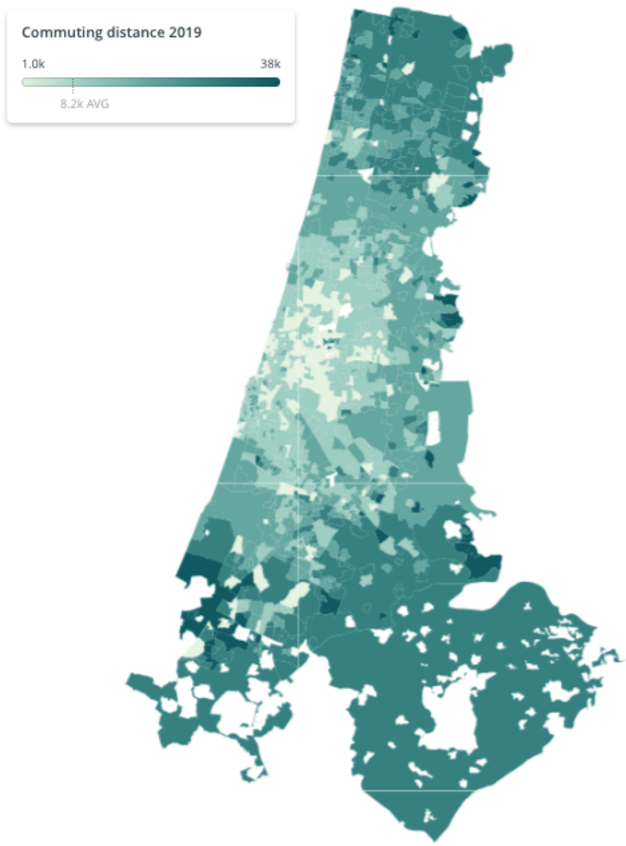

Fig. 2 Outbound Commuting Distances in the TAMA (2019)

4.3 Mobile 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) relating to all of Israel. For the purpose of the study we include the data till 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 presence at home.

The original dataset contains about 400 million anonymized geolocated clusters of signals that belong to 16 million individuals. 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

Cleaning the data comprises several steps in order to retain only users whose data demonstrates high accuracy and consistent stay patterns. This is necessary to ensure reliable WFH estimations:

1. Remove stays with duration < 3min and coordinates outside TAMA
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 3s 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 the metro area 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. Together with 2019, the months excluded are: 12/2020,12/2022, 07/2023 and 08/2023.

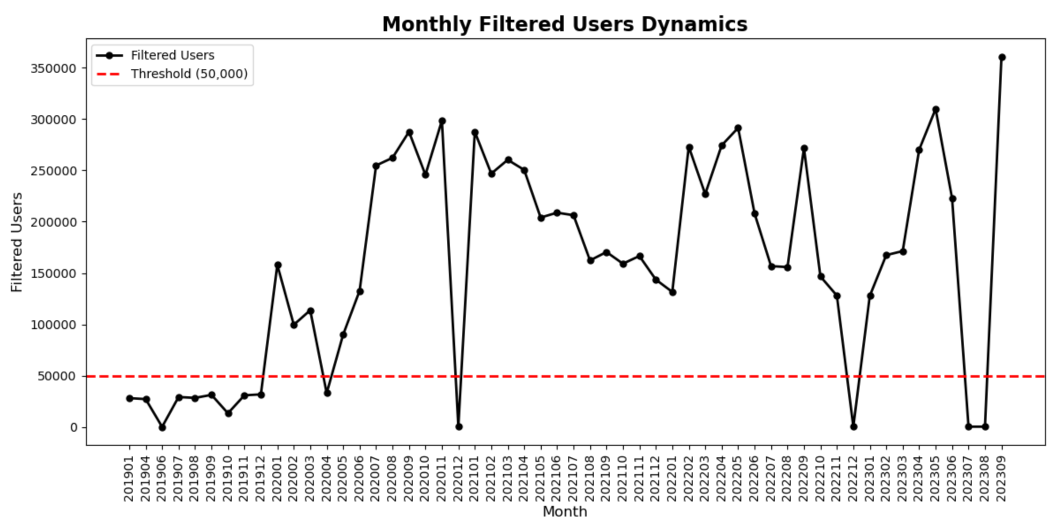

Fig. 3 Monthly volumes of users in mobility dataset

4.4 Rental 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 Central Bureau of Statistics.

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 TAMA. 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%.

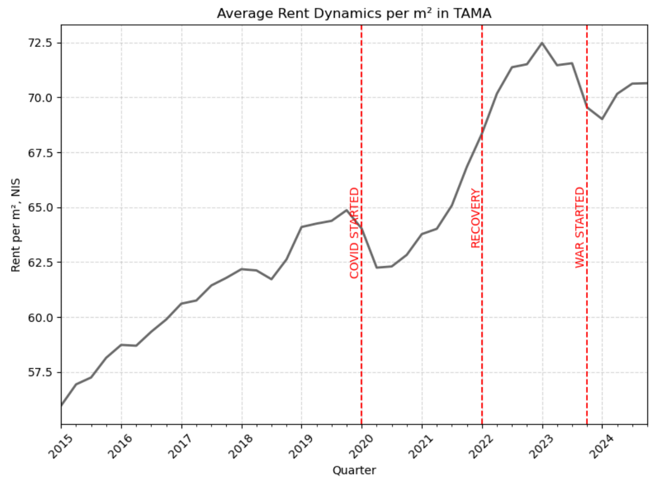

Fig. 4 Rental price dynamic in TAMA

The dynamics of the rental price gradient (Fig.5) reveal patterns consistent with previous research: following the COVID-19 outbreak, the previously negative gradient begins to flatten and eventually is reversed. Rental prices in peripheral areas start to grow at a faster rate than in central locations, despite temporary declines observed in the second and third quarters of 2021 and the first quarter of 2023. Overall, these findings support our hypothesis regarding the positive impact of remote work on rental prices in more remote neighborhoods.

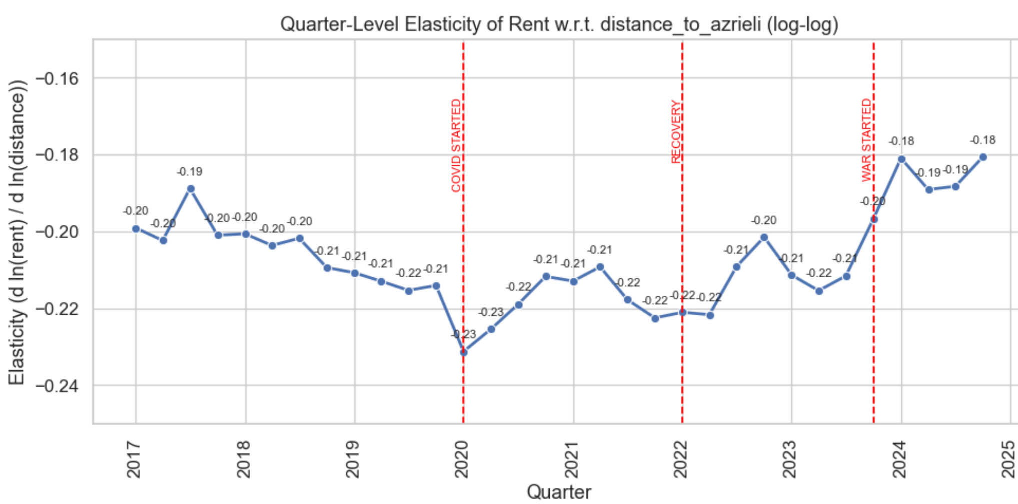

Fig. 5 The dynamics of the rental price per m² gradient 2017-2024

4.5 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

5. The Empirical strategy

5.1 Remote work estimations

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

- Area-based estimation: measures changes in day vs. evening dwell times during work hours across statistical areas.
- Individual-based estimation: tracks 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 by comparing mobile signal density during weekday daytime and evening hours across statistical areas from the 2022 Census. To ensure both variables are comparable, we include the same number of hours in each and weight the evening hours so that the total count across the TAMA is the same during both day and evening—assuming that all people reside within the TAMA.

$$I = \frac{day\ signals - evening\ signals}{day\ signals + evening\ signals} \quad (6)$$

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, 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

The 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 pipeline 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 (Kung et al., 2014) for home-work detection based on mobile data. 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 Su till Thu 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, while work locations are validated against declared employment figures within Israel's designated work zones, both using the Pearson correlation. Additionally, each home location is geolocated to a specific building, and the proportion of 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 estimate typical work hours for each user. To do this we use Bayesian conditional probabilities. For each hour between 8 AM and 7 PM on days when signals are detected at a work location (WD), we calculate the probability of an individual to be at that work location.

$$P_i(W|h) = P_i(W) * P_i(h|W)/P_i(h) \quad (7)$$

Where $P_i(W)$ denotes an individual's share of office location hours in a working day, $P_i(h)$ denotes an individual's share of exact hours in during office days, $P_i(h|W)$ is the share of exact hour at an office location in 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:

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

In order to avoid giving high weights to non-typical office hours, *Remote work hour flag* is weighted using a general monthly probability:

$$RWH\_weighted = RWH * P(O|h)$$

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:

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

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 TAMA $Remote\ Work\ level$ with the monthly share of remote work hours from Labor 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.

5.2 Examining WFH trends in the TAMA and their relations with rent prices

Taking advantage of the high resolution of WFH estimations, we explore the main patterns in WFH temporal dynamics across Statistical Areas (SAs) existing in the TAMA. For this purpose we apply time-series clustering using the Dynamic Time Warping (DTW) distance metric (Vintsyuk, 1972). Traditional Euclidean distance fails to capture temporal shifts and nonlinear variations expected in WFH trends (Petitjean et al., 2011). DTW, by contrast, aligns time series in a flexible manner, allowing for phase shifts and differing time patterns, which results in more meaningful similarity measurements. Using the tslearn.clustering module in Python, we implement a DTW-based k-means algorithm and identified four distinct clusters of SAs, each representing a different dynamics of WFH between 2020 and 2023.

Additionally, we plot rental price dynamics separately for each cluster to facilitate direct comparison across neighborhood types. The resulting clusters reveal distinct patterns in how neighborhoods respondto the COVID-19 outbreak, offering valuable insights into spatial heterogeneity. These patterns provide a foundation for the empirical modeling of neighborhood-level response to the rise in remote work.

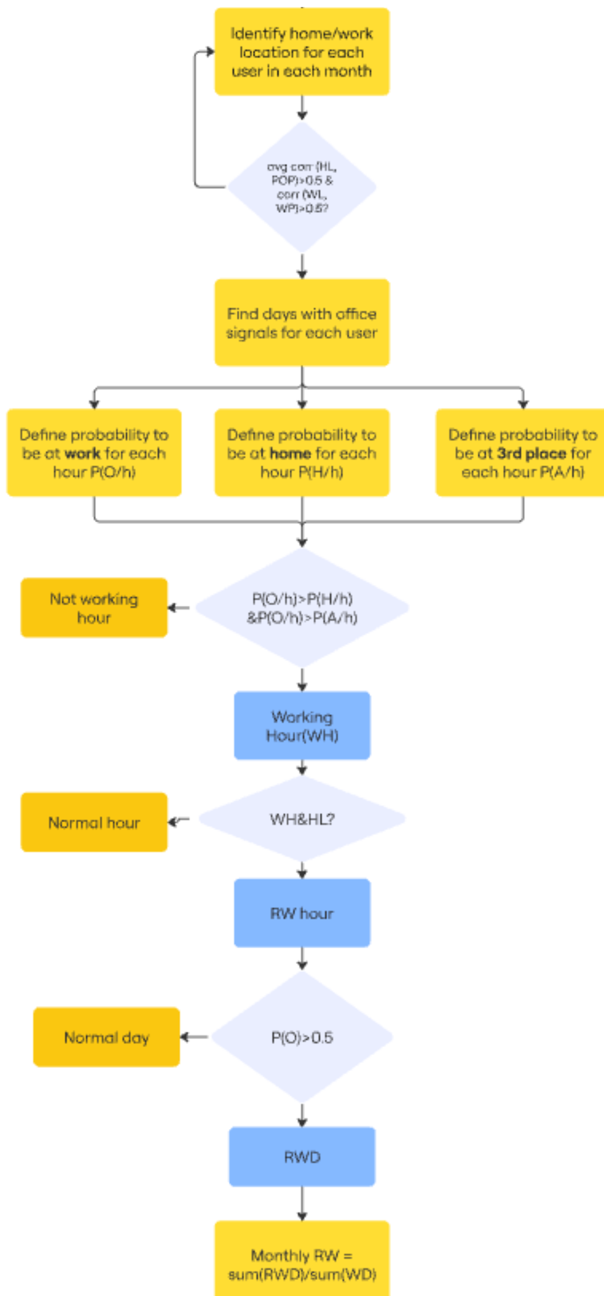

Fig. 6 Remote work estimation process

5.3 Classifying neighborhoods

Additionally, following the theoretical model, each statistical zone is classified into one of three neighborhood types: CBD, residential neighborhood, or satellite city. To better understand remote work trends, residential neighborhoods are further divided into two groups: those within the city of Tel Aviv and those outside it. The classification is based on a plot of robust-scaled values of amenity accessibility within a 1 km buffer from statistical area against the distance to the Azrieli commercial center (Fig.7). Neighborhoods with a positive scaled distance(y-axis) are classified as satellite cities, while those with a negative value are considered part of the central area. The x-axis represents the level of accessibility, where negative values indicate low accessibility and positive values indicate high accessibility.

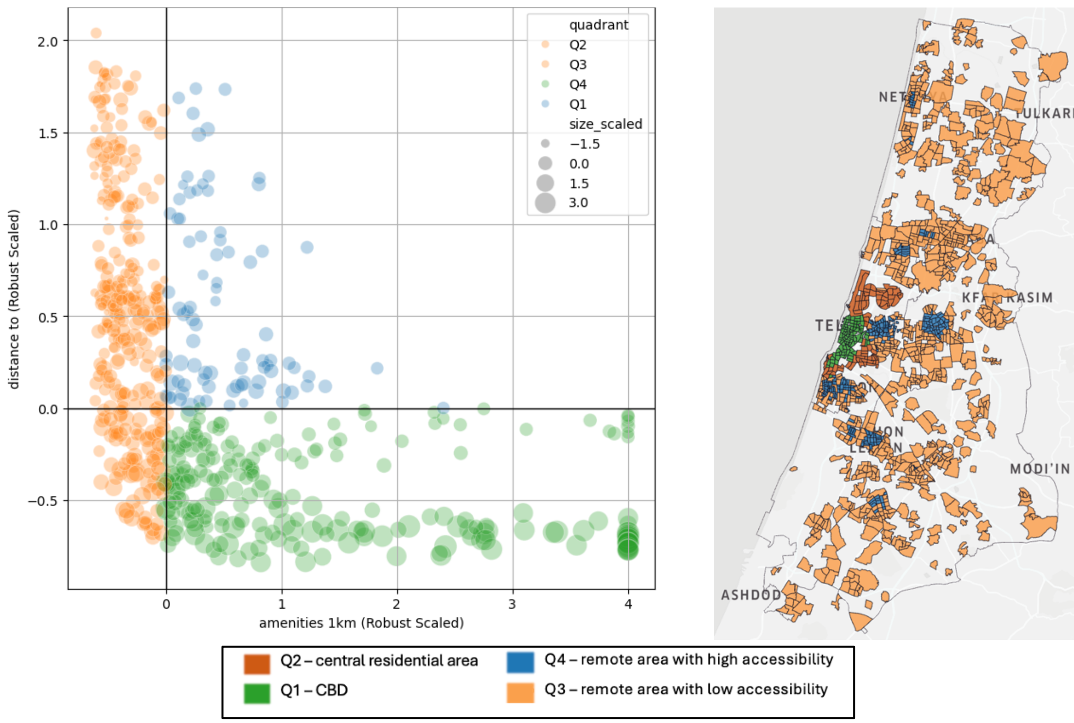

Fig. 7 Neighborhoods Types distribution

5.4 Panel data description

Based on the collected data, we construct a balanced panel that includes only Statistical Areas (SAs) within the TAMA 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 (Type I), 457 residential neighborhoods with low accessibility with 60 in Tel Aviv (Type II) and 397 outside (Type IV), and 119 satellite city centers (Type III). 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.

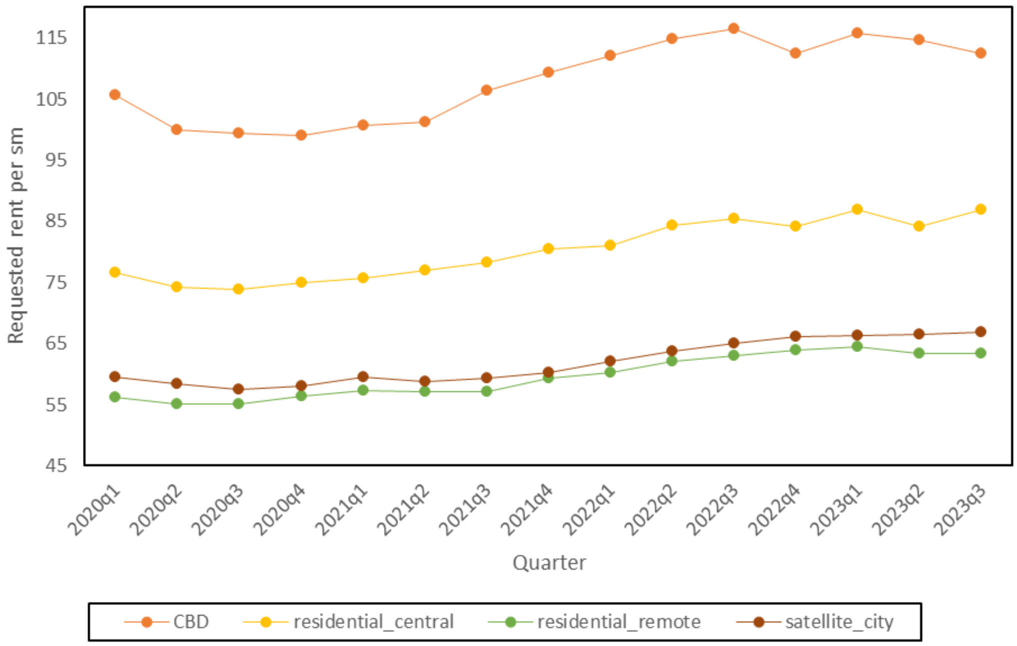

Fig. 8 Rental prices dynamics in 4 groups of neighborhoods

5.5 Empirical testing of WFH impact on rental prices

Following the theoretircal model, the goal of the empirical study is to examine how the opportunity to work from home influences 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 TAMA. Specifically, we specify three equations:

- Equation (8): Assesses the direct effect of WFH on rental prices relative to neighborhood distance from the CBD.
- Equation (9): Assesses the direct effect of WFH on rental prices relative to local accessibility of services.
- Equation (10): Examines the differential impact of WFH across neighborhood types, which incorporates both distance and accessibility dimensions.

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 (8) is specified as follows:

$$R_{n,q} = \alpha + \beta \sum_{i=0}^{k} \mathrm{WFH}_{n,q-i} + \delta(\mathrm{WFH}_{n,q-1} \times \mathrm{CBDdis}_n) + \gamma \sum_{i=1}^{k} \mathrm{R}_{n,q-i} + \tau_q + \varepsilon_{n,q} \quad (8)$$

Where $R_{n,q}$ denotes the log asking rent per square meter in neighborhood n during quarter q, $WFH_{n,q-i}$ is the lagged WFH rate, $CBDdis_n$ is the distance to the CBD, τ_q is quarter fixed effects, and $\varepsilon_{n,q}$ is the error term. We expect δ, indicating that the rent impact of WFH increases with distance.

Equation (9) replaces distance with an accessibility of amenities measure:

$$R_{n,q} = \alpha + \beta \sum_{i=0}^{k} \mathrm{WFH}_{n,q-i} + \delta(\mathrm{WFH}_{n,q-1} \times \mathrm{A}_n) + \gamma \sum_{i=1}^{k} \mathrm{R}_{n,q-i} + \tau_q + \varepsilon_{n,q} \quad (9)$$

Here, A_n captures density of local services and amenities per sq km, with higher values indicating greater accessibility. In this case, we expect that δ has a positive sign, meaning that the higher the accessibility, the larger the positive impact of the work-from-home rate on rental prices is expected.

Equation (10) introduces a vector of neighborhood-type dummy variables Type_n^j to evaluate heterogeneity in the WFH effect:

$$R_{n,q} = \alpha + \beta \sum_{i=0}^{k} \mathrm{WFH}_{n,q-i} + \delta(\mathrm{WFH}_{n,q-1} \times \sum_{j=2}^{4} \mathrm{Type}_n^j) + \gamma \sum_{i=1}^{k} \mathrm{R}_{n,q-i} + \eta_n + \tau_q + \varepsilon_{n,q} \quad (10)$$

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.

6. Results

6.1 Results of area-based remote work estimation

The analysis of mobile signal dynamics reveals the clear presence of remote work in the TAMA 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).

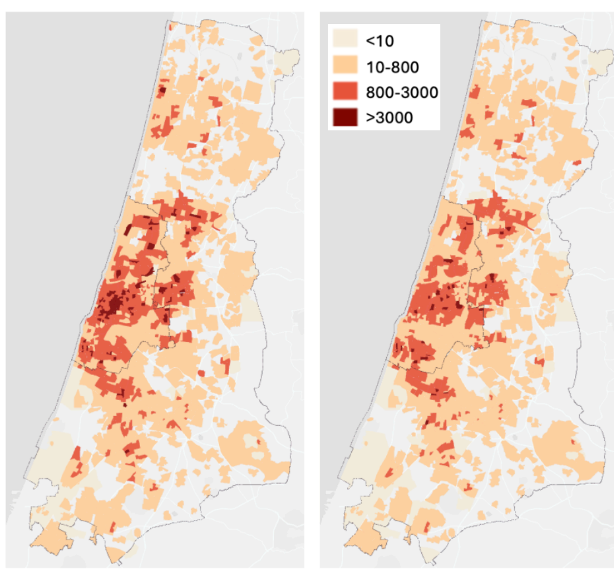

Fig. 9 Mobile signals during work hours in 01/2020 (left) and 09/2020 (right)

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.

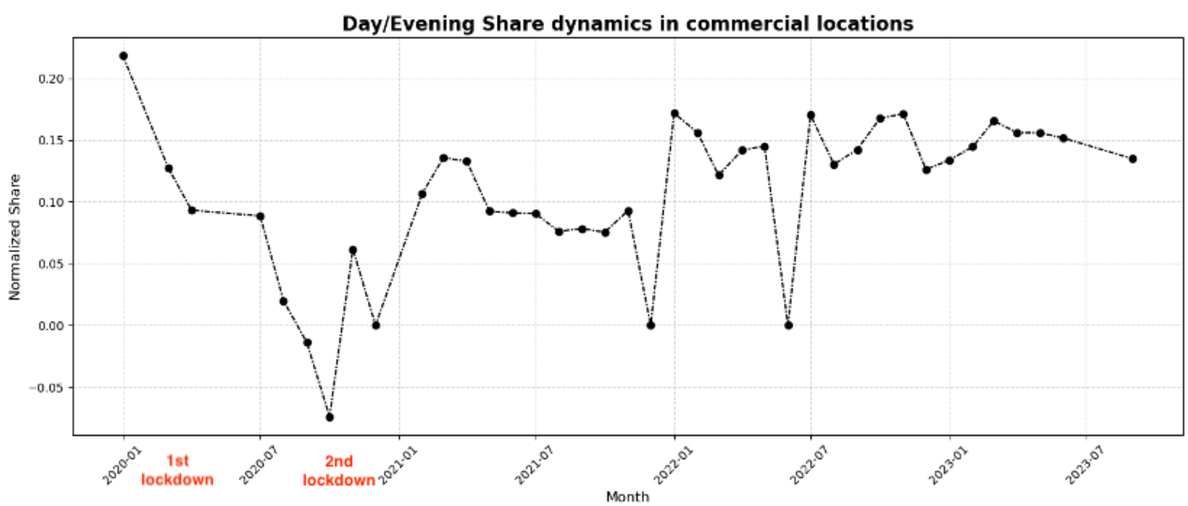

Fig. 10 Day/evening signals ratio dynamic in commercial locations

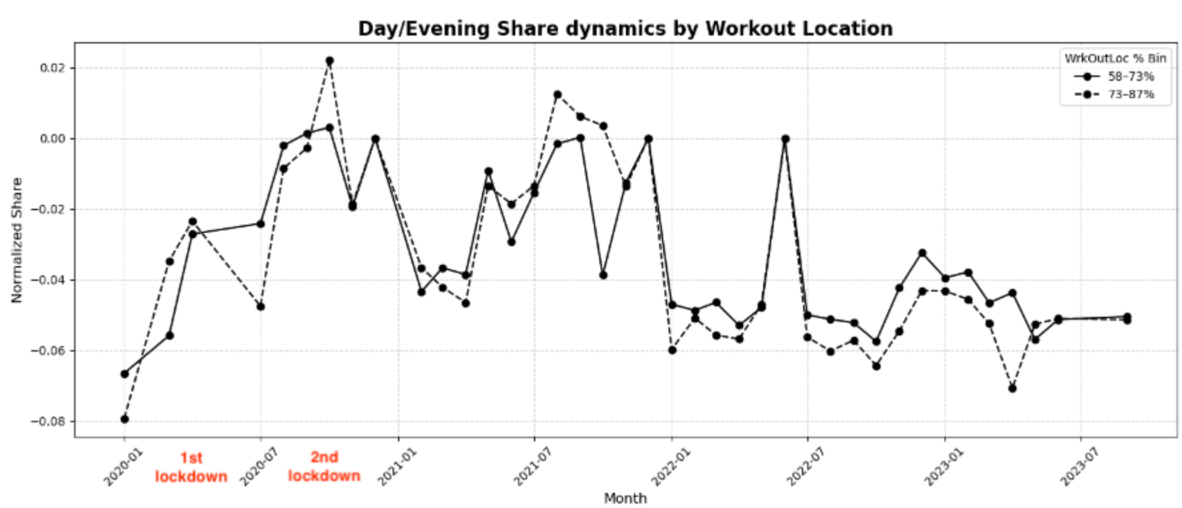

Fig. 11 Day/evening signals ratio dynamic in residential locations with more than 50% of employers working outside their residence location

6.2 Results of individual-based remote work estimations

The results presented in Table 3 demonstrate high accuracy in identifying home and work locations. The not very high average Pearson correlation between SA's population and number of home locations is due to low smartphone penetration as well as complete non-use of smartphones on Saturdays in religious neighborhoods. If we ignore this, values increase till 68%. Additionally, mapping home locations against non-residential buildings confirms quality, with a monthly mismatch below 2.3%.

Table 3. Results of validating home and work location vs official data

Features	Metric	Value	Aggregation level
Home Locations ,Census population	Pearson correlation	57%	Statistical area
Home Locations, Census population	Pearson correlation	90%	Municipality
Home locations, buildings	Accuracy in identifying residential buildings	2.3%	Building
Work Locations, official number of employees	Pearson correlation	91%	Employment zones
Flag work location, flag employment zone	Precision of spatial matching	96%	Geohash
Flag work location, eflag mployment zone	Recall of spatial matching	69%	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.

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 percentage point 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 maintain a 9 ppt increase in work-from-home days through September 2023 compared to January 2020.

6.3 WFH trends in TAMA

Four distinct patterns in remote work dynamics across neighborhoods are identified using DTW-based k-means clustering (Fig. 13). We decided to stop on 4 clusters based on silhouette score. To improve interpretability, each cluster is compared to Cluster 3, which exhibits minimal remote work activity aside from a spike during the second national lockdown.

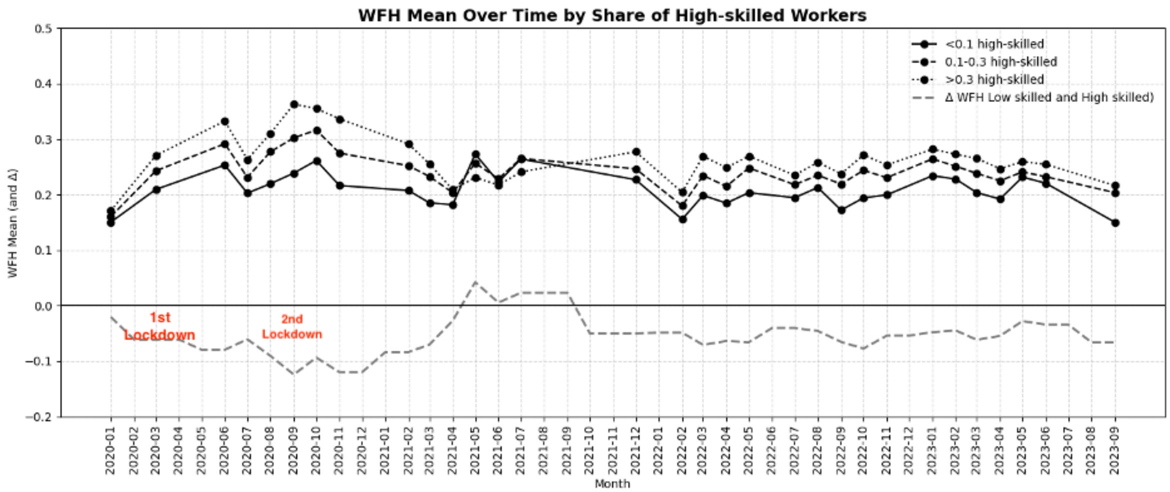

Fig. 12 WFH dynamics by share of high-skilled workers

Cluster 0 (*n = 680*) includes neighborhoods where remote work levels remain consistently high following the COVID-19 lockdown. This group maintains the highest proportion of remote working days—roughly 10 percentage points above the baseline cluster.

Cluster 1 (*n =152*) shows the positive dynamic: remote work levels are initially similar to the baseline, but begin a gradual and sustained increase starting in Q1 2021.

Cluster 2 (*n =146*) represents neighborhoods that experience a steady decline in remote work, with levels gradually converging to the non-remote baseline by Q4 2021.

Cluster 3 (*n = 122*) serves as the baseline group, with consistently low levels of remote work except for a temporary rise during the second lockdown.

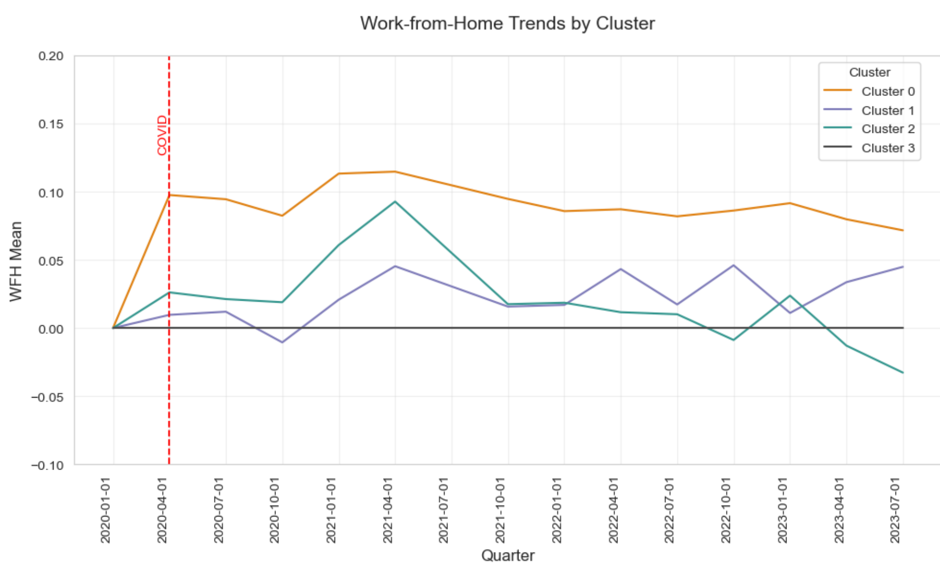

Fig. 13 Clustered WFH trendes in TAMA

Closer examination reveals that the neighborhoods of *Cluster 1* are characterised by the lowest average salaries but the highest local accessibility of amenities. This confirms the theoretical assumption of such neighborhoods being attractive for remote workers. *Cluster 0* represents the most expensive neighborhoods with the highest share of employes in the sectors most suitable for remote work. It is also characterized by the highest annual wage.

Table 4. Average values of statistical indicators in WFH-trend clusters

Cluster	% of high skilled employees	Annual median wage	Num of amenities per sq km withn 1 km buffer around neigborhood
0	23.0	13,0900.0	0.752155
1	20.6	11,6000.0	1.044878
2	21.8	12,1700.0	0.749541
3	21.1	12,2900.0	0.906159

Analysis of rental price dynamics (Fig.14) relative to the 2015–2019 trend reveals that all neighborhood clusters experience a sharp decline in Q1 2020. However, Clusters 0 and 1 exhibit the fastest recovery, returning to trend levels by Q1 2022, while Clusters 2 and 3 require an additional quarter to fully recover.

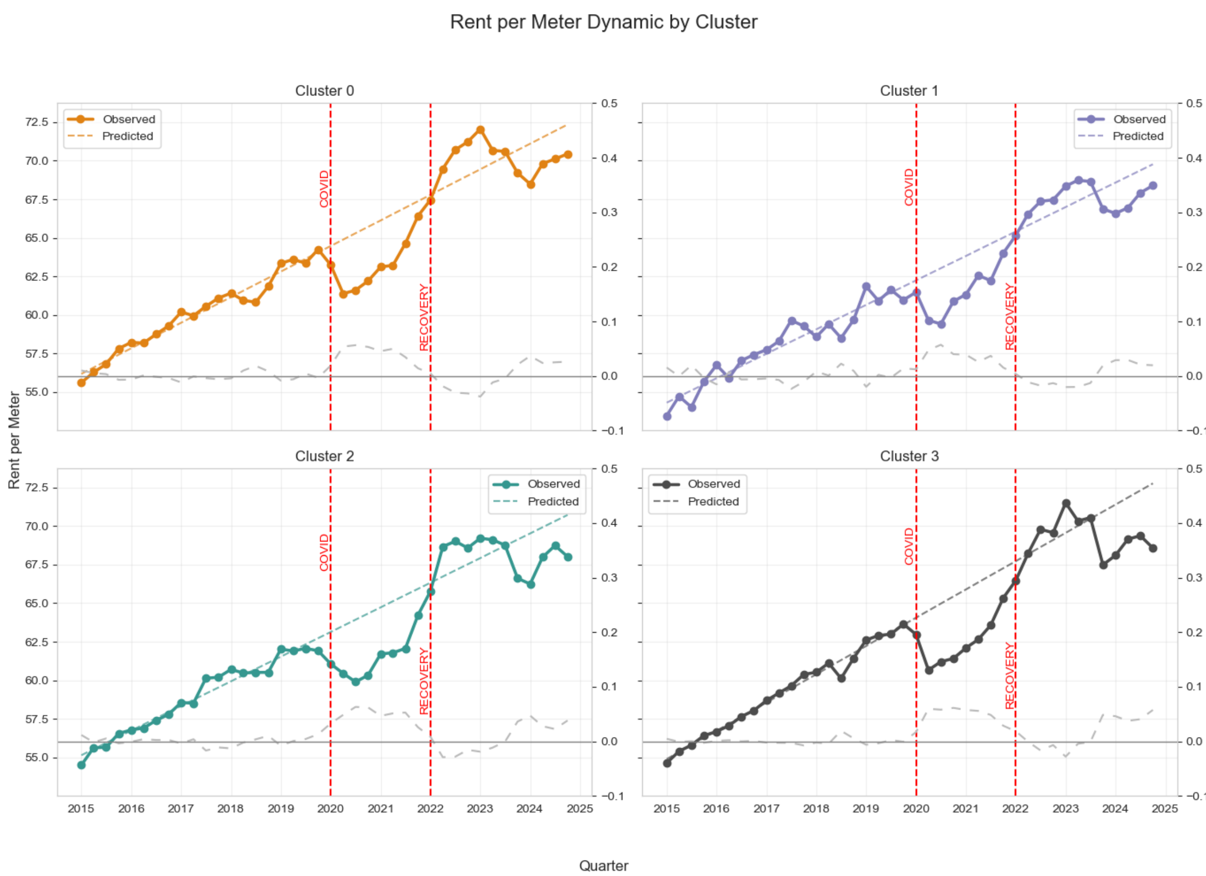

Fig. 14 Dynamics of rent per sq m by WFH-trend Cluster

6.4 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 are based on a rich dataset that includes spatial and temporal variation across neighborhoods, while controlling for fixed effects where applicable (time fixed effect in models 1-2, time and SA (statistical area) fixed effects in model 3).

The results are presented across three tables, each focusing on a different dimension of the housing market's spatial structure. Table 5 examines the interaction between remote work and distance from the CBD, Table 6 focuses on local neighborhood accessibility, and Table 7 introduces neighborhood types based on both distance and accessibility, capturing heterogeneous effects across urban, peripheral, and suburban areas.

Table 5. Estimated results for Equation 8

	(1)	(2)	(3)	(4)
	ln (Rent per m^2)			
VARIABLES				
ln_wfh	0.00425	0.0134***	0.0120***	0.00667
	(0.00294)	(0.00448)	(0.00446)	(0.0278)
lag1_ln_wfh	-0.0779***	-0.0935***	-0.0958***	-0.0950***
	(0.00637)	(0.0166)	(0.0170)	(0.0177)
lag2_ln_wfh			0.00852***	0.00846***
			(0.00158)	(0.00132)
ln_diff				0.0311
				(0.178)
ln_distance_to_CBD	-0.173***	-0.00609	-0.00630	-0.00634
	(0.0382)	(0.00599)	(0.00610)	(0.00631)
lag1_ln_wfh#ln_distance_to_CBD	0.00864***	0.0119***	0.0119***	0.0118***
	(0.000933)	(0.00168)	(0.00172)	(0.00181)
ln_lag1_rentperM		0.514***	0.513***	0.513***
		(0.0213)	(0.0213)	(0.0214)
ln_lag2_rentperM		0.347***	0.346***	0.346***
		(0.0334)	(0.0334)	(0.0335)
Constant	5.654***	0.654**	0.671**	0.663***
	(0.378)	(0.275)	(0.277)	(0.246)
Observations	8,680	8,060	8,060	8,060
Number of CodeSAs	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 and distance from the CBD,.

Table 5 presents the regression estimates aimed at evaluating the relationship between remote work prevalence, spatial proximity to the CBD, and their joint effects on residential rental prices. The results indicate that, controlling for neighborhood characteristics and time fixed effects, neighborhoods located farther 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 0.0086 to 0.0119, implying that, compared to otherwise 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 0.012% in rent prices.

It is important to note that this result does not suggest that peripheral neighborhoods now have higher absolute rents than central areas. Rrather, 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 0.013%. 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 0.1%.

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 0.17% lower. However, in Column (2), once rent lags (*ln_lag1_rentperM* and *ln_lag2_rentperM*) 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.

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 6. Estimated results for Equation 9

VARIABLES	(1)	(2)	(3)	(4)
	ln (Rent per m²)			
ln_wfh	0.00126	0.00656	0.00611	-0.0248
	(0.00383)	(0.00491)	(0.00460)	(0.0327)
lag1_ln_wfh	-0.00351	0.00525*	0.00458	0.00453
	(0.00307)	(0.00310)	(0.00311)	(0.00295)
lag2_ln_wfh			0.00261	0.00231
			(0.00417)	(0.00405)
ln_diff				0.182
				(0.198)
ln_accessibility	0.0495	-0.00786**	-0.00776**	-0.00766***
	(0.0467)	(0.00308)	(0.00306)	(0.00271)
lag1_ln_wfh#ln_accessibility	-0.00618**	-0.00685**	-0.00681**	-0.00659**
	(0.00243)	(0.00309)	(0.00308)	(0.00287)
ln_lag1_rentperM		0.545***	0.545***	0.544***
		(0.0164)	(0.0163)	(0.0174)
ln_lag2_rentperM		0.380***	0.380***	0.380***
		(0.0280)	(0.0280)	(0.0283)
Constant	4.082***	0.311*	0.315*	0.271*
	(0.0724)	(0.174)	(0.175)	(0.144)
Observations	8,653	8,034	8,034	8,034
Number of CodeSAs	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; local neighborhood accessibility.

Table 6 presents regression estimates aimed at evaluating the effect of local accessibility together with the prevalence of remote work on residential rent levels. The results suggest that areas with higher accessibility experience a relative decline in rental prices compared to those with lower accessibility. The coefficient of interest, *lag1_ln_wfh* × *ln_accessibility*, directly informs the research question. This interaction term ranges between –0.0062% and –0.007%, indicating that neighborhoods with 1% lower accessibility and 1% higher remote work rates in the previous quarter experienced, on average, a relative rent increase of up to 0.007%, compared to similar neighborhoods with higher accessibility. This challenges the assumption that high local accessibility alone drives faster rent price growth. Although central Tel Aviv offers the highest local accessibility, it has experiences a decline in rental prices. In this sense this regression also confirms that remote work appears to narrow the rent gap by reducing the relative advantage of highly accessible areas, as proximity becomes less critical when remote work is more prevalent.

As in Table 5, each specification in Table 6 includes a set of control variables. However, unlike Table 5 across all specifications, remote work and its temporal dynamics do not have a statistically significant direct effect on rent levels. Notably, the lagged rent variables from previous quarters (Columns 2–4) exhibit positive and strongly significant coefficients, consistent with persistence in housing prices. The consistent significance of lagged rent variables across models highlights the persistence and path-dependence in housing price dynamics.

Once these controls are included, the coefficient on *ln_accessibility*—which reflects a neighborhood's local accessibility, independent of remote work—changes from statistically insignificant (Column 1) to negative and significant in subsequent models. This suggests that, holding past rental levels constant, neighborhoods with higher accessibility tend to experience lower rent growth in the current period. One interpretation is that these areas may have had inflated rent levels prior to the observed period, and the negative coefficient reflects a market correction as remote work reduces the marginal value of accessibility.

Taken together, these findings provide further support for the theoretical hypothesis that the rise of remote work reshapes the spatial structure of rental prices, weakening traditional urban premia tied to accessibility.

Table 7. Estimated Results for Equation 10

	(1)	(2)	(3)	(4)
	ln (Rent per m^2)			
VARIABLES				
ln_wfh	-0.000379	0.000187	-0.000677	0.0456**
	(0.00316)	(0.00324)	(0.00353)	(0.0138)
lag1_ln_wfh	-0.0165***	-0.0181***	-0.0181***	-0.0196***
	(0.00261)	(0.00261)	(0.00253)	(0.00219)
lag2_ln_wfh			-0.0122*	-0.0124*
			(0.00456)	(0.00452)
ln_diff				-0.273*
				(0.0915)
residential_central#lag1_ln_wfh	-0.00737***	-0.0130***	-0.0120***	-0.0105***
	(0.00101)	(0.000535)	(0.000745)	(0.000709)
residential_remote#lag1_ln_wfh	0.0179***	0.0178***	0.0177***	0.0189***
	(0.00137)	(0.000560)	(0.000652)	(0.000713)
satellite_city#lag1_ln_wfh	0.0106***	0.0216***	0.0208***	0.0225***
	(0.00166)	(0.000786)	(0.000915)	(0.00115)
ln_lag1_rentperM		0.141***	0.141***	0.140***
		(0.0161)	(0.0162)	(0.0170)
ln_lag2_rentperM		-0.0188*	-0.0191*	-0.0198*
		(0.00769)	(0.00780)	(0.00762)
Constant	4.069***	3.571***	3.547***	3.625***
	(0.0104)	(0.0809)	(0.0796)	(0.0972)
Observations	8,680	8,060	8,060	8,060
R-squared	0.324	0.325	0.325	0.326

Number of CodeSAs	620	620	620	620
SA FE	Yes	Yes	Yes	Yes
Time FE	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 7 presents regression estimates that disaggregate the effect of remote work by neighborhood type, where types are defined by both proximity to the CBD and internal accessibility levels. 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 (*residential_central* × *lag1_ln_wfh*, *residential_remote* × *lag1_ln_wfh*, and *satellite_city* × *lag1_ln_wfh*) 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 0.016% and 0.02%. However, this negative effect is attenuated in suburban neighborhoods, as reflected in the positive interaction coefficients for *satellite_city* and *residential_remote*. In aggregate, the effect of lagged remote work on rents is negligible in *residential_remote* neighborhoods and even positive in *satellite_city* areas. In contrast, *residential_central* neighborhoods experience a sharper negative effect than the base category (*CBD*).

The table 8 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 8. 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 remote work, while central and high-accessibility neighborhoods lose ground in relative rental value. A particularly noteworthy finding is that *residential* areas located in the central area but with lower accessibility to 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. In essence, the value of distancing from the CBD rises when commuting constraints are relaxed, making distant, lower-cost neighborhoods more attractive.

Apart from these central findings—which strongly support the theoretical model—the estimated coefficients of the control variables remain broadly consistent with those reported in Table 1 and are therefore not reiterated here.

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 highly accessible 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. The findings reinforce the notion that remote work is not merely a temporary shock but a structural change with long-term implications for spatial equilibrium in urban housing markets.

7. Conclusions and contribution

This study contributes to our understanding of how the rise of remote work influences urban spatial equilibrium and the evolution of neighborhood dynamics. We began with two core research questions:

1. How can GPS-based mobility data be used to measure work-from-home (WFH) dynamics at a fine spatial scale?
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 using visual and statistical analysis. First, we demonstrate that mobile phone signal 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 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 noticable 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.

However our accessibility-based models reveal a consistent pattern: neighborhoods with higher local accessibility have experienced slower rental price growth when remote work becomes more prevalent. This challenges the traditional assumption that accessibility always confers a rental premium. Instead, our findings suggest that in the context of remote work, housing affordability has become a more important factor than accessibility—reducing the marginal value of location advantages that used to play a central role in urban equilibrium.

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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