Research Title: Decoding Place Functionality: Identifying Emerging Third Places and the Drivers of Remote Work Visitation via Human Trajectories

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Abstract

The COVID-19 pandemic has reshaped urban dynamics by disrupting the traditional "home-work-third place" triad, giving rise to a new "home-third place-home" spatial pattern. In this structure, 'third places' (ie non-traditional work places such as coffee shops and public libraries) increasingly function as workplace (office) substitutes, decentralizing professional activity and potentially driving local housing demand. While classic urban economics links local amenities to increased house prices, the specific impact of remote-work-compatible amenities remains under-researched due to identification complexities. This study develops a novel methodology to identify these emerging third places in the Tel Aviv Metropolitan Area (TAM) and measures their heterogeneous impact on residential housing demand. Utilizing an extensive GPS-signal dataset (2019–2023) mapped to Points of Interest, we adapt the Natural Language Processing Word2Vec model to analyze residents' daily trajectories. This approach successfully identifies new behavioral trends, such as work from home, as well as physical locations that have semantically shifted toward a 'work' concept in the post-pandemic era. We validate the list of detected third places against a ground-truth sample augmented with Google Places reviews. Next, we link this final list of venues with visitor behavioral profiles and local spatial externalities to construct a comprehensive cross-sectional dataset. To understand the spatial distribution of these third places and the drivers behind remote workers' location choices, we estimate two models: an Ordinary Least Squares (OLS) regression for the former, and a Multinomial Logit (MNL) discrete choice model for the latter. The results are communicated to policymakers via an interactive dashboard and mapping tool, allowing users to observe the impact of different location characteristics on the emergence of third places. By providing empirical evidence on changing urban mobility patterns, this research offers policymakers novel, data-driven tools for identifying and quantifying real-time shifts in the increasingly complex relationship between the place of work and residence.

Description of the Research Topic

Although the onset of the COVID-19 pandemic occurred six years ago, the hybrid and working from home (WFH) patterns that emerged during that time have now firmly established themselves as the new normal. Consequently, in the US, the share of hybrid and remote workers has remained steady at roughly 30% since 2023(Barrero et al., 2025), while in Europe, the adoption of hybrid schedules varies between 20% and 52% in 2025(Remotly, 2025). In Israel, the most recent official statistics from the end of 2021 suggest that 15% of the workforce is engaged in remote work ((Zontag et al., 2022)).

The impact of remote work on residential housing markets has been confirmed by previous research: residents who no longer need to regularly commute to the Central Business District (CBD) often relocate to the city outskirts to achieve a better trade-off between price and quality of life(Althoff et al., 2022; Brueckner et al., 2021; Monte et al., 2023). As a result, this migration drives faster housing price growth in outer-metropolitan areas. . We have previously demonstrated this phenomenon within the Tel Aviv Metropolitan Area (TAM) for the period 2020–2023(Tregubova & Gdaliahu, 2025)

Urban amenities are one of key factors explaining this movement. Neighborhoods that offer a better functional substitution for the CBD attract more population and experience a higher growth in rental prices(Biagetti et al., 2024; Tregubova & Gdaliahu, 2025). However, few studies specify exactly which amenities positively impact this growth. Meanwhile, the classical urban economic literature literature argues that the ultimate welfare impact on local residents depends heavily on their specific preferences, as different demographic groups favor different types of amenities(Almagro & Domínguez-Iino, 2025; Couture & Handbury, 2023) Given that remote work arrangements primarily facilitate the mobility of highly educated individuals rather than wealthy populations, traditional urban amenities that attract the wealthy, such as restaurants, schools, parks, or personal services, may hold less weight for the highly educated.

Recent studies of the behavior of remote workers highlight a specific interest in the accessibility of "third places"—informal gathering spots that serve as alternative workspaces to WFH(Tomaz & Tabrizi, 2024). Among them, cafés, libraries, and community centers located near residential areas that provide reliable Wi-Fi and power outlets are the most popular hybrid space options, meaning they serve for both leisure and work(Li et al., 2024; Tomaz & Tabrizi, 2024). However the existing literature lacks robust quantitative proof of this phenomenon, largely because the empirical identification of remote work visits remains a highly challenging task. Consequently, only a limited number of studies have explored the connection between residents' home locations and third places, and their analyses are typically confined to physical distance while ignoring other important economic factors (Li et al., 2024)

As such, this study aims to extend our understanding of the specific triggers behind this new behavior and its subsequent impact on housing market dynamics, explicitly linking remote worker daily routine with urban economic shifts.

Description of the 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 relating to metropolitan Tel Aviv from January 2019 to September 2023, collected by a commercial data analytics company. The dataset contains geolocated signals for individuals with information about the beginning and end of the signal (which indicate stays in certain location). After removing noise, these data monthly capture approximately 4% of the Tel Aviv metro area population (Fig1).

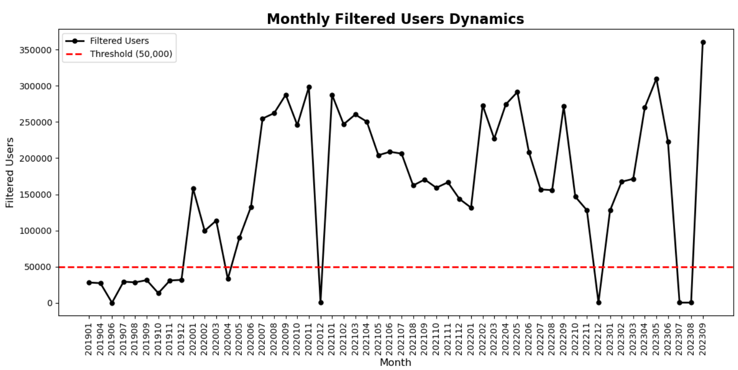

Fig. 1 Monthly volumes of users in mobility dataset

To map signals to physical locations, we utilize several sources for Points of Interest (POIs), specifically the Google Places API and OpenStreetMap (OSM). Although OSM is a frequent choice in academic research, it exhibits a high degree of spatial discrepancy that can potentially compromise mapping quality. Consequently, to ensure accuracy in identifying third places, we we extracted 16,000 potential third places within the TAM from Google Places (Fig 2). Specifically, we collect the data for the following keywords: *bakery, cafe, cafeteria, coffee_shop, tea_house, dessert_restaurant, cat_cafe, dog_cafe, breakfast_restaurant, brunch_restaurant, library, book_store, museum, cultural_center, community_center.*

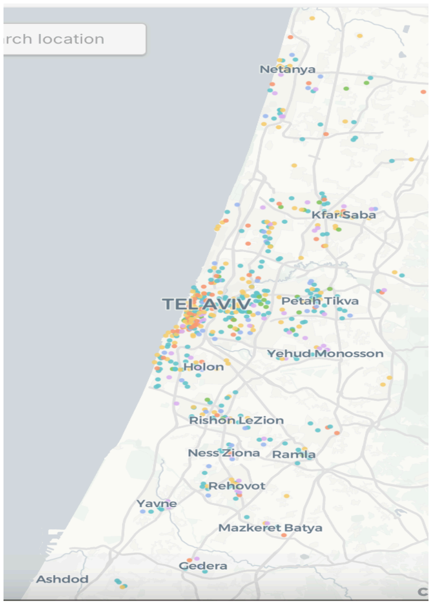

Fig. 2 Map of potential third places extracted via Google Places API

Fig. 3 Relationship between house prices and commuting distance to Azrieli mall (by public transport)

Description of the Research Method

Identifying third places via emerging residents' behavior

To establish a spatial relationship between residential origins and third-place destinations, we will match raw GPS trajectories with established Points of Interest (POIs). This process begins by anchoring each trajectory to previously identified home and primary work locations for each individual based on the frequency of signals in specific time intervals. For all other visits, we will systematically verify the urban context using a hierarchical spatial matching pipeline. We will check if a GPS signal falls within a 20-meter radius of a curated Google third place. If no match is found, we willsubsequently check the OSM dataset within the same 20-meter threshold, or simply retain the isolated geohash if the signal remains unmatched.

Once every visit is categorized, we willempirically capture daily mobility patterns by representing an individual's movement as discrete sequences, analogous to words in a sentence. Each sequence reflects the chronological order of locations visited by a single user within a day, enforcing a minimum stay duration of ten minutes and a maximum gap of three hours between visits to ensure data integrity.

Next, we will divide the data on *pre-treatment* and *post-treatment* samples. The first sample will include trajectories before the Covid-19 in the following months: ‘2019-01-01', '2019-04-01', '2019-07-01', '2019-09-01', '2020-01-01'. The second will include months in a year after the last lockdown in Israel: ‘2022-01-01', '2022-03-01', '2022-07-01', '2022-11-01', '2023-02-01', '2023-04-01', '2023-06-01', '2023-09-01'.

Finally, we will build and apply a popular NLP technique called Word2Vec (Tomas Mikolov et al., 2013) to these contiguous sequences to identify the behavioral emergence of third places by capturing how these spaces are actually utilized. By embedding location "tokens" into a dense vector space, will be able to measure a semantic shift of non-work locations toward ‘work’ locations using the cosine similarity metric(Crivellari & Resch, 2022). This translates associative strength into the angle between normalized vectors.

To qualitatively visualize this high-dimensional embedding space, we will utilize the t-SNE algorithm, effectively projecting the data into two dimensions while preserving the spatial proximity of functionally similar elements. Figure 4 below provides a t-SNE representation of the embeddings from our initial Word2Vec model.

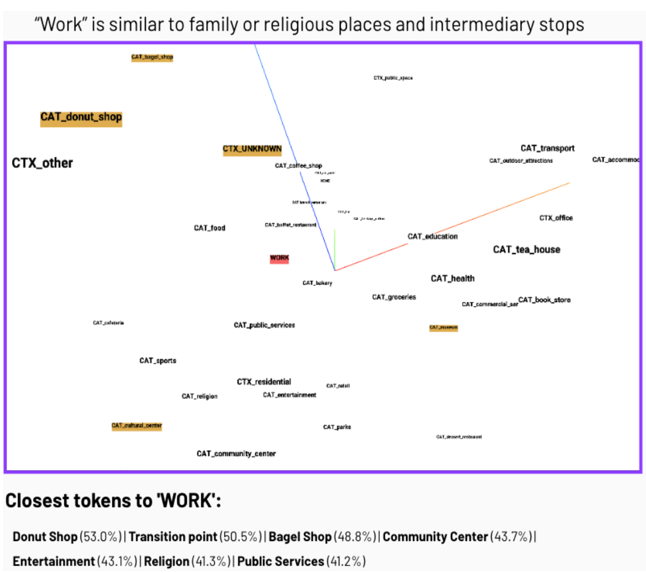

Fig.4 t-SNE visualization of the Word2Vec embeddings build on pre-treatment sample. Locations that are semantically related to the 'work' are highlighted within the vector space

To rigorously identify the exact locations undergoing this functional shift, we experiment with two key variables utilizing the Isolation Forest algorithm for robust, unsupervised anomaly detection without strict distributional assumptions. To ensure strictly intra-categorical and intra-cluster comparisons, we partition the dataset by POI category and geographical area, and independently fit separate models to each cluster. This multi-factored isolates definitive outliers, which we interpret as the strongest newly emerging third places.

- *Variable 1: Post-COVID Absolute Similarity* Sim^{post} Within each category and cluster, we fit the Isolation Forest model to the absolute post-pandemic cosine similarity scores. This method isolates specific POIs exhibiting an unexpectedly high semantic proximity to the 'work' concept relative to their categorical and spatial peers, thereby identifying category and location-specific anomalies.

- *Variable 2: Delta in Similarity* (ΔSim) To capture dynamic temporal variance, we calculate the longitudinal shift in similarity for each venue between pre-treatment and post-treatment samples and fit the algorithm directly to these delta values. This isolates specific POIs experiencing a profound, statistically anomalous jump toward the 'work' token compared to their pre-COVID baselines.

Estimating the drivers of local third places emergence and Local Visitation Patterns

In the second phase, we examine the spatial distribution and micro-level behavioral drivers of these newly identified third places. We integrate the validated list of remote work venues with individual visitor profiles and localized spatial externalities to construct a comprehensive cross-sectional dataset. We then estimate two complementary models to bridge the macro- and micro-spatial scales.

First, an Ordinary Least Squares (OLS) regression is deployed to analyze the macro-spatial distribution of these venues across the study area. This model evaluates how specific location externalities—namely local socio-demographic characteristics, the built environment, and the prevailing level of remote work within the neighborhood—foster the emergence of localized workspaces.

Second, we estimate a Multinomial Logit (MNL) discrete choice model to evaluate individual destination choices. To computationally manage the vast spatial choice set inherent in metropolitan-wide mobility data, we implement a random sampling of non-chosen alternatives for each observed trip. This MNL framework allows us to directly interact user profile attributes with location-specific features, effectively uncovering the heterogeneous preferences and spatial frictions that drive remote workers' localized visitation patterns.

Communication and delivery of results

To make the results of this research accessible and useful for policymakers, this project proposes an interactive spatial dashboard with multiple data layers and tools to navigate and filter the data. First, it will show identified third places with information we collected from POI sources and augmented with visiting metrics from GPS data. Secondly, it will show home origins of the visits to illustrate unique catchment area parameters of each venue. Lastly, it will demonstrate modelling result – by coloring granular spatial units, such as geohashes, it will show the localized influence of each third place on house market in neighboring parcels. In terms of functionally, the interface will feature interactive sliders that allow users to isolate remote work hubs of interest and see their individual impact and visits metrics. Additionally, these sliders will adjust proximity buffers, enabling policymakers to observe how distance from a third place impacts local housing demand. Overall, the visualization tool will serve as a powerful evaluative framework for urban planners to explore the "amenity premium" of residential house market.

Expected Contribution

Theoretical Contribution

By explicitly incorporating the localized mobility patterns of hybrid and remote workers through advanced NLP and trajectory analysis, this study takes a significant step towards retheorizing the traditional role of commuting and daily activities in urban development. While the full urban fallout from the COVID-19 pandemic remains to be completely understood, this proposed research unravels the complex spatio-temporal dynamics of the evolving home-third place relationship. Furthermore, it pioneers a methodological bridge by applying Word2Vec embeddings to physical mobility, demonstrating how the semantic functions of physical spaces continuously shift in response to new macro-behavioral trends.

Practical and Policy Contributions

Beyond theoretical advancement, this study aims to yield direct, actionable policy implications for municipalities seeking to enhance their post-pandemic urban resilience. Because emerging third places are highly popular yet unevenly distributed, identifying their spatial distribution and the specific micro-level drivers of remote workers' destination choices provides critical empirical evidence for local planning and policy-making. This microscale analysis is designed to directly meet decision-makers' needs by operationalizing complex econometric findings through an accessible, interactive dashboard and mapping tool.

Specifically, by linking visitor profiles with location externalities, we intend to equip planners and policymakers with the precise data needed to create environments that reflect the specific needs of diverse neighborhoods. Understanding these localized choice drivers will help define where additional investments in public services are most needed. Ultimately, this will guide where municipalities should prioritize infrastructure—such as the safe pedestrian walkways and cycle lanes essential for actualizing a "15-minute city"—to ensure these highly valued localized workspaces remain accessible and to sustain the environments that drive modern urban vitality.

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