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The Impact of Remote Work on Green Space Values in Regional Housing Markets

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The Impact of Remote Work on Green Space Values in Regional Housing Markets

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Abstract

We examine the extent to which potential changes in work location preferences due to COVID-19 pandemic have been capitalized in local housing markets[1]. Specifically, we estimate how implicit prices for green amenities evolved over the course of the pandemic with a prolonged surge in work from home (WFH). Focusing on ten geographically dispersed cities within the U.S. (Baltimore, Chicago, Cleveland, Los Angeles, Minneapolis/St. Paul, New York City, Philadelphia, Pittsburgh, St. Louis, and Tampa), we use a hedonic pricing approach to identify changes in implicit prices of yard space and park proximity. We employ a combination of the Zillow Transaction and Assessment Database (ZTRAX), Open Street Maps, Environmental Protection Agency's EnviroAtlas dataset and Longitudinal Employer Household Dynamics Origin-Destination Employment Statistics (LODES) to study interactions between exposure of a given location to the WFH shock, yard space, and proximity to green spaces. We find that all cities in the sample, except Los Angeles and New York City, showed an increase in the hedonic price of yard space in the post-COVID period suggesting that home buyers associated more value to private green amenities during the post-COVID period. The hedonic price of proximity to green spaces in the post-COVID period showed little price change. These results suggest that the preferred amenity bundles of people living in the major cities of the U.S. have changed with a change in their commutes and working habits.

JEL code: Q51, R21, R31

Keywords: Zillow data, Property Value Analysis, work from home, yard space, green amenities, hedonic pricing approach, ZTRAX

[1]Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author(s) and do not reflect the position of Zillow Group.

1 Introduction

The global spread of COVID-19 virus constituted a variety of health, economic, and social disruptions, particularly in the way people relate to their workplaces. The COVID-19 pandemic led to a large-scale adoption of work from home (WFH) policies by both private and public sector employers wherever feasible(Dingel and Neiman, 2020) in response to public policy and to mitigate the spread of the virus within the workforce. While there is evidence of nearly half of work hours being supplied from home during the pandemic (Brynjolfsson et al., 2020; Ozimek, 2020; Ramani and Bloom, 2021), one can expect this trend to reverse only partially when the pandemic abates (Barrero et al., 2021). WFH has persisted beyond the immediate responses to the initial shock to become an accepted, though contested, part of the workplace for certain sectors and job types (Aksoy et al., 2022).

This reduction of in-person work changes not just the nature of the workplace, but the lifestyles of those with WFH compatible jobs. Reduced commuting means that workers have more time to spend, as well as flexibility to budget their work-time as they see fit. Depending upon how workers use that time, we might expect well-being flows from local non-tradeable amenities such as access to park or green spaces to increase as local residents reorient their time budgets and use these spaces more. On the contrary, additional free time might make travel to more distant parks or amenities feasible, weakening the salience of immediate park proximity to well-being at a particular location. Workers could also substitute away from public amenities, preferring to spend this time at home on private consumption, thereby increasing the value placed on attributes of the property such as yard space(Cho et al., 2009; Ramani and Bloom, 2021). Another possibility is that post-COVID, residents have a higher preference for less populated areas simply to reduce close contact with others (Liu and Su, 2021). Less populated areas are likely to have more parks, green spaces, and natural amenities, though these spaces need not be publicly accessible. Given the importance of workplace location and commuting in residential housing location choice, reductions in the necessity of daily work commuting lead to shifts in the hedonic price function as housing attributes and amenity bundles shift in importance relative to workplace location (Delventhal et al., 2022). We should expect housing values to reflect adjustments in workers' time and availability as these prices capitalize the desirability of more yard space and/or park-accessible locations as workers adapt to their new schedules and bid for new housing.

While previous literature has provided evidence for a general decrease in demand for housing in more dense locations in the post-COVID period (Liu and Su, 2021; Gupta et al., 2021; Ramani and Bloom, 2021; Rosenthal et al., 2022), there has been less work examining how micro-geographical heterogeneity within urban spaces influence these results. For example, Delventhal et al. (2022) uses a quantitative spatial modeling framework to assess how Los Angeles would change with large scale adoption of WFH, with results suggesting that residents choose locations with cheaper and more available private housing space and that location-specific amenities anchor neighborhood land rents in places previously desired for labor market accessibility. Intuitively, as resident location choices disconnect from the costs of commuting, the model predicts that amenities become a more important element of the relative quality of neighborhoods. In this work, we examine whether and to what extent potential changes in private (yard space) and public (proximity to public parks) amenities preferences due to the changing nature of work have manifested in local housing markets. Specifically, we attempt to determine how implicit prices for yard space and park access evolved and interacted after the pandemic with a prolonged surge of WFH.

We focus our analysis on a set of Metropolitan Statistical Areas (MSAs), referred to as cities in this paper, determined based on the availability of park data in the MSA and which provide a variety of geographic and economic contexts to explore our questions of interest. We use the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) data from the U.S. Census combined with the estimates of industry-level WFH suitability from Dingel and Neiman (2020) to measure location-specific exposure to WFH adoption. Specifically, we assume that the exposure of a location to the

WFH shock varies based on pre-COVID rates of WFH adoption (or WFH job accessibility) at the census tract level. To measure park accessibility, we take advantage of OpenStreetMaps (OSM) data on local land use, providing us with the locations of public parks and green spaces in our cities of interest. For robustness, we also incorporate the Environmental Protection Agency's (EPAs) EnviroAtlas dataset, which shows the estimated walking distance to the nearest park entrance from any location within 250 m, 500 m, 750 m, 2000 m and larger distances. Importantly, we rely on the micro-geographical variation in park access and home characteristics over multiple U.S. cities provided by the Zillow Transaction and Assessment Database (ZTRAX) in combination with the EnviroAtlas dataset. This gives us the ability to observe variation in park distance within a census tract and to examine any shifts in implicit prices for park access across cities with varying climates, density, travel times, and other key characteristics. ZTRAX provides a comprehensive account of housing sales with important housing characteristics that are vital for teasing out the behavioral changes of the buyers (and sellers) in response to changes in conditions, such as the COVID shock. We define yard space as the difference between the lot size and the built area of each house. While a more accurate calculation of yard space should include dividing the built area by the number of stories, the stories data is completely missing for 4 cities (Minneapolis/St. Paul, New York City, Philadelphia, and Tampa) in the ZTRAX dataset. For Chicago and Los Angeles, the story data is missing for a large fraction of units. As a robustness check, we perform analyses on the remaining cities with the story data included in the definition of yard space. Furthermore, we also perform regressions considering the lot space and built area as separate variables.

We find, for the ten cities studied (Baltimore, Chicago, Cleveland, Los Angeles, Minneapolis/St. Paul, New York City, Philadelphia, Pittsburgh, St. Louis, and Tampa) that higher WFH adaptability at a location correlates with higher housing prices, suggesting that access to jobs suitable for remote work is positively valued by residents. For most cities in the post-COVID period (2020-21), the capitalized value of WFH job accessibility declines, implying that areas previously valued for their pre-COVID accessibility decline in relative value as the imposition and normalization of WFH weakens the benefits of WFH-job proximity over space. With respect to private space, we find that residents valued having access to a private green space more during the post-COVID period as the implicit price of our proxy for yard area increased in the post-COVID period for all cities except Los Angeles and New York City. The price gradient of park proximity showed no significant shift in the post-COVID period, which implies that residents did not place additional value to proximity to public parks even with the surge in WFH. Robustness checks using alternative definitions of WFH exposure as well as different data sources for park accessibility show results that align with these general findings. Future work should focus on categorizing local amenities in more detail to examine how continued WFH adoption affects the value residents place on different types of amenities. As more data becomes available, future work should also explore how households are sorting over space as WFH jobs become more available and how this sorting behavior relates to both housing and location attributes.

To the best of our knowledge, the role of commuting patterns and leisure availability in influencing the relative value of private green spaces and public amenities and in particular, the implicit prices associated with park and yard space, is under-explored in the literature. Theoretical and empirical literature (McConnell and Walls, 2005; Cho et al., 2009; Irwin et al., 2014) has underscored how space and natural amenities capitalize into prices of proximate houses and has identified a range of services rendered through them like aesthetics, recreation, wildlife habitat etc. Related literature has focused solely on the value of park access to residents and its capitalization into housing prices (Anderson and West, 2006; Poudyal et al., 2009; Sohn et al., 2020; Wu et al., 2022) and how these effects vary based on park and user characteristics (Fernandez and Bucaram, 2019; Czembrowski et al., 2019), with additional work illustrating the complementarities between park proximity and other amenities such as crime rates (Troy and Grove, 2008; Albouy et al., 2020). The pandemic induced WFH trend has renewed the interest in understanding the preferences of individuals for these amenities. Recent studies have shown that this WFH trend has reshaped the spatial patterns of residential and commercial rent (Gupta et al., 2021; Liu and Su, 2021; Ramani and Bloom, 2021; Rosenthal et al., 2022) and the demand for larger houses (Stanton and Tiwari, 2021). With this study, we not only understand the impact of the COVID shock on the demand for public and private space but also gauge the evolution of housing markets in the future as the technologies that facilitate access to remote work become better. Importantly, this paper utilizes the unique opportunity that ZTRAX data provides to comparatively explore how the hedonic park values have changed in multiple housing markets. This is an additional contribution to the literature, which mostly analyzed the value of park access at the single city level because of the difficulty in obtaining sales data from multiple housing markets.

The rest of the paper is organized as follows: Section 2 explains the empirical strategy, and Section 3 describes data sources. Section 4 presents the main empirical results. Section 5 assesses the robustness of the results. Section 6 summarizes and concludes the paper.

2 Empirical Strategy

We are interested in finding how the implicit price of yard space and access to public green spaces changed after the COVID-19 pandemic, which resulted in a surge of WFH. We hypothesize that this differs based on the exposure to the contemporaneous WFH shock that occurred due to pandemic measures, but likely propagates beyond the time frame of the immediate COVID-19 policy responses. To test whether this is true, we need to specify a pooled regression model of the hedonic price function of a city's housing market that can incorporate marginal prices of private yard space and green space proximity that vary for pre- and post-COVID periods.

In order to examine any heterogeneity in the effects of the WFH shock on home prices, we need some measure of the relative exposure of a location to changes in commuting behavior resulting from WFH adoption. We propose that this can be constructed either through the distribution of employment of workers in the location, or by the accessibility of a location to surrounding jobs. The former method (based on the Resident Area Characteristics (RAC) data from LODES described further in Section 3) is defined as follows. For a given MSA, tract j has WFH exposure:

$$\Omega_j^{RAC} = \sum_{n=1}^{N} (l_{jn}/L_j) * \omega_n \tag{1}$$

where l_{jn} is the total number of workers living in tract j in industry n, L_j is the total workforce in tract j, and ω_n is the share of the labor force in the industry n that can feasibly work from home as defined by (Dingel and Neiman, 2020). In this measure, WFH exposure is defined as the estimated share of residents' employment in tract j that could be conducted remotely and is determined by the pre-COVID employment shares of residents in tract j. In other words, locations with more workers concentrated in industries capable of remote work end up with higher estimated WFH shares.

Alternatively, WFH exposure can be defined by the jobs accessible from tract j weighted by their distance and/or commuting costs to any tract k. This approach is somewhat akin to measures of commuter market access (see Delventhal et al. (2022) for an example within the context of COVID) with the WFH measure representing the spatial distribution of firms in different industries rather than the spatial distribution of the workers. We specify this measure (based on the Workplace Area Characteristics (WAC) data from LODES) as:

$$\Omega_j^{WAC} = \sum_{k=1}^{K} \sum_{n=1}^{N} \omega_n (l_{kn}/d_{jk}^{\theta}) / \sum_{k=1}^{K} L_k/d_{jk}^{\theta} \tag{2}$$

where K is the total number of tracts in an MSA, d_{jk} is the Euclidean distance between tract j and k, L_k is the total employment in k, and θ is a distance-decay parameter specific to each city in our sample[2]. This measure represents the ratio of WFH jobs to overall jobs accessible

[2]Details on how we set θ can be provided upon request. In short, we set this parameter equal to the value that limits any contribution to the job accessibility of the mean tract to zero at the 95th percentile of commuting distance as revealed by the LODES origin-destination (OD) data. In other words, we set theta

from a given tract j. The neighborhood distribution of work from home exposure is given by $F(\Omega^{RAC})$ or $F(\Omega^{WAC})$. We focus on results generated by our RAC-derived measure of WFH exposure (e.g. $F(\Omega^{RAC})$); estimates using $F(\Omega^{WAC})$ are provided as a robustness check in the section 5 below.

Using the distribution specified above, we allow for coefficients that depend on the exposure of a given tract to WFH. The extent of WFH exposure can be specified based on the continuous WFH score as defined above or by discretizing the WFH score in bins. For the latter, first, we create bins of WFH exposure based on the distribution $F(\Omega_j^{RAC})$; create sets $S_m : m = 1, ..., M$ based on the support of $F(.)$ with set membership determined by the percentile of each tract (e.g. $F^{-1}(0) <= F^{-1}(\Omega_j^{RAC}) < F^{-1}(0.25)$) where D_m is equal to 1 when $\Omega_j^{RAC} \in S_m$. We estimate models with the continuous WFH score as well as two and four WFH "bins" (e.g. $M = 2$ and $M = 4$ respectively) with breakpoints determined by the median or quartiles of $F(\Omega_j^{RAC})$. We examine the following hedonic price function specification that pools together the pre- and post-COVID periods:

$$\begin{aligned} ln(P_{ijt}) = \alpha + \sum_{m=1}^{M} \gamma_m D_m ParkD_i + \gamma ParkD_i + \sum_{m=1}^{M} \delta_m D_m Yard_i + \delta Yard_i + \sum_{m=1}^{M} \alpha_m + X_i\beta + \\ Z_j\zeta + s_t + a_t + D_T(\alpha + \gamma_1 ParkD_i + \delta_1 Yard_i + \sum_{m=1}^{M} \alpha_m + X_i\beta) + \epsilon_{ijt} \quad (3) \end{aligned}$$

In this specification, $ParkD_i$ is the distance of house i from the nearest park, D_m is a dummy variable indicating the WFH score of tract j constructed as described above, α_m is a fixed effect for each WFH bin, $Yard_i$ is the yard space in the house i, D_T is the dummy for post-COVID period, Z_j are tract-level characteristics, X_i are house characteristics, and s_t and a_t are seasonal and annual fixed effects respectively. The pooled regression formulation of the hedonic price function allows us to identify shifts in the values of γ and δ between

equal to the value that zeros out contributions to WAC-derived WFH exposure from tracts outside of the observed commuting sheds for each MSA the pre- and post-COVID periods. We would expect the slopes of yard space and distance to parks to steepen in the post-COVID period if the residents start valuing access to private and/or public green spaces more, It is important to note that WFH exposure is calculated for 2019 because the original dataset from which we computed WFH exposure, the LEHD, is not available in 2020 and onward.

3 Data

Our analysis is based on a comprehensive dataset that has been developed by combining data from numerous sources. The dataset includes house transactions, house characteristics, a measure of the level of WFH at the tract level, distance of house to the nearest park, availability of outdoor space in house, and various tract level characteristics during the period from 2015 to 2021 in the ten different cities of the US in our sample.

We computed the WFH exposure for ten cities (Baltimore, Chicago, Cleveland, Los Angeles, Minneapolis/St. Paul, New York City, Philadelphia, Pittsburgh, St. Louis, and Tampa) of the U.S. using the methodology described in Section 2. We considered the job industry distribution of the residents and the number of firms located in various census block groups that form these MSAs as specified in the LEHD Origin-Destination Employment Statistics (LODES) dataset. For our primary results, we use the Residence Area Characteristics (RAC) data, which describes the distribution of employment of residents across industries for a given census tract. The job industries are qualified by the 2-digit North American Industry Classification System (NAICS) code. The WFH exposure was calculated by multiplying the fraction of residents in a block group that can work from home in a certain industry according to the data provided by (Dingel and Neiman, 2020). Therefore, a block group's WFH exposure for an industry represents i) an expected number of people working remotely or ii) an expected exposure to jobs conducive to remote employment. In 2022, the Bureau of Labor Statistics released results of a Business Response Survey that was

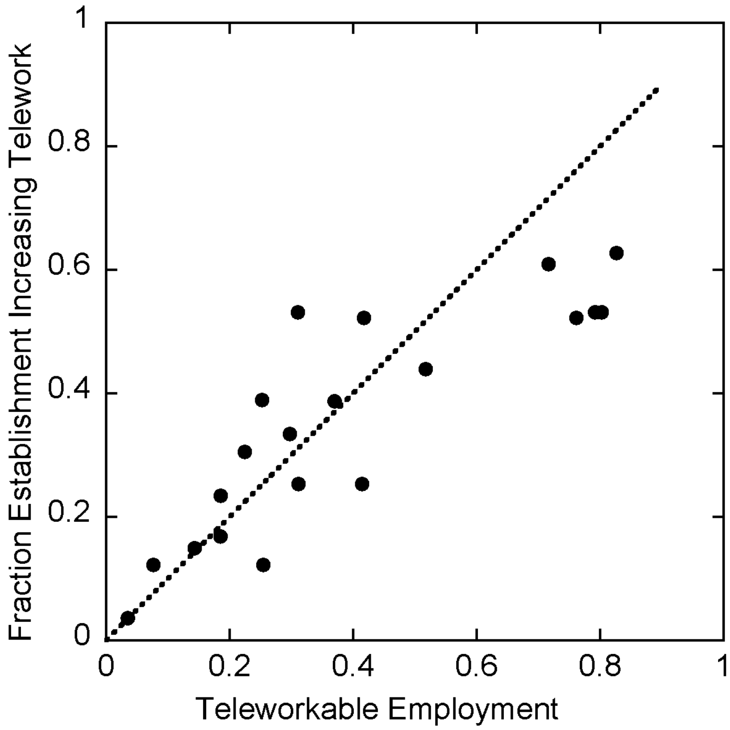

Figure 1: Relationship between the fraction of teleworkable employment in different NAICS groups estimated by Dingel and Neiman (2020) and the fraction of establishments in the same NAICS groups that increased telework during COVID as determined by the Bureau of Labor Business Response Survey (2021). The dashed line is the y = x line.

conducted in 2021 to understand how telework was adopted during COVID by industries belonging to the different NAICS groups. In the Figure 1, we have compared the teleworkable employment of the different NAICS groups estimated by Dingel and Neiman (Dingel and Neiman, 2020) with the fraction of establishments in different NAICS groups that increased telework during COVID. The two estimates are strongly correlated, which gives us confidence in the validity of our WFH score approach.

We use Geographic Information System (GIS) to identify proximity of each house to its nearest green space using two different sources of park proximity data in this analysis. Our main results use data on park locations from OpenStreetMaps (OSM) downloaded state by state from Geofabrik [3], which gives us a dataset of public parks for the entirety of each MSA in our sample. Similarly to Albouy et al. (2020), we identify the locations in the

[3] https://www.geofabrik.de/

OSM dataset that are coded as public parks or public green spaces. Once we create these park shapefiles, we calculate euclidean distance from each property to the nearest park in the OSM dataset. For robustness checks, we also calculate the share of land surrounding each property that is a public park (at 400m and 800m radius distance bands). While slightly different than the distance measure, these measures of local park shares capture how much public green space is available via walking in the surrounding area of each property. Additionally, the EPA EnviroAtlas[4] provides park proximity contour maps, which show the estimated walking distance to the nearest park entrance from any location. The contour lines are drawn in 250-, 500-, 750-, 2000 and higher meter distances from state, county, and local parks. We overlapped the contour map and home location in ArcMap so that the distance to the nearest park for each house sale is known.

House level observations of residential property sales from January 2015 to December 2021 were obtained from the Zillow Transaction and Assessment Dataset (Zillow, 2021). Because we are interested in a household's consumption of private and public green spaces in home sale prices, we limited our sample to arm's-length-sales for single family homes by excluding institutional buyers, inter-family transactions and sales subject to tax-exemption. In addition, we excluded outliers by dropping the top and bottom five percent in the price distribution. The ZTRAX data contains a rich set of sales information among which we included the following house characteristics as covariates: lot size, built / finished area, construction year, story, bedrooms, bathrooms, land use type, and the longitude and latitude. Using the geocode of the house, we computed its distance from the city center, which we identified as a tract with the largest number of employers.

To mitigate the endogeneity which arises from the spatial correlation between neighborhood characteristics and the house prices, we obtained tract-level characteristics from the 2015-2019 five-year American Community Survey (ACS). The tract-level characteristics included land area, water area, population, median age, percentage of White/Asian/Black

[4] https://www.epa.gov/enviroatlas

residents, median household income, percentage of houses occupied by the owners, percentage of college educated, total number of housing units, average travel time to work, percentage of population under 18 years, total school enrollment, and fraction of poor population. We also calculated the development density of tracts by dividing the total number of residential properties with the land area.

4 Empirical Results

4.1 Descriptive Statistics

We studied ten cities of the U.S.: Baltimore, Chicago, Cleveland, Los Angeles, Minneapolis/St. Paul, New York City, Philadelphia, Pittsburgh, St. Louis, and Tampa, which were selected because they provide us a variety of economic and geographic contexts to examine our question. The different characteristics of these cities are shown in the Figure 2 and Table 1. The median house price (price) increased during the post-COVID years in all our cities [Figure 2(a)]. Los Angeles and New York City have the highest median prices. Cleveland and Pittsburgh have the lowest median prices with long tails toward low house prices. Ignoring the tails, the distributions of house prices of all cities are single peaked and roughly log normal. Figure 2(b) shows the distribution of tract-level WFH scores based on the OSM data for the cities. The distribution is broad for all the cities except Tampa. Cleveland has the lowest median WFH score, whereas Minneapolis has the highest. The distributions of tract-level median household incomes are all single peaked [Figure 2(c)]. The distributions for Memphis, Tampa and St. Louis are skewed towards lower income levels. Minneapolis, Baltimore, and New York City have the highest median household incomes. Figure 2(d) shows the distributions of tract-level fraction of white population. The distributions are broad, ranging from 0 to 1 for Baltimore, Chicago, Cleveland, New York City, Philadelphia and St. Louis, which implies that these cities have tracts with predominantly white and non-white populations. Minneapolis, Cleveland, Philadelphia, Pittsburgh, St. Louis, and

Tampa have a majorly white population. Figure 2(e) shows the distributions of tract-level average travel time to work of the cities. New York City has the largest average travel times, followed by Chicago, Baltimore, and Philadelphia. Figure 2(f) shows distributions of distance from downtown of the houses in different cities. There is variation in the distributions of homes from the downtown between the cities.

Spatial distributions of the houses sold during the period of 2016-2021 in the studied cities and their distance to the nearest park is shown in the Figure 3. In this figure, each point represents a sale. The OSM measured distance from green spaces of the houses is discretized in 10 bins and then shown as a color map (lower numbered bin stands for smallest distance). Interestingly, Chicago does not show large heterogeneity in park proximity of the houses. Sparse regions in the figure indicate small density of single family homes. As expected, park proximity has spatial heterogeneity within the cities, and on average, houses in Chicago and Los Angeles have better accessibility to parks.

Table 1: Summary statistics

	Baltimore	Chicago	Cleveland	Los_Angeles	Minneapolis	New_York	Philadelphia	Pittsburgh	St_Louis	Tampa
Mean Price (million $)	0.371	0.278	0.166	0.786	0.306	0.585	0.281	0.178	0.216	0.253
SD Price	0.159	0.139	0.090	0.350	0.114	0.212	0.142	0.107	0.119	0.112
Mean WHF	40.111	38.260	36.745	39.040	40.883	40.642	39.557	38.788	38.919	37.321
SD WHF	3.515	3.930	3.147	4.324	4.137	3.580	4.568	4.518	3.751	2.790
Mean Park Distance (km)	0.614	0.335	0.657	0.489	0.342	0.446	0.471	0.829	0.645	0.882
SD Park Distance	0.688	0.499	0.594	0.366	0.415	0.424	0.484	1.096	0.568	0.885
Mean Density (per km^2)	11.168	24.132	13.921	31.070	16.343	46.421	34.815	12.216	15.262	11.539
SD Density	10.070	20.803	10.414	19.864	11.188	48.080	38.455	11.434	9.742	7.402
Mean Lot acre (Acres)	0.538	0.209	0.416	0.175	0.335	0.236	0.278	0.372	0.262	0.240
SD Lot acre	0.744	0.209	0.672	0.136	0.549	0.545	0.491	0.700	0.376	0.243
Mean Built area (ft^2)	1896.202	1617.580	1620.157	1802.480	1514.880	1705.533	1730.934	1549.435	1562.982	2383.950
SD Built area	763.731	670.883	579.059	711.236	633.519	630.430	660.222	529.636	656.395	872.050
Mean Construction Year	1973.133	1959.432	1957.753	1963.210	1959.687	1951.510	1956.017	1949.692	1961.562	1986.727
SD Construction Year	29.302	27.226	27.899	23.405	30.925	24.941	32.773	31.135	30.068	23.739
Mean Shool Enrollment	0.251	0.262	0.229	0.261	0.248	0.251	0.244	0.205	0.240	0.230
SD Shool Enrollment	0.055	0.050	0.056	0.055	0.058	0.051	0.059	0.054	0.055	0.072
Mean Avr Travel Time	14.842	14.384	11.295	13.653	11.927	17.715	14.226	12.574	11.608	11.987
SD Avr Travel Time	2.769	2.492	2.153	2.388	2.029	3.264	2.626	2.322	1.982	2.935
Mean Median HH Income	103936.970	85764.030	68829.860	98305.920	88065.740	113810.240	84743.350	69397.230	77248.360	67240.380
SD Median HH Income	33901.520	33965.630	25516.210	35375.650	29117.510	37323.350	35224.590	25325.460	31347.690	23096.260
N	110323.000	253252.000	118676.000	304180.000	125598.000	125771.000	161016.000	43422.000	68935.000	238493.000

4.2 Results and Discussion

To apply the model specification of equation 3, we first apply WFH score as a continuous variable common to all the cities (WFH All). The WFH scores are calculated using the RAC data from the LODES dataset using the equation 1. The results so obtained are shown in

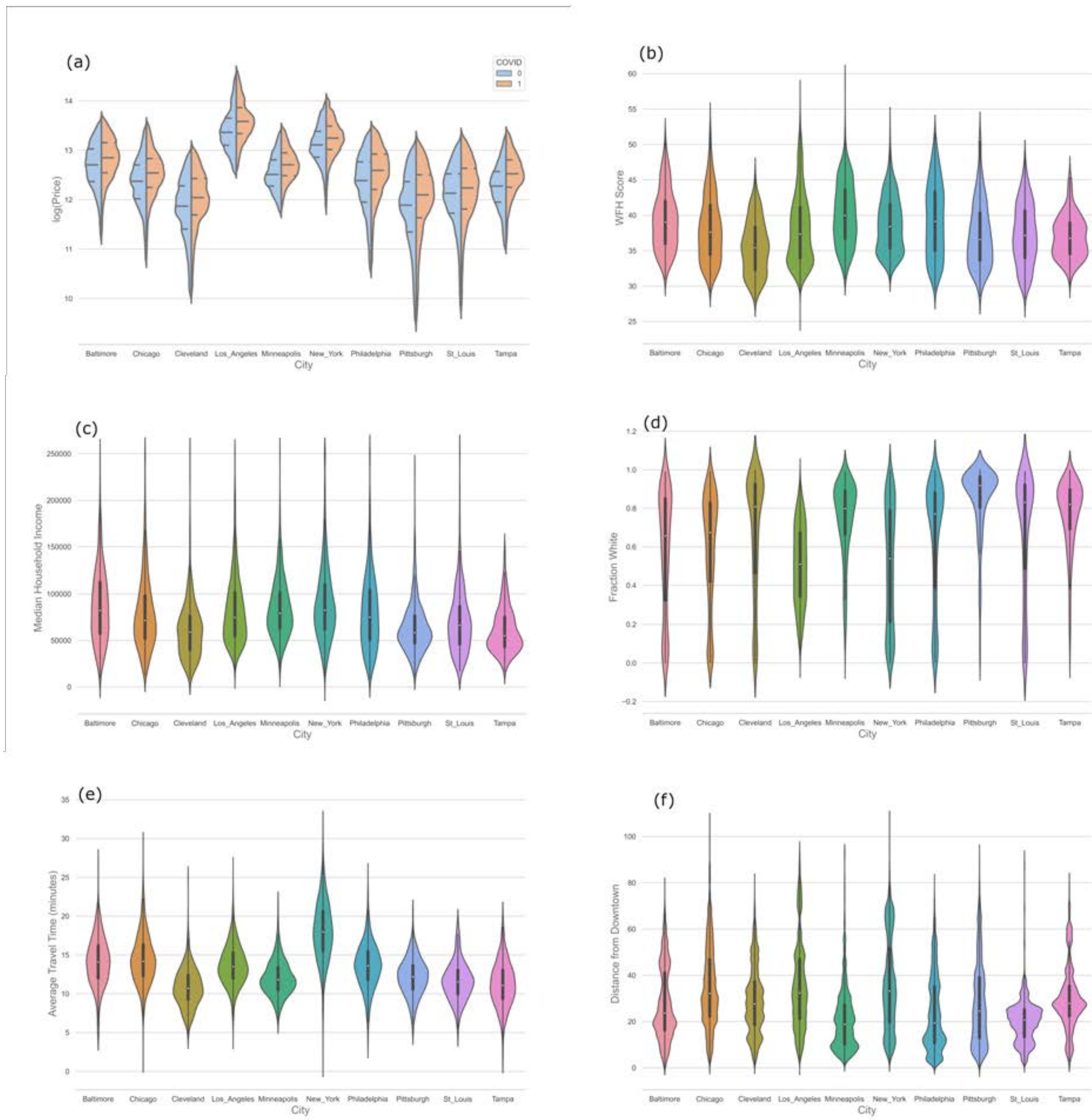

Figure 2: Violin plots showing the distributions of (a) ln(prices) of houses during the pre- and post-COVID periods, (b) tract-level WFH scores, (c) tract-level median household incomes, (d) fraction of white people in the tracts, (e) average travel time to work in different tracts, and (f) distance of houses from downtown for the ten cities.

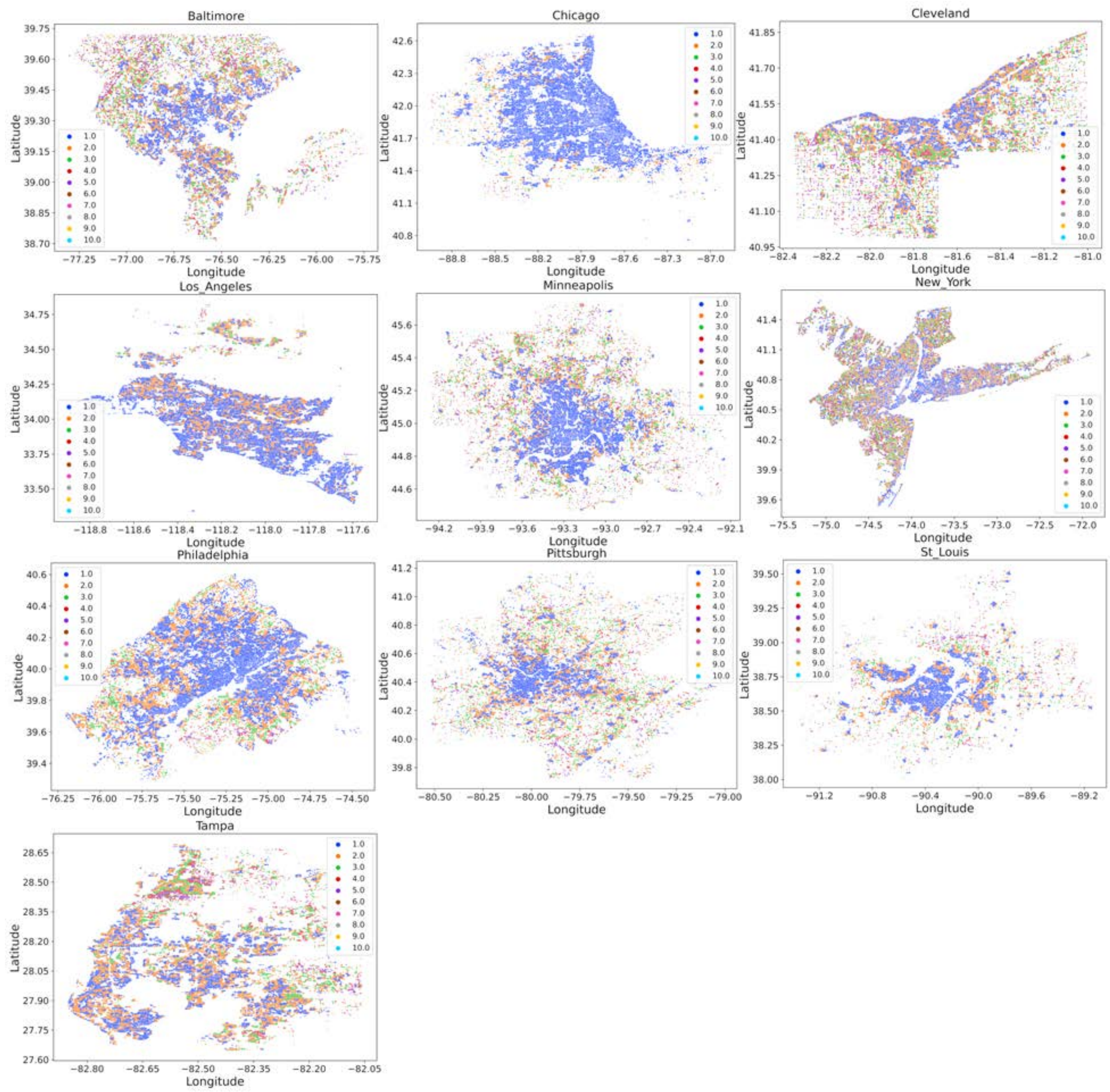

Figure 3: The Spatial distribution of single family homes that were sold during the period of 2016-2021 in the ten cities. The colors represent the distance of a house from the nearest park.The distance to park was discretized into 10 bins for ease of visualization. The lowest number bin stands for closest distance to a park.

the Tables 2 and 3. The total marginal effects are described in table 4. First, it is noted that the hedonic prices increase for the regions with high WFH. We find that the hedonic prices of yard space during the COVID period (captured by the term Yard space $\times$ postCOVID) increases across all cities except Los Angeles. The hedonic prices of park proximity show mixed results across different cities. More importantly, the marginal price effect of yard space dominates that of park proximity in every city (except Los Angeles), which implies that people preferred private green space over access to public parks. The hedonic price for the regions with high WFH flattened at the time of COVID (that is, the coefficient of WFH All $\times$ postCOVID being negative) for all cities. This is another interesting finding, which suggests that post-COVID, the premium of living in regions with high WFH accessibility lowered because WFH became more prevalent. The interaction terms of Yard space with WFH All and Distance to Park with WFH All shows a city-specific trend, and so nothing in general is concluded. As a robustness check, we scaled the range of WFH values for each city between 0 and 1, and then discretized the scaled WFH into four bins = 1, 2, 3, 4 based on the quartile of houses with different WFH scores. This way, we analyze the effects of city-level variation in WFH on the preference bundles of buyers. For this specification as well (Tables 5 and 6), the hedonic price of yard space in the post-COVID period is positive for all cities except Los Angeles and New York City. On the other hand, the hedonic price associated distance to park in the post-COVID period shows heterogeneity between the cities. Therefore, we conclude that for all cities, except Los Angeles and New York City, the preference for private green amenity, that is, yard space, increased during the post-COVID period but the preference for public green amenities did not show any uniform trend. This specification also affirms other conclusions: the regions with high WFH are associated with high hedonic price, and the hedonic price for these regions flattened during the post-COVID period.

Table 2: Effects of yard space, distance to park, and WFH on house prices pre- and post-COVID

	Dependent variable: ln House Price				
	Baltimore	Chicago	Cleveland	LA	Minn./St. Paul
	(1)	(2)	(3)	(4)	(5)
Yard space	0.117***	0.188**	0.165***	0.213*	0.042***
	(0.021)	(0.061)	(0.020)	(0.090)	(0.012)
Distance to Park	0.029	0.004	0.069**	−0.187***	0.014
	(0.026)	(0.010)	(0.024)	(0.030)	(0.015)
WFH_All	1.032***	1.277***	2.204***	1.082***	0.969***
	(0.127)	(0.114)	(0.141)	(0.099)	(0.065)
Yard space x WFH_All	−0.177***	−0.004	−0.367***	0.249	0.062+
	(0.051)	(0.159)	(0.075)	(0.242)	(0.036)
Distance to Park x WFH_All	−0.034	0.026	−0.185*	0.267**	0.024
	(0.073)	(0.063)	(0.083)	(0.088)	(0.052)
Yard space x postCOVID	0.014**	0.019**	0.021**	−0.025+	0.009**
	(0.004)	(0.006)	(0.007)	(0.013)	(0.004)
WFH_All x postCOVID	−0.253***	−0.336***	−0.189***	−0.103***	−0.154***
	(0.022)	(0.014)	(0.038)	(0.013)	(0.013)
Distance to Park x postCOVID	0.002	−0.009**	−0.006	0.013*	0.008+
	(0.004)	(0.003)	(0.007)	(0.006)	(0.005)
Census Tract Char	Y	Y	Y	Y	Y
Seasonal Fixed Effects	Y	Y	Y	Y	Y
Missing Value Flags	Y	Y	Y	Y	Y
Num.Obs.	127 651	411 398	139 558	363 369	220 129
R2	0.533	0.515	0.541	0.617	0.521

Note:
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.0001

Table 3: Effects of yard space, distance to park, and WFH on house prices pre- and post-COVID

	Dependent variable: ln House Price				
	NYC	Philadelphia	Pittsburgh	St. Louis	Tampa
	(1)	(2)	(3)	(4)	(5)
Yard space	0.113**	0.166***	0.123***	0.153***	0.324***
	(0.042)	(0.034)	(0.012)	(0.034)	(0.044)
Distance to Park	0.024	0.089**	−0.007	−0.040+	0.039+
	(0.038)	(0.029)	(0.013)	(0.021)	(0.023)
WFH_All	0.682***	1.182***	1.504***	2.750***	1.059***
	(0.107)	(0.172)	(0.186)	(0.231)	(0.158)
Yard space x WFH_All	−0.118	−0.108	−0.265***	−0.193+	−0.325*
	(0.080)	(0.076)	(0.044)	(0.105)	(0.158)
Distance to Park x WFH_All	−0.190*	−0.236**	0.132*	0.198*	−0.157
	(0.082)	(0.074)	(0.059)	(0.087)	(0.099)
Yard space x postCOVID	0.007	0.022***	0.015+	0.049***	0.035**
	(0.006)	(0.004)	(0.008)	(0.012)	(0.011)
WFH_Full x postCOVID	−0.258***	−0.297***	−0.138**	−0.344***	−0.348***
	(0.026)	(0.018)	(0.053)	(0.042)	(0.042)
Distance to Park x postCOVID	0.042***	0.003	0.000	−0.039**	−0.009+
	(0.008)	(0.005)	(0.006)	(0.014)	(0.005)
Census Tract Char	Y	Y	Y	Y	Y
Seasonal Fixed Effects	Y	Y	Y	Y	Y
Missing Value Flags	Y	Y	Y	Y	Y
Num.Obs.	181 635	237 612	81 461	92 352	268 282
R2	0.378	0.600	0.470	0.593	0.428

Note:
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.0001$

Table 4: Total Marginal Effects

	Baltimore	Chicago	Cleveland	Los Angeles	Minneapolis	New York	Philadelphia	Pittsburgh	Saint Louis	Tampa
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Yard	0.131	0.207	0.186	0.188	0.051	0.12	0.188	0.138	0.202	0.359
Park	0.031	-0.005	0.063	-0.174	0.022	0.066	0.092	-0.007	-0.079	0.03
Num.Obs.	127651	411398	139558	363369	220129	181635	237612	81461	92352	268282

Table 5: Effects of yard space, distance to park, and discretized WFH on house prices pre- and post-COVID

	Dependent variable: ln House Price				
	Baltimore	Chicago	Cleveland	LA	Minn./St. Paul
	(1)	(2)	(3)	(4)	(5)
Yard space	0.069***	0.143**	0.117***	0.291**	0.051***
	(0.017)	(0.050)	(0.018)	(0.091)	(0.008)
Distance to Park	0.050*	0.012*	0.065**	−0.110***	0.017+
	(0.020)	(0.006)	(0.020)	(0.019)	(0.009)
WFH bin 2	0.129***	0.077***	0.212***	0.163***	0.107***
	(0.025)	(0.020)	(0.031)	(0.022)	(0.018)
WFH bin 3	0.200***	0.158***	0.344***	0.265***	0.180***
	(0.029)	(0.024)	(0.036)	(0.029)	(0.024)
WFH bin 4	0.302***	0.279***	0.453***	0.417***	0.286***
	(0.039)	(0.036)	(0.046)	(0.044)	(0.032)
Yard space x WFH bin 2	−0.014	0.049	−0.023	0.039	0.006
	(0.018)	(0.051)	(0.020)	(0.106)	(0.010)
Yard space x WFH bin 3	−0.010	0.081	−0.075***	−0.012	0.013
	(0.018)	(0.053)	(0.020)	(0.114)	(0.012)
Yard space x WFH bin 4	−0.042*	0.021	−0.087***	0.041	0.032+
	(0.019)	(0.054)	(0.023)	(0.119)	(0.018)
Distance to Park x WFH bin 2	−0.038+	−0.011	−0.046*	−0.046	0.010
	(0.022)	(0.023)	(0.022)	(0.033)	(0.012)
Distance to Park x WFH bin 3	−0.046*	0.011	−0.047*	0.055*	0.017
	(0.023)	(0.020)	(0.024)	(0.023)	(0.020)
Distance to Park x WFH bin 4	−0.057*	−0.051*	−0.062*	0.066+	−0.047
	(0.026)	(0.025)	(0.024)	(0.038)	(0.030)
Yard space x postCOVID	0.014***	0.017**	0.020**	−0.031*	0.010**
	(0.004)	(0.006)	(0.007)	(0.013)	(0.003)
WFH bin 2 x postCOVID	−0.040***	−0.047***	−0.008	−0.001	−0.021***
	(0.008)	(0.005)	(0.011)	(0.005)	(0.005)
WFH bin 3 x postCOVID	−0.057***	−0.074***	−0.029**	0.001	−0.049***
	(0.008)	(0.005)	(0.011)	(0.006)	(0.005)
WFH bin 4 x postCOVID	−0.081***	−0.107***	−0.058***	−0.037***	−0.053***
	(0.007)	(0.006)	(0.014)	(0.006)	(0.005)
Distance to Park x postCOVID	0.004	−0.010***	−0.006	0.014*	0.010*
	(0.004)	(0.003)	(0.006)	(0.005)	(0.004)
Census Tract Char	Y	Y	Y	Y	Y
Seasonal Fixed Effects	Y	Y	Y	Y	Y
Missing Value Flags	Y	Y	Y	Y	Y
Num.Obs.	127 651	411 398	139 558	363 369	220 129
R2	0.532	0.508	0.530	0.608	0.509

Note:

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.0001$

Table 6: Effects of yard space, distance to park, and discretized WFH on house prices pre- and post-COVID

	Dependent variable: ln House Price				
	NYC	Philadelphia	Pittsburgh	St. Louis	Tampa
	(1)	(2)	(3)	(4)	(5)
Yard space	0.154***	0.240***	0.107***	0.140***	0.296***
	(0.026)	(0.053)	(0.010)	(0.027)	(0.028)
Distance to Park	0.007	0.051+	−0.002	−0.012	0.009
	(0.022)	(0.030)	(0.010)	(0.015)	(0.011)
WFH bin 2			0.122**		0.113**
			(0.045)		(0.036)
WFH bin 3		0.209***	0.338***	0.482***	0.195***
		(0.042)	(0.051)	(0.071)	(0.040)
WFH bin 4	0.094***	0.326***	0.515***	0.671***	0.227***
	(0.021)	(0.060)	(0.064)	(0.098)	(0.045)
Yard space x WFH bin 2			−0.050**		−0.083*
			(0.016)		(0.042)
Yard space x WFH bin 3		−0.120*	−0.076***	−0.043	−0.067
		(0.055)	(0.017)	(0.032)	(0.044)
Yard space x WFH bin 4	−0.099***	−0.127*	−0.096***	−0.073*	−0.112*
	(0.026)	(0.054)	(0.017)	(0.034)	(0.044)
Distance to Park x WFH bin 2			0.054*		0.003
			(0.023)		(0.024)
Distance to Park x WFH bin 3		−0.058+	0.053*	0.006	−0.018
		(0.032)	(0.025)	(0.024)	(0.020)
Distance to Park x WFH bin 4	−0.074**	−0.063+	−0.021	0.049	−0.021
	(0.025)	(0.033)	(0.019)	(0.040)	(0.040)
Yard space x postCOVID	0.003	0.021***	0.014+	0.041**	0.034**
	(0.005)	(0.004)	(0.008)	(0.014)	(0.011)
WFH bin 2 x postCOVID			0.032+		−0.037***
			(0.017)		(0.009)
WFH bin 3 x postCOVID		−0.063***	0.004	−0.086***	−0.065***
		(0.009)	(0.024)	(0.018)	(0.010)
WFH bin 4 x postCOVID	−0.038***	−0.123***	−0.014	−0.112***	−0.094***
	(0.008)	(0.008)	(0.022)	(0.017)	(0.010)
Distance to Park x postCOVID	0.034***	0.003	0.001	−0.038**	−0.009*
	(0.007)	(0.005)	(0.006)	(0.015)	(0.004)
Census Tract Char	Y	Y	Y	Y	Y
Seasonal Fixed Effects	Y	Y	Y	Y	Y
Missing Value Flags	Y	Y	Y	Y	Y
Num.Obs.	181 635	237 612	81 461	92 352	268 282
R2	0.374	0.595	0.472	0.563	0.427

Note:

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.0001$

5 Robustness Checks

To check the robustness of our results, we re-estimated the coefficient of our interest using a different measure of yard space. Limiting the sample to those four cities (Baltimore, Chicago, Pittsburgh and St. Louis) where the stories data is available for more than 90 percent houses sold, we calculated yard space taking into account the number of stories in a house. In this calculation of yard space, the built area is divided by the number of stories and is then subtracted from the lot size. The regression results are shown in the Table 7. The results are consistent with our findings. As another robustness check, we use fraction of public green space area within 400 m of a house as a measure of proximity to green spaces. The Tables 8 and 9 show the regression results with WFH taken as the continuous variable common to all the cities. In this analysis, the hedonic price of yard space in the post-COVID period steepens for all the cities except Los Angeles. Therefore, this analysis bosters our finding that in the post-COVID period, the buyers preferred private green spaces rather than proximity to public green spaces. As before, the hedonic price associated with the interaction terms of WFH with yard space and fraction of green spaces varies citywise with no general trend.

Table 7: Effects of yard space calculated using story data, distance to park, and WFH on house prices pre- and post-COVID

	Dependent variable: ln House Price			
	Baltimore	Cleveland	Pittsburgh	St. Louis
	(1)	(2)	(3)	(4)
Yard w/ story	0.128***	0.176***	0.109***	0.175***
	(0.021)	(0.020)	(0.012)	(0.036)
Distance to Park	0.024	0.069**	−0.006	−0.038+
	(0.025)	(0.023)	(0.012)	(0.022)
WFH_All	1.029***	2.226***	1.419***	2.765***
	(0.130)	(0.143)	(0.158)	(0.232)
Yard w/ story x WFH_All	−0.194***	−0.380***	−0.179***	−0.233*
	(0.051)	(0.076)	(0.045)	(0.110)
Distance to Park x WFH_All	−0.025	−0.203*	0.033	0.178*
	(0.072)	(0.083)	(0.046)	(0.089)
Yard w/ story x postCOVID	0.018***	0.022**	0.023*	0.063***
	(0.004)	(0.007)	(0.009)	(0.013)
WFH_All x postCOVID	−0.253***	−0.208***	−0.049	−0.289***
	(0.022)	(0.037)	(0.054)	(0.044)
Distance to Park x postCOVID	0.003	−0.010+	0.000	−0.020
	(0.004)	(0.005)	(0.007)	(0.015)
Census Tract Char	Y	Y	Y	Y
Seasonal Fixed Effects	Y	Y	Y	Y
Missing Value Flags	Y	Y	Y	Y
Num.Obs.	115 797	134 616	64 646	91 337
R2	0.531	0.554	0.509	0.596

Note:

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.0001

Table 8: Effects of yard space, green spaces in proximity, and WFH on house prices pre- and post-COVID

	Dependent variable: ln House Price				
	Baltimore	Chicago	Cleveland	LA	Minn./St.Paul
	(1)	(2)	(3)	(4)	(5)
Yard space	0.132***	0.191**	0.193***	0.056	0.050***
	(0.021)	(0.060)	(0.020)	(0.101)	(0.011)
Frac green (400 m)	−0.041	0.179*	0.023	0.472***	0.047
	(0.124)	(0.083)	(0.189)	(0.107)	(0.105)
WFH_All	1.021***	1.297***	2.118***	1.215***	0.969***
	(0.123)	(0.113)	(0.127)	(0.097)	(0.068)
Yard space x WFH_All	−0.205***	−0.002	−0.450***	0.527*	0.058+
	(0.050)	(0.158)	(0.075)	(0.268)	(0.033)
Frac green (400 m) x WFH_All	0.095	−0.437+	−0.155	−0.755***	0.006
	(0.309)	(0.240)	(0.633)	(0.193)	(0.256)
Yard space x postCOVID	0.015***	0.015*	0.020**	−0.020	0.012***
	(0.004)	(0.006)	(0.007)	(0.014)	(0.003)
WFH_All x postCOVID	−0.253***	−0.333***	−0.188***	−0.099***	−0.157***
	(0.022)	(0.014)	(0.038)	(0.014)	(0.013)
Frac green (400 m) x postCOVID	0.004	−0.013	0.051	−0.033	0.003
	(0.023)	(0.018)	(0.064)	(0.022)	(0.022)
Census Tract Char	Y	Y	Y	Y	Y
Seasonal Fixed Effects	Y	Y	Y	Y	Y
Missing Value Flags	Y	Y	Y	Y	Y
Num.Obs.	127 651	411 398	139 558	363 369	220 129
R2	0.533	0.515	0.541	0.609	0.520

Note:
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.0001

Table 9: Effects of yard space, green spaces in proximity, and WFH on house prices pre- and post-COVID

	Dependent variable: ln House Price				
	NYC	Philadelphia	Pittsburgh	St. Louis	Tampa
	(1)	(2)	(3)	(4)	(5)
Yard space	0.126**	0.208***	0.122***	0.134***	0.341***
	(0.041)	(0.036)	(0.011)	(0.036)	(0.043)
Frac green (400 m)	−0.022	0.005	−0.190	0.201	0.525**
	(0.111)	(0.131)	(0.256)	(0.277)	(0.166)
WFH_All	0.569***	1.100***	1.572***	2.848***	0.948***
	(0.105)	(0.167)	(0.187)	(0.221)	(0.151)
Yard space x WFH_All	−0.158+	−0.210**	−0.239***	−0.109	−0.395*
	(0.081)	(0.078)	(0.044)	(0.111)	(0.154)
Frac green (400 m) x WFH_All	0.223	−0.326	0.433	−0.286	−1.201*
	(0.249)	(0.350)	(0.618)	(0.734)	(0.556)
Yard space x postCOVID	0.012*	0.022***	0.015*	0.034**	0.031**
	(0.006)	(0.004)	(0.007)	(0.013)	(0.011)
WFH_All x postCOVID	−0.249***	−0.297***	−0.148**	−0.329***	−0.342***
	(0.026)	(0.018)	(0.053)	(0.043)	(0.043)
Frac green (400 m) x postCOVID	−0.030	−0.021	0.102	0.186**	0.027
	(0.025)	(0.034)	(0.091)	(0.058)	(0.030)
Census Tract Char	Y	Y	Y	Y	Y
Seasonal Fixed Effects	Y	Y	Y	Y	Y
Missing Value Flags	Y	Y	Y	Y	Y
Num.Obs.	181 635	237 612	81 461	92 352	268 282
R2	0.375	0.600	0.469	0.592	0.428

Note:

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.0001$

6 Conclusions

This work provides the first robust empirical evidence of price capitalization of green spaces in housing value in post-COVID era and whether the consumption of private green space (yards) has complementary relationship with the consumption of public green space (parks). Using hedonic pooled regressions with fixed effects strategy, we find for the ten cities studied (Baltimore, Chicago, Cleveland, Los Angeles, Minneapolis/St. Paul, New York City, Philadelphia, Pittsburgh, St. Louis, and Tampa) that residents valued having access to a private green space more during the post-COVID period as the implicit price of our proxy for yard area increased in the post-COVID period for all cities except Los Angeles and New York City. The price gradient of park proximity showed no significant shift in the post-COVID period, which implies that residents did not place additional value to proximity to public parks even with the surge in WFH. While this work does not consider park quality or size, the result is robust to using alternative measures of yard space as well as different data sources for park accessibility.

With respect to WFH, We find that higher WFH adaptability at a location correlates with higher housing prices, suggesting that access to jobs suitable for remote work is positively valued by residents. For most cities in the post-COVID period (2020-21), the capitalized value of WFH job accessibility declines, implying that areas previously valued for their pre-COVID accessibility decline in relative value as the imposition and normalization of WFH weakens the benefits of WFH-job proximity over space.

Future work should focus on categorizing local amenities in more detail to examine how continued WFH adoption affects the value residents place on different types of amenities. As more data becomes available, future work should also explore how households are sorting over space as WFH jobs become more available and how this sorting behavior relates to both housing and location attributes.

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