The 15-minute City Quantified Using Human Mobility Data*

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Abstract

Amid rising congestion and transport emissions, policymakers are embracing the "15-minute city" model, which envisions neighborhoods where basic needs can be met within a short walk from home. Prior research primarily examined amenity access without examining its relationship to behavior. We introduce a measure of local trip behavior using GPS data from 40 million US mobile devices, defining *15-minute usage* as the proportion of consumption-related trips made within a 15-minute walk from home. Our findings show that the median resident makes only 14% of daily consumption trips locally. Differences in access to local amenities can explain 84% and 74% of the variation in 15-minute usage across and within urban areas, respectively. Historical data from New York zoning policies suggest a causal relationship between local access and 15-minute usage. However, we find a trade-off: increased local usage correlates with higher experienced segregation for low-income residents, signaling potential socio-economic challenges in achieving local living.

Keywords: 15-minute city, mobility, sustainability, land use, walkability

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1 Introduction

Urban areas account for over 60% of global greenhouse gas emissions, and the proportion of the global population residing in cities is projected to reach 68% by 2050 ([1, 2]). The call to establish sustainable, inclusive and affordable cities is therefore crucial ([3]). Central to this effort is the restructuring of cities, with a particular emphasis on human mobility. The transportation sector—the second-largest energy consumer worldwide and the leading contributor to US greenhouse gas emissions—requires significant policy intervention ([4, 5]).

As a result, urban policies have transitioned away from automobile-focused designs, favouring instead urban models that emphasize proximity and encourage active transportation. The "15-minute city" concept, which proposes that all daily essentials should be accessible within a short walk from home, exemplifies this shift ([6, 7]). This model aims not only to minimize transportation emissions but also to foster community life by situating day-to-day activities within close reach of residential areas. Nevertheless, the practicality of executing such a model and the social and environmental repercussions of restructuring cities for walkability remain largely unexplored. Amid these uncertainties, current propositions for the "15-minute city" model lack definitive indicators to evaluate the influence of proximity to amenities on travel behaviour, thus calling into question the model's feasibility ([8]).

Existing research that explores the ability of residential neighbourhoods to meet essential needs within a walkable distance typically focuses on the accessibility of essential amenities, such as grocery stores and restaurants ([9–13]). This approach, however, presumes a predictable response in residents' daily travels to changes in proximity to amenities, an assumption that may not always hold true. Although studies do provide evidence of a correlation between accessibility and travel behaviour ([14–16]), these insights are often limited to specific contexts, failing to capture a comprehensive understanding of localized living across the United States. Additionally, these studies tend not to address potential drawbacks of the 15-minute city model, including the risk of heightened socio-economic segregation as a possible consequence of an intensified focus on localized living ([17]).

One promising avenue to explore these issues lies in using large-scale mobile GPS data. This approach can yield unique insights into human mobility patterns beyond the reach of smaller case studies or survey data ([18, 19]). This approach has significant implications, especially for informing climate policy ([20–22]).

In this paper, we present a comprehensive analysis of local living conditions across over 400 urban areas in the United States. Using GPS data that record visits to points of interest (POIs) by more than 40 million mobile phone users, we document a strong relationship

between urban residents' ability to access local urban amenities and their usage of those amenities. Our results suggest a causal relationship and point to the potential benefits of less restrictive zoning rules. Policies promoting mixed-use development could increase access to diverse amenities in residential areas, reduce travel distances and allow for more efficient trip-chaining. This, in turn, may alleviate travel-associated emissions and encourage more sustainable transportation modes.

Increasing local usage could also present a social trade-off: given the state of residential segregation by race and income in the United States, would encouraging local living lead to fewer encounters between socio-economic groups? To explore the potential impact of shorter trips on the diversity of encounters during daily travels, we build on recent literature that quantifies the diversity of social interactions in day-to-day activities ([23]). We found that in low-income areas with higher local amenity usage, socio-economic isolation is more prevalent.

Our findings highlight how mobility data can deepen our understanding of human behaviour and its broader policy implications. We reveal a trade-off between the social and environmental goals of urban policy interventions and offer insights into the conditions under which local living policies might reduce transportation emissions or increase social isolation.

2 Results

2.1 Documenting local trip behavior in the US

We used large-scale mobile phone data that trace daily trips from approximately 40 million smartphone users in the 420 most populated urban areas in the United States. The data were provided by SafeGraph and contain information on trips to 5.3 million POIs, 3.9 million of which are located within our sample urban areas. Further discussion on the quality and representativeness of these data is available in the Methods section.

The dataset provides each POI's geographical coordinates (latitude and longitude), classifies it according to the North American Industry Classification System (NAICS) code and records the number of visits originating from each home census block group in the United States. Our dataset covers 13.6 billion POI visits throughout 2019, our study period. Our primary analysis was conducted at the neighbourhood level, identified by census block groups, with additional analyses performed at the urban area level.

To evaluate trip patterns within a 15-minute walking distance, we obtained 15-minute walking isochrones based on the pedestrian street network, originating from each block group's population-weighted centroid, using the Openrouteservice API. To construct our measure of 15-minute usage, we concentrated on amenities encompassing essential functions

in line with the 15-minute city model ([7]). The essential amenities in our analysis include restaurants, schools, parks, health care, drugstores, arts and cultural institutions, grocery stores, services and religious organizations.

We categorized individual POIs into these nine categories using their NAICS codes. The respective codes are listed in Supplementary Table S.1. These categories make up 30% of the POIs in our dataset and represent 35% of all trips.

We defined our 15-minute usage measure as the proportion of trips originating in each neighbourhood that were aimed explicitly towards these essential amenities and occurred within a 15-minute walk from the neighbourhood's population-weighted centroid. Emphasizing these essential functions allowed us to assess the degree to which urban environments provide convenient access to daily necessities, a core principle of the 15-minute city concept.

To assess how the use of local amenities is related to their accessibility, we computed an access measure. This measure describes the number of essential amenities within a 15-minute walk from a given home census block group. Similar to our usage measure, we concentrated on the previously mentioned nine categories of amenities. For each category, we tallied the POIs within a 15-minute walking distance from the census block group and assigned each neighbourhood a score, reflecting the percentile rank of the neighbourhood with respect to that category. By averaging these scores across all categories and weighting them by the national average trip share per category, we derived an index between 0 and 100 representing local access.

Supplementary Table S.2 shows the correlations between our primary and alternative usage metrics, including the share of trips within 10, 20 and 25 minutes and the median trip distance. Although the 15-minute mark may appear arbitrary, our findings remain consistent when using different time frames or similar measures. Supplementary Table S.3 shows the correlation between our primary and unweighted access metrics, where all categories are weighted equally. These alternative measures are highly correlated across neighbourhoods.

Figure 1 illustrates our methodology for constructing both the access (left) and 15-minute usage measures (right), using a neighbourhood in Chicago as an example. The access measure, indicated by the dashed green boundary, represents the availability of amenities within a 15-minute walk from the neighbourhood's population-weighted centroid. The 15-minute usage measure is determined by the proportion of trips taken by residents of that block group to destinations inside the walking radius instead of outside of it.

Figure 2a plots the cumulative distribution of our measure of 15-minute usage across all US neighbourhoods. Residents of the median US neighbourhood take only 14% of their trips to basic amenities within a 15-minute walking radius. Residents in 84% of US neighbourhoods

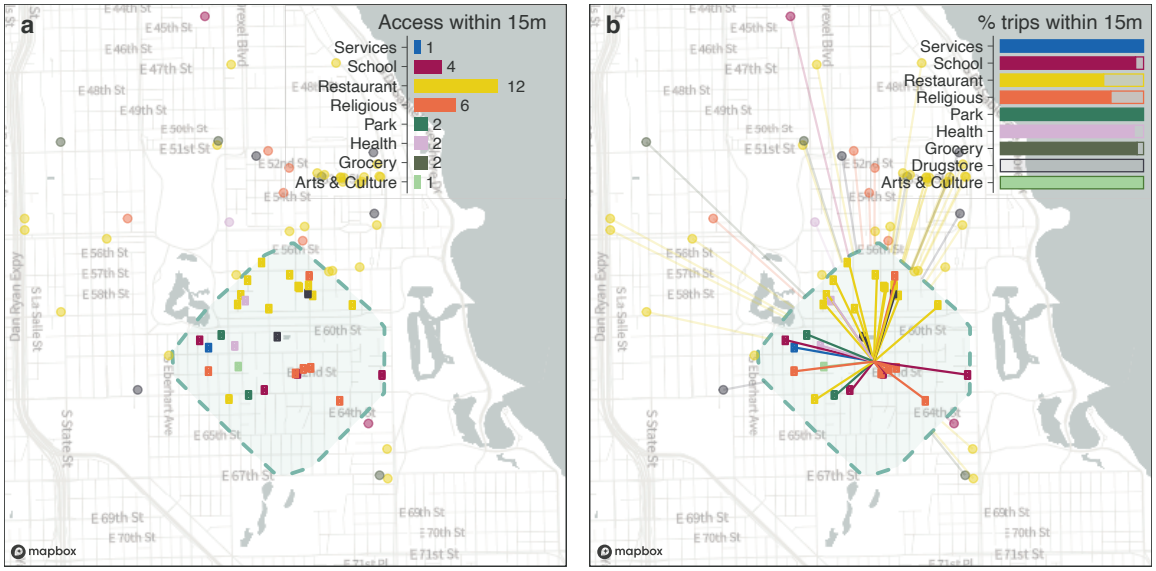

FIGURE 1: **Example of measuring access and usage within a 15-minute walk with SafeGraph data.** a) POIs within and outside of the 15-minute walkshed from the centroid of the neighbourhood and count of POIs within the 15-minute walkshed by type of POI in the upper-right corner. b) Trips to amenities within and outside the 15-minute walkshed and share of trips within the 15-minute walkshed by type of POI in the upper-right corner. Basemap reproduced from Mapbox under CC BY 3.0.

make less than half of their trips within a 15-minute walking radius.

Figure 2b plots 15-minute usage by the median resident across US urban areas, while Figure 2c highlights the top 15 urban areas. A clear regional divide emerges, with urban residents in the Northeast making approximately 34% of their trips within a 15-minute walking distance, whereas those in the South make just 18% or fewer of their trips within that distance. This regional discrepancy aligns with findings from the latest National Household Travel Survey, which indicates that southerners tend to depend more on personal vehicles for local trips ([24]). This observation is also consistent with [25], who noted a lack of walkable and transit-accessible neighborhoods in several southern cities.

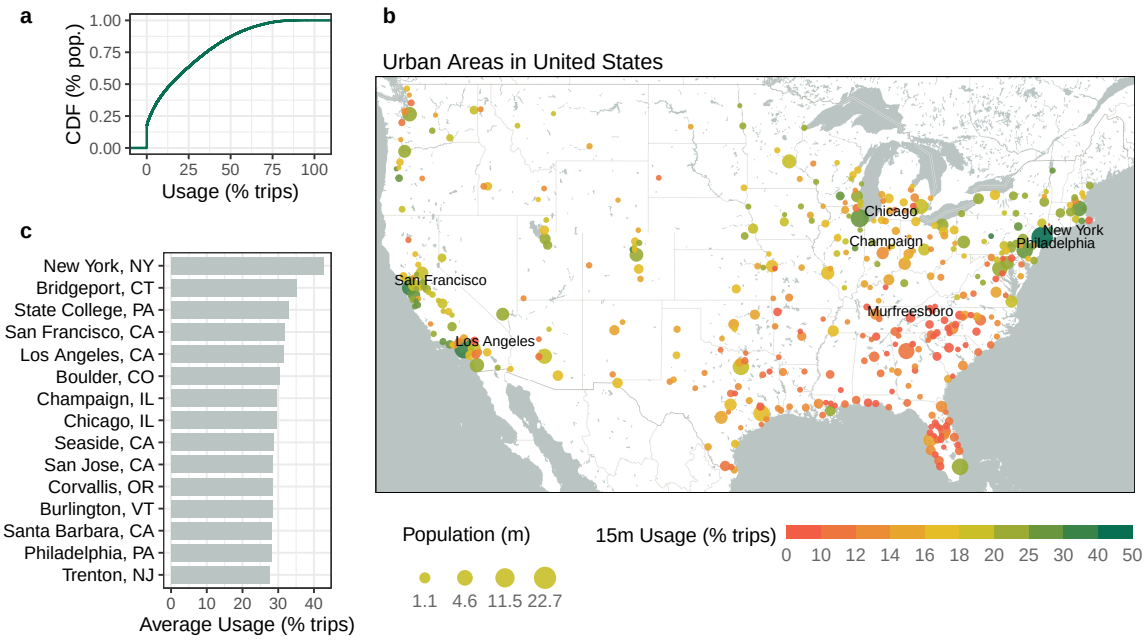

FIGURE 2: **Local trips in the United States.** a) The cumulative distribution of 15-minute usage for US neighbourhoods. CDF, cumulative distribution function. b) 15-minute usage for all urban areas in the United States. Basemap reproduced from Mapbox under CC BY 3.0. c) 15-minute usage for those urban areas that have the highest proportions of local trips.

Figure 3 plots 15-minute usage by median income, binned into deciles within each urban area. As representative examples, New York, Detroit and Atlanta are highlighted to showcase high, medium and low levels of local usage, respectively. Across all urban areas, 15-minute usage decreases sharply with income. While residents in the bottom income decile make on average 41% of their trips within a 15-minute radius, those in the top income decile make only 11% of their trips locally.

2.2 The role of access in local trips

Advocates for 15-minute cities emphasize the provision of accessible amenities, expecting this to increase the frequency of local trips. We thus examined the relationship between local access to amenities and 15-minute usage. In Figure 4a, we plot 15-minute usage against our access measure, using population-weighted averages aggregated to the urban area level. The 15-minute access measure explains 84% of the variation in 15-minute usage across urban areas. Figure 4b demonstrates the relationship between 15-minute usage and access across neighbourhoods. Even within urban areas, 15-minute usage rises sharply with access. As we

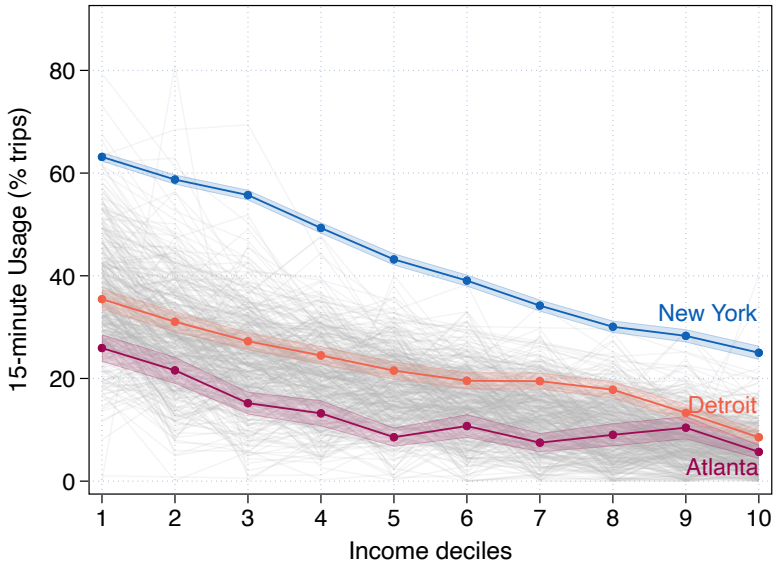

FIGURE 3: **Local trips by income levels.** 15-minute usage by neighbourhood income deciles for all urban areas, including New York (n = 13,908 block groups), Detroit (n = 3,359 block groups) and Atlanta (n = 2,338 block groups). The error bands represent 95% confidence intervals.

transition from neighbourhoods with the lowest local access to those with the highest, the level of 15-minute usage increases as well—the bottom 10% of neighborhoods with respect to access have a usage of close to 0%, while the top 10% have an average usage of 58%. These differences in access explain 74% of the variation in local usage across neighbourhoods within a city.

Table 1 presents regression results where 15-minute usage is regressed against access measures at the neighbourhood level (columns 1-3) and the urban area level (columns 4-6). Column 1 indicates that a one-percentile increase in access corresponds to a 0.77-percentage-point increase in 15-minute usage ($P < 0.001$). The results remain largely unchanged when we factor in neighbourhood sociodemographics (column 2), public transit frequency and commute lengths (column 3).

Column 2 also shows that among the demographic variables, median neighbourhood income is negatively correlated with 15-minute usage ($\beta = -4.62$, $P < 0.001$), confirming a well-established finding from the National Household Travel Survey ([26]). Conversely, population density is positively and significantly associated with 15-minute usage ($\beta = 0.48$, $p = .051$). In column 3, we controlled for transit frequency and average commute length

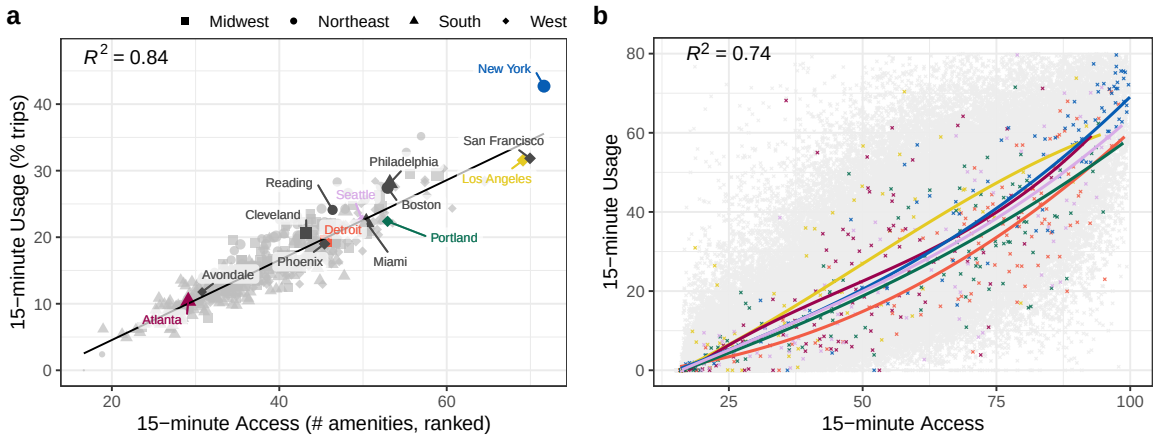

FIGURE 4: **Access and local trips.** a) The relationship between 15-minute usage and access at the urban area level. b) The relationship between 15-minute usage and access across neighbourhoods within urban areas. Block groups in six representative urban areas are emphasized using colours that correspond to the cities indicated in (a). Each of the six urban areas in (b) also features a fitted non-parametric spline regression, denoted by the same colour as the city. The R^2 value in a is derived from a regression analysis of 15-minute usage on 15-minute access at the urban area level ($n = 420$ urban areas). The R^2 value in b is derived from a regression analysis at the census block group level ($n = 150,159$ block groups), incorporating urban area fixed effects.

to ensure that the observed relationship between access and usage is not confounded by the transit availability in neighbourhoods and the geographical proximity between individuals' homes and workplaces. We found that both variables are positively and significantly correlated with 15-minute usage (P = 0.005 and P < 0.001, respectively). Columns 4-6 confirm a robust link between 15-minute access and 15-minute usage across urban areas.

Across all specifications, access has considerable explanatory power. In columns 1-3, we estimate that access explains between 69.1% and 74.8% of the variation in 15-minute usage across neighbourhoods. In columns 4-6, we estimate that access explains between 68.7% to 83.6% of the variation in 15-minute usage across cities. To validate the robustness of our results, we repeated our baseline analyses using all POIs from the SafeGraph dataset, not limiting them to our selected essential categories. This expanded analysis produced similar results, lending further support to the robustness of our method (see Supplementary Table S.4 for the details).

TABLE 1: Relationship between 15-minute usage and access across neighborhoods (census block groups) and urban areas

	Dependent Variable: 15-minute usage (percentage of trips)					
	Across CBGs			Across Urban Areas		
	(1)	(2)	(3)	(4)	(5)	(6)
15-minute Access	0.769^{***}	0.710^{***}	0.715^{***}	0.601^{***}	0.509^{***}	0.493^{***}
	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
Pop Density Log		0.451^{*}	0.183		1.950^{***}	2.124^{***}
		$p = 0.075$	$p = 0.378$		$p = 0.001$	$p < 0.001$
Median Income Log		-4.615^{***}	-4.238^{***}		-2.429^{***}	-3.328^{***}
		$p < 0.001$	$p < 0.001$		$p < 0.001$	$p < 0.001$
% Education: BA +		0.009^{*}	-0.0003		0.042^{***}	0.018
		$p = 0.094$	$p = 0.948$		$p = 0.002$	$p = 0.132$
% White		-0.003	-0.006		0.001	-0.005
		$p = 0.554$	$p = 0.238$		$p = 0.906$	$p = 0.587$
Transit Frequency (per sq. mi)			0.001^{***}			0.003^{***}
			$p = 0.005$			$p = 0.003$
Average Commute (mi)			0.107^{***}			-0.094^{***}
			$p < 0.001$			$p < 0.001$
Urban Area FE	✓	✓	✓			
Observations	150,159	145,862	145,859	420	420	420
R^2	0.738	0.753	0.756	0.836	0.845	0.875
Partial R^2	0.748	0.691	0.696	0.836	0.708	0.687

Notes.— The table reports OLS estimates of the relationship between 15-minute usage and access. Columns 1 to 4 report estimates at the neighborhood level (controlling for urban area fixed effects) and columns 5 to 8 report estimates at the urban area level. The covariates included in columns 2 to 4 and 6 to 8 come from the American Community Survey and the *National Transit Map* from the Bureau of Transportation Statistics. The partial r-squared for access is computed as $\beta \times \frac{\text{cov(15-minute usage,15-minute access)}}{\text{var(15-minute usage)}}$, where β is the regression coefficient for 15-minute access. These partial r-squared estimates might still represent upper bounds, as our regressions do not control for more detailed measures of the built environment. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level. Included P-values correspond to a two-sided t-test for each estimate, using robust standard errors clustered at the county level.

To investigate how public transit accessibility impacts our main findings, we conducted an additional robustness check. In particular, we replicated our baseline results for a subsample comprising neighbourhoods with above-median transit accessibility. Columns 1 and 3 in Supplementary Table S.5 correspond to columns 3 and 6 in Table 1. The resulting estimates indicate that the influence of access on usage within this subsample is comparable to that found in our original baseline analysis. A detailed description of the public transit accessibility variable can be found in the Methods section.

2.3 Towards the causal effect of access on 15-minute usage

The strong positive correlation between local access to amenities and local usage described in the previous section supports the hypothesis that promoting mixed-use development within residential areas could decrease average trip durations. However, the strength of this correlation may not necessarily indicate a causal relationship in which improved access encourages more local trips. For instance, the regression may capture how increased local amenity use attracts businesses, leading to improved access rather than vice versa. Moreover, areas with abundant local amenities might appeal to those who would favour shorter trips regardless, even if the accessibility does not directly encourage the average person to opt for shorter trips.

To address the first concern, we used spatial variation in the zoning code implemented in New York City in 1961 ([27, 28]). The 1961 zoning resolution, for the first time, established city-wide floor-to-area ratio (FAR) regulations, dividing New York City into 2,141 zoning districts, each allowing different maximum densities for residential, commercial and other uses. A map of the 378 commercial zoning districts is provided in Supplementary Figure S.1. Our focus lies on the average maximum commercial FAR permitted in each neighbourhood, which we used to create exogenous variation in present-day access to amenities and services.

This source of variation should address the first but not the second issue mentioned earlier, provided that the variation in business density triggered by the 1961 code does not reflect any preference of present-day residents to attract businesses. The 1961 zoning plan in New York City was primarily informed by previous built-up densities and broad geographic definitions. Therefore, following Shertzer et al. [29], we included controls for population and built-up density, proximity to the city centre, employment composition, poverty and the share of non-white population based on data from the 1960 Census.

Using the 1961 zoning code as a basis for identification does not resolve the issue of people who prefer shorter trips selecting neighbourhoods with ample local access. Even if the retail characteristics of a neighbourhood were entirely random, residents would continue to choose

neighbourhoods that meet their needs. As a result, we view our instrumental variable (IV) estimates as a progression towards understanding causality rather than as conclusive evidence of the impact of access on usage.

Figure 5a reports the first-stage relationship between the average FAR allowed by the 1961 zoning resolution and our measure of access across neighbourhoods in New York City. There is a strong first-stage association, as indicated by an F statistic of 187 (see Table 2 column 2), suggesting that neighbourhoods with fewer FAR restrictions in neighbouring commercial districts see higher contemporary access levels to amenities within a 15-minute walking distance. Figure 5b reports the reduced-form relationship between historical FAR permissions and 15-minute usage. Similarly, residents of neighbourhoods with less historical restrictions on commercial areas tend to take short trips more frequently: residents of the highest-FAR districts take 75% of their trips locally, while residents of the lowest-FAR districts take only about 50% of their trips locally.

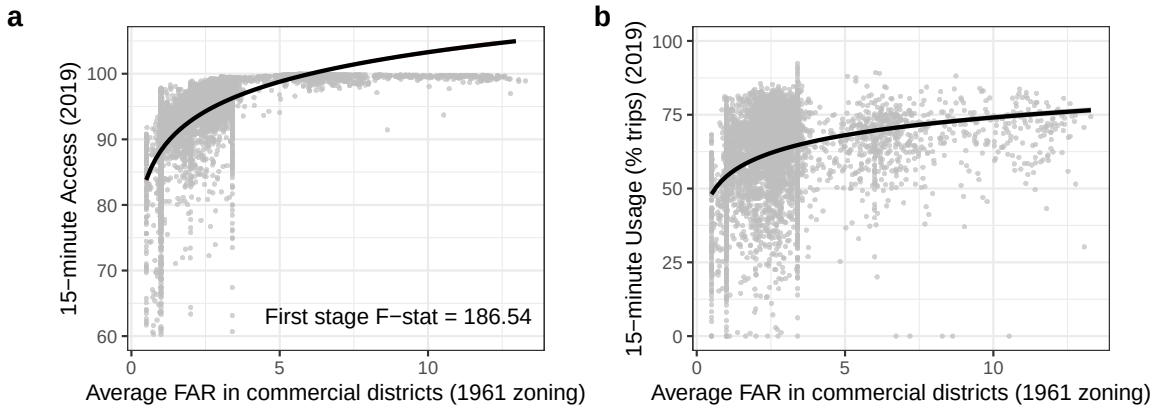

FIGURE 5: **First-stage and reduced-form relationships between historical zoning regulations and current access to local services and 15-minute usage for New York neighborhoods.** a) The first-stage relation between historical zoning and current access. b) The reduced-form relation between historical zoning and current 15-minute usage. Each dot represents a census block group in New York City in New York City ($n = 5,582$ block groups), and each black line corresponds to a log-linear regression model of the form $y_i = \log(x) + \epsilon_i$, where ϵ is a noise term. Supplementary Table S.9 summarizes the regression results from these specifications.

Table 2 reports our IV estimates for New York City. Column 1 reports ordinary least squares (OLS) estimates for the relationship between 15-minute usage and access. The estimated 0.95 coefficient ($P < 0.001$) is slightly higher than the coefficients estimated in Table

1, columns 1-2, which can potentially be explained by the narrower range of access in New York City than in our universe of urban areas.

TABLE 2: OLS and IV estimates of the relationship between 15-minute usage and access across neighborhoods (census block groups) in New York City

	Dependent variable:			
	15-minute Usage (percentage of trips)			
	OLS	IV estimates		
	(1)	(2)	(3)	(4)
15-minute Access	0.951^{***}	1.249^{***}	1.176^{***}	1.228^{***}
	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
Population Density (Log)	4.261^{***}		3.933^{***}	3.973^{***}
	$p < 0.001$		$p < 0.001$	$p < 0.001$
Median Income (Log)	-4.241^{***}		-4.115^{***}	-4.238^{***}
	$p < 0.001$		$p < 0.001$	$p < 0.001$
IV: Log Average Commercial FAR in 1961 Resolution		✓	✓	✓
Distance to City Center	✓	✓	✓	✓
1960 Population and Housing Density	✓	✓	✓	✓
1960 Workers by Industry	✓	✓	✓	✓
1960 Poor and Non-white Families				✓
First stage F-stat	NA	186.54	180.5	164.34
Observations	5,205	5,582	5,205	5,205
R^2	0.502	0.420	0.497	0.494

Notes.— The table reports OLS and IV estimates of the relationship between 15-minute usage and access for neighborhoods in New York City. Column 1 reports OLS estimates of the relationship between 15-minute usage and access for New York City, controlling for distance to the city center and a host of socio-economic controls for 1960, including population and housing density and the share of workers by industry. Columns 2-4 report the IV estimates. Columns 2 and 3 also control for distance to the city center, population and housing density and the share of workers by industry. Column 4 includes additional controls for the share of poor and non-white families in 1960. The covariates included in these models come from [28] and [27]. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level. Included P-values correspond to a two-sided t-test for each estimate, using robust standard errors.

Columns 2-4 provide our IV estimates, each controlling for different covariates. Column 4, our preferred specification, implies that a one-percentile increase in access is associated with a 1.23-percentage-point increase in local usage. This estimate aligns with the national OLS estimates and exceeds its New York City OLS counterpart. This discrepancy might indicate

attenuation in the OLS estimates due to measurement error. Given that we have only a single snapshot of data capturing available amenities in 2019, our access measurement may not perfectly reflect the dynamics of open and closed amenities throughout the year. Hence, the primary independent variable might be measured with error. If so, our OLS estimates would be biased towards zero.

To address the issue of sorting, we conducted an additional robustness check by focusing on a specific subset of census tracts in New York City. This subset consists of the top quartile of census tracts in New York City with respect to the share of residents who were raised in the area as children and continued to reside there as of 2015. By examining this sample, we can reduce the potential for self-selection from residents choosing locations based on current amenity access. The IV estimates corresponding to this subsample are illustrated in Supplementary Table S.6, and they closely match the magnitude of those obtained for the full sample, suggesting that our findings are not likely driven by residential self-selection.

Our results indicate that restrictions on land use, particularly those curtailing commercial development in residential areas, could contribute to extended travel distances and increased carbon use. These results echo the conclusions drawn by [30], who found that residential land-use restrictions appear to increase America's carbon footprint by constraining the growth of environmentally friendly metropolitan areas, such as San Francisco and San Diego, while simultaneously encouraging new household formation in regions with high carbon footprints, such as Atlanta and Houston. The impact of local land-use regulations on global carbon emissions could be a critical factor to consider in any forthcoming cost-benefit analysis of such rules.

2.4 Trade-off between local living and segregation

While it might seem inherently beneficial from an environmental standpoint to limit inter-city travel, reducing travel across neighborhoods could exacerbate the social isolation of disadvantaged communities ([17, 31]). Historical racial segregation within American cities has often been perpetuated by land-use controls and restrictive covenants, which have hindered the migration of Black people into predominantly white areas. A policy encouraging more localized travel could inadvertently limit opportunities for interaction and exchange across different racial and income groups, potentially further diminishing opportunities for economic mobility ([32, 33]).

To analyze this, we created a metric of experienced income segregation for each neighborhood within each city. This measure reflects the extent to which residents are exposed to individuals from diverse income groups in their daily travels. Each user in our dataset

is assigned the median income of their neighborhood, and we calculated the mean income disparity between residents of a given neighbourhood and those they encountered at the same POIs over the duration of our study period. Although our data do not specifically capture interpersonal interactions (as individuals may visit the same grocery store at different times of day or may not interact despite visiting simultaneously), it does capture co-location or exposure, which has been demonstrated as a reliable proxy for interactions ([34]). This information serves as an indicator of the income diversity—or lack thereof—experienced by residents of different neighbourhoods in their daily encounters. Our methodology is guided by [34] and is explained in greater detail in the Methods section.

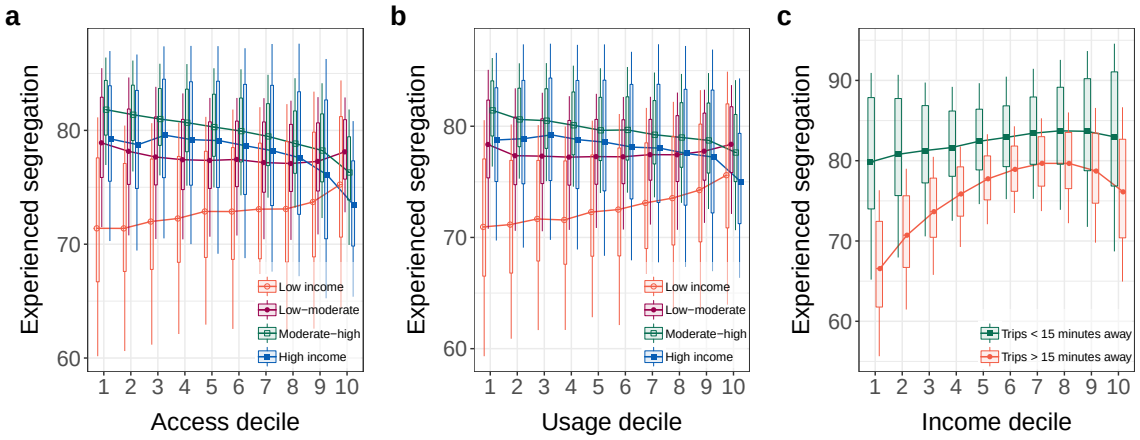

FIGURE 6: **Local trip behavior and experienced segregation.** a) Experienced segregation against 15-minute access for neighbourhoods in different income quartiles. b) Experienced segregation against 15-minute usage for neighbourhoods in different income quartiles. c) Experienced segregation during short (<15 minutes) and long trips (>15 minutes) for residents of neighbourhoods in different income deciles. The box plots show the means and the 10th, 25th, 75th and 90th percentiles. In a), b), $n = 41,998$, 37,676, 34,299 and 31,890 census block groups for income quartiles 1, 2, 3 and 4, respectively. For c) trips taken less than 15 minutes from home, $n = 124,656$ block groups. For c) trips taken further than 15 minutes from home, $n = 145,855$ block groups. (Note that residents of 21,119 census block groups take no trips within 15 minutes in our dataset).

Figure 6a,b plots our experienced segregation index against the 15-minute access and usage measures across neighbourhoods in varying income quartiles. The figure indicates a negative association between 15-minute usage and experienced segregation for residents of upper-middle and high-income neighbourhoods. In fact, as local travel increases, residents

of high-income neighbourhoods experience more social mixing. This trend is reversed for residents of low-income neighbourhoods, where experienced segregation rises 5.4% (from 71.4 to 75.2) as we transition from neighbourhoods with the lowest local usage to the highest. Supplementary Table S.7 shows the results of a regression analysis that formalizes this relationship: a one-unit increase in usage is associated with a 0.071-unit increase in the physical segregation index (column 3). The rise in experienced segregation with usage is more than twice as sharp in the 15 urban areas with the highest usage, where a one-unit increase in usage is associated with a 0.164-unit increase in the physical segregation index (column 1).

The positive association between the percentage of 15-minute trips and our segregation index for residents of less affluent neighbourhoods indicates that these individuals are more likely to interact with a socio-economically diverse group during longer trips than during shorter ones. This is depicted in Figure 6c, where segregation experienced during long and short trips is plotted separately for residents of neighbourhoods across different income deciles. For residents of low-income neighbourhoods, long-distance travel results in a 16.7% reduction in experienced segregation. Residents of high-income neighbourhoods, in contrast, see only an 8.2% decrease in experienced segregation when they travel further from home. This discrepancy underscores the importance of the balance between local living and segregation, especially for lower-income communities.

The regression analysis in Supplementary Table S.7 shows that the differences in experienced segregation for residents of less affluent neighbourhoods, as documented in Figure 6, are statistically significant ($P < 0.001$). Consistent with the findings in Figure 6, we estimate a positive association between local trips and experienced segregation for residents of neighbourhoods in the lowest income quartile and a negative association between local trips and experienced segregation in the highest income quartile. These differences remain robust even when controlling for urban area fixed effects, and the results are comparable if we regress our measure of experienced segregation on access to local amenities instead of 15-minute usage, as seen in columns 2 and 4.

When we repeated the calculation assigning visitors' incomes drawn from the census block group's income distribution instead of relying on the average block group incomes, we found similar results, including a 0.57 Pearson correlation coefficient between this measure and our primary segregation measure. Our main analysis is centred on encounters specifically within our designated POIs. However, when we broaden our scope to include the entire universe of POIs, there is a strong correlation (Pearson correlation coefficient, 0.981), suggesting that the selection of a specific POI set does not influence our findings.

3 Discussion

Our paper presents a large-scale evaluation of local living patterns across US urban areas, exploring their potential social and environmental impacts. We leveraged a large dataset of mobile GPS traces to examine the use of everyday amenities within walkable distance from home.

We developed an index of local living—defined as the proportion of trips made within a 15-minute walk from home—at the neighbourhood level across more than 400 US urban areas, termed the "15-minute usage" index. We anticipate that this index will be a crucial starting point for future environmentally oriented policy interventions. Our index reveals that US urban areas currently fall short of the 15-minute ideal: the median US city resident makes only 14% of daily trips to basic amenities locally. However, substantial regional and socio-economic disparities exist within the United States—for instance, lower-income residents and those living in the northeastern United States make a higher proportion of trips to basic amenities locally, suggesting that these areas might be more receptive to local living policies and interventions.

We found a strong correlation between the accessibility of amenities within a 15-minute walk from home and the usage of these amenities, providing preliminary evidence to support the 15-minute city model's underlying premise: local living is determined by access to local amenities. Furthermore, we provide evidence indicating a causal relationship by leveraging variation in access created by the 1961 New York City zoning ordinance across New York City neighbourhoods. Our findings reveal that areas with more permissive commercial zoning in 1961 have a larger proportion of local trips today, suggesting that local zoning regulations shape the level of access to nearby amenities and that more flexible local zoning could be a natural policy lever for those advocates interested in increasing local trips.

In the final section of the paper, we investigated a potential downside to promoting local living: we examine whether urban residents who stay closer to home are less likely to engage with a diverse group in their daily lives, thus intensifying socio-economic segregation. We found that more localized trips and greater access to local amenities are associated with higher levels of experienced segregation only for low-income residents. This is probably because opportunities for higher-income social interactions in most cities are located away from low-income neighbourhoods.

The findings presented in this paper enhance our understanding of urban travel patterns and highlight the importance of mobility data for addressing environmental and social sustainability in cities. Collectively, our results suggest that the "15-minute city" planning

strategies could significantly reduce trip lengths if they successfully enhance access. However, our dataset also allows us to identify that such policies could inadvertently increase the social isolation of the less affluent. This implies that to gain both environmental and social benefits from the 15-minute approach, policies promoting local living in US cities should be paired with dedicated efforts to create opportunities for social mixing, such as subsidized housing or mandating public spaces catering to diverse groups.

This trade-off would be challenging to uncover using smaller-scale travel surveys or transportation models and underscores the value of using large-scale behavioural data in understanding how people use cities. However, from the planner's perspective, implementing the findings presents certain challenges. Planning policies, such as zoning, land-use regulations and business permits, often do not impact access directly. Moreover, their implementation can face local barriers, particularly factors like NIMBYism (Not in My Back Yard). Nevertheless, our work provides a straightforward empirical framework that could be employed for policy evaluation of urban interventions promoting sustainable mobility and shorter trips.

There are some limitations and potential future extensions worth mentioning. The 15-minute city concept is centred on the idea that everyone should be able to reach their essential social functions within a short, sustainable commute. We did not explicitly include workplaces as one of these essential functions in our analysis; however, since some POIs cater to both work and consumption, our dataset may include some work trips. Also, the dataset used in the analysis does not allow us to infer each person's mode of travel, as it is aggregated at the neighbourhood level, and thus we can only measure the potential for trips within walking distance without conclusively determining whether people are actually walking to meet their daily needs. In addition, we focused exclusively on a measure of experienced segregation based on average block group income. Future work could consider segregation by race and ethnicity or take into account within-block group income distributions so as not to obscure within-block group diversity. Analysing dwell time could also help add nuance to the segregation analysis: incorporating the length of visits to different POIs would lend itself to a more realistic understanding of exposure between socio-economic groups. Finally, our analysis in New York points towards a causal relationship between amenity access and local usage, but we cannot perfectly account for the potential sorting of people into neighbourhoods. Moreover, the direct applicability of these findings to other US regions may be limited due to varying zoning constraints and density demands. These results are thus particularly relevant to larger urban environments with similar zoning influences. Additional studies are necessary to explore these dynamics in less dense or differently regulated areas.

4 Methods

4.1 Measuring 15-minute usage and access

To conduct the analysis within a 15-minute walking radius, we extracted 15-minute walking isochrones using the Openrouteservice API. Openrouteservice is an open-source routing platform that leverages crowdsourced street network data from OpenStreetMap. Using the 'foot-walking' profile, we generated walking isochrones that specifically rely on the pedestrian street network. The platform presumes a pedestrian travel speed of 5 km h^{-1}.

The completeness of OpenStreetMap's street networks, especially in densely populated urban areas and within the United States, has been demonstrated ([35]). In fact, when considering pedestrian pathways, it may surpass the US Census TIGER/LINE data in terms of completeness ([36]). However, it is noteworthy that the completeness tends to decline in less urbanized areas, which may result in a higher probability of errors in the isochrones in smaller cities or the outer, less urbanized areas of large cities.

To calculate our usage index for a given block group, we first restricted our POIs to those within our selected POI categories and located within the block group's urban area. We then calculated the total number of trips taken by residents of that block group to all POIs within the block group's 15-minute walkshed and divided it by the total number of local trips taken by residents of that block group. If the residents of a given block group took no trips within our data, they were given a usage index value of 0.

To aggregate our usage index to the urban area level, we took a population-weighted average as follows:

$$\text{usage}_A = \frac{\sum_{\{a \in A\}} \text{usage}_a * \text{population}_a}{\text{population}_A},$$

where A represents an urban area and $\{a \in A\}$ represent the block groups contained within it.

To calculate our access index for a given block group, we overlaid our walksheds with the POI locations in our dataset, identifying the number of amenities in each category that are reachable within a 15-minute walk of each home block group. We then converted each amenity total by category into a percentile across all census block groups, giving a value between 0 and 100 for every block group for each category. We then constructed weights of relative importance for each category by calculating the total percentage of trips to that category in our dataset. The reasoning here is that access to places that people use more frequently is more important to local living than access to rarely visited places. Finally, we

combined all of this into an access index for block group a as follows:

$$\text{access}_a = \sum_{\{c \in \text{categories}\}} \text{access percentile}_{a,c} * \text{weight}_c, \text{ where}$$

$$\sum_{\{c \in \text{categories}\}} \text{weight}_c = 1$$

Our index, while highly correlated with raw counts of POIs within each walkshed (Spearman R, 0.963), assigns appropriate weight to amenity categories with fewer establishments yet high visitation. For instance, our dataset shows that an average block group contains 22.96 restaurants and 2.63 schools. If we assessed access purely on total counts, restaurants would overwhelmingly dominate the index. Yet, for individuals using them, schools form an integral part of daily life, often visited daily. Therefore, the presence of an additional school within a 15-minute walk radius is probably more impactful than an extra restaurant. Our access calculation methodology acknowledges this significance.

Similar to the usage index, to aggregate our access index to the urban area level, we took a population-weighted average as follows:

$$\text{access}_A = \frac{\sum_{\{a \in A\}} \text{access}_a * \text{population}_a}{\text{population}_A}$$

4.2 Data source description

Safegraph data The data used in this study were sourced by SafeGraph, a company that collects anonymous location data from around 10% of smartphones in the United States. Previous studies have addressed the representativeness of this dataset, showing that overall, it is relatively well balanced across demographics and space when aggregating across large geographic units. For instance, [37] document a strong correlation between the number of devices and population across different levels of geographic aggregation (r-squared = 0.97 for counties, r-squared = 0.47 for tracts, and r-squared = 0.36 for block groups). An internal report by Safegraph reports similar correlations ([38]), which point to a high level of representativeness of the Safegraph data across geographies. [37] also document small sampling biases across states and counties with different gender, age, and income composition. These statistics suggest that the Safegraph data has reasonable coverage across regions and demographic groups. The high coverage presumably reflects the high penetration of smartphone devices across all population segments in the United States ([39]).

SafeGraph primarily collects anonymized location data from numerous smartphone applications where the users have explicitly granted location-sharing permissions. Thus, it may

not fully represent individuals who do not regularly use smartphones or those who opt not to share their location data.

To create the measure of 15-minute usage, we focused on amenities that represent essential functions associated with the 15-minute city model. Supplementary Table S.1 shows the focus categories and their associated six-digit NAICS codes. To evaluate the completeness of the POIs contained in the SafeGraph data, we examined whether the over four million POIs included in the dataset represent all the local opportunities available in a neighbourhood. Supplementary Table S.8 reports the relationship between the number of SafeGraph establishments in our sample and the corresponding number of businesses in the 2019 Census County Business Patterns data. Column 1 corresponds to a pooled OLS regression of census establishment counts on SafeGraph establishment counts, and column 2 presents the results of the same model with two-digit NAICS code fixed effects added. The results suggest that, on average, the relationship between the two measures is almost one-to-one and statistically significant at $P < .01$.

Socioeconomic data For the empirical analysis, we used data from the American Community Survey 5-Year Estimates by census block group for 2015-2019. We gathered socioeconomic data, including population, land area (used to compute densities), income, and education. For each neighborhood, we use median household income as estimated by the 2019 American Community Survey 5-Year Estimates as our measure of neighborhood income. We assign income quartiles and deciles to each block group on the basis of their population-weighted percentile ranking within their respective urban areas.

The variable representing the average commute length was calculated using the 2019 Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics, also referred to as LODES. This dataset offers an aggregate count of jobs linked to a home census block and a work census block. We computed the average commute distance by determining the mean Haversine distance, which was then weighted according to the total jobs for each census block group.

The public transit frequency variable was obtained from the Environmental Protection Agency. This measure was calculated by dividing aggregate transit service frequency by total land acreage and converting it to units per square mile.

Historical data The additional data used in the IV estimation for New York City was obtained from two sources. First, we combined information on the FAR levels assigned to each type of zoning district from the 1961 Zoning Handbook (`https://www1.nyc.gov/assets/planning/download/pdf/about/city-planning-history/zoning_handbook_1961.pdf`) with the map of 1961 zoning districts provided by the Department of City Planning to obtain the

spatial distribution of restrictions established by the 1961 Zoning Resolution. Second, we used the 1960 Census data at the census tract level to control for various neighbourhood characteristics observed pre-1961. FAR restrictions at the census block group level are computed by taking the area-weighted average of 1961 FAR levels assigned to commercial districts that overlap with the 15-minute walkshed around each Census block group. Similarly, historical controls at the CBG level are computed by taking the area-weighted averages of the corresponding variables in the Census by overlapping the 15-minute walkshed around each census block group with the 1961 Census tracts.

For the robustness check addressing the self-selection of residents, we used demographic data obtained from the Opportunity Atlas ([40]).

County Business Patterns data To produce Supplementary Table S.8, we obtained counts of business establishments by industry at the county level from the 2019 Census County Business Patterns data (CBP). This dataset uses 2017 NAICS codes for industry classification, from which we extracted the broader 2-digit industry labels, defined by the Census.

4.3 Physical Segregation Index

For a given individual of income k_i located in POI L, we calculated the integration or diversity of interactions that they experienced in that POI as a weighted average socio-economic difference between them and every other SafeGraph user located in that POI as follows:

$$\text{experienced integration}_{k_i,L} = \frac{\sum_{k_j} p_{k_j,L} \cdot s_{k_i \to k_j}}{\sum_{k_j} p_{k_j,L}},$$
$$s_{k_i \to k_j} = |r_i - r_j|$$

where $p_{k_j,L}$ is the number of people of income k_j who visit L and r_j is the income rank of individuals of income k_j. We then aggregate up to the home block group level, describing the experienced integration of individuals from block group j as:

$$\text{experienced integration}_j = \frac{\sum_{L \in \text{POIs}} \text{experienced segregation}_{k_j,L} \cdot p_{j,L}}{\sum_{L \in \text{POIs}} p_{j,L}},$$

where $p_{j,L}$ is the number of people from j who visit L.

Finally, we defined:

$$\text{experienced segregation}_j = 1 - \text{experienced integration}_j$$

We then scale the measure to range between 0 and 100, where 100 corresponds to the highest level of experienced segregation and 0 to the lowest.

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5 Supplementary Information

Table S.1:

Essential Function Categories and Associated NAICS Code

Category	6-Digit NAICS Code
Healthcare	621111, 621112, 621410, 621492, 621493, 621498, 622110 ..
Drugstores	446110
Schools	611110
Religious Organizations	813110
Restaurants	722511, 722513, 722514, 722515
Groceries	445110, 445120
Parks	712190
Cultural Institutions	711190, 711310, 712110
Services	491110, 522110, 812111, 812112, 812113, 812320

Table S.2: Correlation of various measures of local living with 15-minute usage (percentage of trips)

Alternate measure	Neighborhood level correlation	Neighborhood level mean	Urban area level correlation	Urban area level mean
	(1)	(2)	(3)	(4)
15 min. usage	1.000	0.239	1.000	0.158
10 min. usage	0.839	0.175	0.927	0.108
20 min. usage	0.903	0.284	0.960	0.190
25 min. usage	0.867	0.337	0.945	0.235
Med. trip dist. (km)	-0.728	2.718	-0.599	3.552
Observations	150,159	150,159	420	420

Notes.— The table shows neighborhood-level correlations and means for different measures of local usage. Column 1 provides the correlation between our baseline usage measure and alternative measures defined by the share of trips within 10, 20, and 25 minutes, as well as the median trip length. Column 2 reports (unweighted) means for these alternative variables. Columns 3 and 4 aggregate the data to urban areas and report urban area-level correlations and (unweighted) means.

TABLE S.3: Correlation between different local access measures

		Counts of Amenities within a 15-minute walk (CBG-level)									
	Equal-Weighted Access	All categories	Healthcare	Parks	Restau-rants	Schools	Services	Groceries	Drugstore	Religious	Arts and Culture
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Correlation with baseline access index	0.982	0.984	0.785	0.681	0.969	0.785	0.914	0.858	0.731	0.775	0.379

Notes.— The table shows neighborhood-level Spearman correlations between different measures of local access to services and amenities. Column 1 provides the correlation between our baseline access index and an alternative measure of access, where the scores associated with the number of amenities in each category are added with equal weights. Columns 2–11 provide correlations between our baseline measure and counts of the number of each type of amenity within 15-minute walksheds.

TABLE S.4: Relationship between 15-minute usage and access across neighborhoods (census block groups) and Urban areas: Using all POI destinations

	Dependent Variable: 15-minute Usage (% of trips)					
	Across CBGs			Across Urban Areas		
	(1)	(2)	(3)	(4)	(5)	(6)
15-minute Access	0.621***	0.546***	0.553***	0.414***	0.303***	0.311***
	p < 0.001	p < 0.001	p < 0.001	p < 0.001	p < 0.001	p < 0.001
Pop Density Log		0.825***	0.365		2.781***	2.427***
		p = 0.009	p = 0.138		p < 0.001	p < 0.001
Median Income Log		−5.966***	−5.512***		−4.480***	−5.256***
		p < 0.001	p < 0.001		p < 0.001	p < 0.001
% Education: BA +		0.038***	0.025***		0.062***	0.036***
		p < 0.001	p = 0.001		p < 0.001	p = 0.008
% White		−0.017***	−0.021***		0.012	0.005
		p = 0.002	p < 0.001		p = 0.254	p = 0.617
Transit Frequency (per sq. mi)			0.001***			0.005***
			p = 0.003			p < 0.001
Average Commute (mi)			0.118***			−0.098***
			p < 0.001			p < 0.001
Urban Area FE	✓	✓	✓			
Observations	150,159	145,862	145,859	420	420	420
R^2	0.715	0.741	0.748	0.699	0.731	0.786
Partial R^2	0.712	0.626	0.634	0.699	0.512	0.525

Notes.— The table reports OLS estimates of the relationship between 15-minute usage and access. It uses the specifications from Table 1, but redefines the outcome variable to include trips to all POI destinations (as opposed to only consumption trips). Columns 1 to 3 report estimates at the neighborhood level (controlling for urban area fixed effects) and columns 4 to 6 report estimates at the urban area level. The partial R-squared for access is computed as $\beta \times \frac{\text{cov(15-minute usage,15-minute access)}}{\text{var(15-minute usage)}}$, where β is the regression coefficient for 15-minute access. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level. Included P-values correspond to a two-sided t-test for each estimate, using robust standard errors clustered at the county level.

TABLE S.5: Relationship between 15-minute usage and access across neighborhoods (census block groups) and Urban areas: Role of transit access

	Dependent Variable: 15-minute Usage (% of trips)			
	Across CBGs		Across Urban Areas	
	(1)	(2)	(3)	(4)
15-minute Access	0.715***	0.742***	0.493***	0.460***
	p < 0.001	p < 0.001	p < 0.001	p < 0.001
Pop Density Log	0.183	2.419***	2.124***	3.090**
	p = 0.378	p < 0.001	p < 0.001	p = 0.017
Median Income Log	−4.238***	−5.882***	−3.328***	−3.298**
	p < 0.001	p < 0.001	p < 0.001	p = 0.017
% Education: BA +	−0.0003	−0.002	0.018	0.054**
	p = 0.948	p = 0.867	p = 0.132	p = 0.014
% White	−0.006	0.009	−0.005	0.025
	p = 0.238	p = 0.376	p = 0.587	p = 0.180
Transit Frequency (per sq. mi)	0.001***	0.0003**	0.003***	0.003**
	p = 0.005	p = 0.022	p = 0.003	p = 0.049
Average Commute (mi)	0.107***	0.104***	−0.094***	−0.066***
	p < 0.001	p < 0.001	p < 0.001	p = 0.005
Full sample	✓		✓	
Only transit freq. above median		✓		✓
Urban Area FE	✓	✓		
Observations	145,859	44,492	420	129
R^2	0.756	0.625	0.875	0.819

Notes.— The table reports OLS estimates of the relationship between 15-minute usage and access for areas with high transit access. Columns 1 and 3 report estimates from specifications identical to columns 3 and 6 in Table 1, respectively. Columns 2 and 4 restricts the estimation sample to CBGs and Urban Areas with above-average transit frequency per square mile (obtained from EPA). The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level. Included P-values correspond to a two-sided t-test for each estimate, using robust standard errors clustered at the county level.

TABLE S.6: OLS and IV estimates for New York City: subsample of low-mobility neighborhoods (proxied by a high share of children that live and grew up in the same tract)

	Dependent variable:			
	Usage (% of trips within a 15m walk)			
	OLS	IV estimates		
	(1)	(2)	(3)	(4)
Access to amenities within a 15m walk	0.835***	1.131***	1.088***	1.207***
	p < 0.001	p < 0.001	p < 0.001	p < 0.001
Population Density (Log)	3.776***		3.371***	3.325***
	p < 0.001		p < 0.001	p < 0.001
Median Income (Log)	−4.490***		−4.310***	−4.378***
	p < 0.001		p < 0.001	p < 0.001
IV: Log Average Commercial FAR in 1961 Resolution		✓	✓	✓
Distance to City Center	✓	✓	✓	✓
1960 Population and Housing Density	✓	✓	✓	✓
1960 Workers by Industry	✓	✓	✓	✓
1960 Poor and Non-white Families				✓
First stage F-stat	NA	71.14	67.12	53.01
Observations	1,326	1,385	1,326	1,326
R^2	0.563	0.497	0.556	0.552

Notes.— This table reports OLS and IV estimates of the relationship between 15-minute usage and access for New York City. We use the specifications from Table 2 and restrict the estimation sample to low-mobility neighborhoods, defined as those in the top quartile according to the share of children who grew up and still live in the same Census tract by 2015. These data come from the Opportunity Atlas (Chetty et al. 2018). Column 1 reports OLS estimates controlling for distance to the city center and a host of socio-economic controls for 1960, including population and housing density and the share of workers by industry. Columns 2-4 report IV estimates. Columns 2 and 3 control for distance to the city center, population and housing density and the share of workers by industry. Column 4 includes additional controls for the share of poor and non-white families in 1960. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level. Included P-values correspond to a two-sided t-test for each estimate, using robust standard errors.

TABLE S.7: Relationship between experienced segregation and local trips for neighborhoods of different income levels.

	Dependent variable:			
	Physical Segregation Index (PSI)			
	Main 15 urban areas		Full sample	
	(1)	(2)	(3)	(4)
Usage × Low income	0.164***		0.071***	
	p < 0.001		p < 0.001	
Usage × Moderate-low income	0.041**		0.007	
	p = 0.013		p = 0.318	
Usage × Moderate-high income	-0.069***		-0.056***	
	p < 0.001		p < 0.001	
Usage × High income	-0.103***		-0.060***	
	p < 0.001		p < 0.001	
Access × Low income		0.182***		0.041***
		p < 0.001		p = 0.003
Access × Moderate-low income		0.043***		-0.009
		p = 0.006		p = 0.131
Access × Moderate-high income		-0.084***		-0.069***
		p < 0.001		p < 0.001
Access × High income		-0.114***		-0.070***
		p < 0.001		p < 0.001
Urban area fixed effects	✓	✓	✓	✓
R-squared	0.17	0.20	0.24	0.24
Observations	34739	34739	145855	145855

Notes.— The table reports OLS estimates of the relationship between experienced segregation and 15-minute usage (columns 1 and 3) and access (columns 2 and 4). We provide estimates for neighborhoods in the 15 cities with the highest levels of 15-minute usage and for all neighborhoods in our sample. The table reports estimates interacted with dummies for low income neighborhoods (bottom quartile of income in urban area), moderate-low income neighborhoods (second quartile), moderate-high income neighborhoods (third quartile), and high income neighborhoods (top quartile). Robust standard errors are computed with clustering at the urban area level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level. Included P-values correspond to a two-sided t-test for each estimate, using robust standard errors.

TABLE S.8: Relationship between business counts in Safegraph and Census Data

	All County x Industry Pairs	
	Establishments Count from Census (CBP)	
	(1)	(2)
Establishments Count from Safegraph	0.925***	0.991***
	p < 0.001	p < 0.001
Two-Digit NAICS Code FE	No	Yes
Observations	11,391	11,391
R^2	0.521	0.591

Notes.— This table reports estimates from a regression of the number of businesses in a county (from the 2019 Census County Business Patterns data, CBP) and the number of Safegraph establishments in the same two-digit NAICS category and county. Each observation corresponds to a county and two-digit industry cell. Column (1) reports estimates from a pooled OLS regression of Census establishment counts on Safegraph establishment counts across these cells, and column (2) presents the results of estimating the same model with two-digit NAICS code fixed effects added. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level. Included P-values correspond to a two-sided t-test for each estimate, using robust standard errors clustered at the county level.

TABLE S.9: First-stage and reduced-form estimates of 1961 zoning regulation on current access and usage.

	Dependent variable:			
	Access		Usage (% trips)	
	(1)	(2)	(3)	(4)
Log Average Commercial FAR	6.522***	4.460***	7.187***	5.569***
	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
Controls:				
Distance to City Center		✓		✓
1960 Population and Housing Density		✓		✓
1960 Workers by Industry		✓		✓
Observations	5,582	5,582	5,582	5,582
R^2	0.475	0.696	0.224	0.329

Notes.— The table reports first-stage (columns 1 and 2) and reduced-form (columns 3 and 4) estimates of the relationship between 1961 zoning and access and usage for neighborhoods in New York City. Columns 2 and 4 control for distance to the city center and a host of socio-economic controls for 1960, including population and housing density and the share of workers by industry. The covariates included in these models come from Twinam (2017) and Martynov (2022). The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level. Included P-values correspond to a two-sided t-test for each estimate, using robust standard errors.

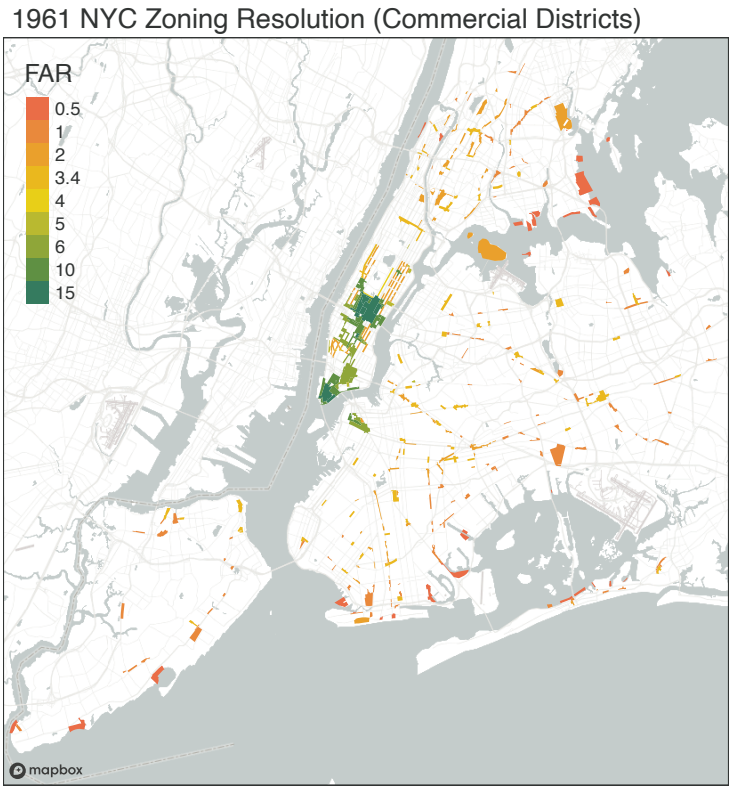

FIGURE S.1: **Historical zoning.** Maximum floor-to-area ratio in commercial uses established according to the 1961 New York City Zoning Resolution.