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The role of transport systems in housing insecurity: a mobility-based analysis

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Abstract

With trends of urbanisation on the rise, providing adequate housing to individuals remains a complex issue to be addressed. Often, the slow output of relevant housing policies, coupled with quickly increasing housing costs, leaves individuals with the burden of finding housing that is affordable and in a safe location. In this paper, we unveil how transit service to employment hubs, not just housing policies, can prevent individuals from improving their housing conditions. We approach this question in three steps, applying the workflow to 20 cities in the United States of America. First, we propose a comprehensive framework to quantify housing insecurity and assign a housing demographic to each neighbourhood. Second, we use transit-pedestrian networks and public transit timetables (GTFS feeds) to estimate the time it takes to travel between two neighbourhoods using public transportation. Third, we apply geospatial autocorrelation to identify employment hotspots for each housing demographic. Finally, we use stochastic modelling to highlight how commuting to areas associated with better housing conditions results in transit commute times of over an hour in 15 cities. Ultimately, we consider the compounded burdens that come with housing insecurity, by having poor transit access to employment areas. In doing so, we highlight the importance of understanding how negative outcomes of housing insecurity coincide with various urban mechanisms, particularly emphasising the role that public transportation plays in locking vulnerable demographics into a cycle of poverty.

Keywords: Housing Insecurity; Human Mobility; Transit Networks; Commuting Patterns; Social Mobility

1 Introduction

The rapidly increasing density of urban areas poses a threat to exacerbate the ever present housing crises around the world [1, 2]. Rising urbanisation poses several challenges in the context of housing, such as higher housing costs, insufficient housing stock, and sub-standard housing conditions [3]. In order to adequately address these challenges, policy-makers must understand not only the current state of housing in their jurisdictions, but also how inadequate housing impacts other facets of urban life, such as employment accessibility, proximity to essential services, and connectivity to support networks [4–6]. Research has shown how car ownership reduces the shock of 'forced' residential moves, by providing the ability to adapt to any changes in commuting or mobility patterns [7].

Studies such as this emphasise the importance of robust transit systems, as they enable transit-dependent households to fulfill their mobility needs, even when they face insecure housing conditions. However, quantitative research remains scarce when considering precisely how transit systems connect households that are vulnerable to housing insecurity with different employment areas.

Previous works have investigated commuting patterns in the context of housing insecurity, with one study using transit smart card data to ultimately categorise city dwellers into four mobility groups depending on how frequently they switch residential or employment locations [8]. Similarly, another paper leverages transit smart card data in Shenzhen, China to reveal how less affordable housing is associated with a corridor-relocation pattern for lower income groups, in which individuals move from inner urban areas to less central locations [9]. This finding shines light on transit constraints, as the relocation trajectories were more dense along transit lines. Furthermore, by studying changes in mobility behaviour before and during the COVID-19 pandemic, researchers have shown how social and environmental disruptions can impact travel behaviour, specifically revealing decreased transit use, but increased transit travel times [10]. A separate body of work analyses how transport facilitates commutes across subsidised housing and employment opportunities, finding correlations between high public transit accessibility and maintaining employment [11]. Similarly, higher rates of transit-dependency have been observed for individuals that qualify for affordable housing [12]. Finally, Cao and Hickman assess the relationship between housing affordability and car dependence by developing an index, based on oil and housing prices, to identify regions in London that have low levels of housing affordability, yet high levels of car dependency [13]. In doing so, they revealing areas that are vulnerable to forced car ownership.

While these works explore the intersection of housing insecurity and mobility inequalities, understanding how the consequences of housing insecurity extend beyond the residential dimension remains an open problem. To address this, our work considers how compounded burdens from housing insecurity, public transit service, and job accessibility can limit the extent to which vulnerable individuals can improve their housing conditions. Furthermore, these studies tend to use a single measure, such as eviction rates or rent burden, as a proxy for housing insecurity. Thus, we pose the following questions:

(i) *How can we reconcile sociological definitions of housing insecurity with empirical approximations, to ultimately provide a comprehensive estimate of housing insecurity?*

(ii) *To what extent does public transportation facilitate job accessibility for households that are vulnerable to housing insecurity?*

To address the first question, we introduce a multidimensional approach to estimating housing insecurity, using housing characteristics from the US Census Bureau and eviction rates from The Eviction Lab. We apply spectral clustering to these housing features, for 20 cities in the United States of America (USA), to identify neighbourhoods that are particularly vulnerable to housing insecurity.

We explore the second research question by drawing upon General Transit Feed Specification (GTFS) from The Mobility Database to define transit features and commuting flows from the Longitudinal Employer-Household Dynamics program to characterise residential-workplace dependencies. Specifically, we use public transit networks to define the efficiency of transit service, when compared to driving times, for each of the 20 cities.

We assess cities' transit systems at a national scale while also considering transit efficiency as a function of distance, within each city. Finally, we use spatial autocorrelation to identify employment hotspots for each housing demographic, in a city. Then, we combine the transit networks, housing demographics, and employment hotspots to explore the relationship between individuals' residential and employment areas.

The structure of this work breaks down the research questions into three separate sections, each with their own set of findings. The next section introduces the data, while the following three sections discuss intermediary results for quantifying housing insecurity, defining transit efficiency, and identifying employment hubs for particular housing demographics, respectively. The section on social mobility ties these three components together, revealing the final results when considering transit-related consequences of housing insecurity. We achieve this by considering how commuting times would be affected if individuals in vulnerable neighbourhoods were to work in employment areas that are associated with better housing conditions.

Ultimately, given empirical commuting behaviour, we observe average commute times of less than 30 minutes in all 20 cities, when using cars as a mode of transport. On the other hand, commuting using public transit increases the average commute time to over 30 minutes for 15 of the cities analysed. The half-hour threshold is significant for commuting patterns, with commuters in the USA spending, on average, 25.1 minutes commuting, and more recent studies revealing a 35 minute catchment area for commuting when they incorporate transport modes [14, 15]. We find that seeking better employment opportunities, while also depending on transport as a mode of commuting, results in increased commuting time for most cities, with travel times of more than an hour for 10 of the 20 cities. Ultimately, we identify disparities in the efficiency with which public transit serves different types of employment hubs. Thus, by exploring how transportation networks connect housing and employment landscapes, we underscore how transport infrastructure can create hurdles for individuals to break the cycle of housing insecurity.

2 Data

In order to assess how transport and employment inequalities pose additional burdens to individuals facing housing insecurity, we draw upon secondary data sources to define the state of housing, the employment landscape, and transit systems for various cities in the USA.

2.1 Housing data sources

In short, housing insecurity can be distilled into seven categories: Housing Stability, Housing Affordability, Housing Quality, Housing Safety, Neighbourhood Safety, Neighbourhood Quality, and Homelessness [16]. In Section S1.2 of Additional file 1, we describe the characteristics of these seven housing dimensions as defined by the author of Ref. [16]. Many quantitative studies tend to use one dimension as a proxy for housing insecurity, and therefore only capture particular disadvantages. Accordingly, in this work, we attempt to define housing insecurity using multiple dimensions. However, we do not include the Neighbourhood Safety, Neighbourhood Quality, and Homelessness dimensions as the available data sources only provide information at larger geographical units. Thus, incorporating these dimensions would require sacrificing the census tract granularity at which we measure housing insecurity. Cox states that the Homelessness dimension is optional in defining housing insecurity, bolstering the decision to not include it in our definition. Finally, we combine the Housing Quality and Safety dimensions because their data sources largely overlapped despite representing distinct concepts.

The majority of our data is sourced from the 2019 American Community Survey (ACS). This enables us to apply our analysis to various cities within the USA. We define housing characteristics at the census tract level. Census tracts are subdivisions of a county and aim to have a population of 4000, although the population can range from 1200 and 8000 people. Although the ACS provides housing data at a census block group level, which are statistical divisions of census tracts, the data availability of eviction rates is limited to the census tract scale. Thus, the data resolution is limited to the tract level. We measure Housing Affordability using the fraction of each tract that is severely rent burdened (spending 50% or more of their income on housing), the median mortgage status, and the number of housing units per capita. The fraction of housing units in each tract that have complete plumbing facilities, kitchen appliances, and telephone service inform the level of Housing Quality for each census tract. Finally, Housing Stability is defined using eviction rates and levels of overcrowding within each tract. All the listed data, barring eviction rates, is defined by the ACS. A more detailed description of the ACS tables that are used, and the data preparation, are outlined in Section S2 of Additional file 1. The Eviction Lab [17] provides rates of tract-level evictions for various cities in the USA. Section S2.3 in Additional file 1 discusses issues in the collection and availability of eviction data.

2.2 Public transportation data sources

The public transportation data that we use is from The Mobility Database [18], which provides a means for extracting GTFS feeds for specific cities. These provide information on stops, schedules, and routes for different forms of public transportation, ranging from buses to ferries. In this manner, we can create a workflow to develop multi-modal transit networks for different cities. We use `UrbanAccess` [19], an open-source tool provided by the Urban Data Science Toolkit, to interpret the transit feeds data for various cities. This tool builds a transit-pedestrian network by combining transit networks, created using the aforementioned GTFS feeds, and pedestrian networks. Each node in the transit network represents a transit stop and edges capture successive stops on transit lines, capturing the minutes of travel between adjacent stops. These edges are weighted using data from the GTFS transit schedules. If data for a particular stop is missing, it is predicted using linear interpolation. The pedestrian network is built using `OpenStreetMap` (`OSM`) [20]. By specifying a bounding box, `UrbanAccess` leverages `OSM`'s compatibility with `NetworkX` [21] to build a network where nodes are particular points in the region and edges represent linear paths such as roads. `UrbanAccess` then merges these two networks to create a more comprehensive travel network. This is done by joining each pedestrian node to its closest transit node. The weight of that edge reflects the time it takes to walk from a pedestrian node to a transit node (or vice versa). The walking time is calculated using the distance between nodes and assuming a walking speed of 3 miles per hour. This network is fed into `Pandana` [22], a Python library for efficiently calculating accessibility metrics of networks.

2.3 Employment data sources

Given that employment opportunities greatly influence residential choices [23], households that are facing forced moves may be limited in housing choices due to constraints in job opportunities. Thus, we incorporate employment data from the Longitudinal Employer-Household Dynamics (LEHD) program, to understand commuting behaviour across census tracts. Specifically, we use the LEHD Origin-Destination Employment Statistics (LODES) [24], which informs commuting flows for each state in the USA, at a census tract level. LODES provides characteristics of survey participants with respect to the census tract that they live in and the census tract in which they work. This information includes income groups, industrial sectors, educational attainment, sex, race, and age. By combining a census tract's housing and public transit characteristics with its employment attributes, we can explore how individuals from various housing demographics may have access to different types and magnitudes of employment opportunities.

3 Exploring measures of housing insecurity

In this section, we detail the multidimensional approach to defining census tracts based on their level of vulnerability to housing insecurity. We apply spectral clustering to the data introduced in the previous section and then evaluate the validity of the identified clusters using a range of sociodemographic indicators.

3.1 Defining vulnerable housing regions: a clustering approach

In order to examine the state of housing for various cities in the USA, we adopt an unsupervised learning approach to define three different housing categories: most vulnerable, mildly vulnerable, and less vulnerable. We apply spectral clustering on the housing features that we mention in the Housing Data Sources section, with a more detailed description of the data in Section S2.2 and Figure S1 of Additional file 1. As a reminder, the housing features we consider are affordability (rent burden, mortgage, and housing units per capita), safety (access to kitchen, plumbing, and phone facilities), and stability (evictions per capita, number of individuals in a household per room and per bedroom). Spectral clustering is a particularly useful approach for clustering high dimensional data, as it makes no assumptions about the shapes of clusters. Alternative approaches for clustering such as Expectation-Maximization and K-Means are extremely sensitive to initialization. The process of spectral clustering can be broken into three steps. First, one must extract an affinity matrix from a graph that is built using the data points. The next step is spectral embedding, which leverages properties of the Graph Laplacian to represent data points in a low-dimensional space. The last step of the algorithm involves applying a classical clustering algorithm, typically K-means, to partition the embedded data into respective clusters. More details about how we preprocess housing data can be found in Section S3 of Additional file 1.

Since we are considering a variety of urban areas, the number of K-Means clusters that are appropriate for each city's housing characteristics differs. Thus, the spectral gap for each city, which can be seen in Figure S2 in Additional file 1 informs the number of clusters for which the K-Means algorithm is applied. To extract meaning from each cluster, we rank the housing clusters based on the mean values of their housing features, where larger values denote worse housing conditions. The group that is most frequently ranked higher across the housing features (highest mode) is deemed most vulnerable to housing insecurity. We break ties using the mean rank across all features, and if ties still exist, as a final

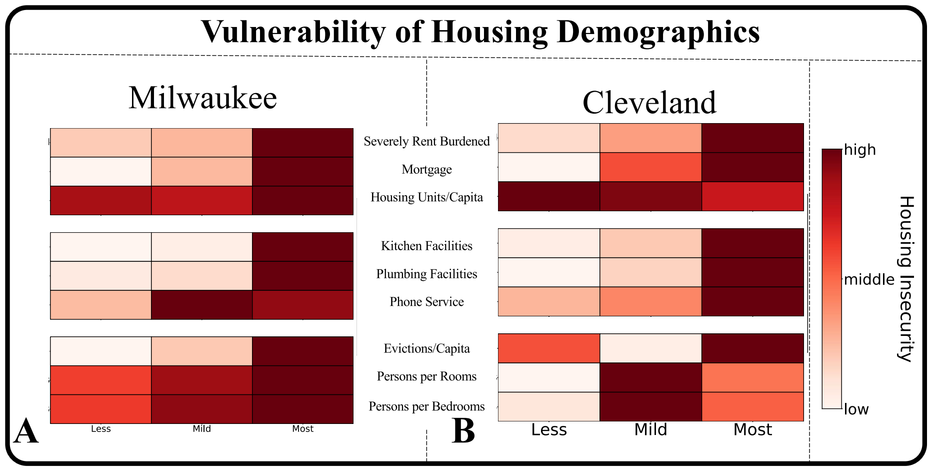

Figure 1 Median characteristics of housing demographics in Milwaukee, Wisconsin and Cleveland, Ohio. Heatmap visualising the average housing characteristics for each housing demographic. From top to bottom, each heatmap captures housing insecurity levels for the dimensions of affordability, safety/quality, and stability, respectively. Columns are the housing demographics, while rows are the housing features. Darker hues of red indicate higher levels of housing insecurity. On one hand, Milwaukee (Panel A) reflects a case where the most vulnerable census tracts consistently have the highest rates of housing insecurity. On the other hand, Cleveland (Panel B) presents a convincing case against using a single housing feature as a proxy for housing insecurity

tie-breaker, we use the average rent burden percentage of each cluster. Then, to address the varying number of clusters across cities, we partition the ranked clusters into three housing demographic groups, in which each group contains a similar number of clusters. These final three groups reflect the tracts that are the most vulnerable, mildly vulnerable, and less vulnerable to housing insecurity, in the context of each city. Figure 1 illustrates the housing features for the resulting housing demographics in Milwaukee (Fig. 1A) and Cleveland (Fig. 1B). Each column represents the final housing demographic groups (Less, Mildly, and Most Vulnerable), while each row illustrates the housing characteristics that were used to define the housing demographic with respect to a city. In this manner, each cell can be defined by the following equation:

$$M_{f,h} = \frac{1}{|T_h|} \sum_{t}^{T_h} HC(f,t) \tag{1}$$

where $HC(f,t)$ refers to the value of a housing feature, f, for a tract, t. Accordingly, for a given housing feature (row), f, and housing demographic (column), h, a cell's value is defined by averaging the housing feature for each census tract in h. Then, we apply row-wise normalisation to compare the differences in demographics within each city. The upper left cell of a heatmap, for example, conveys the mean percentage of severely rent burdened households across all census tracts in the less vulnerable housing demographic.

Figure 1 portrays how the housing features for Milwaukee and Cleveland map to their final housing demographics. That is, the rows represent the features that were considered when applying the clustering framework to end up with the final housing groups, shown by the columns. Thus, we can see the median characteristics of the three housing demographics, with respect to each considered feature. Figure 1A shows how the housing demographics (columns) are clearly distinguishable, in terms of having consistent levels of housing insecurity across most features, in the context of Milwaukee. In these types of cities, using a single housing feature as a proxy for housing insecurity could be an adequate estimation. However, the housing characteristics in Cleveland (Fig. 1B) emphasise the need for a multidimensional approach to defining housing insecurity, illustrating how neighbourhoods may be vulnerable to various forms of housing insecurity, ultimately underscoring the complexities of housing conditions. For instance, the less vulnerable census tracts in Cleveland have higher insecurity than the most vulnerable tracts, in terms of housing stock within the city. Moreover, the mildly vulnerable tracts have the highest insecurity when considering rent burden, housing stock, and the housing stability dimension, represented by the bottom-most group of heatmaps. When considering each housing feature, however, the most vulnerable tracts have the highest levels of insecurity overall. The intricacies of housing conditions, then, becomes clear, with Fig. 1 emphasising the importance of considering the multidimensional nature of housing.

We validate the classification in Section S3.3 of Additional file 1 against other socioeconomic indicators of inequality. Figure S3, and Tables S1 to S6, reveal that census tracts that are most vulnerable to housing insecurity tend to be associated with lower education attainment and income levels, while also expressing higher unemployment and poverty rates. When considering commute times, irrespective of commute mode, we observe less distinct disparities between the housing demographics. We hypothesise that this has to do with spatial organisation of residential and employment areas for each housing demographic. That is individuals organise their residential and employment locations to be close to one another, an idea that is consistent in urban commuting literature [23]. While, at first glance, it does not appear that significant disparities exist when comparing transit commuting features of various housing demographics, we leverage detailed transport modelling tools to explore whether the lack of transit commuting disparities is reflective of effective transit service, or is an artefact of spatial inequalities across residential and employment landscapes.

Ultimately, this section highlights the pertinence of understanding the residential dynamics of a city by incorporating the various aspects of housing insecurity. That is, by estimating household characteristics of affordability, safety, quality, and stability, we introduce a framework for defining a neighbourhood's vulnerability to housing insecurity. We use Milwaukee as an example of a city in which vulnerability to housing insecurity is consistent across the majority of housing dimensions. Meanwhile, Cleveland serves as an example of a city that has more ambiguity across housing demographics, with the mildly vulnerable neighbourhoods having higher rates of overcrowding and less housing stock. We show how neighbourhoods that are identified as most vulnerable to housing insecurity align with lower income levels and educational attainment, while having higher rates of unemployment and poverty. The spatial relationship between housing and employment landscapes, as well as how public transit intersects with commuting behaviour, is further explored in the final sections of this report. However, we first define the efficiency of cities' transport infrastructure to understand how urban services connect different parts of a city.

4 Interpreting public transit infrastructure

In the previous section, we introduced a clustering framework for identifying census tracts that are vulnerable to housing insecurity. In doing so, we can interpret the state of housing in various North American cities. To begin exploring whether indirect policies, such as transportation accessibility, pose further obstacles to individuals in precarious housing situations, we draw on GTFS feeds to characterise public transportation systems. We begin by defining a metric for public transportation efficiency, by comparing transit and driving times of various journeys. With this metric, we proceed to define cities based on their transit characteristics, categorising their public infrastructure as highly efficient, adequately efficient or inefficient public transportation infrastructure. Furthermore, we highlight how transit inequalities may be overlooked by neglecting to account for the spatial organisation of the housing landscape. This section aims to elucidate how transit systems serve housing demographics by measuring efficiency between and within cities and exploring residential attributes associated with proximity to transport infrastructure.

4.1 Comparing transit efficiency across the USA

We begin our analysis by examining the current landscape of public transportation across all 20 cities, with a particular emphasis on how effectively transit serves each city. To investigate differences in efficiency of transportation systems, we build a transit pedestrian network using `UrbanAccess` and the GTFS feeds outlined in Data Section. Each city's network consists of transit nodes and pedestrian nodes. Edges linking transit nodes reflect transit lines, while edges between pedestrian nodes represent paths in the road network, which is informed by `OpenStreetMap`. Building off these two networks, `UrbanAccess` connects the transit and pedestrian networks by mapping each transit node to the closest pedestrian node. Accordingly, the travel time via public transit from any two points in an urban area can be calculated as a series of transit and/or pedestrian paths. It should be noted that `UrbanAccess` assumes a walking speed of 3 miles per hour to calculate pedestrian travel times. With a given city's transit network, we can calculate the time it would take to travel from one census tract to another in a given day, during a given time frame. We construct a network for each of the 20 North American cities from 06:30AM to 10:30AM on Mondays, as that window of time captures the bulk of commutes during rush hour [25]. The properties of the transit layer of these networks can be seen in the second and third columns of Table S7 in Additional file 1 Transit time, alone, is not particularly informative when comparing cities of different sizes, as travel time is a function of distance and road networks. Thus, we define the efficiency of a city's transportation system by measuring how much longer a trip takes using public transit, compared to driving. We refer to this concept as *travel impedance*. The impedance, $\mathcal{Z}$, from a location x to location y can be formally defined as:

$$\mathcal{Z}_{x,y} = \frac{\text{transit time}_{x,y}}{\text{driving time}_{x,y}} \tag{2}$$

A travel impedance of one implies that driving between two points takes as long as using public transit during the specified day and time range. A travel impedance, t, greater than one suggests that transit trips take longer than driving trips by a factor of t.

We calculate driving times between the centroids of census tracts using `Openrouteservice`. `Openrouteservice` leverages `OpenStreetMap` to construct a road network, in which edges have attributes pertaining to their length and the speed of travel, depending on the type of road it is labelled as (i.e. motorway, residential, etc.). In this manner, the speed and distance can be combined to assign each edge an additional attribute of travel time. Then, a routing algorithm, typically contraction hierarchies [26], core-ALT [27], or A* [28], is applied to the road network to identify driving times between specified locations. In short, contraction hierarchies make use of the hierarchical structure of road networks to devise speed-up techniques for Dijkstra's routing algorithm. While contraction hierarchies are useful in the context of driving, not all travel modes follow a hierarchical structure. Thus, core-ALT offers travel time estimates when alternative or multiple transport modes need to be considered. In this manner, the algorithm chosen depends on the query sent to `Openrouteservice`. It is crucial to note that the driving times from `Openrouteservice` do not account for congestion. We emphasise, that driving times serve to provide a lower bounded baseline, against which we can compare transit travel times. In this manner, we conceptualise travel impedance, and consequently transit efficiency, such that it reflects how transit travel times between two locations contrast the corresponding shortest path in a road network, in a comparable unit of measure (minutes).

To compare the efficiency of public transportation systems across cities, we define the efficiency of a city's transport system as the mean efficiency for all potential commutes (all possible pairs of census tract origins and destinations in a city). Mathematically, this is calculated by averaging the travel impedance between each pair of census tracts, where T reflects the set of census tracts in a city, c:

$$\text{eff}_c = \frac{\sum_{t_1,t_2}^{t_1,t_2 \in T} \mathcal{Z}_{t_1,t_2}}{|T|^2} \tag{3}$$

Figure 2 captures the efficiency of transport infrastructure for each of the cities we analyse, calculated using Equation (3). Darker hues of green reflect more efficient systems, while cities with whiter hues reflect regions where using transit takes significantly longer than driving. The efficiency values range from 1.896 (Milwaukee) to 7.261 (Fort Worth), with a median of 4.95 and a mean of 4.64 across all cities. For further details, Table S1 in

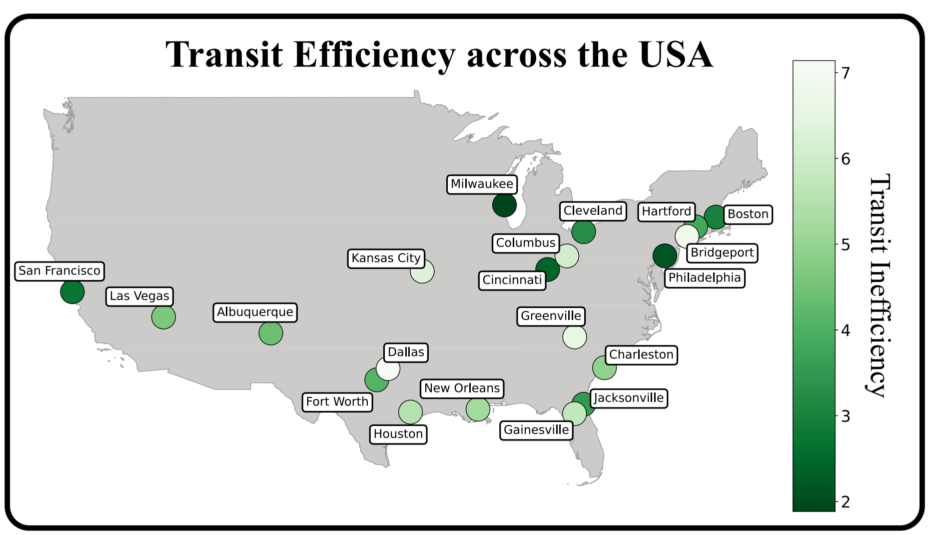

Figure 2 Transit efficiency of 20 cities in the USA. Map of the 20 cities in our analysis and their corresponding levels of transit efficiency. Darker hues of green indicate more efficient public transport systems, with efficiency defined as the ratio of travel time of transit to driving

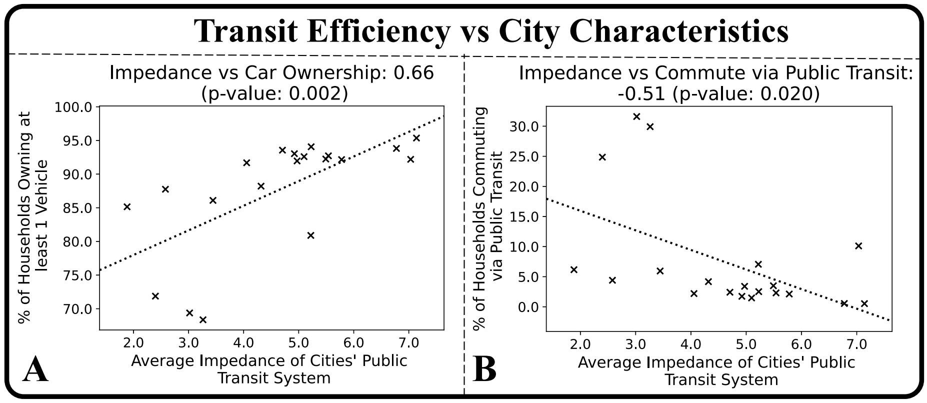

Figure 3 Transit system efficiency and reported levels of car dependence and public transit use. Exploring the relationship between transit efficiency and mobility characteristics for 20 cities in the USA. Panel A shows a positive relationship between inefficient transit systems and the percentage of households with one or more vehicles. Panel B highlights how more efficient transit systems tend to have a higher proportion of households that commute using public transport. The Pearson correlation coefficients for car dependence and transit commutes are 0.55 and –0.45, respectively

Additional file 1 lists the corresponding transit efficiency for each city. Notably, Milwaukee is the only city with a transit system that, on average, serves its residents in less than double the time it takes to drive. On the other hand, the transportation in Fort Worth, Bridgeport, and Greenville generally takes more than six times as long as it would when driving.

The above results demonstrate that using transit systems in North American cities typically results in longer travel times than driving would. Moreover, Fig. 3A illustrates how cities with less efficient transit systems tend to have higher rates of car ownership, with a Pearson correlation coefficient of 0.66 between the two variables. These results are consistent with research that reveals how the quality and reliability of transport infrastructure impacts the frequency with which residents use public transit [29, 30].

Moreover, Fig. 3B shows the negative correlation (Pearson correlation coefficient of –0.51) between transit inefficiency and the percentage of the population that uses transit for commuting. Thus, we observe that less efficient transit systems are associated with a higher dependence on cars and lower levels of transit commutes. In this manner, we can reflect on how less efficient transit systems contribute to the burden of insecure housing, as the financial cost of cars depletes resources that could be otherwise invested in savings or spent on higher quality housing and choosing to commute using inefficient transit is costly from a time perspective.

4.2 Identifying transit systems that facilitate urban mobility

Our analysis of the state of public transportation in the USA has been at a city-level, allowing us to compare cities to one another. However, the cities in this analysis vary largely in size, ranging from approximately 120 km^2 to 20,500 km^2. It should be acknowledged that there is a possibility that cities which err on the side of transit inefficiency may have effective transportation, but are larger, therefore obscuring the density and quality of the transit system. Table S7 in Additional file 1 shows how smaller cities are not necessarily the cities with the more efficient transit systems, with New Orleans having an impedance

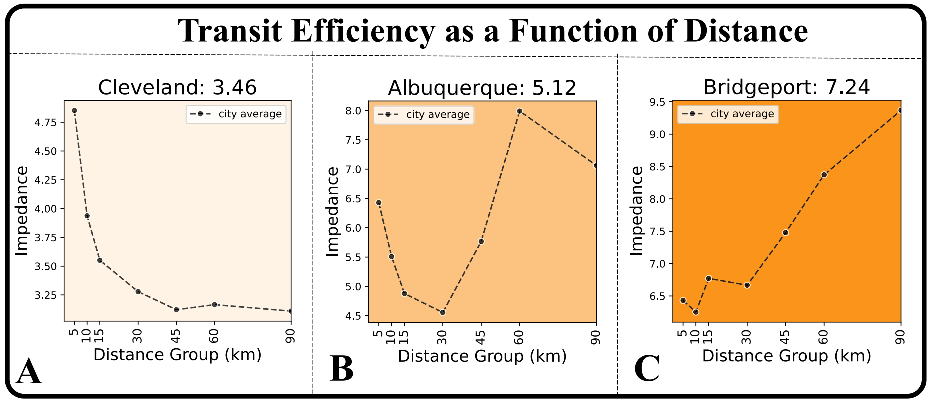

Figure 4 Transit system signatures, when characterising trip efficiency as a function of distance. Examples of each of the three signatures we identify when analysing transit efficiency as a function of trip distance. Cleveland (Panel A) reflects efficient systems in which travel impedance decreases as trip distance increases. Albuquerque (Panel B) is a case of moderately efficient transit service, in which the relationship between travel impedance and trip distance switches from negative to positive at a given trip distance threshold. Panel C uses Bridgeport as an instance of inefficient transit systems, with increasing travel impedance as trip distance increases

of 5.468. Similarly, Table S7 contains large cities that are both efficient and inefficient, indicating that region size may not be a confounding factor. To further address this potential issue, we analyse travel impedance as a function of distance. We accomplish this by creating 6 classes of transit journeys, with each category defined by how long a journey is. We refer to each class as a *distance group*. We map each pair of census tracts to its respective distance group, based on how far the tracts are from one another. Then, for each distance group, we find the average impedance for all trips within that group. In doing so, we identify three signatures of transit efficiency with respect to trip distance, which correspond with the overall transit quality in cities. This is highlighted in Fig. 4, which uses Cleveland, Albuquerque, and Bridgeport to exemplify each of the discovered trends for the most, moderately, and least efficient transport systems respectively. For a more comprehensive look at the results for all 20 cities, we refer readers to Figure S4 of Additional file 1.

The first signature we observe is for the cities with the most efficient transit systems (Fig. 4A): Philadelphia, Boston, San Francisco, Cleveland, Jacksonville, Hartford, and Dallas. In these cities, the travel impedance of longer journeys (30 km or more) is, on average, lower than shorter trips, indicating that the transit system is generally more efficient for trips of larger distances. These cities all tend to be more efficient, with the mean efficiency of all cities following this signature being 3.704 and the median being 3.462. The average transit impedances of these cities never exceed 5, conveying that transit times in these cities are typically upper-bounded at 5 times as long as driving times. Another signature we unveil is for cities with the least efficient public transit (Fig. 4C): Gainesville, Kansas City, Greenville, Fort Worth, Bridgeport. These cities exhibit an increasing travel impedance as the distance of trips increases, implying public transit becomes less effective than driving when journey distances increase. The mean and median efficiency for cities in this signature are 6.518 and 6.776, respectively

The final signature we identify is a combination of the first two signatures and is found in cities that have moderately efficient public transportation (Fig. 4B): Milwaukee, Cincinnati, New Orleans, Albuquerque, Las Vegas, and Houston. These cities reveal characteristics of the first signature until a particular distance threshold. That is, travel impedance decreases as trip distances increase for shorter length trips in that region. Trips that are longer than the distance threshold follow the behaviour of the second signature, displaying increasing travel impedance with trip distance. Cities in this group have a mean transit efficiency of 4.589 and a median of 5.180. These cities may express mixed characteristics as a result of their transit systems not adapting to increasing levels of urban sprawl. Thus, transit service in these cities could be more efficient in dense, central neighbourhoods, but may not have caught up with rising populations in the peripheral suburbs. This aligns with previous research that has shown how the popularisation of cars, coupled with increasing urban sprawl, has deprived more vulnerable sociodemographic groups of essential services, such as access to food [31, 32]. Future work can focus on how urban form and the coverage area of public transportation intersect.

Thus far, we have introduced the metrics of travel impedance and transit efficiency to compare cities to one another, based on the time it takes to travel using transit between various locations in a region. We find that cities with less efficient transport infrastructure also have higher rates of car ownership. Finally, we identify different trends for how efficient trips of varying lengths are for the most efficient, moderately efficient and inefficient transit systems. While this analysis highlights transit inequalities, disparities may also exist within each city, in terms of how different demographics are served by the transit system, for particular trip purposes. The next section focuses on this concept, evaluating the accessibility of employment areas for different housing demographics based on transit efficiency and proximity.

5 Defining employment landscapes

Many works have highlighted the various reasons why proximity plays a role in connecting employment and housing landscapes. Some explanations include the cost of commuting [33] and residential markets supplying housing to particular demographics, resulting in dense commuting flows between specific neighbourhoods [34]. Moreover, the interconnected nature of residential and workplace segregation emphasises how housing markets and employment opportunities further contribute to experienced inequalities [35, 36]. Thus, we argue that of the urban and economic forces that contribute to segregated experiences, transport infrastructure should, at the very least, not add to such constraints, ideally providing sustainable alternatives to accessing better opportunities. Thus, we identify residential and employment hotspots for each housing demographic to understand how transit connects these clusters.

We apply exploratory spatial data analysis techniques on a global and a local scale. The Moran's I statistic, a common method for assessing global spatial autocorrelation, tests whether spatial clustering of a specified metric exists in a geographic data set. The metric we consider is the workforce composition of a census tract, defined by the percentage of a workforce that is made up by a particular housing demographic. The extent of clustering is highly dependent on a spatial weights matrix, which characterises the proximity between two areas in a city. Moreover, each census tract can be defined by how much the tract's employment of a housing group deviates from the mean value, across all tracts. Thus, by combining the tract-level data with the spatial weights matrix, one can derive the degree of spatial clustering in a city, for the workforce composition of a housing demographic. This provides some insight as to whether clustering is a spatial pattern for the entire city. However, it does not define where the high rates of employment occur in the city.

To identify these clusters, we use Local Indicators of Spatial Association (LISAs) [37] to analyse spatial autocorrelation on a local level. Thus, we can determine the census tracts that have high values of employment for a housing vulnerability group, that are also surrounded by tracts with similarly high employment rates for that demographic. In this manner, LISAs can pinpoint, what we refer to as, *employment hotspots*, which indicate regions that employ a high percentage of individuals that live in a particular housing demographic. Both the local and global analysis are inferential statistics, comparing the empirical data to their randomized counterparts, in which the empirical values are maintained, but are assigned to random locations to determine the significance of spatial clustering in the data.

Global spatial autocorrelation, in this context, assesses whether a housing group relies on particular areas of a city for job opportunities. To accomplish this, we define census tracts by the percentage of individuals working there that belong to a particular housing group. Then, we compare the employment rates of each census tract to its neighbours, characterising neighbours using Queen contiguity, in which neighbouring tracts are those that share a vertex with the focal tract. Table S9 lists the Moran's I statistic, with respect to employment rates for each housing demographic, in which bold cells reflect statistically significant values. For example, the second column conveys the extent of spatial concentration, in regard to how many individuals from less vulnerable residential areas make up the workforce composition. Meanwhile, the last column captures the spatial autocorrelation of areas that employ similar rates of individuals from the most vulnerable census tracts. Table S9 is sorted by Moran's I value for the most vulnerable demographic, showing the notable role that space plays when considering the worker composition of individuals highly vulnerable to housing insecurity.

Higher values of Moran's I in the last column of Table S9 indicate that areas in a city tend to have similar employment rates of individuals that live in the most vulnerable tracts. To distinguish between areas that have high and low employment rates of each housing group, we apply local spatial autocorrelation using Local Indicators of Spatial Associations (LISAs) [37]. In this context, LISAs use the variance of employment rates and the associated spatial weights of a region to identify clusters with a high concentration of employment for a specific housing group, which are deemed employment hotspots. Figure 5A illustrates the housing landscape in Philadelphia and Bridgeport, with darker hues of red corresponding to census tracts that are more vulnerable to housing insecurity. Meanwhile, the purple geovisualisations convey employment hotspots for each of the housing groups, with darker hues of purple reflecting employment hotspots for individuals from the most vulnerable tracts. When we focus on the employment hotspots and residential tracts for the most vulnerable housing group, indicated by the dark purple and red, respectively, we can observe how home and workplace locations are often dependent on one another.

In this section, we analyse the intersection of housing and employment landscapes by assessing whether areas with similar workforce characteristics express a notion of spatial proximity. Then, we identify particular census tracts that employ an unusually high concentration of its workforce from a particular housing demographic. Specifically, we use spatial autocorrelation on a global and local level to define census tracts based on the labour force that works there. Having defined the housing demographics of neighbourhoods in a city, the transit service between neighbourhoods, and employment hubs for each housing demographic, we can explore how transit systems connect residential and employment areas.

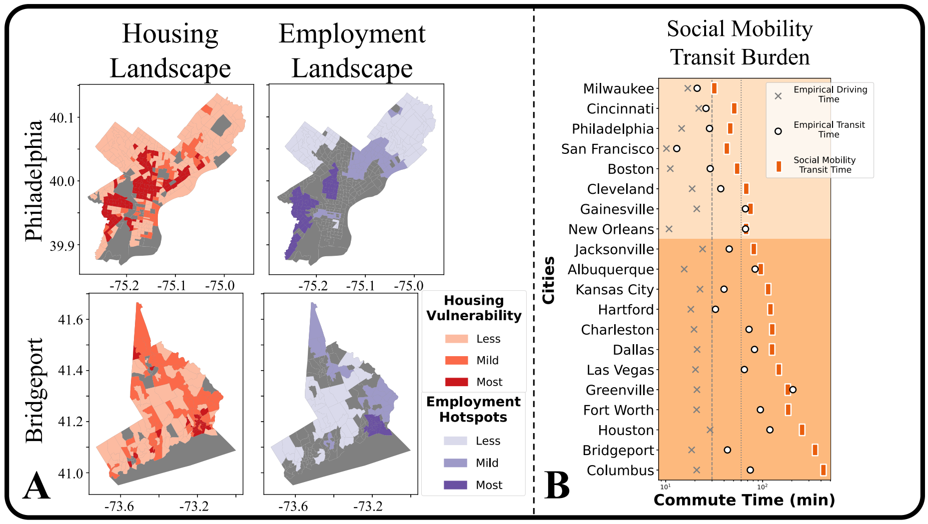

Figure 5 Employment hotspots in Philadelphia and Bridgeport and the cost of commuting to areas with better job opportunities for 20 cities in the USA. Panel A reflects the spatial distribution of the housing and employment landscapes in Philadelphia and Bridgeport. Darker shades of red convey higher levels of housing insecurity, while darker shades of purple reflect employment hotspots for the more vulnerable housing demographics. Panel B depicts how transit commute times change for individuals living in the most vulnerable neighbourhoods if they were to start working in employment areas that would facilitate social mobility. The grey cross and white circle indicate empirical median commute times via driving and transit, respectively. Meanwhile, the orange rectangle refers to median transit commute times, averaged over 1000 of the social mobility simulations

6 Simulating potential avenues for social mobility

To highlight the integral role transport infrastructure plays in job accessibility, we explore how commuting times change when individuals in vulnerable housing areas start working in employment areas that provide opportunities for social mobility. We leverage the housing demographics, transit networks, and employment hotspots, defined in earlier sections, to examine how transit infrastructure interfaces with upwards social mobility. We focus on social mobility because wealth is often the underlying constraint preventing individuals from improving their housing conditions [38–40]. We define upwards social mobility for individuals living in the most vulnerable neighbourhoods as having reasonable transit access to 'better job opportunities.' Furthermore, we refer to 'better job opportunities,' as a shorthand for employment hotspots for the mildly vulnerable housing demographic. This choice is based of the assumption that mildly vulnerable housing demographics have higher incomes and employment benefits, keeping in mind that income largely determines housing conditions. To implement this, we reassign the employment tracts of individuals from the most vulnerable demographic to randomly sampled employment hotspots for the mildly vulnerable demographic. In doing so, we assume that the hotspots for the mildly and less vulnerable housing demographics provide better economic compensation compared to that of the most vulnerable housing group. This assumption stems from the positive relationship between median household income and lower levels of vulnerability in Section S3.3 and shown in Figure S3B. Thus, this section explores how changing the workplaces of individuals commuting from the most vulnerable housing tracts impacts commuting characteristics.

Figure 5B compares the commuting times for different scenarios, across each of the 20 cities in our analysis. The grey crosses reflect median empirical driving times of individuals that both live in census tracts that are the most vulnerable to housing insecurity and commute to the most vulnerable employment hotspots. Similarly, the white circles represent the median empirical transit times for the same set of individuals. Meanwhile, the orange rectangles symbolise the median transit times for the modeled social mobility. Over 1000 iterations, we reassign the workplaces of the same set of individuals to randomly sampled mildly vulnerable employment hotspots. We note that the x-axis is in logarithmic scale, emphasising differences between shorter commutes. The dashed line indicates a 30-minute commute, whereas the dotted line marks an hour-long commute. Moreover, we reiterate that driving times do not account for traffic, but are a reflection of the cities' road networks. Figure 5B underscores the dependence between housing and employment locations, as mean driving times for all cities is approximately a half hour or less.

We observe how commuting times via transit increase for all cities, when compared to commute times using cars. However, for Milwaukee, Cincinnati, Philadelphia, San Francisco, and Boston, transit commute times remain under a half hour. The change from empirical driving to empirical transit times in San Francisco, Cincinnati, and Milwaukee is under five minutes. We attribute the short average commuting times via car for cities, such as San Francisco, to the spatial dependence between home and work locations for individuals commuting from the most vulnerable housing tracts to employment hotspots for the most vulnerable demographic. Figure S6in Additional file 1 conveys this concept, illustrating the different driving time distributions across various subsets of housing demographics and employment locations.

Moreover, shifting from the empirical data to the social mobility scenario reveals how commuting using public transit to areas with better opportunities leads to even longer commute times, barring Greenville and New Orleans. We note that transit commutes in the social mobility simulations for Gainesville, Milwaukee, and Albuquerque only increases travel time by less that 15 minutes, in comparison to its empirical counterparts. While empirical transit commuting times remain under an hour for the 10 of the 20 cities, only 5 cities maintain this characteristic in the social mobility context. Similarly, only Milwaukee transit infrastructure provides access to improved employment opportunities within approximately a half-hour transit commute (31.15 minutes).

By using housing demographics and commuting behaviour to simulate potential for social mobility, we reveal how in half of the 20 cities we analyse, individuals in the most vulnerable housing demographic (a demographic which tends to rely more on transit for commuting – Figure S3E in Additional file 1), have transit commute times of over an hour. Furthermore, we show how the majority of cities in our analysis do not have the adequate transport service for supporting commutes, which fall under an hour-long journey, to workplaces that provide better employment opportunities.

7 Discussion

This work underscores how urban infrastructure can contribute to housing insecurity by perpetuating inequalities in how accessible areas which facilitate social mobility are. We, first, introduce a classification framework that adopts a comprehensive approach to estimating levels of housing insecurity, accounting for the various dimensions of housing conditions. Then, we use public transit and street network data to characterise cities in the USA, based on their transport infrastructure. Finally, we highlight how transit systems in most cities pose obstacles to accessing employment areas that are associated with improved housing conditions. In this manner, we show how urban infrastructure impedes individuals' abilities to live in improved housing in various cities.

We begin our analysis by combining census and eviction data to estimate levels of housing insecurity on a census tract level in 20 cities in the USA. The code to reproduce such estimates and apply a similar approach to other counties is available on Github. Considering Cox's definition of housing insecurity, we quantify housing insecurity with respect to affordability, quality, and stability [16]. Existing approaches to defining housing insecurity, in the context of urban analytics, include using a specific housing feature as a rough proxy, such as rent burden or forced moves [41, 42]. Others have multiple housing features characterising one dimension, We focus on Cox's definition as it captures financial, structural, and social forces that influence the state of housing. It is important to note that the seven dimensions proposed by Cox stem from a Global North perspective, with its definition based on housing policies in the USA. Attempts to develop a comprehensive measure for the Global South incorporate features such as sanitation and water access [43]. The distinction between these two definitions is imperative, considering that different histories, cultures, and environments can re-frame the relevance of a housing dimension, and the features that can be used to estimate said dimension. Thus, the accompanying code to generate housing clusters must be used with great care and in the proper context. Ultimately, our approach aims to capture various mechanisms that contribute to poor housing experiences, which we validate by comparing to a range of socioeconomic characteristics such as income, educational attainment, and mobility behaviour.

Moreover, this work is limited in data availability of housing conditions. Accordingly, the neighbourhood and homelessness dimensions are yet to be incorporated. However, given the flexibility of the proposed framework, introducing these dimensions is simply a matter of modifying the rank-based approach to. Potential neighbourhood characteristics can be defined using crime data sources for safety or built form metrics for quality. Future work can aim to disentangle what aspects of housing insecurity (i.e. low affordability, stability, neighbourhood safety, etc.) correspond with different forms of employment accessibility. In this manner, researchers can develop both a high-level understanding of negative outcomes that are associated with housing insecurity (introduced in this work) and a more nuanced perspective of what dimensions of housing insecurity are intertwined with fewer opportunities to improve one's housing conditions.

Furthermore, our work leverages open source tools to define travel impedance based on how much longer a journey takes using transit than by car. By averaging travel impedance over potential trips in a city, we identify Philadelphia, Milwaukee, and San Francisco as the three cities in the USA, with the most efficient transit systems, of those considered. Moreover, we observe three types of transit systems based on how transit efficiency relates to trip distance. In line with research that demonstrates the decreasing significance of distance due to improved transit systems, we find that the cities with the most efficient transit service overall tend to have equally, if not more, efficient transit impedance for trips of longer distances [44].

Finally, by incorporating mobility behaviour between residential and work areas, we unveil how transit infrastructure can impose additional hurdles to accessing workplaces that provide better financial opportunities. Studies have shown that targeted efforts in improving transit access to job opportunities has a positive effect on individual employment probability and individual income, particularly improving employment probabilities for lower income individuals [45, 46]. However, we explore the geospatial layout of employment opportunities with residential landscapes to see how these efforts may also perpetuate inequalities in accessing jobs with different characteristics. Thus, this analysis contributes to research that motivates exploring inequality analyses from a spatial perspective, emphasising the importance of space and the built environment in social processes. Ultimately, housing conditions impact the level of comfort and belonging individuals experience within their environment [47, 48]. Thus, we aim to highlight how the strain of housing insecurity is exacerbated by urban features that can hinder vulnerable populations from breaking out of the cycle of poverty.

Abbreviations
USA, United States of America; GTFS, General Transit Feed Specification; ACS, American Community Survey; LEHD, Longitudinal Employer-Household Dynamics; LODES, LEHD Origin-Destination Employment Statistics; OSM, OpenStreetMap; LISA, Local Indicators of Spatial Association.

Supplementary information

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Additional file 1. (PDF 1.6 MB)

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Author contributions
NI designed the research, acquired and analysed the data, and wrote the mansucript with RM, and HB providing important feedback throughout the process. All authors approved the final version of the manuscript.

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Data availability
The census and geographic data datasets analysed during the current study are available at https://data.census.gov/
The eviction datasets analysed during the current study are available, for most cities, are available at https://evictionlab.org/eviction-tracking/. The eviction rates for San Francisco and New York can be found at https://data.sfgov.org/Housing-and-Buildings/Eviction-Notices/5cei-gny5 and https://data.cityofnewyork.us/City-Government/Evictions/6z8x-wfk4, respectively.
The commuting datasets analysed during the current study are available in the LODES7 repository, https://lehd.ces.census.gov/data/lodes/
Code for reproducing the framework for identifying census tracts based on their vulnerability ot housing insecurity, as well as housing demographics' employment hotspots is available at https://github.com/nandini10/Housing-Insecurity.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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