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Exposures at Day Labor Corners: Using Existing Location-enabled Datasets to Describe Features of Urban Environments

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Abstract

Objectives.—Latino day laborers are male immigrants from mainly Mexico and Central America who congregate at *corners*, i.e., informal hiring sites, to solicit short-term employment. Studies describing the occupational environment of Latino day laborers traditionally measure jobsite exposures, not corner exposures. We sought to elucidate exposures at corners by describing their demographic, socioeconomic, occupational, business, built, and physical environmental characteristics and by comparing corner characteristics to other locations in a large urban county in Texas.

Methods.—We used multiple publicly available datasets from the U.S. Census, local tax authority, Google's Nearby Places Application Programming Interface, and Environmental Protection Agency at fine spatial scale to measure 34 characteristics of corners with matched comparison locations.

Results.—Corners were located close to highways, high-traffic intersections, hardware and moving stores, and gas stations. Corners were in neighborhoods with large foreign-born and Latino populations, high rates of limited English proficiency, and high construction-sector employment.

Conclusions.—Publicly available data sources describe demographic, socioeconomic, occupational, business, built, and physical environment characteristics of urban environments at fine spatial scale. Using these data, we identified unique corner-based exposures experienced by day laborers. Future research is needed to understand how corner environments may influence health for this uniquely vulnerable population.

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COMPETING INTERESTS
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Keywords

day laborers; neighborhood exposures; Latino health; urban context; occupational exposures

INTRODUCTION

In the United States in 2004, an estimated[1] 115,000 Latino day laborers waited for work for up to 12 hours a day[1] at "corners," e.g., intersections, bus stops, gas stations, and home improvement stores, to solicit short-term construction, landscaping, moving, or service-based employment from contractors and individual homeowners.[2] There is variability in type of employment sought (full vs part-time) and amount of time spent on location (quick vs delayed hires),[1,3] but many Latino Day Laborers return to the same location to seek employment at the same corner for months or even years.[2] Therefore, corners repeatedly expose laborers to adverse environmental conditions, like weather and crowding, that can become a source of stress and poor health.[4–6] Although it is well-documented that Latino day laborers work at job sites with multiple safety hazards causing high rates of occupational injury and death[7–9]—and that risk is exacerbated by personal stressors including poverty, immigration status, depression, and substance abuse[10–12]—very little is known about environmental conditions experienced by this vulnerable population while they wait for work.

Features of neighborhood environments can influence health. Significant evidence has demonstrated associations between neighborhood socioeconomic and physical environment and both physical and mental health outcomes of individuals.[13–16] However, existing studies of place-based exposures traditionally focus on residential (vs occupational) exposures,[17] even though adults, including Latino day laborers, spend large percentages of their time away from home. Most prior public health studies define neighborhoods using relatively large geographic footprints (e.g., census tracts), neglecting the variation occurring at a smaller scale. To date there are no previous explorations of fine-scale (e.g., smaller than a census tract) exposures at day laborer corners, even though corners have very small geographic footprints.

Many prior studies measure demographic (e.g., neighborhood % Hispanic) and socioeconomic (e.g., neighborhood % poverty) features of neighborhoods using U.S. Census data. Although other publicly available data sources provide additional information about the physical (e.g., air pollution) and built (e.g., proximity to roadways, building quality, value) environments, no existing studies of corner exposures describe physical or built environments. Very few existing studies explore the local business (e.g., types of nearby stores) environment, and those that do focus on how a corner's physical and geographic location is critical for workers' employment success;[1,18–20] for example, in California, corners are located near affluent neighborhoods with more employment opportunities.[18]

[1]The National Day Labor Study has not been replicated since 2004. Factors such as an increase in immigration from Central America, a decrease in immigration from Mexico, changes in the economy, and the availability of competing forms of contingency labor may have altered the day labor population size.

The goal of this study was to describe environmental exposures at corners where Latino day laborers look for work—and in doing so, demonstrate the use of novel data sources and methods to describe diverse features of urban environments that may be relevant for health. Our aims were to (1) describe demographic, socioeconomic, occupational, business, built, and physical environment characteristics of corners and (2) compare neighborhood-level characteristics of Latino day-labor corners to other neighborhoods located the same urban area. Although prior studies using U.S. Census data at the census tract level demonstrated how day labor corner locations differed from surrounding regions across demographic and economic characteristics.[18,20,21], we focus on identifying diverse exposures in day laborers' immediate environment, thereby expanding our understanding of workers' repeated encounters with environmental burdens.[22]

MATERIALS AND METHODS

We identified street locations, convenience stores, parking lots, parks or shopping malls as day labor corners and geocoded these locations to obtain latitude and longitude coordinates. We obtained publicly available exposure data, and used geospatial matching to compare exposures at corners to those at other comparison locations. Figure 1 gives an overview of the geospatial methods we used to define corners and exposure measures using multiple sources of publicly available data. The internal review board at University of Texas Health Science Center at Houston approved the original study that collected corner locations.[23]

Corner selection, definition, and study area

Observations of corners conducted between November 2013 and July 2014 identified 44 day-labor corners in Houston; descriptions of the original study are available elsewhere.[2,24,25]

Figure 1A provides an overview of how we defined the spatial extent of corners. We geocoded addresses for each corner using Google's Geocoding application programming interface (API). We defined each corner's geographic unit as a 0.25-mile buffer surrounding each location. If two corner units overlapped, we randomly selected one; if three or more overlapped, we retained the most centrally located corner. The final sample included 28 corners with non-overlapping footprints. During formative data collection conducted in previous studies[2,24] including discussions with local authorities, day laborers, and community organizations serving this population, all parties generally agreed that these locations were well-established and comprised all known corners in Houston.

To define our study area, we drew a 2-mile buffer around the smallest possible shape drawn around the corners, i.e., the convex hull polygon. This yielded a 638.1-square mile study area centered on Houston, Texas and roughly corresponding to the Sam Houston Tollway perimeter. Comparison neighborhoods, analyses, and maps were constrained to this area; however, air pollution data processing calculations utilized information outside of the area.

Measuring exposures at day labor corners

Figure 1B provides an overview of the geospatial methods we used to measure exposures using different data sources. In order to define exposures within a 0.25 mile buffer, we processed data as follows. For continuous data (e.g., housing value), we computed area-based weighted average for the geographic corner unit. For categorical data (e.g., housing type), we calculated the mode of all values within the geographic corner unit. We used simple kriging to create air quality data with continuous support across Harris County.

We measured *built-environment* characteristics using 2015 parcel-level housing data from Harris County Appraisal District,[26] the municipal property tax authority. Parcels reflect the extent, value, and ownership of land. We measured land usage (residential [single-family residence, multiple-family residence, or condominium], commercial, or vacant) and included existing measures of building quality (below average, average, above average).[27] We also measured year built, tax value in dollars per square foot, and valuation type (building or land).

We measured *demographic* and *socioeconomic characteristics* using block-group level 2011–2015 American Community Survey (ACS) 5-year estimates.[28] These measures included the percentage of all residents within the block group who are Latino, non-Latino (NL) White, NL Black, and NL Asian and those who earned a high school degree; percentage of all households speaking no English, speaking limited English, and earning less than the federal poverty level (FPL); and percentage of houses that were vacant. We collected the percentage of foreign-born residents at the census-tract level, the smallest geographic unit for which this variable was available.

We measured the *occupational environment* by describing unemployment and types of jobs in areas surrounding corners. Using 2011–2015 ACS 5-year estimates, we measured the percentage of unemployed residents and of residents employed in building-grounds cleaning and maintenance, material moving, and construction and extraction operations. We selected these occupations because Latino day laborers previously interviewed in the local area reported jobs captured by these categories.[2]

We assessed the *business environment* by measuring distance from corners to relevant labor-oriented retail outlets. We used Google's Nearby Places API to identify the closest hardware, home painting supply, landscaping material supply, and moving supply or rental stores,[29] and Google's Distance Matrix API to calculate street network distance between corners and the nearest retail store of each type.[30]

We described the physical environment by calculating *air quality* following measurements described in the National Ambient Air Quality Standards (NAAQS) using Environmental Protection Agency (EPA) data from 2012–2014.[31] We measured 6 pollutants with documented potential to harm human health: ozone, fine and course particulate matter ($\leq$2.5 and $\leq$10 microns in diameter), carbon monoxide, lead, sulfur dioxide, and nitrogen dioxide. Because pollutant concentrations are measured only at air-monitoring stations, we interpolated measurements between stations using kriging procedures available in Geostatistical Analyst in ArcMap 10.3.[32]

Comparison locations

To explore if exposures at corners differ from those at other intersections, we selected four sets of comparison strata and within those randomly selected comparison areas. For each corner, we selected a comparison intersection from block groups that did not already contain a corner and were similar to corners based on four strata: geographic region, population density, highway proximity, or road intersection type. These strata were identified based on our *a priori* knowledge of corners throughout Houston. Previous research on corner typology,[3,18,20] also identified some of these characteristics as important for day labor corner location.

This approach allowed us to contextualize and understand characteristics of corners that are likely co-located with these attributes, allowing us to identify unique exposures at corners while holding certain features (e.g., population density) constant. Our use of comparison areas allowed us to measure specific exposures that cannot be calculated for the city as a whole. For example, it is not possible to measure point-to-point distance to a hardware store for the whole city. Lastly, some exposures, measured across the entire city, such as average building quality or building date, are not particularly meaningful.

Geographic region—We divided the study area into 27 geographic regions using ArcMap 10.3 and street network data from Tele Atlas's Street Map North America product.[32,33] Typical city segmentation algorithms use major streets and highways as dividing lines, but Latino day laborers in Harris County congregate at intersections of these thoroughfares. Therefore, we applied vector-realized Euclidean allocation algorithms to Harris County's highway network [34–36] to define geographic regions in which intra-regional points are closer to the major highway that runs through the region than to any other highway.

Population density—We divided study area block groups into tertiles of population density (0–4120.5, 4120.5–7343.3, and 7343.3–75067.6 people per square mile) using population data from 2011–2015 ACS 5-year estimates.

Intersection type—Using road classification data from the U.S. Census Bureau,[32] we defined all intersections in the study area as primary, secondary, or local intersections. These types reflect road size, traffic access, and flow. In general, primary roads are U.S. highways, secondary roads are undivided state or county highways, and local roads have a lane of traffic in each direction. For intersections of differing types, we assigned the highest-usage type; for example, the intersection of a primary and secondary road was defined as a primary intersection.

Proximity to highway—We calculated straight-line distance between each corner and the nearest highway and grouped those distances into three tertiles of proximity (defined as 0–0.13, 0.13–0.35, and 0.36–3.30 miles). We created buffers that reflected these tertiles for all highways.

Comparison areas were identified using R[37] unless noted otherwise above. Creation of all 0.25-mile buffers, spatial overlay operations, Google API access, statistical analysis, and mapping were implemented in R with the rgeos,[38] spdep,[39,40] rjson,[41] raster,[42] and RColorBrewer[43] packages.

Analyses

We used descriptive statistics (number, mean, percentage) to describe exposures. To compare exposures between corners and comparison locations, we used chi-squares or Fisher's exact tests for categorical and *t*-tests for continuous measures.

RESULTS

Figure 2 presents locations for corners overlaid on the street network. Figure 3 provides corners and matched comparison locations separately by comparison type, including geographic region (A), population-density tertiles (B), intersection type (C), and highway proximity (D). In all figures, we used random perturbation masking to prevent disclosure of actual corner locations.

Ozone concentrations at corners and comparison areas exceeded the NAAQS standard (0.070). No other measures of air quality exceeded NAAQS. One air quality measure and only a few built environment exposures were different between corners and comparison locations (Table 1). Concentrations of particulate matter ≤ 10 microns in diameter were higher at density-matched comparison areas than at corners. Corners were located more often in commercial (vs residential) areas compared to their geographically matched counterparts. Compared to their highway-proximity matched counterparts, corners were located more often at primary or secondary intersections, and were less likely to be surrounded by poor quality buildings. Corners were located closer to highways in regard to density-matched comparisons.

Numerous demographic and socioeconomic characteristics differed between corners and comparison locations. Corners were located in areas almost twice as densely populated as their highway-proximity matched comparisons. Corners were located in areas with statistically significantly higher populations that were foreign-born (34.4%) or Latino (62.8%), or who had limited English proficiency (24.4%), compared to density (25.2%, 37.1%, and 13.3% respectively), intersection type (26.6%, 49.1%, and 16.1% respectively), and highway proximity (26.7%, 47.2%, and 14.3% respectively) matched comparison areas. Corners were located in areas where statistically significantly less of the population was Black (12.1%) compared to geographically and highway proximity (27.5% and 22.5% respectively) matched areas. Corners were located in areas in which more than a quarter (26.6%) of the population live at or under the federal poverty level, which was statistically significantly higher only for intersection-matched comparison locations. No other demographic or socioeconomic exposures were statistically significantly different between corners and geography-matched comparison locations.

The occupational and business environment differed in several ways between corners and comparison areas. Corners were located significantly closer to hardware stores (0.017 miles) and moving supply stores (0.48 miles) than all sets of comparisons. Corners were located in areas in which 14.8% of residents were employed in construction, which was higher than that of all comparison areas; three of four of those comparisons were significantly different. In contrast, the percentage of population employed in building-grounds cleaning and maintenance and material moving was higher for corners only in the proximity-matched comparisons.

DISCUSSION

Our study used several novel methods and publicly available data sources to describe a diverse array of exposures in an urban environment at a small spatial scale. First, we used novel, publicly available data (e.g., property appraisal data, Google) to characterize features of the built, business, and physical environment that are unmeasured by the U.S. Census. Second, we defined exposures by aggregating measures to 0.25 square mile units around each corner. In contrast, study area census tracts average 1.44 square miles. Thus, our approach allows more granular exposure measurements compared to many existing studies. Third, we designed unique geospatial matching methods incorporating prior knowledge of day laborer corners to account for meaningful known differences across our urban setting related to geographic region, population density, type of intersection, and highway proximity. For example, because laborers congregate at locations near major highways, we split the study area into similar geographic regions surrounding highways using vector-realized Euclidean allocation algorithms for line data. Our study is among the first to assess environmental exposures at day laborer corners, and therefore provides important preliminary data for future occupational and environmental health research and intervention for this vulnerable population. These methods could be applicable to other occupations wherein workers are exposed to urban environments and potentially stressful conditions (e.g., fruit stand operators in Los Angeles[44]).

The demographic and socioeconomic similarity between day laborers and nearby residents agrees with previously published studies about social ties in Latino communities. The high representation of foreign-born individuals in a neighborhood may help confer a “barrio advantage” arising from increased size and strength of local social networks and increased access to linguistically appropriate resources available to residents and day laborers.[45–47] However, the socioeconomic similarity between residents and day labors waiting for work in poor neighborhoods may also signal social exclusion,[48] which could harm both the growth and diversity of social networks and the ability of laborers to find local employment.

In our study, no day labor corners were located in affluent areas. Another study, conducted in San Diego, described some day laborer corners located near affluent neighborhoods.[18] Our study focused on a single city, whereas the San Diego study spanned a metropolitan area with distinct regions. Many regional and cultural differences within and between these the study areas could have contributed to differences between the two studies. For example, Houston has no zoning, which may lead to different patterns of *NIMBY* (not in my backyard) discrimination, and may preclude formation of corners in affluent neighborhoods. Importantly, although residence in high-poverty neighborhoods is associated with poor mental and physical health,[13–15,49,50] the pathways and resulting health effects of occupational exposure to high poverty neighborhoods for day laborers are unknown.

We observed differences in the occupational and business environments of corners that could contribute to the chances of a day laborer being hired, which is important because significant research underscores the connections among employment, economic stability, and health.[51] Differences in business environments of corners vs comparison areas indicated that corners are located close to hardware stores, moving stores, and gas stations. This spatial pattern is found in other cities where laborers established corners close to businesses whose patrons are likely to hire them, thereby maximizing their opportunities to be hired.[1,20] Clustering of businesses in related industries results in part from the benefits of consumer shopping behaviors like trip-chaining, e.g., "running errands."[52–55] In light of other published work describing "connected" sites (e.g., corners located next to retail stores in the same industries as day laborers) and one-stop-shops,[3,56] our results may indicate that trip-chaining behaviors of day laborer employers enter into the natural evolution of corner locations. In other words, Houston Latino day laborers may return to corner locations where potential employers frequently visit because they can conveniently purchase related goods or services.

Corners are located in neighborhoods with a relatively high proportion (9.4%) of residents employed in the construction sector. Co-location of businesses in the same industry can create a local labor pool from which businesses hire, which can increase demand for skilled and knowledgeable employees. In prior research, industrial job seekers have higher employment rates when they apply for work at co-located businesses.[57] It is possible that day laborers waiting for construction work in an area with a local labor pool may benefit from it. For example, construction contractors in the corner neighborhood may hire day laborers when demand is high, which could help laborers form a connection to that contractor, secure other jobs, and improve their financial well-being.

Certain types of business environments may contribute to exposures or health risks. For example, laborers who wait near fueling centers or loading docks might sustain heightened environmental exposures to benzene, which can cause chromosomal aberrations,[58] and diesel particulate matter,[59] which is a Group 1 carcinogen for humans.[60] Although we only detected one difference in air pollutants between corners and comparisons, future research should employ onsite sampling, and explore exposure to environmental toxicants between corners with different types of business environments. Ozone concentrations at corners and comparison areas exceeded levels determined by the EPA to be harmful to human health. Future work should focus on ozone exposure abatement for day laborers and others who spend time outdoors, and on identification of other harmful exposures that are regulated by the Occupational Safety and Health Administration for traditional workers but not for day laborers.

Our study has several limitations. We defined all corners as the same size. In reality, corner size depends on the built environment and number of workers present. We provided a cross-sectional snapshot of corner exposures; however, over time, workers move to other corners, new corners emerge, locations shift, and neighborhood contexts change. Our study comprised one urban area; corners in other places may experience different exposures. We used interpolated, cross-sectional air quality measurements that might not have been sensitive enough to detect cumulative differences over time. We compared corners to a single comparison area per strata, future teams with adequate computing power for spatial processing could consider use of multiple comparison areas. We focused on using existing data to measure proximal characteristics of the social and geographical environment. We did not incorporate broader social forces such as federal, state, and city policies towards immigrants, racial profiling, and hate crimes. Future studies should incorporate such features of the urban environment given recent evidence that presence of police or immigration enforcement officers increases immigration-related stress among Latino Day Laborers.[5][4]

CONCLUSION

Latino day laborers in Houston face unique demographic, socioeconomic, occupational, business, and built environment exposures via the corners at which they wait for work. These exposures are under-studied, yet have implications for understanding the health inequalities day laborers experience, and for future public health interventions to protect the health and safety of this underserved, vulnerable population. Future research will need to articulate the connection between corner exposures and the health and well-being of Latino day laborers. Methods used in this study provide a model for future studies seeking to better characterize the diversity of neighborhood environmental exposures relevant for health, particularly in urban settings.

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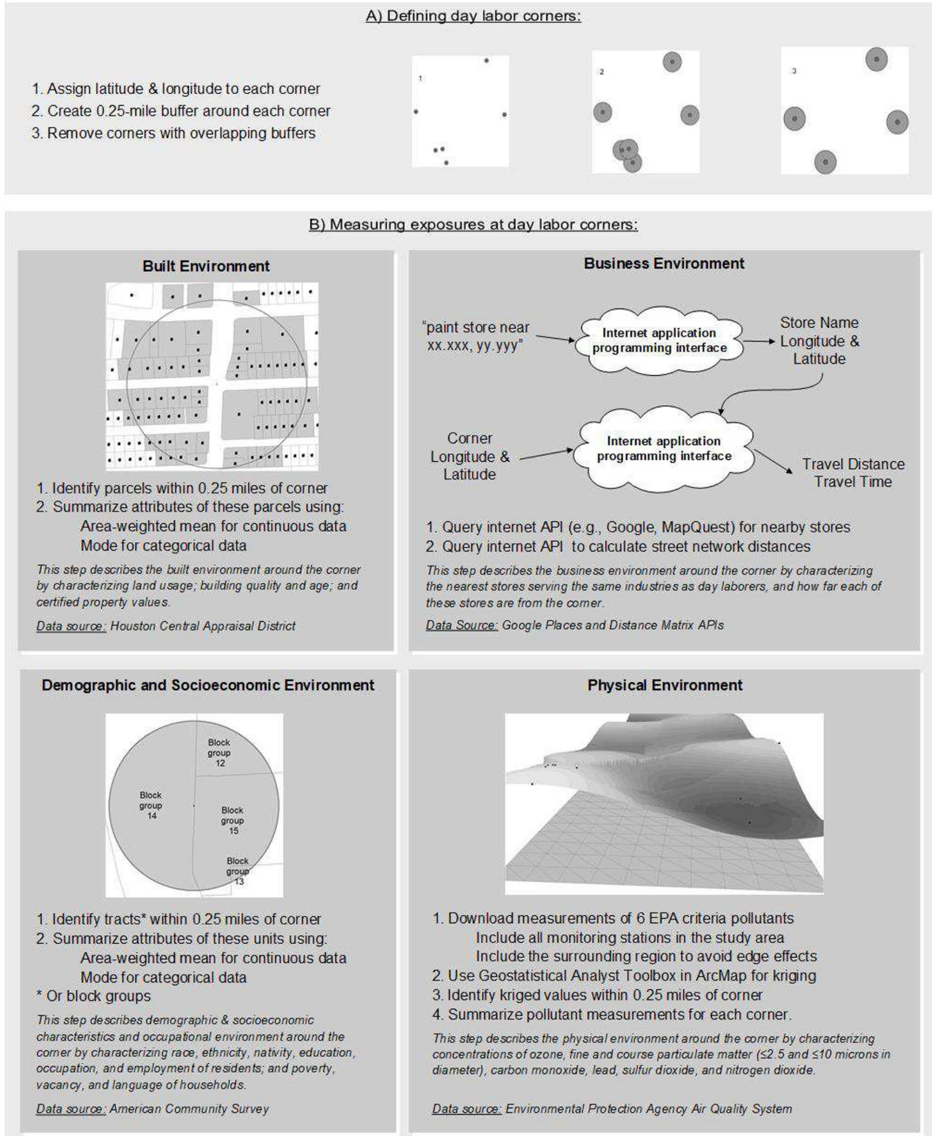

Figure 1.

Summary of geospatial methodology applied to define day laborer corners and their spatial units (Panel A) and measure the built, business, demographic and socioeconomic, and physical environmental exposures at corners using different types of publicly available data (Panel B).

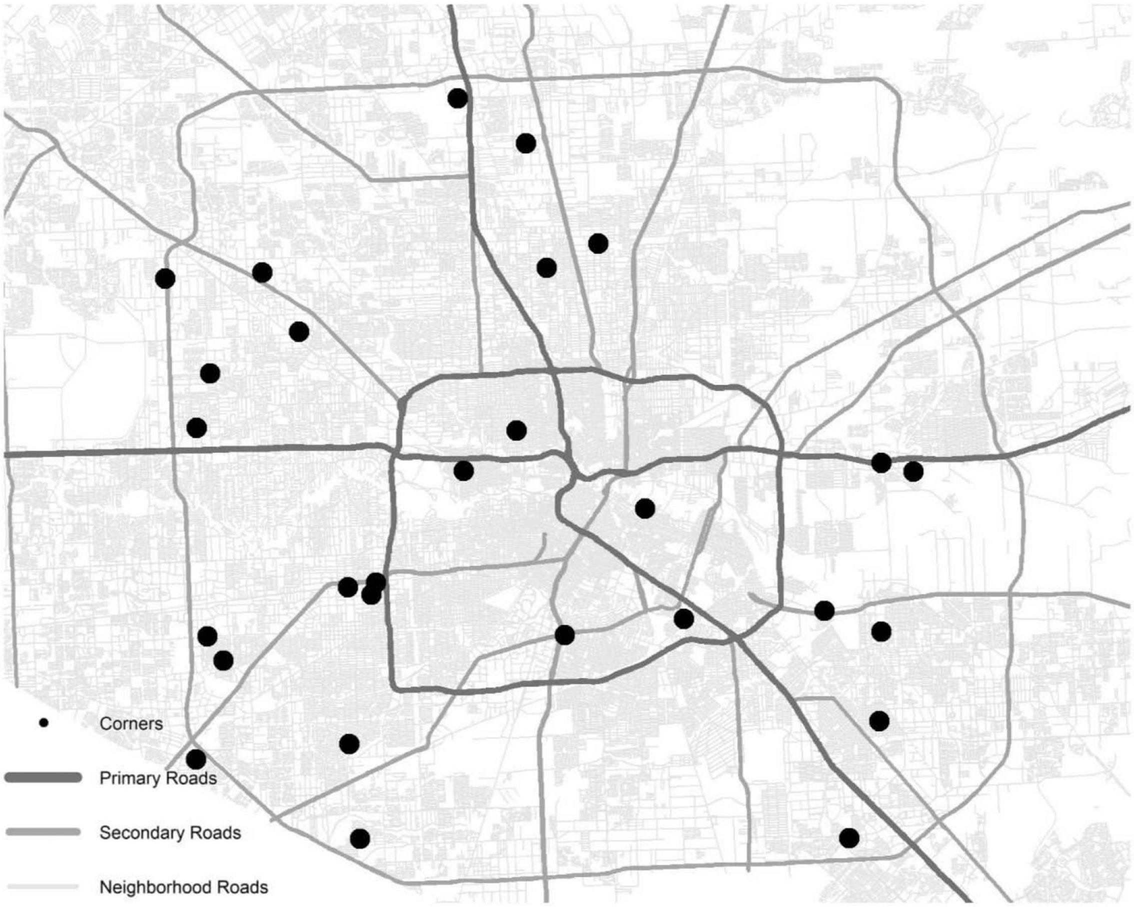

Figure 2.

Latino day-labor corner locations in Houston, Texas.

Note. Random perturbation masking was used to prevent identification of exact locations of Latino day-labor corners.

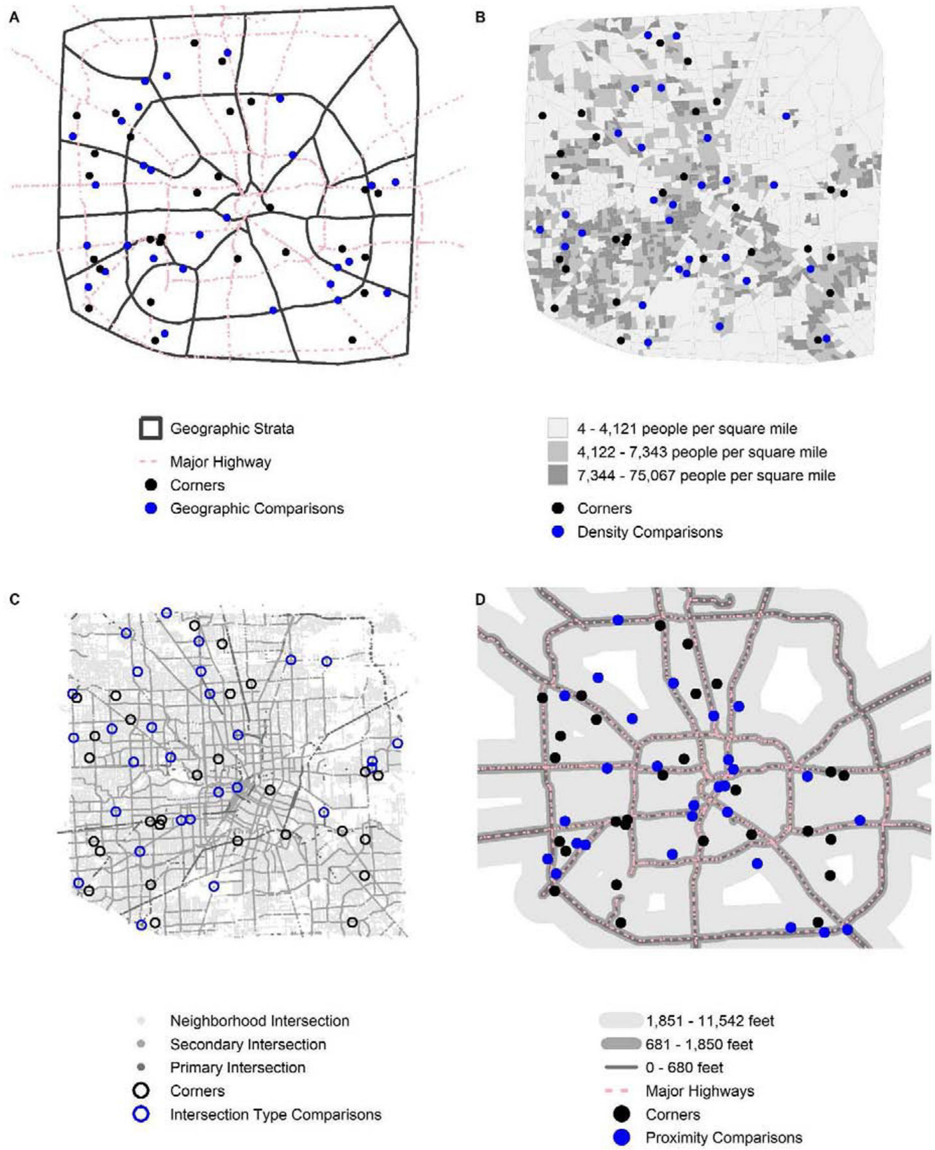

Figure 3:

Latino day-labor corner locations and comparison locations in Houston, Texas, by matched comparison type, including geographic region (Panel A), population density tertiles (Panel B), intersection type (Panel C), and highway proximity (Panel D).

Note. Random perturbation masking was used to prevent identification of exact locations of Latino day-labor corners.

Table 1.

Environmental exposures at day labor corners (A) and matched comparison locations (B-E)

Characteristic	(A) Day-Labor Corners	(B) Geographic Comparisons		(C) Density Comparisons		(D) Intersection Type Comparisons		(E) Proximity Comparisons	
	Mean (SD) *n* [%]	Mean (SD) *n* [%]	*p*-value	Mean (SD) *n* [%]	*p*-value	Mean (SD)] *n* [%]	*p*-value	Mean (SD) *n* [%]	*p*-value
Built environment									
Distance to nearest highway	0.47 (0.6)	0.81 (0.89)	0.10	**0.64 (0.73)**	**0.03**	0.64 (0.79)	0.38	0.40 (0.47)	0.61
Intersection type									
Primary	4 [14.3]	0 [0]	0.16	1 [3.6]	0.37	4 [14.3]	1.00	**0 [0]**	**<0.001**
Secondary	19 [67.9]	21 [75]		23 [82.1]		19 [67.9]		**8 [28.6]**	
Neighborhood	5 [17.9]	7 [25]		4 [14.3]		5 [17.9]		**20 [71.4]**	
Usage									
Residential	18 [64.3]	**22 [78.6]**	**0.02**	24 [85.7]	0.12	21 [75]	0.56	23 [82.1]	0.23
Commercial	10 [35.7]	**6 [21.4]**		4[14.3]		7 [25]		5 [17.9]	
Quality									
Above average[a]	5 [17.9]	6 [21.4]	0.46	6 [21.4]	0.22	5 [17.9]	0.59	**4 [14.3]**	**0.01**
Average	18 [64.3]	18 [64.3]		18 [64.3]		19 [67.9]		**14 [50]**	
Below average[b]	5 [17.9]	4 [14.3]		4 [14.3]		4 [14.3]		**10 [35.7]**	
Building date	1976 (14)	1977(13)	0.77	1972 (14)	0.33	1977(12)	0.74	1971 (14)	0.15
Value per square foot	77.66 (42.04)	85.05 (61.44)	0.60	87.53 (66.66)	0.52	94.69 (69.87)	0.28	78.36 (67.48)	0.96
Valuation Type									
Building	25 [89.3]	25 [89.3]	0.30	26 [92.9]	1.00	23 [82.1]	0.46	25 [89.3]	1.00
Land	3 [10.7]	3 [10.7]		2 [7.1]		5 [17.9]		3 [10.7]	
Demographic and socioeconomic									
Population density	6212.72 (5936.44)	4492.87 (3467.24)	0.19	5652.83 (5967.08)	0.73	4312.66 (3431.07)	0.15	**3781.36 (2417.64)**	**0.05**
% Hispanic/Latino residents[c]	62.8 (24.57)	50.72 (25.28)	0.08	**37.18 (26.5)**	**<0.001**	**49.12 (22.75)**	**0.04**	**47.2 (20.4)**	**0.01**
% HH speak limited English[c]	24.36 (15.29)	19.31 (10.95)	0.16	**13.25 (12.06)**	**<0.001**	**16.1 (12.31)**	**0.03**	**14.3 (10.15)**	**0.01**
% NH White residents[c]	18.82 (17.97)	22.62 (22.13)	0.48	26.88 (27.04)	0.20	27.05 (24.03)	0.15	22.44 (20.49)	0.49
% NH Black residents[c]	12.1 (13.28)	18.08 (21.06)	0.21	**27.47 (26.95)**	**0.01**	17.79 (16.07)	0.16	**22.53 (16.4)**	**0.01**

Characteristic	(A) Day-Labor Corners	(B) Geographic Comparisons		(C) Density Comparisons		(D) Intersection Type Comparisons		(E) Proximity Comparisons	
	Mean (SD) *n* [%]	**Mean (SD) *n* [%]**	***p*-value**	**Mean (SD) *n* [%]**	***p*-value**	**Mean (SD)] *n* [%]**	***p*-value**	**Mean (SD) *n* [%]**	***p*-value**
% NH Asian residents[c]	5.05 (5.85)	7.41 (8.45)	0.23	6.55 (10.36)	0.51	4.98 (5.36)	0.96	6.18 (6.41)	0.49
% HH earn ≤ 100% of federal poverty level[c]	26.58 (11.85)	22.22 (9.97)	0.14	21.83 (12.17)	0.14	**19.28 (10.52)**	**0.02**	24.78 (14.18)	0.61
% Residents HS degree[c]	25.57 (7.24)	24.75 (9.8)	0.72	22.37 (11.87)	0.23	25.16 (9.81)	0.86	23.16 (9.04)	0.28
% Vacant housing[c]	11.1 (4.45)	10.32 (5.53)	0.56	11.39 (5.24)	0.82	8.83 (4.15)	0.05	13.15 (9.61)	0.31
% Residents foreign born[d]	34.37 (10.22)	31.01 (11.13)	0.24	**25.28 (11.4)**	**<0.001**	**26.62 (9.25)**	**<0.001**	**27.61 (9.64)**	**0.01**
Occupational environment									
% Unemployed residents[c]	8.36 (3.51)	8.92 (5.28)	0.64	8.68 (5.75)	0.80	7.05 (3.24)	0.15	8.97 (6.1)	0.65
% Residents employed in building grounds cleaning and maintenance[e]	7.79 (3.95)	7.39 (4.52)	0.72	5.64 (4.44)	0.06	6.44 (4.48)	0.24	**5.37 (3.36)**	**0.02**
% Residents employed in material moving[e]	4.55 (4.6)	3.8 (3.46)	0.49	3.08 (2.3)	0.14	3 (2.24)	0.12	3.59 (3.08)	0.36
% Residents employed in construction and extraction operations[e]	14.76 (9.38)	11.35 (6.61)	0.12	**7.51 (7.08)**	**0.00**	**9.86 (8.21)**	**0.04**	**9.74 (7.79)**	**0.03**
Business environment									
Distance to nearest hardware store[f]	0.17 (0.14)	**0.34 (0.22)**	**<0.001**	**0.35 (0.24)**	**<0.001**	**0.34 (0.33)**	**0.02**	**0.48 (0.35)**	**<0.001**
Distance to nearest paint store[f]	1.28 (0.93)	1.47 (1.28)	0.54	1.36 (0.87)	0.74	1.69 (1.2)	0.16	1.26 (0.83)	0.94
Distance to nearest landscape supply store[f]	1.81 (1.07)	**1.27 (0.77)**	**0.03**	2.09 (0.69)	0.26	1.81 (1)	0.98	2.05 (0.99)	0.39
Distance to nearest moving supply store[f]	0.48 (0.42)	0.53 (0.36)	0.62	**0.86 (0.51)**	**<0.001**	**0.86 (0.62)**	**0.01**	**0.85 (0.39)**	**< 0.001**
Distance to nearest gas station[f]	0.09 (0.09)	0.16 (0.19)	0.08	0.13 (0.13)	0.17	**0.22 (0.25)**	**0.02**	**0.25 (0.38)**	**0.04**
Distance to nearest bus stop[f]	0.18 (0.21)	0.17 (0.19)	0.81	0.14 (0.14)	0.39	0.26 (0.28)	0.25	0.39 (0.65)	0.12
Air quality									
Ozone[g] (ppm)	0.072 (0)	0.072 (0)	0.98	0.072 (0)	0.89	0.072 (0)	0.59	0.072 (0)	0.85
PM 2.5[g] (μg/m^3)	10.56 (0.01)	10.56 (0.01)	0.949	10.56 (0.01)	0.44	10.55 (0.01)	0.44	10.56 (0.01)	0.49

Characteristic	(A) Day-Labor Corners Mean (SD) *n* [%]	(B) Geographic Comparisons Mean (SD) *n* [%]	*p*-value	(C) Density Comparisons Mean (SD) *n* [%]	*p*-value	(D) Intersection Type Comparisons Mean (SD)] *n* [%]	*p*-value	(E) Proximity Comparisons Mean (SD) *n* [%]	*p*-value
PM 10[h] (p μg/m^3)	87.37 (1.21)	87.48 (0.99)	0.71	**88.01 (1.22)**	**0.05**	87.52 (1.58)	0.69	87.95 (1.54)	0.12
Carbon monoxide[g] (ppm)	1.84 (0.37)	1.84 (0.38)	0.97	1.91 (0.31)	0.45	1.95 (0.33)	0.25	1.87 (0.35)	0.76
Lead[g] (μg/m^3)	0.01 (0)	0.01 (0)	0.99	0.01 (0)	0.53	0.01 (0)	0.21	0.01 (0)	0.98
Sulfur dioxide[g] (ppb)	15.50 (1.49)	15.55 (1.60)	0.89	15.84 (1.71)	0.43	14.91 (1.71)	0.18	15.70 (1.35)	0.60
Nitrogen dioxide[g] (ppb)	76.68 (11.76)	76.99 (10.06)	0.92	79.84 (11.89)	0.32	78.81 (11.36)	0.50	79.08 (13.98)	0.49

Note. NH = non-Hispanic, HH = household, PPB = parts per billion, max = maximum. Bold indicates comparisons are statistically significantly different from corners (p<.05)

[a.] Above average includes superior, excellent, and good quality buildings

[b.] Below average includes low, very low, and poor-quality buildings

[c.] Calculated with 2011–2015 American Community Survey (ACS) 5-year Census block group estimates

[d.] Calculated with 2011–2015 ACS 5-year Census tract estimates

[e.] Calculated with 2013 Longitudinal Origin Destination Employment Survey (LODES) estimates

[f.] Calculated using Google Nearby Places application programming interface (API) search function and measured in miles

[g.] Calculated using the following National Ambient Air Quality Standards (NAAQS) measurements for primary standards: Ozone—annual 4th highest daily maximum 8-hour concentration averaged over 3 years; PM 2.5—annual mean averaged over 3 years; Carbon monoxide—annual maximum 8-hour average; Lead—highest rolling 3-month average; Sulfur dioxide—99th percentile of 1-hour daily maximum concentrations averaged over 3 years; Nitrogen dioxide—98th percentile of 1-hour daily maximum concentrations averaged over 3 years

[h.] Not calculated using the NAAQs measurement (maximum 24-hour concentration from 3 years not to exceed primary standard value more than once per year on average over 3 years) but instead a similar method (annual maximum 24-hour concentration averaged over 3 years)