Greening neighbourhoods in high crime areas

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Abstract—High crime rates cast a stigma over one's view of where they live. No matter how successful economies are, crime undermines how people feel about their neighbourhood. What's the use of living in a nice house if it is not safe to walk out on the street where you live? Taking data from a recent American Community Census Survey for six major cities, machine learning algorithms were used to review demographic American Census features and were contrasted with crime. Greening of neighbourhoods has been shown to work as an intervention to reduce crime. In one piece of research, it was found that densely packed street trees with a high canopy reduced crime. But greening is not just associated with reducing crime; it also improves mental health and wellbeing. Using machine learning, crime rates for census blocks in the borough of Brooklyn in New York are predicted. The predicted results and actual results are compared in addition to seeing what level of street trees are present and if the level of street trees is in line with crime rates. Given the beneficial effect of street trees on crime, it is argued that those areas experiencing high crime should have more trees to mitigate high crime rates.

Keywords—machine learning, predicting crime, social disorganisation, poverty, social inequality, greening, street trees

I. Introduction

There are many theories about crime speculating which societal factors are most associated with crime. This research looks at common social determinants of crime as indicated by other researchers in this area. The factors are not seen as causes of crime, but factors which are associated with crime. The emergence of big data has made it possible to view crime data at a granular local micro level. People are interested in knowing what is happening outside their door as opposed to knowing what it happening within a 5-mile radius of where they live. This requirement is putting pressure on government agencies to be more accountable at a micro level. For instance, police authorities need to account for their spend on crime and how, and how effective these resources are at a micro level. One societal strategy to help combat crime has been the greening of neighbourhoods. This research looks at greening a neighbourhood and the effect on residents. Census data from several cities throughout the United States is used and run through several machine learning algorithms to see which factors are most heavily associated with crime. Then looking at the possible greening impacts on crime, street tree data from New York Parks department is overlayed on neighbourhood crime data in New York to see if the levels of street trees in high crime areas compare favourably with the level of street trees present in those areas.

II. Data

A. Crime Data

Data was extracted at a census block group level [1] from the 2018 American Community Survey for this research [2]. Previous research looked at income levels, employment, housing ownership, female-led single households and population so these social demographics were included in this research [3] [4] [5] [6] [7] plus some more demographics to see which if any demographic factors were more heavily associated with crime than others. Crime data is not available from the Census Bureau and is not available centrally in the USA. So, crime data was collected individually from each cities' open data portal portals using API links. Each city records their crime rates using different criteria. This invariably leads to inconsistencies across jurisdictions comparing and collating this data. To combat such inconsistencies, this research only looked at relative crime levels within a city, checking whether crime was high or low for a given city crime area. This was the strategy for all cities, which negated the requirement that the crime datasets were equivalent and comparable.

All census and crime data were geocoded using the United States Census Bureau geocoding shape files. Only cities that provided longitude and latitude geocoding for their crime incidences were used in this research. Nonetheless, there are complexities when interpreting geocoded crime data. Has the crime address been entered correctly? Was it where the crime began or ended? If crime occurs at a junction, which address is used. If at a park, is the park address or nearest street address used? [8]. So, there are issues interpreting such data at a street level as the crime rates may not be totally representative of crime in that street.

III. Social Disorganization

Shaw and McKay coined the phrase *social disorganization* in the 1940s based on their research in the 1920s and 1930s on the rural to urban migration and urban industrialization. They described how when the migration results in increased crime, it is down to *social disorder* [9]. The saw social disorder/disorganization as the inability of communities to arrive at a shared cultural value system which helped moderate criminal and anti-social behaviour. Social instability, poor housing, little home ownership, poverty, a racial mix constituted social disorganization and consequently resulted in a breakdown in social organization and social cohesion resulting in few social norms moderating against crime. Social disorganization also includes a breakdown of social, economic, religious and family influences that would normally work in a unified way to encourage societal beneficial behaviour.

In the 1980s, Wilson and Kelling came up with the *Broken Windows* theory which acted as a metaphor social disorganization [10]. If someone sees one window broken and not fixed, it is an invitation to break more windows.

Who cares; no one is going to do anything about it? Similarly, small crimes if left untreated and ignored are an invitation to commit further more serious crimes. Police Commissioner William Bratton in New York in the 1990s was the most notable applier of this theory [11]. Bratton first started off his application of this theory with a the zero-tolerance crime approach on the New York transit system. All crimes such as jumping turnstiles and graffiti were outlawed. Then Bratton branched out onto general crimes, where panhandling, public drinking, street prostitution and unsolicited windshield washing were outlawed. When Bratton resigned in 1996, felonies were down 40% and homicide rates were halved. More recently, Aiyer in 2015 described social disorganization as open street selling of drugs, littering, easy alcohol availability and blighted properties [10]. Encyclopaedia Britannica describe two different types of disorder. One that is physical where there are vacant buildings, broken windows, abandoned vehicles and vacant lots filled with trash and the other is social where there are aggressive panhandlers, noisy neighbours and gangs hanging out at street corners [12]. Jibbetts and Hemmens in their research described one aspect of social disorganization as people admitting to not knowing their neighbours by name or having observed unsupervised peer groups hanging around [7].

A. *Exception to social disorganization theory*

But social disorganization theory does not apply in all instances. Shaw and McKay identified some inner-city Chicago districts where social disorganization and crime continued despite a population change as if the location and its inner-city attributes were a key driver of its social disorganization and high crimes rates.

Inner-city crime districts experience crime similarly across all races. However, Japanese communities are the exception. Japanese living is inner cities high-crime areas of Chicago, despite being poor and unemployed were not exhibiting the same juvenile delinquency and high crime rates [7]. It may be that despite the lack of social cohesion in the wider community, Japanese families were able to mitigate the community influence and found it easier to avoid crime related activities.

B. *Underclass Subculture*

However, there is a segment of society that are immune to social organization attempts. Urban slums create a value system that values toughness, smartness, excitement and fatalism. There is an underclass subculture. Walter Miller in the 1950s and Elizjah Anderson in the 1990s wrote extensively on the underclass subculture [7]. Their value system emerges where there are few or no opportunities for advancement and there is extreme social inequality. People exhibit a "general state of disorganization, distrust, and smoldering aggression which easily erupts into violence" [13].

IV. Greening

A. *Outdoor Green Spaces*

There is evidence that improving the physical environment helps improves people's lives, mental and physical health and wellbeing. Even patients who have a view of greenery have been found to recover faster and need less medication [14]. Using aerial imaging, Lanza, in his study of 25 American cities during the period 2013 to 2014 found that increased vegetation improved people's outdoor activity in all communities that were investigated [15]. Kuo in his study of 98 public housing apartment blocks in Chicago in 2001 found well maintained outdoor green spaces reduced crime [16]. Kuo also found that physical neighbourhood exhibited less graffiti, vandalism and littering and people's outdoor behaviour was less noisy, disruptive and illegal. In general, several studies found that vegetation and green spaces reduced crime [17]. The World Health Organization (WHO) concluded in its 2016 report that urban green spaces improve mental health, cardiovascular disease, Type 2 diabetes and obesity [18]. In Philadelphia, a program was started in 2014 to increase urban street trees by up to 30% by 2025, particularly in poorer neighbourhoods, with the goal of reducing premature deaths [4].

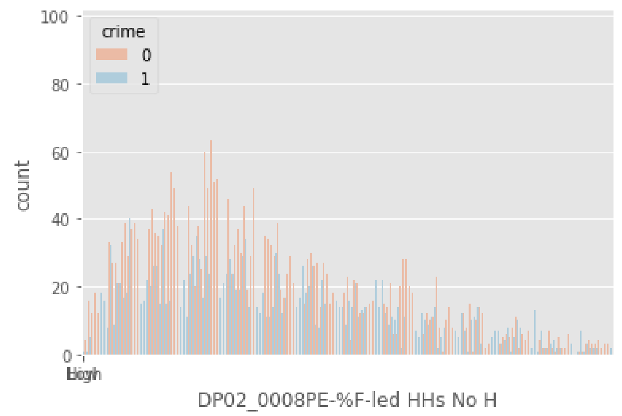

Figure 1- Female Led Households - crime 0 = Low and 1 = High

B. *Tree Coverage*

Extensive tree coverage has stress-reducing benefits and improves health and well-being according to Mouratidis in his research on neighbourhoods around Oslo, Norway. Tree coverage had positive impacts on perceived safety [19]. But research has also found direct relationships with tree coverage and reduced crime [17] [19] [20]. In Bogota, Columbia, a city with a population of 9 million which had a homicide rate of 80 per 100,000 in 1990 that went down to 20 per 100,000 in 2000 is a city that has experienced massive social upheaval. It has had a population explosion due to the rural to urban migration in the 1980s and 1990s. The affected urban areas experienced similar social disorganization as experienced in Chicago during the 1920s and 1930s. However, despite slow economic growth and employment during the population expansion period, crimes rates have declined from their peak in 1990. Some of this has been attributed to marked improvements in living conditions and educational access. Escobedo in his research in Columbia investigated the number of crimes per districts compared to their tree coverage during the 2004 to 2006 period and found that lower socio-economic areas with high and wide trees with sufficient tree density experienced lower crime rates [21].

V. Findings

A. *Machine Learning*

A Knn means machine learning algorithm was developed and had a 73% accuracy. The data was sourced from the American Census American Community Survey in addition to crime data from individual cities. The data was streamlined as percentages for easy comparison and for pca (principal component analysis). Where estimates were only available, a percentage of tract value for county and tract was used instead. With correlations, where several variables were similarly correlated, a choice had to be made to reduce redundant overlapping unnecessary variables. For instance, ' DP02_0008PE-%F-led HHs No H' (family led households with no husband) were correlated with ' DP03_0119PE-% Fam <Pov' (family below the poverty level) and 'DP02_0060PE-%NoSchDiploma' (people with no highschool diploma) were correlated with negative high earnings, health insurance, and home ownership.

As we can see in Figure 1, female led households is not correlated with crime.

VI. Tableau

A. *Visualizations*

Tableau was used to look at patterns. As noted already, correlations do not mean causation, but the information can point towards more resources and assistance in areas where demographics indicate that these demographics suffer when there is high crime in an area. The following crime rates were found in the cities included in the research.

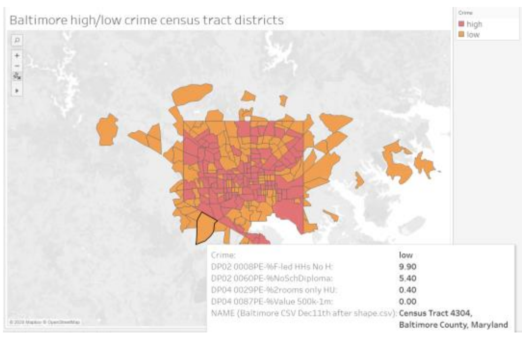

Figure 3 - Baltimore Crime

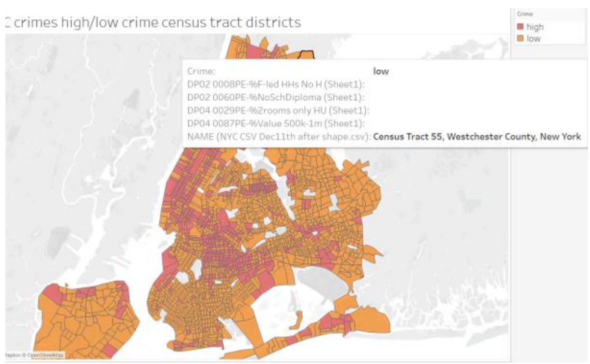

Figure 4 - NYC Crime

VII. Conclusion

A. *Outdoor Green Spaces*

Shaw and McKay in their seminal study of Chicago suburbs in the early parts of the 20^{th} century described how once an area settles down and there is less social instability, that crime rates come down across all communities [9]. It has also been found that once economic inequality is sorted, poverty does not play a role in crime [13]. That said, poverty and inequality are seen as the strongest determinants of crime [19]. There are a few provisos about all research into crime and societal factors contributing to crime. We should be wary of over interpreting the data used in this research as the contributing factors to crime in one area might not be representative of factors conducive to crime in another area [8].

There are concerns about greening a neighbourhood to make the physical environment more attractive. It can result in increased house prices and gentrification and displacement of the very vulnerable people the policy was designed to help. In Figure 6 – NYC Trees and Crime, we can see that some neighbourhood can have low crime and high trees. More planting is needed to see a greater number of trees and the benefit it can bring to a community. Policies designed to improve the outdoor green space should be

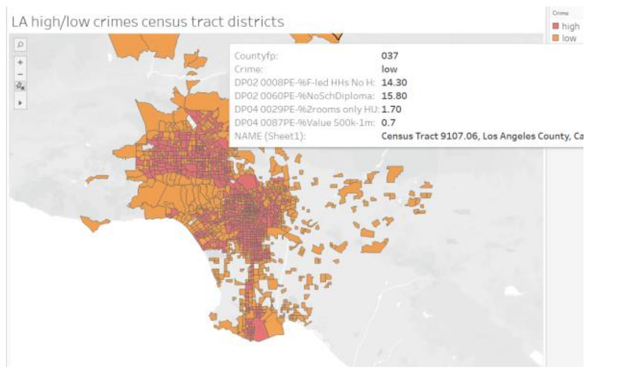

Figure 2 - LA Crime

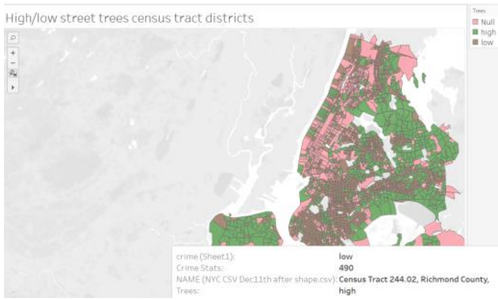

Figure 6 - NYC Trees and Crime

accompanied with strategies to counteract possible displacement. These strategies might include a combination of house pricing controls and renter protection measures [5].

This research was limited to social demographic information available from the United States Community Survey Census. Further studies should include broader social, physical environment and economic factors such as ease and cost of setting up a business, cost of credit, ease of getting credit, the number of start-ups, the number of fore-closures and defaulters, the presence of active community and sports facility centres, how people vote and voting turn-out rates, % dilapidated and vacant abandoned property lots, sentencing rates for misdemeanours and serious crimes, government spend on various amenities. It is only when a broad collection of neighbourhood data is collected, that it may be possible to gauge the social inequality in the neighbourhoods. Collecting such information broadens the responsibility for addressing social inequality on all government agencies with a holistic solution to respond to the social needs of the community that incorporates social, physical environment, economic, health, education and policing policy.

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IX. Appendix 1 – Extracted United States Census Variables

Code	Column Headings	Census Actual Label
DP05_0001E	DP05_0001E-T Popo	Estimate!!SEX AND AGE!!Total population
DP02_0001E	DP02_0001E-T HHs	Estimate!!HOUSEHOLDS BY TYPE!!Total households
DP02_0002E	DP02_0002E-T Fam HHs	Estimate!!HOUSEHOLDS BY TYPE!!Total households Family households (families)
DP02_0008PE	DP02_0008PE-%F-led HHs No H	Percent Estimate!!HOUSEHOLDS BY TYPE!!Total households!!Family households (families)!!Female householder, no husband present, family
DP02_0010PE	DP02_0010PE-% Non-Fam HHs	Percent Estimate!!HOUSEHOLDS BY TYPE!!Total households!!Nonfamily households
DP02_0015E	DP02_0015E-Avg HH Size	Estimate!!HOUSEHOLDS BY TYPE!!Total households!!Average household size
DP02_0016E	DP02_0016E-Avg Fam Size	Estimate!!HOUSEHOLDS BY TYPE!!Total households!!Average family size
DP02_0022PE	DP02_0022PE-%Non Rel in Hs	Percent Estimate!!RELATIONSHIP!!Population in households!!Nonrelatives
DP02_0038E	DP02_0038E-per1000-F-U-RecentPreg	Estimate!!FERTILITY!!Number of women 15 to 50 years old who had a birth in the past 12 months!!Unmarried women (widowed, divorced, and never married)!!Per 1,000 unmarried women
DP02_0046PE	DP02_0046PE-%GPwParent&Gc1-2yrs	Percent Estimate!!GRANDPARENTS!!Number of grandparents living with own grandchildren under 18 years!!Years responsible for grandchildren!!1 or 2 years
DP02_0048PE	DP02_0048PE--%GPwParent&Gc>5yrs	Percent Estimate!!GRANDPARENTS!!Number of grandparents living with own grandchildren under 18 years!!Years responsible for grandchildren!!5 or more years
DP02_0060PE	DP02_0060PE-%NoSchDiploma	Percent Estimate!!EDUCATIONAL ATTAINMENT!!Population 25 years and over!!9th to 12th grade, no diploma
DP02_0063PE	DP02_0063PE-%AssDeg	Percent Estimate!!EDUCATIONAL ATTAINMENT!!Population 25 years and over!!Associate's degree
DP02_0079PE	DP02_0079PE-% SameHouse_1YrAgo	Percent Estimate!!RESIDENCE 1 YEAR AGO!!Population 1 year and over!!Same house
DP02_0085PE	DP02_0085PE-%LivAbroad1YrAgo	Percent Estimate!!RESIDENCE 1 YEAR AGO!!Population 1 year and over!!Abroad
DP02_0088PE	DP02_0088PE-%BornUS	Percent Estimate!!PLACE OF BIRTH!!Total population!!Native!!Born in United States
DP02_0112PE	DP02_0112PE-HomeLangNotEng	Percent Estimate!!LANGUAGE SPOKEN AT HOME!!Population 5 years and over!!Language other than English
DP02_0134PE	DP02_0134PE-%IrishAnc	Percent Estimate!!ANCESTRY!!Total population!!Irish
DP03_0009PE	DP03_0009PE-%Unemploy	Percent Estimate!!EMPLOYMENT STATUS!!Civilian labor force!!Unemployment Rate

DP03_0027PE	DP03_0027PE-%WorkingMgt,Bus,Sc,Arts	Percent Estimate!!OCCUPATION!!Civilian employed population 16 years and over!!Management, business, science, and arts occupations
DP03_0028PE	DP03_0028PE%WorkingService	Percent Estimate!!OCCUPATION!!Civilian employed population 16 years and over!!Service occupations
DP03_0037PE	DP03_0037PE-Retail	Percent Estimate!!INDUSTRY!!Civilian employed population 16 years and over!!Retail trade
DP03_0040PE	DP03_0040PE-%Fin&Ins	Percent Estimate!!INDUSTRY!!Civilian employed population 16 years and over!!Finance and insurance, and real estate and rental and leasing
DP03_0041PE	DP03_0041PE-%ProfSc,Mgt,Admin	Percent Estimate!!INDUSTRY!!Civilian employed population 16 years and over!!Professional, scientific, and management, and administrative and waste management services
DP03_0050PE	DP03_0050PE-%UnpaidFamilyWk	Percent Estimate!!CLASS OF WORKER!!Civilian employed population 16 years and over!!Unpaid family workers
DP03_0052PE	DP03_0052PE-Inc<10k	Percent Estimate!!INCOME AND BENEFITS (IN 2018 INFLATION-ADJUSTED DOLLARS)!!Total households!!Less than $10,000
DP03_0054PE	DP03_0054PE-Inc15-24k	Percent Estimate!!INCOME AND BENEFITS (IN 2018 INFLATION-ADJUSTED DOLLARS)!!Total households!!$15,000 to $24,999
DP03_0058PE	DP03_0058PE-Inc75-99	Percent Estimate!!INCOME AND BENEFITS (IN 2018 INFLATION-ADJUSTED DOLLARS)!!Total households!!$75,000 to $99,999
DP03_0061PE	DP03_0061PE-Inc200k>	DP03_0061PE
DP03_0065E	DP03_0065E-HH-MeanEarnings	Estimate!!INCOME AND BENEFITS (IN 2018 INFLATION-ADJUSTED DOLLARS)!!Total households!!With earnings!!Mean earnings (dollars)
DP03_0066PE	DP03_0066PE-%HHsWithSocSec	Percent Estimate!!INCOME AND BENEFITS (IN 2018 INFLATION-ADJUSTED DOLLARS)!!Total households!!With Social Security
DP03_0072PE	DP03_0072PE-%HH Inc with Cash public Ass	Percent Estimate!!INCOME AND BENEFITS (IN 2018 INFLATION-ADJUSTED DOLLARS)!!Total households!!With cash public assistance income
DP03_0074PE	DP03_0074PE-%HH Inc with Food Stamps SNAP	Percent Estimate!!INCOME AND BENEFITS (IN 2018 INFLATION-ADJUSTED DOLLARS)!!Total households!!With Food Stamp/SNAP benefits in the past 12 months
DP03_0085PE	DP03_0085PE-%Families Inc>200k	Percent Annotation of Estimate!!INCOME AND BENEFITS (IN 2018 INFLATION-ADJUSTED DOLLARS)!!Families!!$200,000 or more
DP03_0092E	DP03_0092E-Median Earning Workers	Estimate!!INCOME AND BENEFITS (IN 2018 INFLATION-ADJUSTED DOLLARS)!!Median earnings for workers (dollars)
DP03_0093E	DP03_0093E-Median Earnings Male FT Workers	Estimate!!INCOME AND BENEFITS (IN 2018 INFLATION-ADJUSTED DOLLARS)!!Median earnings for male full-time, year-round workers (dollars)
DP03_0094E	DP03_0094E-Median Earnings Female FT Workers	Estimate!!INCOME AND BENEFITS (IN 2018 INFLATION-ADJUSTED DOLLARS)!!Median earnings for female full-time, year-round workers (dollars)

DP03_0097PE	DP03_0097PE-%PHI-Priv	Percent Estimate!!HEALTH INSURANCE COVERAGE!!Civilian noninstitutionalized population!!With health insurance coverage!!With private health insurance
DP03_0099PE	DP03_0098PE-%PHI-Pub	Percent Estimate!!HEALTH INSURANCE COVERAGE!!Civilian noninstitutionalized population!!No health insurance coverage
DP03_0119PE	DP03_0099PE-No PHI	Percent Estimate!!PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL!!All families
DP03_0121PE	DP03_0121PE-%Fam with child U18&U5 <pov	Percent Estimate!!PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL!!All families!!With related children of the householder under 18 years!!With related children of the householder under 5 years only
DP03_0126PE	DP03_0126PE-%F-Led Families with u18 <pov	Percent Estimate!!PERCENTAGE OF FAMILIES AND PEOPLE WHOSE INCOME IN THE PAST 12 MONTHS IS BELOW THE POVERTY LEVEL!!Families with female householder, no husband present!!With related children of the householder under 18 years
DP04_0001PE	DP04_0001E-T H U	Percent Estimate!!HOUSING OCCUPANCY!!Total housing units
DP04_0002PE	DP04_0002PE-%Occ H U	Percent Estimate!!HOUSING OCCUPANCY!!Total housing units!!Occupied housing units
DP04_0004E	DP04_0004E-%Ow Vac Rate	Estimate!!HOUSING OCCUPANCY!!Total housing units!!Homeowner vacancy rate
DP04_0005E	DP04_0005E-%Rn Vac Rate	Estimate!!HOUSING OCCUPANCY!!Total housing units!!Rental vacancy rate
DP04_0006E	DP04_0006E-T HU	Estimate!!UNITS IN STRUCTURE!!Total housing units
DP04_0013PE	DP04_0013PE-%20+HU	Percent Estimate!!UNITS IN STRUCTURE!!Total housing units!!20 or more units
DP04_0017PE	DP04_0017PE-%Built2014+	Percent Estimate!!YEAR STRUCTURE BUILT!!Total housing units!!Built 2014 or later
DP04_0029PE	DP04_0029PE-%2rooms_only_HU	Percent Estimate!!ROOMS!!Total housing units!!2 rooms
DP04_0039PE	DP04_0039PE-Zero bedrooms	Percent Estimate!!BEDROOMS!!Total housing units!!No bedroom
DP04_0045PE	DP04_0045PE-%Occup HU	Percent Estimate!!HOUSING TENURE!!Occupied housing units
DP04_0046PE	DP04_0046PE-%Owner Occup HU	Percent Estimate!!HOUSING TENURE!!Occupied housing units!!Owner-occupied
DP04_0048E	DP04_0048E-Owner Ave Household size	Estimate!!HOUSING TENURE!!Occupied housing units!!Average household size of owner-occupied unit
DP04_0049E	DP04_0049E-Renter Ave Household size	Estimate!!HOUSING TENURE!!Occupied housing units!!Average household size of renter-occupied unit
DP04_0051PE	DP04_0051PE-%moved since 2017+	Percent Estimate!!YEAR HOUSEHOLDER MOVED INTO UNIT!!Occupied housing units!!Moved in 2017 or later
DP04_0054PE	DP04_0054PE-%moved 2000 to 2009	Percent Estimate!!YEAR HOUSEHOLDER MOVED INTO UNIT!!Occupied housing units!!Moved in 2000 to 2009

DP04_0082PE	DP04_0082PE-%Value 50-99k	Percent Estimate!!VALUE!!Owner-occupied units!!$50,000 to $99,999
DP04_0083PE	DP04_0083PE-%Value 100-149k	Percent Estimate!!VALUE!!Owner-occupied units!!$100,000 to $149,999
DP04_0084PE	DP04_0084PE-%Value 150-199k	Percent Estimate!!VALUE!!Owner-occupied units!!$150,000 to $199,999
DP04_0087PE	DP04_0087PE-%Value 500k-1m	Percent Estimate!!VALUE!!Owner-occupied units!!$500,000 to $999,999
DP04_0101E	DP04_0101E-Med Onwer Monthly Mortgage	Estimate!!SELECTED MONTHLY OWNER COSTS (SMOC)!!Housing units with a mortgage!!Median (dollars)
DP04_0134E	DP04_0134E-Median Gross Rent	Estimate!!GROSS RENT!!Occupied units paying rent!!Median (dollars)
DP05_0005PE	DP05_0005PE-%under 5 yrs	Percent Estimate!!SEX AND AGE!!Total population!!Under 5 years
DP05_0023PE	DP05_0023PE-%62 yrs+	Percent Estimate!!SEX AND AGE!!Total population!!62 years and over
DP05_0059PE	DP05_0058PE-% w & B or AM	Percent Estimate!!RACE!!Total population!!Two or more races!!White and Black or African American
DP05_0061PE	DP05_0061PE-%White & Asian	Percent Estimate!!RACE!!Total population!!Two or more races!!White and Asian
DP05_0064PE	DP05_0064PE-%White with others	Percent Estimate!!Race alone or in combination with one or more other races!!Total population!!White
DP05_0070PE	DP05_0070PE-%H&L race	Percent Estimate!!HISPANIC OR LATINO AND RACE!!Total population