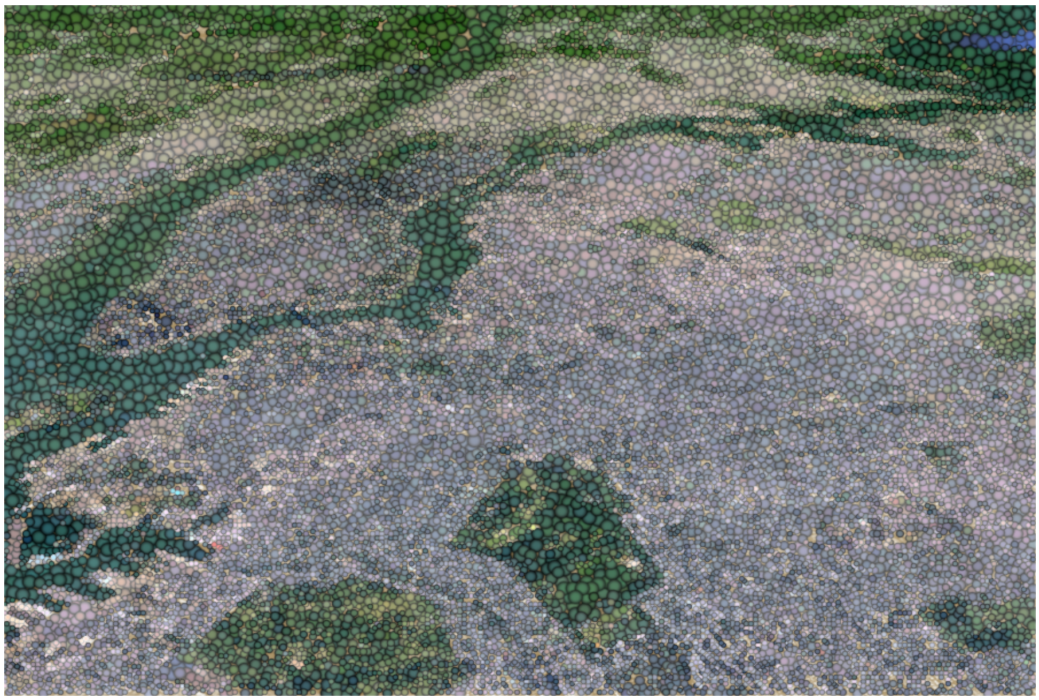
The New York Academy of Medicine Urban-MSM Project

Data Dictionary – NYC Tracts Only Version (2014.10.20)



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Useful Definitions

Areal Weighting Interpolation – Areal weighting interpolation is a data transfer procedure between incompatible zonal systems. There are diverse zonal systems used for aggregating and reporting spatial data, say, census tracts, administrative districts, school districts, and so forth. Since they are often geographically incompatible, integration of spatial data requires data transfer between zonal systems. This process is called areal interpolation, and the areal weighting interpolation method is one of the most popular interpolation methods in GIS (Markoff and Shapiro, 1973; Lam, 1983; Flowerdew and Green, 1991). Assuming a uniform distribution of spatial objects, the areal weighting interpolation divides the count of spatial objects according to area in each zone, and sums up the counts in another incompatible zone.

Kernel Density Estimation (KDE) – KDE is a GIS analysis technique that creates a continuous surface based on point data in a neighborhood as defined by a circular distance. Conceptually, a smoothly curved surface is fitted over each point. The continuous surface value is highest at the location of the point and diminishes with increasing distance from the point, reaching zero at the search radius distance from the point (i.e., distance decay function). Density surfaces are effective at identifying where features are concentrated – highlighting areas of intense activity. For a more thorough explanation of KDE, please see Appendix F.

Network Analysis – Network analysis incorporates a network dataset such as street centerlines into a spatial model which then allows for the representation of advanced connectivity models and scenarios. In do so, a more accurate depiction of how people encounter and move around their real-work environment can be quantified.

Point-in-Polygon Analysis – Point and polygon analysis is also referred to, and known as, a spatial join. A spatial join is a geoprocessing method for combining information between GIS layers, and results in the attribute information from one layer being combined with the attribute table of another layer based on their relative X-Y location. This then makes further analysis possible, such as aggregating the number of point features or the length of polyline features within different geographies.

Network Buffers Explained

Network buffers use the street network as the organizing geography. This type of buffer requires a point of origin and a travel distance to measure away from following the street network. Once those two parameters are defined, all points on the street network that are *n-distance* from the point of origin are found. Those points are then joined together using a sort of connect-the-dots method to create an irregular polygon. The basic idea behind network buffers is that people use the street network to move about and something that is a 0.50-mile as a straight line may be several times that far in an area with a winding or discontinuous street pattern. Prior to creating these network buffers all primary highways with limited access and access ramps would be removed since these street features are not used by pedestrians to move about the city.

As can be seen in the 3 figures below, the area that could be reached along the street network (the central, reddish-orange area) is smaller in the loop and long block road arrangements than in the more gridded street pattern. The three figures below each show two 0.50-mile buffers – a straight line or bird-flies buffer in green and 0.50-mile street-network buffer in reddish-orange. The point of origin is the red dot and the streets are the white lines. The left graphic was generated in The Bronx with many loops and longer blocks, the middle graphic in Manhattan with a more gridded area and smaller median block sizes, and the right in Queens with no loops but still longer blocks and larger median block sizes than found in Manhattan. As can be seen visually, the ratio of the area within a network buffer to area within the bird-flies buffer is much smaller in the looped and long block areas than in the gridded area, indicating that it is harder to get around.

Figures. – Comparison of bird-fly and network buffers in different borough neighborhoods.

Geoprocessing Methods Explained

The process of characterizing neighborhoods with social and built environment variables is an ideal job for a Geographical Information System (GIS). A GIS is unique in that it harnesses the power of both relational databases and geographic space and place. Combined you have an efficient means of statistically aggregating and describing what lies within a specific measurement geography (e.g., state, county, community district, zip code, custom buffer). By overlaying spatial features from multiple layers (e.g., streets, census block groups, land-use, and crime) which are attached to descriptive variables (e.g., length, area, speed, total population, name, category) that task is achieved.

Areal Weighting Interpolation is a data transfer procedure between incompatible zonal systems. There are diverse zonal systems used for aggregating and reporting spatial data, say, census tracts, administrative districts, school districts, and so forth. Since they are often geographically incompatible, integration of spatial data requires data transfer between zonal systems. This process is called areal interpolation, and the areal weighting interpolation method is one of the most popular interpolation methods in GIS (Markoff and Shapiro, 1973; Lam, 1983; Flowerdew and Green, 1991). Assuming a uniform distribution of spatial objects, the areal weighting interpolation divides the count of spatial objects according to area in each zone, and sums up the counts in another incompatible zone.
Take for example Census block groups. Say you want to calculate census related variables for custom measurement geographies such as the 0.50-mile network buffers created for this project. Some census geographies [e.g., block groups] will fall completely within your buffers, while others, only portions will fall within your buffers. You therefore need to decide how to deal with those census geographies that do not fall completely within your buffers. You really only have four options:

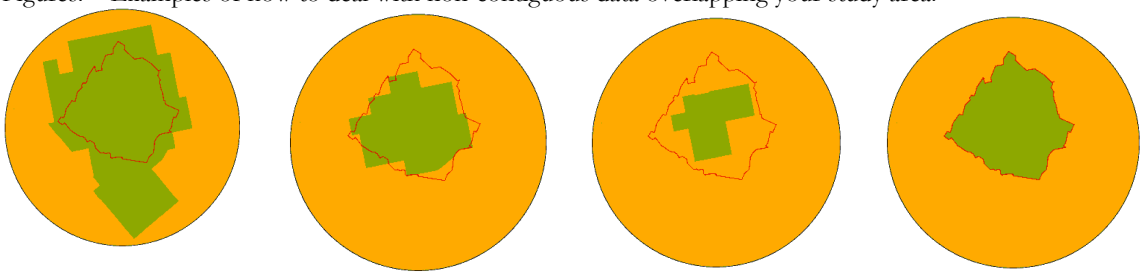
1) Include all full block groups that intersect your measurement geographies and their full variables.
2) Include all block groups with their centroid within the measurement geographies and their full variables.
3) Include all block groups completely contained within the measurement geographies and their full variables.
4) Include only those portions of block groups that intersect the measurement geographies and their apportioned variables.

The four figures on the following page demonstrate examples of these four options using a single network buffer and block group boundaries.

This analysis utilized option 4. Where block groups (or any other spatial feature) are cut by the end of the buffer measurement geographies, the census variables are apportioned according to the percentage of land area falling inside and outside the buffers before calculating the results. Take for example the total population variable. Since we do not know where the population actually lives within each block group, all we can do is assume a normal distribution of the population. Where census blocks are cut by the end of the buffer measurement geographies, the population needs to be apportioned according to the percentage of block group falling inside the buffer. So we should know or you can easily calculate the area of the original block in whatever unit of measure you wish. Next, INTERSECT (Figure, page 7) or compute the geometric

intersection of the input features (i.e., census block groups) where features or portions of features which overlap the intersect features (i.e., custom network buffers) will be written to the final output feature. Then, recalculate the area of the output, and find the ratio of each block group falling inside the buffer. Finally, take that ratio times your total population value of each block to get your apportioned value.

Figures. – Examples of how to deal with non-contiguous data overlapping your study area.



Option 1: full intersecting block groups

Option 2: centroid within block groups

Option 3: completely contained block groups

Option 4: apportioned intersecting block groups.

For example, where a block group falls completely within the buffer the ratio will be 1.00 which in turns means the total population will be accounted for. But say you have a block group with 1,300 people living in it that is 250-km2 in total area but only 115-km2 of the block falls within the buffer. You would take 115 / 250 to get 0.46, which you then multiple against the total population for the block 0.46 * 1,300 to get 598 people. That is your apportioned population.

*apportioned population = (new_area / original_area) * total_population*

Figure. – Intersect overlay tool example.

Kernel Density Settings

All of the Kernel Density surfaces were created using the following settings:

Cell Size	= 150 (feet)
Search Radius	= 3280.83 (feet or 1 kilometer)
Area Unit Scale Factor	= "SQUARE_KILOMETERS"

Neighborhood Definitions

Prefixes and Buffer Distances (cb, ct, n1, n2, r1)

2010 Census Block, abbrev - cb

US Census Block 2010 unit of geography that place point falls in (from NYC DCP – Clipped to Shoreline) [http://www.nyc.gov/html/dcp/html/bytes/districts_download_metadata.shtml].

2010 Census Tract, abbrev - ct
US Census Tract 2010 unit of geography that place point falls in (from NYC DCP – Clipped to Shoreline) [http://www.nyc.gov/html/dcp/html/bytes/districts_download_metadata.shtml].

Radial Buffer 264 feet, abbrev - r1
Radial (Euclidean) buffer of **264 feet** from place point.

Network Buffer 1,320 feet, abbrev - n1
Street network buffer of **1,320** feet from place point.

Network Buffer 2,640 feet, abbrev – n2
Street network buffer of **2,640 feet** from place point.

Variables:

All data was projected into a common projection system;
NAD_1983_StatePlane_New_York_Long_Island_FIPS_3104_Feet - WKID: 2263 Authority: EPSG.
See **Appendix C** for details.

All Variables will look like this (grey-bold):

****samplevariable1**

** is the wildcard the geography type prefix (see above **Prefixes and Buffer Distances (cb, ct, n1, n2, r1)**)

Study Subject, Location and Neighborhood Geography Variables

geoid
The unique identification for the census tract. There are **2,164** unique 2010 census tracts.
US Census Tract 2010 boundary identification (geoid) from spatial join-intersection performed by James Quinn of BEH.

NTAName
Tract-based Neighborhood name.

NTACode
Tract-based Neighborhood code.

BoroName
NYC Borough Name.

CT2010
Census Tract 2010 id.

BoroCT2010
Boro Census Tract 2010 id.

****areasqmtr**
Area of Neighborhood Geography (**) in square meters.

comdis (Community District)
Community District ID (for New York City) that each point falls inside.

Census Demographic Variables

Census Tract ACS 2008-2012 & Census Block US Census 2010 variables were acquired from the US Census Bureau API [https://www.census.gov/developers/] at the 2010 Census Tract, Block unit or level of geography. These variables were created using areal weighting interpolation. The original census variable names were slightly modified in order to provide a systematic naming convention across all project neighborhood definitions and to provide an indicator of the type of variable being provided. The ACS census variable names use the following naming convention:

**** (for Neighborhood Geography (ct)) + ^^^ (Census Year-Type) + variable**
Example: **r1acspctage35up**. (Percent population 34 years of age and younger in neighborhood geography radial buffer 1 (264 foot radial distance from place point) using area weighted interpolation calculation).

Census Year-Type (^^^) ['acs','c10']

acs = American Community Survey 2008-2012 5 Year
For a full list of all variables mined and calculated for each neighborhood using area-weighted interpolation see Appendix A for American Community Survey (ACS) 2008-2012 5 Year (Census Tract Level variables).

Total Population Variables

****acstotpop**
Area weighted total population derived from American Community Survey (ACS) 2008-2012 5 Year (Census Tract Level variables) in Neighborhood Geography (**).

Age-related Variables

****^^^pctage34nunder**
Percent population 34 years of age and younger in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)

```
( df[geo+'B01001003E'] + df[geo+'B01001004E'] + df[geo+'B01001005E'] +
df[geo+'B01001006E'] + df[geo+'B01001007E'] + df[geo+'B01001008E'] + df[geo+'B01001009E']
+ df[geo+'B01001010E'] + df[geo+'B01001011E'] + df[geo+'B01001012E'] +
df[geo+'B01001027E'] + df[geo+'B01001028E'] + df[geo+'B01001029E'] + df[geo+'B01001030E']
+ df[geo+'B01001031E'] + df[geo+'B01001032E'] + df[geo+'B01001033E'] +
df[geo+'B01001034E'] + df[geo+'B01001035E'] + df[geo+'B01001036E'] ) /
df[geo+'B01001001E']
```

US Census 2010

```
( df[geo+'P0120003'] + df[geo+'P0120004'] + df[geo+'P0120005'] + df[geo+'P0120006'] +
df[geo+'P0120007'] + df[geo+'P0120008'] + df[geo+'P0120009'] + df[geo+'P0120010'] +
df[geo+'P0120011'] + df[geo+'P0120012'] + df[geo+'P0120027'] + df[geo+'P0120028'] +
df[geo+'P0120029'] + df[geo+'P0120030'] + df[geo+'P0120031'] + df[geo+'P0120032'] +
df[geo+'P0120033'] + df[geo+'P0120034'] + df[geo+'P0120035'] + df[geo+'P0120036'] ) /
df[geo+'P0120001']
```

****^^^pctage35up**
Percent population 35 years of age and older in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)

```
( df[geo+'B01001013E'] + df[geo+'B01001014E'] + df[geo+'B01001015E'] +
df[geo+'B01001016E'] + df[geo+'B01001017E'] + df[geo+'B01001018E'] + df[geo+'B01001019E']
+ df[geo+'B01001020E'] + df[geo+'B01001021E'] + df[geo+'B01001022E'] +
df[geo+'B01001023E'] + df[geo+'B01001024E'] + df[geo+'B01001025E'] + df[geo+'B01001037E']
+ df[geo+'B01001038E'] + df[geo+'B01001039E'] + df[geo+'B01001040E'] +
df[geo+'B01001041E'] + df[geo+'B01001042E'] + df[geo+'B01001043E'] + df[geo+'B01001044E']
+ df[geo+'B01001045E'] + df[geo+'B01001046E'] + df[geo+'B01001047E'] +
df[geo+'B01001048E'] + df[geo+'B01001049E'] ) / df[geo+'B01001001E']
```

US Census 2010

```
( df[geo+'P0120013'] + df[geo+'P0120014'] + df[geo+'P0120015'] + df[geo+'P0120016'] +
df[geo+'P0120017'] + df[geo+'P0120018'] + df[geo+'P0120019'] + df[geo+'P0120020'] +
df[geo+'P0120021'] + df[geo+'P0120022'] + df[geo+'P0120023'] + df[geo+'P0120024'] +
```

```
df[geo+'P0120024'] + df[geo+'P0120025'] + df[geo+'P0120037'] + df[geo+'P0120038'] +
df[geo+'P0120039'] + df[geo+'P0120040'] + df[geo+'P0120041'] + df[geo+'P0120042'] +
df[geo+'P0120043'] + df[geo+'P0120044'] + df[geo+'P0120045'] + df[geo+'P0120046'] +
df[geo+'P0120047'] + df[geo+'P0120048'] + df[geo+'P0120049'] ) / df[geo+'P0120001']
```

****^^^pctage60up**

Percent population 60 years of age and older in Neighborhood Geography (**).

American Community Survey 2008-2012 (5-year)

```
( df[geo+'B01001018E'] + df[geo+'B01001019E'] + df[geo+'B01001020E'] +
df[geo+'B01001021E'] + df[geo+'B01001022E'] + df[geo+'B01001023E'] + df[geo+'B01001024E']
+ df[geo+'B01001025E'] + df[geo+'B01001042E'] + df[geo+'B01001043E'] +
df[geo+'B01001044E'] + df[geo+'B01001045E'] + df[geo+'B01001046E'] + df[geo+'B01001047E']
+ df[geo+'B01001048E'] + df[geo+'B01001049E'] ) / df[geo+'B01001001E']
```

US Census 2010

```
( df[geo+'P0120018'] + df[geo+'P0120019'] + df[geo+'P0120020'] + df[geo+'P0120021'] +
df[geo+'P0120022'] + df[geo+'P0120023'] + df[geo+'P0120024'] + df[geo+'P0120025'] +
df[geo+'P0120042'] + df[geo+'P0120043'] + df[geo+'P0120044'] + df[geo+'P0120045'] +
df[geo+'P0120046'] + df[geo+'P0120047'] + df[geo+'P0120048'] + df[geo+'P0120049'] ) /
df[geo+'P0120001']
```

****^^^pctage18_24**

Percent population 18-24 years of age in Neighborhood Geography (**).

American Community Survey 2008-2012 (5-year)

```
( df[geo+'B01001007E'] + df[geo+'B01001008E'] + df[geo+'B01001009E'] +
df[geo+'B01001010E'] + df[geo+'B01001031E'] + df[geo+'B01001032E'] + df[geo+'B01001033E']
+ df[geo+'B01001034E']  ) /  df[geo+'B01001001E']
```

US Census 2010

```
( df[geo+'P0120007'] + df[geo+'P0120008'] + df[geo+'P0120009'] + df[geo+'P0120010'] +
df[geo+'P0120031'] + df[geo+'P0120032'] + df[geo+'P0120033'] + df[geo+'P0120034']  ) /
df[geo+'P0120001']
```

****^^^pctage25_34**

Percent population 25-34 years of age in Neighborhood Geography (**).

American Community Survey 2008-2012 (5-year)

```
( df[geo+'B01001011E'] + df[geo+'B01001012E'] + df[geo+'B01001035E'] +
df[geo+'B01001036E'] ) / df[geo+'B01001001E']
```

US Census 2010

```
( df[geo+'P0120011'] + df[geo+'P0120017'] + df[geo+'P0120035'] + df[geo+'P0120036'] ) /
df[geo+'P0120001']
```

****^^^pctage35_44**

Percent population 35-44 years of age in Neighborhood Geography (**).

American Community Survey 2008-2012 (5-year)

```
( df[geo+'B01001013E'] + df[geo+'B01001014E'] + df[geo+'B01001037E'] +
df[geo+'B01001038E'] ) / df[geo+'B01001001E']
```

US Census 2010

```
( df[geo+'P0120013'] + df[geo+'P0120014'] + df[geo+'P0120037'] + df[geo+'P0120038'] ) /
df[geo+'P0120001']
```

****^^^pctage45_54**

Percent population 45-54 years of age in Neighborhood Geography (**).

American Community Survey 2008-2012 (5-year)

```
( df[geo+'B01001015E'] + df[geo+'B01001016E'] + df[geo+'B01001039E'] +
df[geo+'B01001040E'] ) / df[geo+'B01001001E']
```

US Census 2010

```
( df[geo+'P0120015'] + df[geo+'P0120016'] + df[geo+'P0120039'] + df[geo+'P0120040'] ) /
df[geo+'P0120001']
```

****^^^pctage55_64**

Percent population 55-64 years of age in Neighborhood Geography (**).

American Community Survey 2008-2012 (5-year)

```
( df[geo+'B01001017E'] + df[geo+'B01001018E'] + df[geo+'B01001019E'] +
df[geo+'B01001041E'] + df[geo+'B01001042E'] + df[geo+'B01001043E']) /
df[geo+'B01001001E']
```

US Census 2010

```
( df[geo+'P0120017'] + df[geo+'P0120018'] + df[geo+'P0120019'] + df[geo+'P0120041'] +
df[geo+'P0120042'] + df[geo+'P0120043']) / df[geo+'P0120001']
```

^^^^pctage65up
Percent population 65 years of age and older in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
( df[geo+'B01001020E'] + df[geo+'B01001021E'] + df[geo+'B01001022E'] +
df[geo+'B01001023E'] + df[geo+'B01001024E'] + df[geo+'B01001025E'] + df[geo+'B01001044E']
+ df[geo+'B01001045E'] + df[geo+'B01001046E'] + df[geo+'B01001047E'] +
df[geo+'B01001048E'] + df[geo+'B01001049E'] ) / df[geo+'B01001001E']
```
US Census 2010
```
( df[geo+'P0120020'] + df[geo+'P0120021'] + df[geo+'P0120022'] + df[geo+'P0120023'] +
df[geo+'P0120024'] + df[geo+'P0120025'] + df[geo+'P0120044'] + df[geo+'P0120045'] +
df[geo+'P0120046'] + df[geo+'P0120047'] + df[geo+'P0120048'] + df[geo+'P0120049'] ) /
df[geo+'P0120001']
```

Sex, Race, Economic, Etc. Variables

^^^^pctmale
Percent population Male in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
df[geo+'B01001002E'] / df[geo+'B01001001E']
```
US Census 2010
```
df[geo+'P0120002'] / df[geo+'P0120001']
```

^^^^pctwhite
Percent population white in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
df[geo+'B02001002E'] / df[geo+'B02001001E']
```
US Census 2010
```
df[geo+'P0030002'] / df[geo+'P0030001']
```

^^^^pcthisp
Percent population Hispanic in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
df[geo+'B03002012E'] / df[geo+'B03002001E']
```
US Census 2010
```
df[geo+'P0040003'] / df[geo+'P0040001']
```

^^^^pctblack
Percent population Black in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
df[geo+'B02001003E'] / df[geo+'B02001001E']
```
US Census 2010
```
df[geo+'P0030003'] / df[geo+'P0030001']
```

^^^^pctasian
Percent population Asian in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
df[geo+'B02001005E'] / df[geo+'B02001001E']
```
US Census 2010
```
df[geo+'P0030005'] / df[geo+'P0030001']
```

^^^^pctother
Percent population Other (than Asian, Black or White) in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
( df[geo+'B02001004E'] + df[geo+'B02001006E'] + df[geo+'B02001007E'] +
df[geo+'B02001008E']) / df[geo+'B02001001E']
```
US Census 2010
```
( df[geo+'P0030004'] + df[geo+'P0030006'] + df[geo+'P0030007'] + df[geo+'P0030008'] ) /
df[geo+'P0030001']
```

^^^^pctforborn
Percent population foreign born in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
( df[geo+'B05001005E'] + df[geo+'B05001006E'] ) / df[geo+'B05001001E']
```

^^^^pctlingiso
Percent population linguistic isolation in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
( df[geo+'B16002004E'] + df[geo+'B16002007E'] + df[geo+'B16002010E'] +
df[geo+'B16002013E']) / df[geo+'B16002001E']
```

^^^^pcthhownocc
Percent household owner in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
df[geo+'B25003002E'] / df[geo+'B25003001E']
```
US Census 2010
```
( df[geo+'H0040002'] + df[geo+'H0040003'] ) / df[geo+'H0040001']
```

^^^^pctsameh1y
Percent population in same house 1 year ago in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
df[geo+'B07001017E'] / df[geo+'B07001001E']
```

^^^^pctpov
Percent population in poverty in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
( df[geo+'C17002002E'] + df[geo+'C17002003E']  ) / df[geo+'C17002001E']
```

^^^^pctpub
Percent population with public assistance in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
df[geo+'B19057002E'] / df[geo+'B19057001E']
```

^^^^pctfemheadhh
Percent households with Female householder, no husband present in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
df[geo+'B11001006E'] / df[geo+'B11001001E']
```

^^^^pctearn50kup
Percent population 15 years and over who work full-time in past 12 months that make $50,000 and over in income in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
( df[geo+'B19325021E'] + df[geo+'B19325022E'] + df[geo+'B19325023E'] +
df[geo+'B19325024E'] +df[geo+'B19325025E'] + df[geo+'B19325044E'] + df[geo+'B19325045E']
+ df[geo+'B19325046E'] + df[geo+'B19325047E'] + df[geo+'B19325048E'] ) /
df[geo+'B19325001E']
```

^^^^pctunemploy
Percent population 16 years and over who are civilians in the labor force that are unemployed in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
( df[geo+'B23001008E'] + df[geo+'B23001015E'] + df[geo+'B23001022E'] +
df[geo+'B23001029E'] + df[geo+'B23001036E'] + df[geo+'B23001043E'] + df[geo+'B23001050E']
+ df[geo+'B23001057E'] + df[geo+'B23001064E'] + df[geo+'B23001071E'] +
df[geo+'B23001076E'] + df[geo+'B23001081E'] + df[geo+'B23001086E'] + df[geo+'B23001094E']
+ df[geo+'B23001101E'] + df[geo+'B23001108E'] + df[geo+'B23001115E'] +
df[geo+'B23001122E'] + df[geo+'B23001129E'] + df[geo+'B23001136E'] + df[geo+'B23001143E']
+ df[geo+'B23001150E'] + df[geo+'B23001157E'] + df[geo+'B23001162E'] +
df[geo+'B23001167E'] + df[geo+'B23001172E'] )  / df[geo+'B23001001E']
```

^^^^pctjobmanagr
Percent population 16 years and over in Management, business, science, and arts occupations in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
( df[geo+'C24010003E'] + df[geo+'C24010039E'] ) / df[geo+'C24010001E']
```

^^^^pctednohisch
Percent population 25 years and over with no high school diploma or GED or alternative in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
( df[geo+'B15002003E'] + df[geo+'B15002004E'] + df[geo+'B15002005E'] +
df[geo+'B15002006E'] +  df[geo+'B15002007E'] + df[geo+'B15002008E'] +
df[geo+'B15002009E'] +  df[geo+'B15002010E'] + df[geo+'B15002020E'] +
df[geo+'B15002021E'] + df[geo+'B15002022E'] + df[geo+'B15002023E'] + df[geo+'B15002024E']
+ df[geo+'B15002025E'] + df[geo+'B15002026E'] + df[geo+'B15002027E'] ) /
df[geo+'B15002001E']
```

^^^^pctedyeshisch
Percent population 25 years and over with at least a high school diploma or GED or alternative in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
( df[geo+'B15002011E'] + df[geo+'B15002012E'] + df[geo+'B15002013E'] +
df[geo+'B15002014E'] + df[geo+'B15002015E'] + df[geo+'B15002016E'] + df[geo+'B15002017E']
+ df[geo+'B15002018E'] + df[geo+'B15002028E'] + df[geo+'B15002029E'] +
df[geo+'B15002030E'] + df[geo+'B15002031E'] + df[geo+'B15002032E'] + df[geo+'B15002033E']
+ df[geo+'B15002034E'] + df[geo+'B15002035E'] ) / df[geo+'B15002001E']
```

^^^^pctedcolgeup
Percent population 25 years and over with at least Associate's degree, Bachelor's degree, Master's degree, Professional school degree or Doctorate degree in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
( df[geo+'B15002014E'] + df[geo+'B15002015E'] + df[geo+'B15002016E'] +
df[geo+'B15002017E'] + df[geo+'B15002018E'] + df[geo+'B15002031E'] + df[geo+'B15002032E']
+ df[geo+'B15002033E'] + df[geo+'B15002034E'] + df[geo+'B15002035E'] ) /
df[geo+'B15002001E']
```

^^^^medhhinc
Median Household Income in Neighborhood Geography (**).
American Community Survey 2008-2012 (5-year)
```
df[geo+'B19013001E'] / df[geo+'countrows']
```

Unmarried Partner Households Variables

^^^^pctunmarprhh
Percent Unmarried partner households in Neighborhood Geography (**).
```
df[geo+'B11009002E'] /  df[geo+'B11009001E']
```

^^^^pctsamsexhh
Percent Male Householder and male partner OR Female Householder and female partner Unmarried partner households in Neighborhood Geography (**).
```
( df[geo+'B11009003E'] + df[geo+'B11009005E'] ) /  df[geo+'B11009001E']
```

^^^^pctmalparhh
Percent Male Householder and male partner Unmarried partner households in Neighborhood Geography (**).
```
df[geo+'B11009003E'] /  df[geo+'B11009001E']
```

^^^^pctfemparhh
Percent Female Householder and female partner Unmarried partner households in Neighborhood Geography (**).

```
df[geo+'B11009005E'] /  df[geo+'B11009001E']
```

Public Transportation Access Variables

Two datasets were used for the subway station counts. One dataset is from CUNY-R and the other is from New York City Department of Information Technology and Telecommunications (NYC DOITT). The CUNY-R data came from; [http://spatialityblog.com/2010/05/06/mta-data-in-gis-format/]. The NYC DOITT data came from the following locations; [https://data.cityofnewyork.us/Transportation/Subway-Stations/arq3-7z49
],[https://data.cityofnewyork.us/Transportation/Subway-Entrances/drex-xx56
].

****busstopscunycount**
Count of bus stops (CUNY-R bus stops) in Neighborhood Geography (**).

****subwayentrdoittcount**
Count of subway entrances (NYC DOITT) in Neighborhood Geography (**).

****subwaystopcunycount**
Count of subway stops (CUNY-R) in Neighborhood Geography (**).

****subwaystopdoittcount**
Count of subway stops (NYC DOITT) in Neighborhood Geography (**).

See Kernel Density Settings section for Kernel Density settings.

****kdtransitbusstopscunymean**
Mean zonal statistics of bus stops (CUNY-R) kernel density surface in Neighborhood Geography (**).

****kdtransitsubwayentrdoittmean**
Mean zonal statistics of subway entrances (NYC DOITT) kernel density surface in Neighborhood Geography (**).

****kdtransitsubwaystopcunymean**
Mean zonal statistics of subway stations (CUNY-R) kernel density surface in Neighborhood Geography (**).

****kdtransitsubwaystopdoittmean**
Mean zonal statistics of subway stations (NYC DOITT) kernel density surface in Neighborhood Geography (**).

Tree Canopy Variables

The Tree Canopy dataset used for this project was developed as part of the Urban Tree Canopy (UTC) Assessment for NYC. As such, it represents a 'top down' mapping perspective in which tree canopy over hanging other features was assigned to the tree canopy class. The minimum mapping unit for the delineation of features was set at 3-ft². The primary sources used to derive this dataset were 2010 LiDAR and 2008 4-band orthoimagery data. Ancillary GIS data sources included city boundaries, building footprints, water, parking lots, roads, railroads, railroad structures, and ball fields. This land cover dataset is considered current as of 2008.

****treecanopyareasqmtr**
Tree Canopy Area in Neighborhood Geography (**) in square meters.
arcpy - `!shape.area@squaremeters!`

****treepcthoodcanopy**
Percent of Neighborhood Geography (**) covered in tree canopy.
pandas - `df[geo+'treepcthoodcanopy'] = df[geo+'treecanopyareasqmtr']/df[geo+'areasqmtr']`

Sidewalk Cafes

The following variables are the counts of sidewalk cafes by type in neighborhood geographies. The sidewalk cafes were mined from NYC Open Data.

A list of legally operating sidewalk cafes in New York City. This list may include establishments that are currently within the license review process but legally operating. The data was accessed at:
[https://data.cityofnewyork.us/Business/Sidewalk-Cafes/6k68-kc8u]

****cntcafeenclosed**
Count of Enclosed Sidewalk Cafes in Neighborhood Geography (**).

****cntcafeunenclosed**
Count of Unenclosed Sidewalk Cafes in Neighborhood Geography (**).

****cntcafeall**
Count of All Sidewalk Cafes in Neighborhood Geography (**).

See Kernel Density Settings section for Kernel Density settings.

****kdcafeenclosedmean**
Mean zonal statistics of enclosed sidewalk cafes kernel density surface in Neighborhood Geography (**).

****kdcafeunenclosedmean**
Mean zonal statistics of enclosed sidewalk cafes kernel density surface in Neighborhood Geography (**).

****kdcafeallmean**
Mean zonal statistics of all sidewalk cafes kernel density surface in Neighborhood Geography (**).

Parks-Greenstreets

****greenstcount**
Count of Green Streets in Neighborhood Geography (**).

****largepkcount**
Count of Large Parks in Neighborhood Geography (**).

****otherpkcount**
Count of Other Parks in Neighborhood Geography (**).

****smallpkcount**
Count of Small Parks in Neighborhood Geography (**).

****waterpkcount**
Count of Water Area in Parks layer in Neighborhood Geography (**).

****allparkcount**
Count of All Parks in Neighborhood Geography (**).

****greenstsqmtr**
Area (in square meters) of Green Streets in Neighborhood Geography (**).

****largepksqmtr**
Area (in square meters) of Large Parks in Neighborhood Geography (**).

****otherpksqmtr**
Area (in square meters) of Other Parks in Neighborhood Geography (**).

****smallpksqmtr**
Area (in square meters) of Small Parks in Neighborhood Geography (**).

****waterpksqmtr**
Area (in square meters) of Water Area in Parks in Neighborhood Geography (**).

****allparksqmtr**
Area (in square meters) of All Parks in Neighborhood Geography (**).

****greenstpcthood**
Percent area Green Streets in Neighborhood Geography (**).

****largepkpcthood**
Percent area Large Parks in Neighborhood Geography (**).

****otherpkpcthood**
Percent Other Parks in Neighborhood Geography (**).

****smallpkpcthood**
Percent area Small Parks in Neighborhood Geography (**).

****waterpkpcthood**
Percent area Water Area in Parks in Neighborhood Geography (**).

****allparkpcthood**
Percent area All Parks in Neighborhood Geography (**).

Street Intersections

The following variables represent the count of unique street intersections (LION) per Neighborhood Geography (**).

****cntstreetint**
Count of street intersections in Neighborhood Geography (**). This version of the counts is pre-clipping using MapPluto block and lot boundary.

****cntstreetintm**
Count of street intersections in Neighborhood Geography (**). This version of the counts removes any intersections that are coincidental with MapPluto block and lot parcels (ie. Intersections in developments like in Staten Island or Breezy Point).

Retail Floor Area

The following variables represent the count of retail floor area (MapPluto) per Neighborhood Geography (**).

**** retailareasqft**
Sum of retail area in square feet in Neighborhood Geography (**).

Walkability Index Scales

Walkability
A number of researchers have constructed walkability indices which summarize built environment features believed to promote walking. Although specification details vary, these indices typically include measures of population density, land use, and street network. Our walkability measure was adapted from that employed in recent papers by Frank and colleagues (2005 and 2006), which includes four components: residential population density (density of population per total residential land area), intersection density, an entropy measure of land use based on the distribution of building floor area among six land use types (education, entertainment, single-family residential, multi-family residential, retail, and office), and the retail floor area ratio, or the ratio of retail building floor area to retail land area. All of the Frank components were z-scored and summed, with intersection density receiving a double weight for the *Frank Scale*, but not for the *Neckerman Scale.*

Frank et al. Linking objectively measured physical activity with objectively measured urban form: findings from SMARTRAQ. American Journal of Preventive Medicine. 2005;28(2 Suppl 2):117-125.

Walkability Index Scale "Input" Variables

A couple of the variables employed in the "Walkability Index Scales" were previously calculated and are aforementioned in this data dictionary. To avoid duplication of variables in the dataset itself, the "Walkability Index Scale" variables flagged with a "♦" are also found in other sections of this data dictionary but are listed again here in an abridged definition for the sake of convenience. The variables are not, however, duplicated in the dataset.

♦**_**intuqd** – Density of unique streets intersections per km2 [**_intunq / **_lndkm2].
♦**_**sub07d** – Density of subway stations per km2 [**_sub07c / **_lndkm2].
_rtlfar** – Retail floor area ratio – Retail building floor area divided by retail land area in km2.
_resdn1** – Density of residential units – Number of residential units divided by total residential building floor area in km2 [**_resunt / **_b3].
_resdn2** – Density of residential units – Number of housing units divided by buffer area in km2 [**_resunt / **_lndkm2].
_numlot** – Total number of unique MapPLUTO tax lots per measurement geography.
_resunt** – Total number of residential units per measurement geography.
entrpy** – Land Use Mix – An entropy measure using the five of the six land use types employed in Frank et al. (2006). Single- and multi-family residential areas were combined because most housing in New York City is multi-family. Parcel-level measures of residential, office, and retail floor area were available from the MapPLUTO (version 11v2) database. We used the MapPLUTO building class codes to identify buildings associated with education (schools) or entertainment (theaters, recreational facilities), and attributed the entire floor area of the identified building to education or entertainment. The entropy formula used was adapted from Frank et al. (2005), which yielded more plausible results: Land Use Mix = A/ln(N) where: A= –((b1/a)*ln(b1/a)+(b2/a)*ln(b2/a)+…) and b1 is the building floor area covered by the first land use, b2 is the building floor area covered by the second land use, etc., a is the total floor area across the five land uses, and N is the total number of land uses represented in the census tract. Zero values for b1…b5 were set to .000001 to avoid zero or undefined terms. *There are also measurement geographies where ****n** = 1 and have an **_**entrpy** variable value of '0'. These are examples where the land use classes within the measurement geography pertained to only one of the five types of BLDGCLASS code components, such as Retail Area.*

Components of the Entropy Measure:

_b1** – Total building area for Education uses in square feet (set to .000001 if 0)
_b2** – Total building area for Entertainment uses in square feet (set to .000001 if 0)
_b3** – Total building area Residential uses in square feet (set to .000001 if 0)
_b4** – Total building area for Retail uses in square feet (set to .000001 if 0)
_b5** – Total building area for Office uses in square feet (set to .000001 if 0)
_a** – Total floor area across the five land uses in square feet (set to .000001 if 0)
_n** – The total number of land uses represented (between 1 and 5)

ArcMap Entropy Field Calculation Expression:
entropy = –((([b1] / [a]) * log ([b1] / [a])) + (([b2] / [a]) * log ([b2] / [a])) + (([b3] / [a]) * log ([b3] / [a])) + (([b4] / [a]) * log ([b4] / [a])) + (([b5] / [a]) * log ([b5] / [a]))) / log ([n])

Walkability Index Scale Variables

To date, BEH has created and used two different versions of the Walkability Index Scales, which are referred to as the *"Frank et al. 2006"* and the "*Neckerman et al. 2009"* scales. The *"Frank 2006"* includes z-scored variables: residential density, land use mix using 5 land use types, intersection density * 2, and retail area ratio. The *"Neckerman 2009"* includes z-scored variables: residential density, land use mix using 5 land use types, intersection density, retail area ratio, and subway stop density. Note that *"Neckerman 2009"* does not multiple intersection density by 2 and subway density is added. The Stata code documenting the components for each version and that performs the z-scoring and construction of the two Walkability Index Scales variables is below.

ct_km2
US Census 2010 Tract area in square kilometers.

ct_lndkm2
US Census 2010 Tract land area in square kilometers.

ct_resdn1_z
Density of residential units: z-scored.

ct_intden_z
Density of unique streets intersections per km2: z-scored.

ct_entrpy_z
Entropy land use mix: z-scored.

ct_rtlfar_z
Retail floor area ratio: z-scored.

ct_sub07d_z
Density of subway stations per km2: z-scored.

ct_walk
Neckerman, et al. (2009) Walkability Scale.

ct_walk_cat
Quintiles of Neckerman, et al. (2009) Walkability Scale.

Walkability Index Scales: Stata Code
♠ *Please note that the variable names in the below Stata code may differ from the actual variables names in this dataset.*

```
//.. Create 'Variable Name Prefix' as appropriate.
local n25Abbr     n25_
local n1Abbr      n1_

//.. Create z-score walkability variables for comparison to our measures.
foreach level in network buffers {
    local abbr ``level'Abbr'
foreach var in `abbr'resdn1 `abbr'intden `abbr'entrpy `abbr'rtlfar `abbr'sub07d {
        summ `var'
        gen `var'_z = (`var'-`r(mean)')/`r(sd)'
    }

// Frank, et al. (2006) Scale
    gen `abbr'frank = `abbr'resdn1_z + `abbr'intden_z*2 + `abbr'entrpy_z + `abbr'rtlfar_z
    label var `abbr'frank "Frank, et al. (2006) Walkability Scale"
    xtile `abbr'frankcat = `abbr'frank, nquantiles(5)
    label var `abbr'frankcat "Quintiles of Frank, et al. (2006) Walkability Scale"

// Neckerman, et al. (2009) Scale
    gen `abbr'nckmn = `abbr'resdn1_z + `abbr'intden_z + `abbr'entrpy_z + `abbr'rtlfar_z +
`abbr'sub07d_z
    label var `abbr'nckmn "Neckerman, et al. (2009) Walkability Scale"
    xtile `abbr'nckmncat = `abbr'nckmn, nquantiles(5)
    label var `abbr'nckmncat "Quintiles of Neckerman, et al. (2009) Walkability Scale"
```

Average Number of Floors

The following variables represent the average number of floors in the primary buildings in their respective tax block and lot (BBL) from the MapPluto database. Included are the count of unique BBLs in Neighborhood Geography (**) as well as the average number of floors calculated using area-weighted average as well as un-weighted average (non area-dependent).

****countbbls**
Count of unique Borough Block and Lot (BBL) ids that contribute to weighted count of floors in Neighborhood Geography (**).

****floorswghted**
Area-weighted average number of floors per BBL in Neighborhood Geography (**).

****floorsunwght**
Un-weighted average number of floors per BBL in Neighborhood Geography (**).

New York City Housing and Vacancy Survey Variables

Overview
The New York City Housing and Vacancy Survey (NYCHVS), sponsored bythe New York City Department of Housing Preservation and Development, is conducted every 3 years to comply with New York state and New York City's rent regulation laws. The Census Bureau has conducted the survey for the City since 1965. The 2011 NYCHVS is the 15th such survey.

Detailed data from the survey cover many characteristics of the City's housing market, including characteristics of the City's population, households, housing stock, and neighborhoods. The rental vacancy rate is the primary focus of the survey, because that value is crucial to the current rent regulation laws. Other important survey data on housing include rent regulatory and homeownership status, structural conditions, unit maintenance and neighborhood conditions; crowding, rents, utility costs, type of heating fuel, rent/income ratios; owner purchase price and estimated value, mortgage status and interest rate; number of stories and units in building, cooperative/condominium status, wheelchair accessibility, and much more about housing and households in New York City.

For more information about the 2011 NYCHVS, visit:
http://www.census.gov/housing/nychvs/data/2011/overview.pdf
To view a copy of the NYCHVS questionnaire, visit:
http://www.census.gov/housing/nychvs/data/2011/questionnaire.pdf

Data Files & Record Layouts

o 2011 Data Files: http://www.census.gov/housing/nychvs/data/2011/data.html
o Household Records – Vacant Units: http://www.census.gov/housing/nychvs/data/2011/vac_11_long.pdf
o Household Records – Occupied Units:
http://www.census.gov/housing/nychvs/data/2011/occ_11_long.pdf

Universe Description
The universe includes all occupied and vacant housing units (except housing units in special places) in the five boroughs of the City of New York. In 2011, the number of household or occupied surveys conducted was: 16,358; and the number of vacant surveys conducted was: 1,569.

Sub-Borough Area Definitions
The 2011 NYCHVS is based primarily on a new sample drawn from the 2010 Census, which, for the first time since 1970, did not include the long-form questionnaire. The Census Bureau now uses the American Community Survey (ACS) to collect this additional demographic information on a continuous basis. ACS data for "smaller" areas employs Public Use Microdata Areas (PUMAs) as the basis for examining these smaller geographical areas.

In order to maintain a comparison between NYCHVS and ACS data, the sub-borough areas for NYCHVSs based on the 2010 census have been slightly re-configured to reflect ACS PUMAs. The most notable change from sub-boroughs dating back to the 1991 NYCHVS is in the reassignment of Manhattan tract 309 from the Bronx/sub-borough 6 to Manhattan/sub- borough 10. This tract, known as Marble Hill, is legally in Manhattan, but was tabulated in the Bronx, until now. Other minor changes to sub-borough areas reflect tract boundary changes made by the Census Bureau for the 2010 Census. There are 55 sub-borough areas in New York City. For a list of those areas by borough, please see the below PDFs.

o Queens, Staten Island: http://www.census.gov/housing/nychvs/data/2011/11subcom2.pdf
o Bronx, Brooklyn, Manhattan: http://www.census.gov/housing/nychvs/data/2011/11subcom1.pdf

GIS Calculated Variables
The NYCHVS data file provides data on many characteristics of housing units, their occupants, buildings and neighborhoods. However, for the purposes of this project, only characteristics on window conditions and building conditions were considered, for both vacant and occupied housing units. NYCHVS variables are aggregated to 1 of 55 Sub-Borough Areas. Variables are available for 2011 only. These variables were created using an area-weighted methodology, so if a buffer fell completely within a single Sub-Borough Area, it received the count characteristics on window conditions and building conditions only from that Sub-Borough Area. However, if a buffer fell partially within two or more Sub-Borough Areas, it received a proportion of the count characteristics on window conditions and building conditions from each of the contributing Sub-Borough Areas based on the proportion of the buffer area within each Sub-Borough Area.

Neighborhood Geography (**)

****_sborocnt**
Count of Sub-Borough Areas participating in the area-weighted spatial analysis technique.

****_hvs_units**
Count of vacant and occupied housing units surveyed.

****_vacant_units**
Count of vacant units housing units surveyed.

****_vacant_pct**
Percent of vacant units housing units surveyed [**_vacant_units / **_hvs_units]. **_occupied_units
Count of occupied units housing units surveyed.

****_occupied_pct**
Percent of occupied units housing units surveyed [**_occupied_units / **_hvs_units].

With the exception of the six variables defined above, all other NYCHVS related vars use the following naming convention:

1 Variables are prefixed with Neighborhood Geography (**).

2 & 3 Variables are next suffixed with either '_win' (window) or '_bld' (building), and are then suffixed with either '_vnt' (vacant units), '_ocp' (occupied units), or '_hvs' (vacant + occupied units) represented below by 'uuu'.

Condition of Windows:
o _win1 = Broken or missing windows?
_uuu1 = Response selected
_uuu8 = No condition reported
_uuu9 = Response not selected
o _win2 = Rotten/loose window frames/sashes?
_uuu1 = Response selected
_uuu8 = No condition reported
_uuu9 = Response not selected

o _win3 = Boarded-up windows?
_uuu1 = Response selected
_uuu8 = No condition reported Response not selected
_uuu9 = Response not selected
o _win4 = None of these problems with windows?
_uuu1 = Response selected
_uuu8 = No condition reported
_uuu9 = Response not selected
o _win5 = Unable to observe windows?
_uuu1 = Response selected
_uuu8 = No condition reported
_uuu9 = Response not selected
o _win6 = Any buildings with broken or boarded-up windows (observation)?
_uuu1 = Yes
_uuu2 = No
_uuu8 = Not reported

Condition of Building:

o _bld1 = Condition of building (observation)?
_uuu1 = Dilapidated
_uuu2 = Sound
_uuu3 = Deteriorating
_uuu8 = Not reported

Variable Summary (see above to concation of 2 & 3, 1 is Neighborhood geography, 4 is suffix (see below):

Example: r1_win1_uuu1_pct (radial buffer 240 feet – housing and vacancy variable – percent).

_win1_uuu1_*

_win1_uuu8_*

_win1_uuu9_*

_win2_uuu1_*

_win2_uuu8_*

_win2_uuu9_*

_win3_uuu1_*

_win3_uuu8_*

_win3_uuu9_*

_win4_uuu1_*

_win4_uuu8_*

_win4_uuu9_*

_win5_uuu1_*

_win5_uuu8_*

_win5_uuu9_*

_win6_uuu1_*

_win6_uuu2_*

_win6_uuu8_*

_bld1_uuu1_*

_bld1_uuu2_*

_bld1_uuu3_*

_bld1_uuu8_*

4 Variables are suffixed with either '_cnt' (count) or '_pct' (percent).
o _cnt = count
o _pct = percent

Sidewalk and Street Cleanliness Scores

Project Scorecard Overview
Since 1973, the City of New York has used a litter measurement tool called "Project Scorecard" to evaluate and measure the cleanliness of its streets and sidewalks. Trained evaluation teams use the Scorecard to "rate" the degree of surface litter by comparing actual street conditions to photographic standards. This measurement tool provides objective information about street and sidewalk cleanliness. Project Scorecard is managed by the Mayor's Office of Operations because they are responsible for tracking and monitoring the City's cleanliness over time. To learn more about Scorecard, please visit: [http://www.usmayors.org/USCM/best_practices/litter/NewYork.html]

Street and Sidewalk Scorecard Variables: Individual Years
Scorecard variables are aggregated to 1 of 234 NYC Sanitation Sections. Variables are available from 1999-2012, where ^^ in the variable name denotes the year ((99-12) for years 1999-2012). These variables were created using an area-weighted methodology.

XY neighborhood definition (prefix)
This measure includes Street and Sidewalk Cleanliness Scores for the X,Y location of the place point. In addition to ct, r1, n1 and n2 prefixes this includes an xy prefix so the measures of the Sanitation District the point resides in are also provided here without area-weighted interpolation.

****sanitation**
Sanitation district id (variable only for xy prefix).

****stclnavg^^**
Mean street cleanliness as a numerical value ranging from 1.0 [cleanest] to 3.0 [filthiest]. Ratings below 1.5 are considered "acceptable" according to both the consensus arrived at in public surveys conducted by Scorecard and the Department's own operating standards.

****staccpct^^**
Percent streets acceptable as a range of 0.0 to 100.0.

****stfilpct^^**
Percent streets filthy as a range of 0.0 to 100.0.

****swclnavg^^**
Mean sidewalk cleanliness as a numerical value ranging from 1.0 [cleanest] to 3.0 [filthiest]. Ratings below 1.5 are considered "acceptable" according to both the consensus arrived at in public surveys conducted by Scorecard and the Department's own operating standards.

****swaccpct^^**
Percent sidewalks acceptable as a range of 0.0 to 100.0.

****swfilpct^^**
Percent sidewalks filthy as a range of 0.0 to 100.0.

What is Scorecard?
o An inspection program run by the New York City Mayor's Office of Operations o A measurement of cleanliness of City streets and sidewalks

o A source of information for:
- The Department of Sanitation used for policy development, planning and evaluation of citywide operations
- The Mayor's Office for tracking and monitoring the City's cleanliness over time
- Community Boards and other public interest groups to learn about cleanliness conditions in local neighborhoods
- Business Improvement Districts (BIDS) to evaluate the conditions of neighborhood shopping and central business districts.

How is Cleanliness Measured?
o Scorecard cleanliness measures were developed by studying the public's perception and expectations of street and sidewalk cleanliness.

o The measurements are based on rigorous photographic standards of cleanliness for streets and sidewalks. o Actual inspections and ratings of streets and sidewalks are based on a seven-point scale of cleanliness.
- 1.0 is the cleanest rating
- 3.0 is the dirtiest rating
- there are five intermediate cleanliness ratings

· only ratings below 1.5 are "acceptably clean"

Scorecard Rating Scale

♠ Acceptably Clean:

o 1.0 = Clean street. No litter.

o 1.2 = Clean street, except for a few traces of litter.

♠ Not Acceptably Clean:

o 1.5 = More than a few traces, but no concentration of litter.
There are no piles of litter, and there are large gaps between pieces of litter.

♠ Filthy:

o 1.8 = Litter is concentrated in spots; there may either be large gaps between piles of litter, or small gaps between pieces of litter.

o 2.0 = Litter is concentrated, there are small gaps between piles of litter.

o 2.5 = Litter is highly concentrated, there are no gaps in the piles of litter.
The litter is a straight line along the curb.

o 3.0 = Litter is very highly concentrated, there are no gaps in the piles of litter.
The litter is a straight line along and over the curb.

Scorecard Rating Procedures

o Scorecard samples the average cleanliness of the City's blockfaces (one side of the street, corner to corner). New York has over 120,000 blockfaces.

o Scorecard Inspections:

· Record separate ratings for 2-4 individual "segments" of a street and sidewalk
· Report monthly for each Sanitation District and quarterly for B.I.D.s and other special rating areas
· Rate a citywide sample of 6,900 blockfaces each month

o The monthly schedule of district ratings is designed to vary to ensure representative inspections of actual street conditions, including:

· Who rates the district
· What time of day the ratings are conducted
· Which day of the week the ratings are done
· Which week during the month the ratings are scheduled

o Inspections can occur either before or after street cleaning is done.

Scorecard Ratings For Sanitation Districts

o Scorecard figures are based on a fixed sample of streets in each Sanitation section and district. o The sample of streets is statistically and geographically representative:

· Statistically because average ratings for sample streets are equivalent to average ratings for all streets in a section.
· Geographically because sample streets are distributed evenly through all parts of the section.

o Monthly Scorecard reports provide information on both the average ratings given to streets and sidewalks, as well as the percent of total streets rated acceptably clean

o District and zone figures are weighted by street mileage. Sections with more mileage along the streets have more weight in determining overall district, zone, borough, and citywide figures.

Quality Control for Scorecard Ratings

o Inspectors undergo continual quality assurance checks and retraining.
o "Cross checks" evaluate rating consistency between inspectors.

o Inspections are continuously monitored to detect potentially biased ratings.
o Ratings which may be in error are dropped, with the streets rated again when necessary.

Deriving Scorecard % Acceptable and Average Ratings Figure.

Deriving Scorecard % Acceptable and Average Ratings

1	2	3	4
Blockface A			

1	Blockface B
2	

Blockface Ratings:

	---Segment Rating---				Rating Total		# of Segments		Mean Rating
	1	2	3	4					
Blockface A	1.0	1.2	1.5	2.0	5.7	÷	4	=	1.43
Blockface B	1.5	1.8	--	--	3.3	÷	2	=	1.65

Blockface Ratings:

	Blockface A	Blockface B	Acceptable Total		# of Segments		% Acceptable
Rating Average	1.43	1.65					
% Acceptable (is average rating below 1.5?)	Yes	No	1	÷	2	=	50%

District Totals:

	Actual Miles in Section	Section Weight of District		% Acceptable Rating		Weighted %
Section 1	1	.17	×	50%	=	8.5
Section 2	2	.33	×	75%	=	24.8
Section 3	3	.50	×	100%	=	50.0
District Total	6					83.%

Pedestrian & Bicyclist Injuries and Fatalities

BEH compiled a comprehensive dataset of pedestrian and bicyclist injury and fatalities from 1995 through August of 2013 (201308) by merging CrashStat (2012-201308) and Open Scrape/Crash Mapper (1995-2011).

The main difference between Open Scrape/Crash Mapper and CrashStat, besides the timeframe, is that Open Scrape/Crash Mapper includes many types of collisions whereas CrashStat only includes ones that have a pedestrian or bicyclist injury or fatality.

Crash data comes from the New York State Department of Transportation. Variables are aggregated by both pedestrian—motorist injuries, pedestrian—motorist fatalities, bicyclist—motorist injuries, and bicyclist—motorist fatalities.

Open Scrape/Crash Mapper
[http://nypd.openscrape.com/data/] – map view: [http://nyc.crashmapper.com/about]

CrashStat
Main landing page: [http://crashstat.org/] – data source: [http://crashstat.org/about]. James Quinn (BEH) received a 2011 file via email from Transportation Alternatives.

ACCD_TYP
02 - COLLISION WITH PEDESTRIAN
03 - COLLISION WITH BICYCLIST
from NYSDOTAccidentDataFilesDescription.doc

List of Crash Types:
For ^^^^ in Years 1995-2013:

****bikinj^^^^**
Count of Bicyclist Injuries in Neighborhood Geography (**).

****bikkil^^^^**
Count of Bicyclist Fatalities in Neighborhood Geography (**).

****pedinj^^^^**
Count of Pedestrian Injuries in Neighborhood Geography (**).

****pedkil^^^^**
Count of Pedestrian Fatalities in Neighborhood Geography (**).

Weighted Average Speed Limit

$$WGHT\_SPEED = \frac{\sum_{j=1}^{N} LENGTH(S(j)) \times S(j)}{\sum_{j=1}^{N} LENGTH(S(j))}$$

Where: the N possible speed limits in the dataset are indexed 1,2,…,N (in this case N=7)

S = {1, 15, 25, 35, 45, 55, 65} is the set of possible speed limits (e.g. S(3) = 25)

LENGTH(S(j))= length in km of roads with speed limit S(j) in buffer

****wghtavgspeed**
Length weighted average speed limit in miles per hour (mph) in Neighborhood Geography (**).

Street Length

****sumstreetlenft**
Length of streets in Feet in Neighborhood Geography (**).

****sumstreetlenmeters**
Length of streets in Meters in Neighborhood Geography (**).

Truck Routes

The following variables represent data related to DOT truck route data in neighborhood geography.
[http://www.nyc.gov/html/dot/html/about/datafeeds.shtml]

****truckrlen**
Length in meters of Truck Routes in Neighborhood Geography (**) for year 2011 Truck Routes.

****truckrratiolen**
Length in meters of Truck Routes in Neighborhood Geography (**) for year 2011 Truck Routes divided by **sumstreetlenmeters.

```
df[geo+'truckrratiolen'] = df[geo+'truckrlen'] / df[geo+'sumstreetlenmeters']
```

Bike Routes

Bike routes calculate total length and also all the subcategories. If you add up all the subcategories length it may be larger than the total length and some sections of the bike route features have two classes (ie, 'II,III'). The data represents 2011 Bike Routes and was downloaded from:
[http://www.nyc.gov/html/dot/html/about/datafeeds.shtml]

I = Class I Facility - Greenway/Multi-use path
II = Class II Facility - On-street striped bicycle lane
III =Class III Facility - On-street signed bicycle route
L = Links or Connectors
S = Stairs

****bikertleni**
Length in meters of Class I Facility - **Greenway/Multi-use path** in Neighborhood Geography (**) for year 2011 Bike Routes.

****bikertlenii**
Length in meters of Class II Facility - **On-street striped bicycle lane** in Neighborhood Geography (**) for year 2011 Bike Routes.

****bikertleniii**
Length in meters of Class III Facility - **On-street signed bicycle route** in Neighborhood Geography (**) for year 2011 Bike Routes.

****bikertlenl**
Length in meters of **Links or Connectors** in Neighborhood Geography (**) for year 2011 Bike Routes.

****bikertlens**
Length in meters of **Stairs** in Neighborhood Geography (**) for year 2011 Bike Routes.

****bikertlenall**
Total length in meters of Bike Route of any class in Neighborhood Geography (**) for year 2011 Bike Routes. This number may not in all instances match the summed length of all three (3) classes and/or Links or Connectors and Stairs as some segments are classified as more than one (1) Class (ie, I,II;II,III). See # below;

#Lists all facility classes (separated by commas where 2 or more classesare present on the same segment) present of a given segment.
Source: *nyccyclingmap_shapefile_readme.pdf* DOITT from [
http://www.nyc.gov/html/dot/html/about/datafeeds.shtml]

For types in Bike Route Types = ['i','iii','iii','l','s','all']

> ****bikertratiolen##**
> Length in meters of Bike Routes in Neighborhood Geography (**) by type (## - ['i','iii','iii','l','s','all']) for Bike Routes divided by **sumstreetlenmeters.

```
bikeRtypes = ['i','iii','iii','l','s','all']
for b in bikeRtypes:
        df[geo+'bikerrationlen'+b]= df[geo+'bikertlen'+b] /
        df[geo+'sumstreetlenmeters']
```

Alcohol

From LAMP [http://lamp.sla.ny.gov/nysla/index.htm] which is [http://www.sla.ny.gov/].
Email SLA in 2013. Received via email 04/21/2013. Sent a filegeodatabase named 'data.gdb' with feature classes name Licenses.

Types of Alcohol-Related Licenses
1 = On Premise
2 = Off Premise
3 = Wholesale
4 = Pending
5 = Disabled

****cntalcoholclass1**
Count of Alcohol Related for On Premise Licenses in Neighborhood Geography (**).

****cntalcoholclass2**
Count of Alcohol Related for Off Premise Licenses in Neighborhood Geography (**).

****cntalcoholclass3**
Count of Alcohol Related for Wholesale Licenses in Neighborhood Geography (**).

****cntalcoholclass4**
Count of Alcohol Related for Pending Licenses in Neighborhood Geography (**).

****cntalcoholclass5**
Count of Alcohol Related for Disabled Licenses in Neighborhood Geography (**).

****cntalcoholall**
Count of Alcohol Related for all License types in Neighborhood Geography (**).

See Kernel Density Settings section for Kernel Density settings.

****kdalcoholclass1mean**
Mean zonal statistics of Alcohol Related for On Premise Licenses in Neighborhood Geography (**).

****kdalcoholclass2mean**
Mean zonal statistics of Alcohol Related for Off Premise Licenses in Neighborhood Geography (**).

****kdalcoholclass3mean**
Mean zonal statistics of Alcohol Related for Wholesale Licenses in Neighborhood Geography (**).

****kdalcoholclass4mean**
Mean zonal statistics of Alcohol Related for Pending Licenses in Neighborhood Geography (**).

****kdalcoholclass5mean**
Mean zonal statistics of Alcohol Related for Disabled Licenses in Neighborhood Geography (**).

****kdalcoholall_clipmean**
Mean zonal statistics of Alcohol Related for all License types in Neighborhood Geography (**).

Crime – Esri Crime Indexes 2012 and NY Times Homicide Data.

Esri Crime Indexes from 2012
Please see **Appendix D** for further information regarding the database methodology of the CrimeRisk Index data.

Please note that a crime index value of '100' is considered the national average. The CrimeRisk Index variables provided for this project are the original index values and **have not** been scaled in any way.

****cravgtotc**
Average Total Crime Index in Neighborhood Geography (**).

****cravgperc**
Average Personal Crime Index in Neighborhood Geography (**).

****cravgmurd**
Average Murder Index in Neighborhood Geography (**).

****cravgrape**
Average Rape Index in Neighborhood Geography (**).

****cravgrobb**
Average Robbery Index in Neighborhood Geography (**).

****cravgasst**
Average Assault Index in Neighborhood Geography (**).

****cravgproc**
Average Property Crime Index in Neighborhood Geography (**).

****cravgburg**
Average Burglary Index in Neighborhood Geography (**).

****cravglarc**
Average Larceny Index in Neighborhood Geography (**).

****cravgmveh**
Average Motor Vehicle Theft Index in Neighborhood Geography (**).

NY Times Homicides Map: *Murder: New York City*

This data set was mined from the NY Times web site [http://projects.nytimes.com/crime/homicides/map]. It includes homicides in NYC from 2003 to August 2011 (the latest homicide). There is a note included in the web page that states that 'Map does not show 39 locations that the police have not release,' meaning 39 homicides are excluded from the dataset over the range of years due to having no coordinate data. The dataset includes the year of the homicide and the number of victims.

****cnthomicide^^^^**
Count of homicides in Neighborhood Geography (**) per year (^^^^) [2003-2011]. Note: until August 2011, not full year.

****cnthomicide20032011**
Count of homicides in Neighborhood Geography (**) across years 2003-2011. Note: until August 2011, not full year.

****ratehomicid^^^^**
Count of homicides by Year (^^^^) per 100,000 using underlying population variable **acstotpop. Note: until August 2011, not full year.

****ratehomicid20032011**
Count of homicides across years 2003-2011 per 100,000 using underlying population variable **acstotpop. Note: until August 2011, not full year.

Also note, the rate variables are not next to the count variable in the tables.

```
for year in range(2003,2012):
        y = str(year)
        df[geo+'ratehomicid'+y]   = df[geo+'cnthomicide'+y] / (
        df[geo+'acstotpop'] / 100000 )
        df[geo+'ratehomicid20032011'] = df[geo+'cnthomicide20032011'] / (
        df[geo+'acstotpop'] / 100000 )
```

See Kernel Density Settings section for Kernel Density settings.

****kdhomicidemean^^^^**
Mean zonal statistics of homicide kernel density surface in Neighborhood Geography (**) by Year ^^^^. Note: until August 2011, not full year. Note: This was only performed for years 2008-2011.

****kdhomicidemean200320111**
Mean zonal statistics of homicide kernel density surface in Neighborhood Geography (**) across years 2003-2011. Note: until August 2011, not full year.

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Appendix A: 2008-2012 5-Year American Community Survey (ACS) Variables:

Census Tract ACS 2008-2012 variables were acquired from the US Census Bureau API [https://www.census.gov/developers/] at the 2010 Census Tract, Block unit or level of geography. These variables were created using areal weighting interpolation. The original census variable names were slightly modified in order to provide a systematic naming convention across all project neighborhood definitions and to provide an indicator of the type of variable being provided. The ACS census variable names use the following naming convention:

**** (for Neighborhood Geography (cb, ct, r1, n1, n2)) + variable (for ACS data an 'E' is appended to the variable name as all values are 'Estimates' – for example B01001001E for B01001001.)**

B01001			**SEX BY AGE**
B01001			*Universe: Total population*
B01001	1	**B01001001**	Total:
B01001	2	**B01001002**	Male:
B01001	3	**B01001003**	Under 5 years
B01001	4	**B01001004**	5 to 9 years
B01001	5	**B01001005**	10 to 14 years
B01001	6	**B01001006**	15 to 17 years
B01001	7	**B01001007**	18 and 19 years
B01001	8	**B01001008**	20 years
B01001	9	**B01001009**	21 years
B01001	10	**B01001010**	22 to 24 years
B01001	11	**B01001011**	25 to 29 years
B01001	12	**B01001012**	30 to 34 years
B01001	13	**B01001013**	35 to 39 years
B01001	14	**B01001014**	40 to 44 years
B01001	15	**B01001015**	45 to 49 years
B01001	16	**B01001016**	50 to 54 years
B01001	17	**B01001017**	55 to 59 years
B01001	18	**B01001018**	60 and 61 years
B01001	19	**B01001019**	62 to 64 years
B01001	20	**B01001020**	65 and 66 years
B01001	21	**B01001021**	67 to 69 years
B01001	22	**B01001022**	70 to 74 years

B01001	23	**B01001023**	75 to 79 years
B01001	24	**B01001024**	80 to 84 years
B01001	25	**B01001025**	85 years and over
B01001	26	**B01001026**	Female:
B01001	27	**B01001027**	Under 5 years
B01001	28	**B01001028**	5 to 9 years
B01001	29	**B01001029**	10 to 14 years
B01001	30	**B01001030**	15 to 17 years
B01001	31	**B01001031**	18 and 19 years
B01001	32	**B01001032**	20 years
B01001	33	**B01001033**	21 years
B01001	34	**B01001034**	22 to 24 years
B01001	35	**B01001035**	25 to 29 years
B01001	36	**B01001036**	30 to 34 years
B01001	37	**B01001037**	35 to 39 years
B01001	38	**B01001038**	40 to 44 years
B01001	39	**B01001039**	45 to 49 years
B01001	40	**B01001040**	50 to 54 years
B01001	41	**B01001041**	55 to 59 years
B01001	42	**B01001042**	60 and 61 years
B01001	43	**B01001043**	62 to 64 years
B01001	44	**B01001044**	65 and 66 years
B01001	45	**B01001045**	67 to 69 years
B01001	46	**B01001046**	70 to 74 years
B01001	47	**B01001047**	75 to 79 years
B01001	48	**B01001048**	80 to 84 years
B01001	49	**B01001049**	85 years and over

B02001			**RACE**
B02001			*Universe: Total population*

B02001	1	**B02001001**	Total:
B02001	2	**B02001002**	White alone
B02001	3	**B02001003**	Black or African American alone
B02001	4	**B02001004**	American Indian and Alaska Native alone
B02001	5	**B02001005**	Asian alone
B02001	6	**B02001006**	Native Hawaiian and Other Pacific Islander alone
B02001	7	**B02001007**	Some other race alone
B02001	8	**B02001008**	Two or more races:
B02001	9	**B02001009**	Two races including Some other race
B02001	10	**B02001010**	Two races excluding Some other race, and three or more races
B03002			HISPANIC OR LATINO ORIGIN BY RACE
B03002			Universe: Total population
B03002	1	**B03002001**	Total:
B03002	2	**B03002002**	Not Hispanic or Latino:
B03002	3	**B03002003**	White alone
B03002	4	**B03002004**	Black or African American alone
B03002	5	**B03002005**	American Indian and Alaska Native alone
B03002	6	**B03002006**	Asian alone
B03002	7	**B03002007**	Native Hawaiian and Other Pacific Islander alone
B03002	8	**B03002008**	Some other race alone
B03002	9	**B03002009**	Two or more races:
B03002	10	**B03002010**	Two races including Some other race
B03002	11	**B03002011**	Two races excluding Some other race, and three or more races
B03002	12	**B03002012**	Hispanic or Latino:
B03002	13	**B03002013**	White alone
B03002	14	**B03002014**	Black or African American alone
B03002	15	**B03002015**	American Indian and Alaska Native alone
B03002	16	**B03002016**	Asian alone
B03002	17	**B03002017**	Native Hawaiian and Other Pacific Islander alone
B03002	18	**B03002018**	Some other race alone

B03002	19	**B03002019**	Two or more races:
B03002	20	**B03002020**	Two races including Some other race
B03002	21	**B03002021**	Two races excluding Some other race, and three or more races
B05001			**NATIVITY AND CITIZENSHIP STATUS IN THE UNITED STATES**
B05001			*Universe: Total population in the United States*
B05001	1	**B05001001**	Total:
B05001	2	**B05001002**	U.S. citizen, born in the United States
B05001	3	**B05001003**	U.S. citizen, born in Puerto Rico or U.S. Island Areas
B05001	4	**B05001004**	U.S. citizen, born abroad of American parent(s)
B05001	5	**B05001005**	U.S. citizen by naturalization
B05001	6	**B05001006**	Not a U.S. citizen
B05002			**PLACE OF BIRTH BY NATIVITY AND CITIZENSHIP STATUS**
B05002			*Universe: Total population*
B05002	1	**B05002001**	Total:
B05002	2	**B05002002**	Native:
B05002	3	**B05002003**	Born in state of residence
B05002	4	**B05002004**	Born in other state in the United States:
B05002	5	**B05002005**	Northeast
B05002	6	**B05002006**	Midwest
B05002	7	**B05002007**	South
B05002	8	**B05002008**	West
B05002	9	**B05002009**	Born outside the United States:
B05002	10	**B05002010**	Puerto Rico
B05002	11	**B05002011**	U.S. Island Areas
B05002	12	**B05002012**	Born abroad of American parent(s)
B05002	13	**B05002013**	Foreign born:
B05002	14	**B05002014**	Naturalized U.S. citizen
B05002	15	**B05002015**	Not a U.S. citizen

B07001			**GEOGRAPHICAL MOBILITY IN THE PAST YEAR BY AGE FOR CURRENT RESIDENCE IN THE UNITED STATES**
B07001			*Universe: Population 1 year and over in the United States*
B07001	1	**B07001001**	Total:
B07001	2	**B07001002**	1 to 4 years
B07001	3	**B07001003**	5 to 17 years
B07001	4	**B07001004**	18 and 19 years
B07001	5	**B07001005**	20 to 24 years
B07001	6	**B07001006**	25 to 29 years
B07001	7	**B07001007**	30 to 34 years
B07001	8	**B07001008**	35 to 39 years
B07001	9	**B07001009**	40 to 44 years
B07001	10	**B07001010**	45 to 49 years
B07001	11	**B07001011**	50 to 54 years
B07001	12	**B07001012**	55 to 59 years
B07001	13	**B07001013**	60 to 64 years
B07001	14	**B07001014**	65 to 69 years
B07001	15	**B07001015**	70 to 74 years
B07001	16	**B07001016**	75 years and over
B07001	17	**B07001017**	Same house 1 year ago:
B07001	18	**B07001018**	1 to 4 years
B07001	19	**B07001019**	5 to 17 years
B07001	20	**B07001020**	18 and 19 years
B07001	21	**B07001021**	20 to 24 years
B07001	22	**B07001022**	25 to 29 years
B07001	23	**B07001023**	30 to 34 years
B07001	24	**B07001024**	35 to 39 years
B07001	25	**B07001025**	40 to 44 years
B07001	26	**B07001026**	45 to 49 years
B07001	27	**B07001027**	50 to 54 years
B07001	28	**B07001028**	55 to 59 years

B07001	29	**B07001029**	60 to 64 years
B07001	30	**B07001030**	65 to 69 years
B07001	31	**B07001031**	70 to 74 years
B07001	32	**B07001032**	75 years and over
B07001	33	**B07001033**	Moved within same county:
B07001	34	**B07001034**	1 to 4 years
B07001	35	**B07001035**	5 to 17 years
B07001	36	**B07001036**	18 and 19 years
B07001	37	**B07001037**	20 to 24 years
B07001	38	**B07001038**	25 to 29 years
B07001	39	**B07001039**	30 to 34 years
B07001	40	**B07001040**	35 to 39 years
B07001	41	**B07001041**	40 to 44 years
B07001	42	**B07001042**	45 to 49 years
B07001	43	**B07001043**	50 to 54 years
B07001	44	**B07001044**	55 to 59 years
B07001	45	**B07001045**	60 to 64 years
B07001	46	**B07001046**	65 to 69 years
B07001	47	**B07001047**	70 to 74 years
B07001	48	**B07001048**	75 years and over
B07001	49	**B07001049**	Moved from different county within same state:
B07001	50	**B07001050**	1 to 4 years
B07001	51	**B07001051**	5 to 17 years
B07001	52	**B07001052**	18 and 19 years
B07001	53	**B07001053**	20 to 24 years
B07001	54	**B07001054**	25 to 29 years
B07001	55	**B07001055**	30 to 34 years
B07001	56	**B07001056**	35 to 39 years
B07001	57	**B07001057**	40 to 44 years
B07001	58	**B07001058**	45 to 49 years

B07001	59	**B07001059**	50 to 54 years
B07001	60	**B07001060**	55 to 59 years
B07001	61	**B07001061**	60 to 64 years
B07001	62	**B07001062**	65 to 69 years
B07001	63	**B07001063**	70 to 74 years
B07001	64	**B07001064**	75 years and over
B07001	65	**B07001065**	Moved from different state:
B07001	66	**B07001066**	1 to 4 years
B07001	67	**B07001067**	5 to 17 years
B07001	68	**B07001068**	18 and 19 years
B07001	69	**B07001069**	20 to 24 years
B07001	70	**B07001070**	25 to 29 years
B07001	71	**B07001071**	30 to 34 years
B07001	72	**B07001072**	35 to 39 years
B07001	73	**B07001073**	40 to 44 years
B07001	74	**B07001074**	45 to 49 years
B07001	75	**B07001075**	50 to 54 years
B07001	76	**B07001076**	55 to 59 years
B07001	77	**B07001077**	60 to 64 years
B07001	78	**B07001078**	65 to 69 years
B07001	79	**B07001079**	70 to 74 years
B07001	80	**B07001080**	75 years and over
B07001	81	**B07001081**	Moved from abroad:
B07001	82	**B07001082**	1 to 4 years
B07001	83	**B07001083**	5 to 17 years
B07001	84	**B07001084**	18 and 19 years
B07001	85	**B07001085**	20 to 24 years
B07001	86	**B07001086**	25 to 29 years
B07001	87	**B07001087**	30 to 34 years
B07001	88	**B07001088**	35 to 39 years

B07001	89	**B07001089**	40 to 44 years
B07001	90	**B07001090**	45 to 49 years
B07001	91	**B07001091**	50 to 54 years
B07001	92	**B07001092**	55 to 59 years
B07001	93	**B07001093**	60 to 64 years
B07001	94	**B07001094**	65 to 69 years
B07001	95	**B07001095**	70 to 74 years
B07001	96	**B07001096**	75 years and over
B11001			**HOUSEHOLD TYPE (INCLUDING LIVING ALONE)**
B11001			*Universe: Households*
B11001	1	**B11001001**	Total:
B11001	2	**B11001002**	Family households:
B11001	3	**B11001003**	Married-couple family
B11001	4	**B11001004**	Other family:
B11001	5	**B11001005**	Male householder, no wife present
B11001	6	**B11001006**	Female householder, no husband present
B11001	7	**B11001007**	Nonfamily households:
B11001	8	**B11001008**	Householder living alone
B11001	9	**B11001009**	Householder not living alone
B11009			**UNMARRIED-PARTNER HOUSEHOLDS BY SEX OF PARTNER**
B11009			Universe: Households
B11009	1	**B11009001**	Total:
B11009	2	**B11009002**	Unmarried-partner households:
B11009	3	**B11009003**	Male householder and male partner
B11009	4	**B11009004**	Male householder and female partner
B11009	5	**B11009005**	Female householder and female partner
B11009	6	**B11009006**	Female householder and male partner
B11009	7	**B11009007**	All other households

B16001			**LANGUAGE SPOKEN AT HOME BY ABILITY TO SPEAK ENGLISH FOR THE POPULATION 5 YEARS AND OVER**
B16001			*Universe: Population 5 years and over*
B16001	1	**B16001001**	Total:
B16001	2	**B16001002**	Speak only English
B16001	3	**B16001003**	Spanish or Spanish Creole:
B16001	4	**B16001004**	Speak English "very well"
B16001	5	**B16001005**	Speak English less than "very well"
B16001	6	**B16001006**	French (incl. Patois, Cajun):
B16001	7	**B16001007**	Speak English "very well"
B16001	8	**B16001008**	Speak English less than "very well"
B16001	9	**B16001009**	French Creole:
B16001	10	**B16001010**	Speak English "very well"
B16001	11	**B16001011**	Speak English less than "very well"
B16001	12	**B16001012**	Italian:
B16001	13	**B16001013**	Speak English "very well"
B16001	14	**B16001014**	Speak English less than "very well"
B16001	15	**B16001015**	Portuguese or Portuguese Creole:
B16001	16	**B16001016**	Speak English "very well"
B16001	17	**B16001017**	Speak English less than "very well"
B16001	18	**B16001018**	German:
B16001	19	**B16001019**	Speak English "very well"
B16001	20	**B16001020**	Speak English less than "very well"
B16001	21	**B16001021**	Yiddish:
B16001	22	**B16001022**	Speak English "very well"
B16001	23	**B16001023**	Speak English less than "very well"
B16001	24	**B16001024**	Other West Germanic languages:
B16001	25	**B16001025**	Speak English "very well"
B16001	26	**B16001026**	Speak English less than "very well"
B16001	27	**B16001027**	Scandinavian languages:
B16001	28	**B16001028**	Speak English "very well"

B16001	29	**B16001029**	Speak English less than "very well"
B16001	30	**B16001030**	Greek:
B16001	31	**B16001031**	Speak English "very well"
B16001	32	**B16001032**	Speak English less than "very well"
B16001	33	**B16001033**	Russian:
B16001	34	**B16001034**	Speak English "very well"
B16001	35	**B16001035**	Speak English less than "very well"
B16001	36	**B16001036**	Polish:
B16001	37	**B16001037**	Speak English "very well"
B16001	38	**B16001038**	Speak English less than "very well"
B16001	39	**B16001039**	Serbo-Croatian:
B16001	40	**B16001040**	Speak English "very well"
B16001	41	**B16001041**	Speak English less than "very well"
B16001	42	**B16001042**	Other Slavic languages:
B16001	43	**B16001043**	Speak English "very well"
B16001	44	**B16001044**	Speak English less than "very well"
B16001	45	**B16001045**	Armenian:
B16001	46	**B16001046**	Speak English "very well"
B16001	47	**B16001047**	Speak English less than "very well"
B16001	48	**B16001048**	Persian:
B16001	49	**B16001049**	Speak English "very well"
B16001	50	**B16001050**	Speak English less than "very well"
B16001	51	**B16001051**	Gujarati:
B16001	52	**B16001052**	Speak English "very well"
B16001	53	**B16001053**	Speak English less than "very well"
B16001	54	**B16001054**	Hindi:
B16001	55	**B16001055**	Speak English "very well"
B16001	56	**B16001056**	Speak English less than "very well"
B16001	57	**B16001057**	Urdu:
B16001	58	**B16001058**	Speak English "very well"

B16001	59	**B16001059**	Speak English less than "very well"
B16001	60	**B16001060**	Other Indic languages:
B16001	61	**B16001061**	Speak English "very well"
B16001	62	**B16001062**	Speak English less than "very well"
B16001	63	**B16001063**	Other Indo-European languages:
B16001	64	**B16001064**	Speak English "very well"
B16001	65	**B16001065**	Speak English less than "very well"
B16001	66	**B16001066**	Chinese:
B16001	67	**B16001067**	Speak English "very well"
B16001	68	**B16001068**	Speak English less than "very well"
B16001	69	**B16001069**	Japanese:
B16001	70	**B16001070**	Speak English "very well"
B16001	71	**B16001071**	Speak English less than "very well"
B16001	72	**B16001072**	Korean:
B16001	73	**B16001073**	Speak English "very well"
B16001	74	**B16001074**	Speak English less than "very well"
B16001	75	**B16001075**	Mon-Khmer, Cambodian:
B16001	76	**B16001076**	Speak English "very well"
B16001	77	**B16001077**	Speak English less than "very well"
B16001	78	**B16001078**	Hmong:
B16001	79	**B16001079**	Speak English "very well"
B16001	80	**B16001080**	Speak English less than "very well"
B16001	81	**B16001081**	Thai:
B16001	82	**B16001082**	Speak English "very well"
B16001	83	**B16001083**	Speak English less than "very well"
B16001	84	**B16001084**	Laotian:
B16001	85	**B16001085**	Speak English "very well"
B16001	86	**B16001086**	Speak English less than "very well"
B16001	87	**B16001087**	Vietnamese:
B16001	88	**B16001088**	Speak English "very well"

B16001	89	**B16001089**	Speak English less than "very well"
B16001	90	**B16001090**	Other Asian languages:
B16001	91	**B16001091**	Speak English "very well"
B16001	92	**B16001092**	Speak English less than "very well"
B16001	93	**B16001093**	Tagalog:
B16001	94	**B16001094**	Speak English "very well"
B16001	95	**B16001095**	Speak English less than "very well"
B16001	96	**B16001096**	Other Pacific Island languages:
B16001	97	**B16001097**	Speak English "very well"
B16001	98	**B16001098**	Speak English less than "very well"
B16001	99	**B16001099**	Navajo:
B16001	100	**B16001100**	Speak English "very well"
B16001	101	**B16001101**	Speak English less than "very well"
B16001	102	**B16001102**	Other Native North American languages:
B16001	103	**B16001103**	Speak English "very well"
B16001	104	**B16001104**	Speak English less than "very well"
B16001	105	**B16001105**	Hungarian:
B16001	106	**B16001106**	Speak English "very well"
B16001	107	**B16001107**	Speak English less than "very well"
B16001	108	**B16001108**	Arabic:
B16001	109	**B16001109**	Speak English "very well"
B16001	110	**B16001110**	Speak English less than "very well"
B16001	111	**B16001111**	Hebrew:
B16001	112	**B16001112**	Speak English "very well"
B16001	113	**B16001113**	Speak English less than "very well"
B16001	114	**B16001114**	African languages:
B16001	115	**B16001115**	Speak English "very well"
B16001	116	**B16001116**	Speak English less than "very well"
B16001	117	**B16001117**	Other and unspecified languages:
B16001	118	**B16001118**	Speak English "very well"

B16001	119	**B16001119**	Speak English less than "very well"
B16002			**HOUSEHOLD LANGUAGE BY HOUSEHOLDS IN WHICH NO ONE 14 AND OVER SPEAKS ENGLISH ONLY OR SPEAKS A LANGUAGE OTHER THAN ENGLISH AT HOME AND SPEAKS ENGLISH "VERY WELL"**
B16002			*Universe: Households*
B16002	1	**B16002001**	Total:
B16002	2	**B16002002**	English only
B16002	3	**B16002003**	Spanish:
B16002	4	**B16002004**	No one 14 and over speaks English only or speaks English "very well"
B16002	5	**B16002005**	At least one person 14 and over speaks English only or speaks English "very well"
B16002	6	**B16002006**	Other Indo-European languages:
B16002	7	**B16002007**	No one 14 and over speaks English only or speaks English "very well"
B16002	8	**B16002008**	At least one person 14 and over speaks English only or speaks English "very well"
B16002	9	**B16002009**	Asian and Pacific Island languages:
B16002	10	**B16002010**	No one 14 and over speaks English only or speaks English "very well"
B16002	11	**B16002011**	At least one person 14 and over speaks English only or speaks English "very well"
B16002	12	**B16002012**	Other languages:
B16002	13	**B16002013**	No one 14 and over speaks English only or speaks English "very well"
B16002	14	**B16002014**	At least one person 14 and over speaks English only or speaks English "very well"
B16003			**AGE BY LANGUAGE SPOKEN AT HOME FOR THE POPULATION 5 YEARS AND OVER IN HOUSEHOLDS IN WHICH NO ONE 14 AND OVER SPEAKS ENGLISH ONLY OR SPEAKS A LANGUAGE OTHER THAN ENGLISH AT HOME AND SPEAKS ENGLISH "VER**
B16003			*Universe: Population 5 years and over in households in which no one 14 and over speaks English only or speaks a language other than English at home and speaks English "very well"*
B16003	1	**B16003001**	Total:
B16003	2	**B16003002**	5 to 17 years:
B16003	3	**B16003003**	Speak only English
B16003	4	**B16003004**	Speak Spanish
B16003	5	**B16003005**	Speak other Indo-European languages
B16003	6	**B16003006**	Speak Asian and Pacific Island languages

B16003	7	**B16003007**	Speak other languages
B16003	8	**B16003008**	18 years and over:
B16003	9	**B16003009**	Speak Spanish
B16003	10	**B16003010**	Speak other Indo-European languages
B16003	11	**B16003011**	Speak Asian and Pacific Island languages
B16003	12	**B16003012**	Speak other languages

B15002			**SEX BY EDUCATIONAL ATTAINMENT FOR THE POPULATION 25 YEARS AND OVER**
B15002			*Universe: Population 25 years and over*
B15002	1	**B15002001**	Total:
B15002	2	**B15002002**	Male:
B15002	3	**B15002003**	No schooling completed
B15002	4	**B15002004**	Nursery to 4th grade
B15002	5	**B15002005**	5th and 6th grade
B15002	6	**B15002006**	7th and 8th grade
B15002	7	**B15002007**	9th grade
B15002	8	**B15002008**	10th grade
B15002	9	**B15002009**	11th grade
B15002	10	**B15002010**	12th grade, no diploma
B15002	11	**B15002011**	High school graduate, GED, or alternative
B15002	12	**B15002012**	Some college, less than 1 year
B15002	13	**B15002013**	Some college, 1 or more years, no degree
B15002	14	**B15002014**	Associate's degree
B15002	15	**B15002015**	Bachelor's degree
B15002	16	**B15002016**	Master's degree
B15002	17	**B15002017**	Professional school degree
B15002	18	**B15002018**	Doctorate degree
B15002	19	**B15002019**	Female:
B15002	20	**B15002020**	No schooling completed
B15002	21	**B15002021**	Nursery to 4th grade

B15002	22	**B15002022**	5th and 6th grade
B15002	23	**B15002023**	7th and 8th grade
B15002	24	**B15002024**	9th grade
B15002	25	**B15002025**	10th grade
B15002	26	**B15002026**	11th grade
B15002	27	**B15002027**	12th grade, no diploma
B15002	28	**B15002028**	High school graduate, GED, or alternative
B15002	29	**B15002029**	Some college, less than 1 year
B15002	30	**B15002030**	Some college, 1 or more years, no degree
B15002	31	**B15002031**	Associate's degree
B15002	32	**B15002032**	Bachelor's degree
B15002	33	**B15002033**	Master's degree
B15002	34	**B15002034**	Professional school degree
B15002	35	**B15002035**	Doctorate degree

B15003			**EDUCATIONAL ATTAINMENT FOR THE POPULATION 25 YEARS AND OVER**
B15003			*Universe: Population 25 years and over*
B15003	1	**B15003001**	Total:
B15003	2	**B15003002**	No schooling completed
B15003	3	**B15003003**	Nursery school
B15003	4	**B15003004**	Kindergarten
B15003	5	**B15003005**	1st grade
B15003	6	**B15003006**	2nd grade
B15003	7	**B15003007**	3rd grade
B15003	8	**B15003008**	4th grade
B15003	9	**B15003009**	5th grade
B15003	10	**B15003010**	6th grade
B15003	11	**B15003011**	7th grade
B15003	12	**B15003012**	8th grade
B15003	13	**B15003013**	9th grade

B15003	14	**B15003014**	10th grade
B15003	15	**B15003015**	11th grade
B15003	16	**B15003016**	12th grade, no diploma
B15003	17	**B15003017**	Regular high school diploma
B15003	18	**B15003018**	GED or alternative credential
B15003	19	**B15003019**	Some college, less than 1 year
B15003	20	**B15003020**	Some college, 1 or more years, no degree
B15003	21	**B15003021**	Associate's degree
B15003	22	**B15003022**	Bachelor's degree
B15003	23	**B15003023**	Master's degree
B15003	24	**B15003024**	Professional school degree
B15003	25	**B15003025**	Doctorate degree
B19013			**MEDIAN HOUSEHOLD INCOME IN THE PAST 12 MONTHS (IN 2012 INFLATION-ADJUSTED DOLLARS)**
B19013			*Universe: Households*
B19013	1	**B19013001**	Median household income in the past 12 months (in 2012 inflation-adjusted dollar
B19055			**SOCIAL SECURITY INCOME IN THE PAST 12 MONTHS FOR HOUSEHOLDS**
B19055			*Universe: Households*
B19055	1	**B19055001**	Total:
B19055	2	**B19055002**	With Social Security income
B19055	3	**B19055003**	No Social Security income
B19056			**SUPPLEMENTAL SECURITY INCOME (SSI) IN THE PAST 12 MONTHS FOR HOUSEHOLDS**
B19056			*Universe: Households*
B19056	1	**B19056001**	Total:
B19056	2	**B19056002**	With Supplemental Security Income (SSI)
B19056	3	**B19056003**	No Supplemental Security Income (SSI)
B19057			**PUBLIC ASSISTANCE INCOME IN THE PAST 12 MONTHS FOR HOUSEHOLDS**
B19057			*Universe: Households*
B19057	1	**B19057001**	Total:

B19057	2	**B19057002**	With public assistance income
B19057	3	**B19057003**	No public assistance income
B19058			**PUBLIC ASSISTANCE INCOME OR FOOD STAMPS/SNAP IN THE PAST 12 MONTHS FOR HOUSEHOLDS**
B19058			*Universe: Households*
B19058	1	**B19058001**	Total:
B19058	2	**B19058002**	With cash public assistance or Food Stamps/SNAP
B19058	3	**B19058003**	No cash public assistance or Food Stamps/SNAP
B19067			**AGGREGATE PUBLIC ASSISTANCE INCOME IN THE PAST 12 MONTHS (IN 2012 INFLATION-ADJUSTED DOLLARS) FOR HOUSEHOLDS**
B19067			*Universe: Households*
B19067	1	**B19067001**	Aggregate public assistance income in the past 12 months (in 2012 inflation-adjusted dollars)
B19101			**FAMILY INCOME IN THE PAST 12 MONTHS (IN 2012 INFLATION-ADJUSTED DOLLARS)**
B19101			*Universe: Families*
B19101	1	**B19101001**	Total:
B19101	2	**B19101002**	Less than $10,000
B19101	3	**B19101003**	$10,000 to $14,999
B19101	4	**B19101004**	$15,000 to $19,999
B19101	5	**B19101005**	$20,000 to $24,999
B19101	6	**B19101006**	$25,000 to $29,999
B19101	7	**B19101007**	$30,000 to $34,999
B19101	8	**B19101008**	$35,000 to $39,999
B19101	9	**B19101009**	$40,000 to $44,999
B19101	10	**B19101010**	$45,000 to $49,999
B19101	11	**B19101011**	$50,000 to $59,999
B19101	12	**B19101012**	$60,000 to $74,999
B19101	13	**B19101013**	$75,000 to $99,999
B19101	14	**B19101014**	$100,000 to $124,999
B19101	15	**B19101015**	$125,000 to $149,999
B19101	16	**B19101016**	$150,000 to $199,999

B19101	17	**B19101017**	$200,000 or more
B19325			**SEX BY WORK EXPERIENCE IN THE PAST 12 MONTHS BY INCOME IN THE PAST 12 MONTHS (IN 2012 INFLATION-ADJUSTE DOLLARS) FOR THE POPULATION 15 YEARS AND OVER**
B19325			*Universe: Population 15 years and over*
B19325	1	**B19325001**	Total:
B19325	2	**B19325002**	Male:
B19325	3	**B19325003**	Worked full-time, year-round in the past 12 months:
B19325	4	**B19325004**	No income
B19325	5	**B19325005**	With income:
B19325	6	**B19325006**	$1 to $2,499 or loss
B19325	7	**B19325007**	$2,500 to $4,999
B19325	8	**B19325008**	$5,000 to $7,499
B19325	9	**B19325009**	$7,500 to $9,999
B19325	10	**B19325010**	$10,000 to $12,499
B19325	11	**B19325011**	$12,500 to $14,999
B19325	12	**B19325012**	$15,000 to $17,499
B19325	13	**B19325013**	$17,500 to $19,999
B19325	14	**B19325014**	$20,000 to $22,499
B19325	15	**B19325015**	$22,500 to $24,999
B19325	16	**B19325016**	$25,000 to $29,999
B19325	17	**B19325017**	$30,000 to $34,999
B19325	18	**B19325018**	$35,000 to $39,999
B19325	19	**B19325019**	$40,000 to $44,999
B19325	20	**B19325020**	$45,000 to $49,999
B19325	21	**B19325021**	$50,000 to $54,999
B19325	22	**B19325022**	$55,000 to $64,999
B19325	23	**B19325023**	$65,000 to $74,999
B19325	24	**B19325024**	$75,000 to $99,999
B19325	25	**B19325025**	$100,000 or more
B19325	26	**B19325026**	Other:

B19325	27	**B19325027**	No income
B19325	28	**B19325028**	With income:
B19325	29	**B19325029**	$1 to $2,499 or loss
B19325	30	**B19325030**	$2,500 to $4,999
B19325	31	**B19325031**	$5,000 to $7,499
B19325	32	**B19325032**	$7,500 to $9,999
B19325	33	**B19325033**	$10,000 to $12,499
B19325	34	**B19325034**	$12,500 to $14,999
B19325	35	**B19325035**	$15,000 to $17,499
B19325	36	**B19325036**	$17,500 to $19,999
B19325	37	**B19325037**	$20,000 to $22,499
B19325	38	**B19325038**	$22,500 to $24,999
B19325	39	**B19325039**	$25,000 to $29,999
B19325	40	**B19325040**	$30,000 to $34,999
B19325	41	**B19325041**	$35,000 to $39,999
B19325	42	**B19325042**	$40,000 to $44,999
B19325	43	**B19325043**	$45,000 to $49,999
B19325	44	**B19325044**	$50,000 to $54,999
B19325	45	**B19325045**	$55,000 to $64,999
B19325	46	**B19325046**	$65,000 to $74,999
B19325	47	**B19325047**	$75,000 to $99,999
B19325	48	**B19325048**	$100,000 or more
B19325	49	**B19325049**	Female:
B19325	50	**B19325050**	Worked full-time, year-round in the past 12 months:
B19325	51	**B19325051**	No income
B19325	52	**B19325052**	With income:
B19325	53	**B19325053**	$1 to $2,499 or loss
B19325	54	**B19325054**	$2,500 to $4,999
B19325	55	**B19325055**	$5,000 to $7,499
B19325	56	**B19325056**	$7,500 to $9,999

B19325	57	**B19325057**	$10,000 to $12,499
B19325	58	**B19325058**	$12,500 to $14,999
B19325	59	**B19325059**	$15,000 to $17,499
B19325	60	**B19325060**	$17,500 to $19,999
B19325	61	**B19325061**	$20,000 to $22,499
B19325	62	**B19325062**	$22,500 to $24,999
B19325	63	**B19325063**	$25,000 to $29,999
B19325	64	**B19325064**	$30,000 to $34,999
B19325	65	**B19325065**	$35,000 to $39,999
B19325	66	**B19325066**	$40,000 to $44,999
B19325	67	**B19325067**	$45,000 to $49,999
B19325	68	**B19325068**	$50,000 to $54,999
B19325	69	**B19325069**	$55,000 to $64,999
B19325	70	**B19325070**	$65,000 to $74,999
B19325	71	**B19325071**	$75,000 to $99,999
B19325	72	**B19325072**	$100,000 or more
B19325	73	**B19325073**	Other:
B19325	74	**B19325074**	No income
B19325	75	**B19325075**	With income:
B19325	76	**B19325076**	$1 to $2,499 or loss
B19325	77	**B19325077**	$2,500 to $4,999
B19325	78	**B19325078**	$5,000 to $7,499
B19325	79	**B19325079**	$7,500 to $9,999
B19325	80	**B19325080**	$10,000 to $12,499
B19325	81	**B19325081**	$12,500 to $14,999
B19325	82	**B19325082**	$15,000 to $17,499
B19325	83	**B19325083**	$17,500 to $19,999
B19325	84	**B19325084**	$20,000 to $22,499
B19325	85	**B19325085**	$22,500 to $24,999
B19325	86	**B19325086**	$25,000 to $29,999

B19325	87	**B19325087**	$30,000 to $34,999
B19325	88	**B19325088**	$35,000 to $39,999
B19325	89	**B19325089**	$40,000 to $44,999
B19325	90	**B19325090**	$45,000 to $49,999
B19325	91	**B19325091**	$50,000 to $54,999
B19325	92	**B19325092**	$55,000 to $64,999
B19325	93	**B19325093**	$65,000 to $74,999
B19325	94	**B19325094**	$75,000 to $99,999
B19325	95	**B19325095**	$100,000 or more
B23001			**SEX BY AGE BY EMPLOYMENT STATUS FOR THE POPULATION 16 YEARS AND OVER**
B23001			*Universe: Population 16 years and over*
B23001	1	**B23001001**	Total:
B23001	2	**B23001002**	Male:
B23001	3	**B23001003**	16 to 19 years:
B23001	4	**B23001004**	In labor force:
B23001	5	**B23001005**	In Armed Forces
B23001	6	**B23001006**	Civilian:
B23001	7	**B23001007**	Employed
B23001	8	**B23001008**	Unemployed
B23001	9	**B23001009**	Not in labor force
B23001	10	**B23001010**	20 and 21 years:
B23001	11	**B23001011**	In labor force:
B23001	12	**B23001012**	In Armed Forces
B23001	13	**B23001013**	Civilian:
B23001	14	**B23001014**	Employed
B23001	15	**B23001015**	Unemployed
B23001	16	**B23001016**	Not in labor force
B23001	17	**B23001017**	22 to 24 years:
B23001	18	**B23001018**	In labor force:
B23001	19	**B23001019**	In Armed Forces

B23001	20	**B23001020**	Civilian:
B23001	21	**B23001021**	Employed
B23001	22	**B23001022**	Unemployed
B23001	23	**B23001023**	Not in labor force
B23001	24	**B23001024**	25 to 29 years:
B23001	25	**B23001025**	In labor force:
B23001	26	**B23001026**	In Armed Forces
B23001	27	**B23001027**	Civilian:
B23001	28	**B23001028**	Employed
B23001	29	**B23001029**	Unemployed
B23001	30	**B23001030**	Not in labor force
B23001	31	**B23001031**	30 to 34 years:
B23001	32	**B23001032**	In labor force:
B23001	33	**B23001033**	In Armed Forces
B23001	34	**B23001034**	Civilian:
B23001	35	**B23001035**	Employed
B23001	36	**B23001036**	Unemployed
B23001	37	**B23001037**	Not in labor force
B23001	38	**B23001038**	35 to 44 years:
B23001	39	**B23001039**	In labor force:
B23001	40	**B23001040**	In Armed Forces
B23001	41	**B23001041**	Civilian:
B23001	42	**B23001042**	Employed
B23001	43	**B23001043**	Unemployed
B23001	44	**B23001044**	Not in labor force
B23001	45	**B23001045**	45 to 54 years:
B23001	46	**B23001046**	In labor force:
B23001	47	**B23001047**	In Armed Forces
B23001	48	**B23001048**	Civilian:
B23001	49	**B23001049**	Employed

B23001	50	**B23001050**	Unemployed
B23001	51	**B23001051**	Not in labor force
B23001	52	**B23001052**	55 to 59 years:
B23001	53	**B23001053**	In labor force:
B23001	54	**B23001054**	In Armed Forces
B23001	55	**B23001055**	Civilian:
B23001	56	**B23001056**	Employed
B23001	57	**B23001057**	Unemployed
B23001	58	**B23001058**	Not in labor force
B23001	59	**B23001059**	60 and 61 years:
B23001	60	**B23001060**	In labor force:
B23001	61	**B23001061**	In Armed Forces
B23001	62	**B23001062**	Civilian:
B23001	63	**B23001063**	Employed
B23001	64	**B23001064**	Unemployed
B23001	65	**B23001065**	Not in labor force
B23001	66	**B23001066**	62 to 64 years:
B23001	67	**B23001067**	In labor force:
B23001	68	**B23001068**	In Armed Forces
B23001	69	**B23001069**	Civilian:
B23001	70	**B23001070**	Employed
B23001	71	**B23001071**	Unemployed
B23001	72	**B23001072**	Not in labor force
B23001	73	**B23001073**	65 to 69 years:
B23001	74	**B23001074**	In labor force:
B23001	75	**B23001075**	Employed
B23001	76	**B23001076**	Unemployed
B23001	77	**B23001077**	Not in labor force
B23001	78	**B23001078**	70 to 74 years:
B23001	79	**B23001079**	In labor force:

B23001	80	**B23001080**	Employed
B23001	81	**B23001081**	Unemployed
B23001	82	**B23001082**	Not in labor force
B23001	83	**B23001083**	75 years and over:
B23001	84	**B23001084**	In labor force:
B23001	85	**B23001085**	Employed
B23001	86	**B23001086**	Unemployed
B23001	87	**B23001087**	Not in labor force
B23001	88	**B23001088**	Female:
B23001	89	**B23001089**	16 to 19 years:
B23001	90	**B23001090**	In labor force:
B23001	91	**B23001091**	In Armed Forces
B23001	92	**B23001092**	Civilian:
B23001	93	**B23001093**	Employed
B23001	94	**B23001094**	Unemployed
B23001	95	**B23001095**	Not in labor force
B23001	96	**B23001096**	20 and 21 years:
B23001	97	**B23001097**	In labor force:
B23001	98	**B23001098**	In Armed Forces
B23001	99	**B23001099**	Civilian:
B23001	100	**B23001100**	Employed
B23001	101	**B23001101**	Unemployed
B23001	102	**B23001102**	Not in labor force
B23001	103	**B23001103**	22 to 24 years:
B23001	104	**B23001104**	In labor force:
B23001	105	**B23001105**	In Armed Forces
B23001	106	**B23001106**	Civilian:
B23001	107	**B23001107**	Employed
B23001	108	**B23001108**	Unemployed
B23001	109	**B23001109**	Not in labor force

B23001	110	**B23001110**	25 to 29 years:
B23001	111	**B23001111**	In labor force:
B23001	112	**B23001112**	In Armed Forces
B23001	113	**B23001113**	Civilian:
B23001	114	**B23001114**	Employed
B23001	115	**B23001115**	Unemployed
B23001	116	**B23001116**	Not in labor force
B23001	117	**B23001117**	30 to 34 years:
B23001	118	**B23001118**	In labor force:
B23001	119	**B23001119**	In Armed Forces
B23001	120	**B23001120**	Civilian:
B23001	121	**B23001121**	Employed
B23001	122	**B23001122**	Unemployed
B23001	123	**B23001123**	Not in labor force
B23001	124	**B23001124**	35 to 44 years:
B23001	125	**B23001125**	In labor force:
B23001	126	**B23001126**	In Armed Forces
B23001	127	**B23001127**	Civilian:
B23001	128	**B23001128**	Employed
B23001	129	**B23001129**	Unemployed
B23001	130	**B23001130**	Not in labor force
B23001	131	**B23001131**	45 to 54 years:
B23001	132	**B23001132**	In labor force:
B23001	133	**B23001133**	In Armed Forces
B23001	134	**B23001134**	Civilian:
B23001	135	**B23001135**	Employed
B23001	136	**B23001136**	Unemployed
B23001	137	**B23001137**	Not in labor force
B23001	138	**B23001138**	55 to 59 years:
B23001	139	**B23001139**	In labor force:

B23001	140	**B23001140**	In Armed Forces
B23001	141	**B23001141**	Civilian:
B23001	142	**B23001142**	Employed
B23001	143	**B23001143**	Unemployed
B23001	144	**B23001144**	Not in labor force
B23001	145	**B23001145**	60 and 61 years:
B23001	146	**B23001146**	In labor force:
B23001	147	**B23001147**	In Armed Forces
B23001	148	**B23001148**	Civilian:
B23001	149	**B23001149**	Employed
B23001	150	**B23001150**	Unemployed
B23001	151	**B23001151**	Not in labor force
B23001	152	**B23001152**	62 to 64 years:
B23001	153	**B23001153**	In labor force:
B23001	154	**B23001154**	In Armed Forces
B23001	155	**B23001155**	Civilian:
B23001	156	**B23001156**	Employed
B23001	157	**B23001157**	Unemployed
B23001	158	**B23001158**	Not in labor force
B23001	159	**B23001159**	65 to 69 years:
B23001	160	**B23001160**	In labor force:
B23001	161	**B23001161**	Employed
B23001	162	**B23001162**	Unemployed
B23001	163	**B23001163**	Not in labor force
B23001	164	**B23001164**	70 to 74 years:
B23001	165	**B23001165**	In labor force:
B23001	166	**B23001166**	Employed
B23001	167	**B23001167**	Unemployed
B23001	168	**B23001168**	Not in labor force
B23001	169	**B23001169**	75 years and over:

B23001	170	**B23001170**	In labor force:
B23001	171	**B23001171**	Employed
B23001	172	**B23001172**	Unemployed
B23001	173	**B23001173**	Not in labor force
B25003			**TENURE**
B25003			*Universe: Occupied housing units*
B25003	1	**B25003001**	Total:
B25003	2	**B25003002**	Owner occupied
B25003	3	**B25003003**	Renter occupied
C17002			RATIO OF INCOME TO POVERTY LEVEL IN THE PAST 12 MONTHS
C17002			Universe: Population for whom poverty status is determined
C17002	1	**C17002001**	Total:
C17002	2	**C17002002**	Under .50
C17002	3	**C17002003**	.50 to .99
C17002	4	**C17002004**	1.00 to 1.24
C17002	5	**C17002005**	1.25 to 1.49
C17002	6	**C17002006**	1.50 to 1.84
C17002	7	**C17002007**	1.85 to 1.99
C17002	8	**C17002008**	2.00 and over
C24010			SEX BY OCCUPATION FOR THE CIVILIAN EMPLOYED POPULATION 16 YEARS AND OVER
C24010			Universe: Civilian employed population 16 years and over
C24010	1	**C24010001**	Total:
C24010	2	**C24010002**	Male:
C24010	3	**C24010003**	Management, business, science, and arts occupations:
C24010	4	**C24010004**	Management, business, and financial occupations:
C24010	5	**C24010005**	Management occupations
C24010	6	**C24010006**	Business and financial operations occupations
C24010	7	**C24010007**	Computer, engineering, and science occupations:
C24010	8	**C24010008**	Computer and mathematical occupations
C24010	9	**C24010009**	Architecture and engineering occupations

C24010	10	**C24010010**	Life, physical, and social science occupations
C24010	11	**C24010011**	Education, legal, community service, arts, and media occupations:
C24010	12	**C24010012**	Community and social service occupations
C24010	13	**C24010013**	Legal occupations
C24010	14	**C24010014**	Education, training, and library occupations
C24010	15	**C24010015**	Arts, design, entertainment, sports, and media occupations
C24010	16	**C24010016**	Healthcare practitioners and technical occupations:
C24010	17	**C24010017**	Health diagnosing and treating practitioners and other technical occupations
C24010	18	**C24010018**	Health technologists and technicians
C24010	19	**C24010019**	Service occupations:
C24010	20	**C24010020**	Healthcare support occupations
C24010	21	**C24010021**	Protective service occupations:
C24010	22	**C24010022**	Fire fighting and prevention, and other protective service workers including supervisors
C24010	23	**C24010023**	Law enforcement workers including supervisors
C24010	24	**C24010024**	Food preparation and serving related occupations
C24010	25	**C24010025**	Building and grounds cleaning and maintenance occupations
C24010	26	**C24010026**	Personal care and service occupations
C24010	27	**C24010027**	Sales and office occupations:
C24010	28	**C24010028**	Sales and related occupations
C24010	29	**C24010029**	Office and administrative support occupations
C24010	30	**C24010030**	Natural resources, construction, and maintenance occupations:
C24010	31	**C24010031**	Farming, fishing, and forestry occupations
C24010	32	**C24010032**	Construction and extraction occupations
C24010	33	**C24010033**	Installation, maintenance, and repair occupations
C24010	34	**C24010034**	Production, transportation, and material moving occupations:
C24010	35	**C24010035**	Production occupations
C24010	36	**C24010036**	Transportation occupations
C24010	37	**C24010037**	Material moving occupations
C24010	38	**C24010038**	Female:
C24010	39	**C24010039**	Management, business, science, and arts occupations:

C24010	40	**C24010040**	Management, business, and financial occupations:
C24010	41	**C24010041**	Management occupations
C24010	42	**C24010042**	Business and financial operations occupations
C24010	43	**C24010043**	Computer, engineering, and science occupations:
C24010	44	**C24010044**	Computer and mathematical occupations
C24010	45	**C24010045**	Architecture and engineering occupations
C24010	46	**C24010046**	Life, physical, and social science occupations
C24010	47	**C24010047**	Education, legal, community service, arts, and media occupations:
C24010	48	**C24010048**	Community and social service occupations
C24010	49	**C24010049**	Legal occupations
C24010	50	**C24010050**	Education, training, and library occupations
C24010	51	**C24010051**	Arts, design, entertainment, sports, and media occupations
C24010	52	**C24010052**	Healthcare practitioners and technical occupations:
C24010	53	**C24010053**	Health diagnosing and treating practitioners and other technical occupations
C24010	54	**C24010054**	Health technologists and technicians
C24010	55	**C24010055**	Service occupations:
C24010	56	**C24010056**	Healthcare support occupations
C24010	57	**C24010057**	Protective service occupations:
C24010	58	**C24010058**	Fire fighting and prevention, and other protective service workers including supervisors
C24010	59	**C24010059**	Law enforcement workers including supervisors
C24010	60	**C24010060**	Food preparation and serving related occupations
C24010	61	**C24010061**	Building and grounds cleaning and maintenance occupations
C24010	62	**C24010062**	Personal care and service occupations
C24010	63	**C24010063**	Sales and office occupations:
C24010	64	**C24010064**	Sales and related occupations
C24010	65	**C24010065**	Office and administrative support occupations
C24010	66	**C24010066**	Natural resources, construction, and maintenance occupations:
C24010	67	**C24010067**	Farming, fishing, and forestry occupations
C24010	68	**C24010068**	Construction and extraction occupations
C24010	69	**C24010069**	Installation, maintenance, and repair occupations

C24010	70	**C24010070**	Production, transportation, and material moving occupations:
C24010	71	**C24010071**	Production occupations
C24010	72	**C24010072**	Transportation occupations
C24010	73	**C24010073**	Material moving occupations

Appendix B: Projected Coordinate System Information:

NAD_1983_StatePlane_New_York_Long_Island_FIPS_3104_Feet
WKID: 2263 Authority: EPSG

Projection: Lambert_Conformal_Conic
False_Easting: 984250.0
False_Northing: 0.0
Central_Meridian: -74.0
Standard_Parallel_1: 40.66666666666666
Standard_Parallel_2: 41.03333333333333
Latitude_Of_Origin: 40.16666666666666
Linear Unit: Foot_US (0.3048006096012192)

Geographic Coordinate System: GCS_North_American_1983
Angular Unit: Degree (0.0174532925199433)
Prime Meridian: Greenwich (0.0)
Datum: D_North_American_1983
  Spheroid: GRS_1980
    Semimajor Axis: 6378137.0
    Semiminor Axis: 6356752.314140356
    Inverse Flattening: 298.257222101

Appendix C: CrimeRisk Database Methodology Guide

Content
CrimeRisk is a block group and higher level geographic database consisting of a series of standardized indexes for a range of serious crimes against both persons and property. It is derived from an extensive analysis of several years of crime reports from the vast majority of law enforcement jurisdictions nationwide. The crimes included in the database are the "Part 1" crimes and include murder, rape, robbery, assault, burglary, theft, and motor vehicle theft. These categories are the primary reporting categories used by the FBI in its Uniform Crime Report (UCR), with the exception of Arson, for which data is very inconsistently reported at the jurisdictional level. Part II crimes are not reported in the detail databases and are generally available only for selected areas or at high levels of geography.

In accordance with the reporting procedures using in the UCR reports, aggregate indexes have been prepared for personal and property crimes separately, as well as a total index. While this provides a useful measure of the relative "overall" crime rate in an area, it must be recognized that these are unweighted indexes, in that a murder is weighted no more heavily than a purse snatching in the computation. For this reason, caution is advised when using any of the aggregate index values.

Methodology
The primary source of CrimeRisk was a careful compilation and analysis of the FBI Uniform Crime Report databases. On an annual basis, the FBI collects data from each of about 16,000 separate law enforcement jurisdictions at the city, county, and state levels and compiles these into its annual Uniform Crime Report (UCR). The latest national crime report can be obtained either from the FBI web site in Adobe Portable Document (PDF) format or can be ordered directly from the FBI. While useful, the UCR provides detailed data only for the largest cities, counties, and metropolitan areas.

The original analysis was undertaken by obtaining detailed jurisdictional level data for the years 1990 through 1996, which were supplemented with 1999 preliminary UCR statistics at the State level and for cities and metropolitan areas where those have been released. We are now using UCR data from 1998-2006. The preliminary 2007 release data was used to balance the models to the latest available data.

A considerable effort was made to correct a number of problems that are prevalent within the FBI databases, including:

- The standardization of jurisdictional names: the FBI does not employ Census bureau codes in its databases and the jurisdictional names contain numerous typographical errors and format discrepancies which needed to be manually corrected

- Reporting by individual jurisdictions can be inconsistent from year to year, in that data for some jurisdictions is missing for one or more years and required handling

- Reporting for some crime types is inconsistent between jurisdictions. The FBI handles this by simply suppressing the statistics entirely for those areas. This primarily affects the rape category for Illinois, where statistics are suppressed for all but the largest jurisdictions. These missing values were handled via the modeling process, in which rape estimates were prepared for these jurisdictions by using a model which related rape incidence to other crime types

- The standardization of the database to account for jurisdictional overlaps. For example, the California Highway

Patrol has jurisdiction over only state and interstate highways in urban areas.

- Crime rates in general have been declining over the past several years, so it was necessary to adjust the historical data to reflect current crime rates.

Once this correction and standardization effort was completed, the database consisted of a time series of six years of data covering:

- All cities and towns which have their own police agency
- All cities and towns where policing for the local jurisdiction is contracted to a higher level agency but which tracks statistics separately (e.g. the city of Thousand Oaks, California contracts with the Ventura County Sheriff's Department for police services, but the incident reports are separately compiled)
- A record for each county which covers the population not covered by either of the two cases above. This is normally either a County Sheriff (or equivalent) or a State level jurisdiction which reports incidence of crime by county (e.g. in New York, the State Trooper).

For a very limited number of areas, such as New York City, the local jurisdiction spans several counties.

The initial models were undertaken using a subset of this database. In the smallest cities, a single murder will have a profound effect on the crime rate per 100,000 population that would severely distort the resulting models. Cities with less than 2,500 people were reassigned to their parent counties for the purpose of the analysis. A wide range of 1990 Census and current year demographic attributes was extracted from AGS' databases for the remaining areas (approximately 8,500 separate "jurisdictions"). This database was then used as the primary modeling database and was used later for scaling purposes.

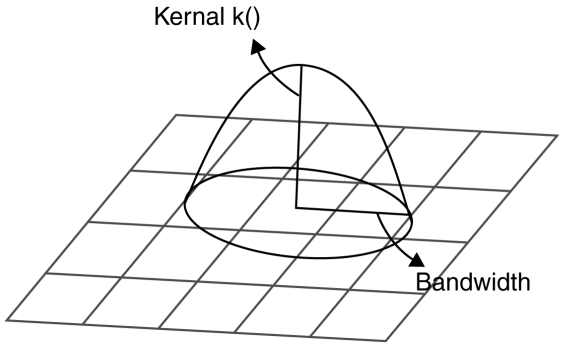
Each of the seven crime types was modeled separately, using an initial range of about 65 socio-economic characteristics taken from the 2000 Census and AGS' current year estimates. Separate models were constructed for each of the nine Census regions (e.g. New England, East North Central, Pacific) in order to account for regional differences in crime rates and the demographic characteristics which underlay them. The models constructed typically accounted for over 85% of the variance in crime rates at this "jurisdiction" level, although it should be noted that the results for property crimes were generally more reliable than for personal crimes.

The results of these models were then applied to the block group level using the same demographic attributes compiled at the block group level. The resulting estimates were then scaled to match the master database of 8,500 jurisdictions. For cities, the block groups within each city were scaled to match the city total. For areas outside of these cities (or for smaller centers), results were scaled to match the county total after adjusting for those cities scaled separately.

The final crime rate estimates were then weighted by population and aggregated to the national totals. The results were then scaled to match the 2007 preliminary estimates (at a state level) and converted to indexes relative to the national total.

Source: Applied Geographic Solutions, Inc. v2, May 2010

Appendix D: Kernel Density Estimation (KDE)



The GIS analysis conducted for this project utilized Kernel density estimation (KDE) in order to construct several neighborhood resource facility variables. KDE is a GIS analysis technique that creates a continuous surface based on point data in a neighborhood as defined by a circular distance. Conceptually, a smoothly curved surface is fitted over each point. The surface value is highest at the location of the point and diminishes with increasing distance from the point, reaching zero at the search radius distance from the point (i.e., distance decay function). Density surfaces are effective at identifying where features are concentrated – highlighting areas of intense activity. More a more thorough explanation of KDE, please read the following three paragraphs in this section.
When KDE was employed for this project, a consistent output grid resolution of 150 square feet, a 1-kilometer bandwidth (search radius), and output area units of square kilometers were used. Once the kernel density grids had been created, zonal summary statistics were used to calculate a statistical summary of the values in each raster density grid that fell within the bounds of each neighborhood definition polygon [min, max, mean, standard deviation, and count]. That is, for each neighborhood definition, a statistical summary of the values in cells falling within the bounds of each zonal polygon was calculated for inclusion in the models. These zonal aggregations average out any high precision errors that may appear at the individual cell level (Longley et al. 2001).

Kernel Density Description
Kernel density-based approaches create measures that are freed from underlying arbitrarily-bounded administrative units such as Census tracts and zip codes by incorporating distance decay functions. These functions can be used to include information about attributes in a given bandwidth outside a Census tract into the measures generated for each Census tract. This technique uses an arbitrary set of points in a grid overlaid on the study area and uses a three-dimensional floating function to estimate a continuous density surface representing the measure in question (for instance, population density). The density surface is a function of the distances between each grid point and each neighborhood resource facility or Census block group centroid that falls within a predefined distance or bandwidth. The contribution of each neighborhood resource facility to the local density value at a given grid point is based on its distance from the center. Nearby neighborhood resource facilities are given more weight in the density calculation than those farther away. The weights given to neighborhood resource facilities near the boundary defined by the bandwidth approach zero.
In kernel density estimation, the influence of each data point is formally modeled using a mathematical function called a kernel (Silverman 1986, Scott 1998, Wand 1995). When using a kernel function, the population is spread or distributed around the areal unit according to the shape of the kernel. Typical examples of kernels are parabolic, square wave, Gaussian, and the quadratic function. The exact shape or form of the kernel function has a relatively marginal effect on the resulting density estimates (Silverman 1986, Wand 1995). We will use a "Gaussian kernel" method for creating our density grids. This function is the industry standard and is preprogrammed in the ArcGIS Spatial Analyst extension; it utilizes a kernel function based on the quadratic kernel function described in Silverman (1986, p. 76, equation 4.5, Gatrell et al. 1996). This KDE

methodology will be used to create continuous surfaces from discrete point data representing two broad categories: neighborhood resource facilities (represented as single points); and Census variables (areal units represented as centroids).

The general form of the kernel density estimator is:

$$w_{i,j} = \begin{cases} \left[1 - \left(\frac{d_{i,j}}{D}\right)^2\right]^2 & d_{i,j} < D \\ 0 \end{cases}$$

where dij is the distance from point i to neighborhood resource facility j and D is the value of the bandwidth. The points, I, represent grid points with a given resolution.

When kernel density estimation is applied, two user-specified parameters can have a dramatic effect on the resulting density: the output resolution of the density grid, and the radius or bandwidth of the kernel function. The grid resolution defines the locations at which estimates are made. (The choice of location of this grid marginally affects the density estimates made, although provided the grid resolution is substantially smaller than the bandwidth the location effect is negligible.) The density estimate is also strongly dependent on the bandwidth parameter of the kernel function: increasing the kernel bandwidth leads to smoothly varying output rasters; decreasing bandwidth produces more localized surface patterns (O'Sullivan and Unwin 2002). It is important to choose a bandwidth that reflects the underlying distribution of the discrete point data (O'Sullivan and Unwin 2002). Research using kernel density functions in dense, urban environments typically uses small grid resolutions and bandwidths to preserve local variation in the underlying Census geographies; decisions are also based on the theoretical understanding of service areas or distances people are likely to travel for a given service (Guagliardo et al. 2004). Using an iterative process, we determined an appropriate grid resolution and bandwidths that maintained the local variation in our data and didn't over-generalize density estimates (O'Sullivan and Unwin 2002).

Appendix E: Network Buffer Process

The following steps were performed in ArcGIS 10.1 (ArcInfo – aka Desktop Advanced) using scripting in python. The Network Analyst extension is required.

Radial Buffers

Radial Buffers are necessary to clip Network Buffer polygons as the Network Buffer polygons sometimes generate artifact slivers that extend past the set distance. For quality control purposes.

1) Generate 264, 1320, 2640 feet radial buffers.

- a) Create standard radial buffers for r1 geography and n1, n2 geographies for clip

Network Buffers

1) Check out Network Analyst extension.

Necessary for python script

2) Create Detailed Network Buffer for 1320 & 2640 ft.

- a) Make service area layer
    - 1320 Feet to meters is 402.336 Meters, the lion_ped_nd.nd (pedestrian network dataset) is in meters
    - 2640 Feet to meters is 804.672 Meters, the lion_ped_nd.nd (pedestrian network dataset) is in meters
- b) Add locations
- c) Solve
- d) Feature class to feature class: polygons

3) Create Line Network Buffer for 1320 & 2640 ft.

- a) Make service area layer
- b) Add locations
- c) Solve
- d) Feature class to feature class: lines
- e) Buffer line network buffers by 50 feet with flat end-type
- f) Merge **Detailed Network Buffers** along with **Line Network Buffers** output buffered 50 feet
- g) Dissolve the merged **Detailed Network Buffers** along with **Line Network Buffers** output buffered 50 feet by unique FacilityID
- h) Add msmuid text field to network buffers, these dont come thru network analysis so regenerate
- i) Calculate msmuid text field for network buffers

4) Select each Network Buffer feature and then clip by its corresponding radial buffer and append to new feature class.

- a) Create empty feature classes for clip ouput to be appended to
- b) Add ID fields so the append carries over the unique id (msmuid)
- c) For n1 & n2 (1320 and 2640 ft) select each network buffer feature and then clip by its corresponding radial buffer.
    - Select Network Buffer and make into its own feature class
    - Select Radial Buffer and make into its own feature class
    - Clip Network Buffer by Radial Buffer
    - Append clipped feature to feature class from step 4a