"The Validity of the Monocentric City Model in a Polycentric Age"

US Metropolitan Areas in 1990, 2000 and 2010

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1 Code Notebook

This document presents the code and steps neccesary to reproduce the results in the paper *"The Validity of the Monocentric City Model in a Polycentric Age: US Metropolitan Areas in 1990, 2000 and 2010"*, by Dani Arribas-Bel and Fernando Sanz-Gracia, forthcoming in the journal Urban Geography. If you want to cite the paper or use any of the code and/or results in it, please use the following citation:

```
@article{arribasbel_sanzgracia_centersUS,
        author = "Arribas-Bel, Daniel and Sanz-Gracia, Fernando",
        journal = "Urban Geography",
        title = "{The Validity of the Monocentric City Model in a Polycentric Age:
                US Metropolitan Areas in 1990, 2000 and 2010}",
        year = "2014",
        volume = "",
        pages = {}
}
```

1.1 Access and software requirements

```
In [43]: %matplotlib inline
         import os
         import pandas as pd
         import employment_centers_tools as tools
```

1.2 Data

Employment data for 1990 and 2000 comes from the "Census 2000 Special Tabulation Product 64" (`stp64`), which offers tract- to-tract commuting flows for the whole country. We consider only tracts within boundaries of the MSAs studied and sum over inflows to obtain employment numbers at the tract level. For 2010, there is no `stp64` so we use the Census Transportation Planning Products (CTPP) 5-year small area data, which is based on ACS 2006-2010 Census Data and provides employment counts at the tract level for 2010.

Since it is not clear to the authors whether it is legal to redistribute original Census data (particularly when the `stp64` is not available as a free download), **the raw dataset used for this paper is not included**. However, in order to illustrate how the process was carried out, below we show the structure of the data and how that is entered into the code to identify employment centers. This should allow users who have accessed the original data from the Census to replicate our results. We do provide the output of the center identification in the form of shapefiles (one per MSA per year). These can be found in the repository where this notebook and other code is hosted.

We store employment data in `csv` files, using a separate one for each MSA for each year. The raw format of these files is as follows, where the top of the file for MSA 10180 in 1990 is shown:

```
In [14]: !head /Users/dani/AAA/LargeData/T-CentersData/attributes/3-empDen/empDen1990/10180.csv
```

```
gisjoin2,emp,area,dens,densEB
48044100102,2855.0,45088315.8862,6.33201738385e-05,6.32174061116e-05
48044100105,357.0,16138974.527,2.212036455e-05,2.20337682175e-05
48044100104,272.0,18017057.8625,1.5096804488e-05,1.56769988243e-05
48044100107,565.0,18156353.5203,3.11185833305e-05,3.18837079257e-05
48044100108,1484.0,25713732.5898,5.77123525267e-05,5.73154004704e-05
48044100106,342.0,25402742.4933,1.34631132875e-05,1.35600665231e-05
48044100110,1095.0,12176093.1624,8.99303237414e-05,8.84590480255e-05
48044100112,1339.0,20690727.6527,6.47149787323e-05,6.86296980824e-05
48044100113,2364.0,30324316.5093,7.79572393421e-05,7.73806762075e-05
```

These files can be loaded and combined for 1990 in one DataFrame with the following code:

```
In [8]: empF90 = '/Users/dani/AAA/LargeData/T-CentersData/attributes/3-empDen/empDen1990/'
        emp90 = pd.concat([tools.load_msa_data(empF90+f, y90=True) for f in os.listdir(empF90)])
```

```
In [16]: emp90.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 54994 entries, G48044100102 to G04001900049
Data columns (total 3 columns):
emp           54994 non-null float64
Shape_area    54994 non-null float64
msa           54994 non-null object
dtypes: float64(2), object(1)
```

```
In [12]: emp90.head()
```

```
Out[12]:                 emp  Shape_area     msa
         gisjoin2
         G48044100102  2855    4.188840  m10180
         G48044100105   357    1.499359  m10180
         G48044100104   272    1.673839  m10180
         G48044100107   565    1.686780  m10180
         G48044100108  1484    2.388883  m10180
```

Similar steps can be taken for 2000:

```
In [9]: empF00 = '/Users/dani/AAA/LargeData/T-CentersData/attributes/3-empDen/empDen2000/'
        emp00 = pd.concat([tools.load_msa_data(empF00+f) for f in os.listdir(empF00)])
```

Steps for 2010 are slightly different as the data are collected from a different source. We begin with a csv that looks as follows:

```
In [25]: !head /Users/dani/AAA/LargeData/ctpp/data2010/tractPOW_all.csv
```

```
head: /Users/dani/AAA/LargeData/ctpp/data2010/tractPOW_all.csv: No such file or directory
```

```
In [6]: emp10_link = '/Users/dani/AAA/LargeData/ctpp/data2010/tractPOW_all.csv'
        shp_link = '/Users/dani/AAA/LargeData/nhgis/shapeFiles/nhgis0019_shapefile_tl2010_us_tract_2010/
        cty2msa = pd.read_csv('cty2msa.csv', names=['cty', 'msa'], index_col=0, squeeze=True)
        shpW_out = '/Users/dani/AAA/LargeData/nhgis/shapeFiles/nhgis0019_shapefile_tl2010_us_tract_2010/
        emp10 = pd.read_csv(emp10_link)[['GISJOIN', 'emp', 'Shape_area']]
        emp10['Shape_area'] = emp10['Shape_area'] * 0.000001 #Area in Km2
        emp10['msa'] = emp10['GISJOIN'].apply(lambda x: \
                tools.msafy('c'+x[1:3]+x[4:7], cty2msa))
        emp10 = emp10.dropna() # Only tracts in MSA && w/ employment
```

Once all the data are loaded, it is very straightforward to replicate Table 1 in the paper:

```
In [10]: table = pd.DataFrame()
         for year, emp in [(1990, emp90), (2000, emp00), (2010, emp10)]:
             minTpMSA = emp.groupby('msa').count()['emp'].min()
             maxTpMSA = emp.groupby('msa').count()['emp'].max()
             meanTpMSA = emp.groupby('msa').count()['emp'].mean()
             summary = pd.Series({'N. MSAs': len(emp['msa'].unique()), \
                                  'N. Tracts': len(emp), \
                                  'Min. N. Tracts/MSA': minTpMSA, \
                                  'Max. N. Tracts/MSA': maxTpMSA, \
                                  'Average. N. Tracts/MSA': meanTpMSA})
             table[year] = summary
         table.reindex(['N. MSAs', 'N. Tracts', 'Min. N. Tracts/MSA', \
                        'Max. N. Tracts/MSA', 'Average. N. Tracts/MSA'])
```

```
Out[10]:                               1990           2000           2010
         N. MSAs                  359.00000     359.000000     359.000000
         N. Tracts              54994.00000   52329.000000   58808.000000
         Min. N. Tracts/MSA        17.00000      10.000000      13.000000
         Max. N. Tracts/MSA      4565.00000    4493.000000    4510.000000
         Average. N. Tracts/MSA   153.18663     145.763231     163.810585
```

1.3 Center identification

We use the data we have just loaded and combine them with geographical data to derive spatial relationships (these are needed to run the main identification algorithm). We use shapefiles of the tracts for each year downloaded from NHGIS and projected to state plane so areas can be calculated (not included in the repository either for similar redistribution reasons as with employment data).

Since the data are not shipped in the repository, the code below will only run if you provide it separately. This implies you need to point `cent_inYY` (replace `YY` by the year) to the folder where you have separate files for each MSA. Once you run the code below, shapefiles and `.gal` files will be created in the `cent_outYY` directory.

```
In [11]: import numpy as np
         import multiprocessing as mp
         #pool = mp.Pool(mp.cpu_count())
         seed = np.random.seed(1234)
```

For 1990, this would identify the centers (make sure to modify `cent_in90` and `cent_out90` to fit your setup):

```
In []: cent_in90 = '/Users/dani/AAA/LargeData/T-CentersData/shapes/msaTracts1990polygonsSP/'
       cent_out90 = '/Users/dani/Desktop/test90/'

       emp90['dens_raw'] = (emp90['emp'] * 1.) / emp90['Shape_area']
       emp90['GISJOIN'] = emp90.index
       pars = [(emp90[emp90['msa']==msa], cent_in90+msa[1:]+'.shp', cent_out90) \
               for msa in emp90['msa'].unique()]

       out = pool.map(tools.act_on_msa, pars[:2])
```

For 2000, this would identify the centers (make sure to modify `cent_in00` and `cent_out00` to fit your setup):

```
In []: cent_in00 = '/Users/dani/AAA/LargeData/T-CentersData/shapes/msaTracts2000polygonsSP/'
       cent_out00 = '/Users/dani/Desktop/test00/'

       emp00['dens_raw'] = (emp00['emp'] * 1.) / emp00['Shape_area']
       emp00['GISJOIN'] = emp00.index
       pars = [(emp00[emp00['msa']==msa], cent_in00+msa[1:]+'.shp', cent_out00) \
               for msa in emp00['msa'].unique()]

       out = pool.map(tools.act_on_msa, pars[:2])
```

For 2010, this would identify the centers (make sure to modify `cent_in10` and `cent_out10` to fit your setup). Note that in this case, the way the shapefile is passed is slightly different because we are using 2010 data that we have sourced differently.

```
In []: cent_out10 = '/Users/dani/Desktop/test10/'
       shp_link = '/Users/dani/AAA/LargeData/nhgis/shapeFiles/nhgis0019_shapefile_tl2010_us_tract_2010/

       emp10['dens_raw'] = (emp10['emp'] * 1.) / emp10['Shape_area']
       emp10['GISJOIN'] = emp10.index
       pars = [(emp10[emp10['msa']==msa], shp_link, cent_out10) \
               for msa in emp10['msa'].unique()]

       out = pool.map(tools.act_on_msa, pars[:2])
```

1.4 Evolution tables

Once this has run, we have created three folders that contain shapefiles with the identified centers in each MSA in each period. A compilation of these can be found in the repository in the `geojson` format, one for each year. The output can be reloaded again and used to recreate Tables 2-4 in the paper.

```
In [54]: cent_out90 = '/Users/dani/Desktop/test90/'
         cent_out00 = '/Users/dani/Desktop/test00/'
         cent_out10 = '/Users/dani/Desktop/test10/'

         # Collect all results
         years = [1990, 2000, 2010]
         links = [cent_out90, cent_out00, cent_out10]
         db = []
         for year, link in zip(years, links):
             temp = pd.concat(map(lambda l: pd.read_csv(l, index_col=0), \
                     [link+l for l in os.listdir(link) if l[-4:]=='.csv']))
             temp['year'] = year
             db.append(temp)
         db = pd.concat(db)

In [55]: tab = tools.evol_tab(db)
         tab

Out[55]: 1990         2000         2010
         empty        empty        empty           1
                      monocentric  monocentric    15
                                   polycentric     2
                      polycentric  monocentric     1
         monocentric  empty        monocentric     1
                      monocentric  empty           2
```

```
                          monocentric    148
                          polycentric     22
             polycentric  monocentric      7
                          polycentric     23
polycentric  monocentric  empty            1
                          monocentric     29
                          polycentric     11
             polycentric  monocentric      6
                          polycentric     90
dtype: int64
```

Which we can re-format to make it look more appealing:

```
In [37]: print "Table 2"
         tab2 = tab.groupby(level=[0, 1]).sum().unstack().fillna(0)
         tab2['Total 1990'] = tab2.sum(axis=1)
         tab2.loc['Total 2000', :] = tab2.sum(axis=0)
         tab2
```

```
Table 2
```

```
Out[37]: 2000         empty  monocentric  polycentric  Total 1990
         1990
         empty            1           17            1          19
         monocentric      1          172           30         203
         polycentric      0           41           96         137
         Total 2000       2          230          127         359
```

```
In [42]: print "Table 3"
         tab3 = tab.groupby(level=[1, 2]).sum().unstack().fillna(0)
         tab3['Total 2000'] = tab3.sum(axis=1)
         tab3.loc['Total 2010', :] = tab3.sum(axis=0)
         tab3
```

```
Table 3
```

```
Out[42]: 2010         empty  monocentric  polycentric  Total 2000
         2000
         empty            1            1            0           2
         monocentric      3          192           35         230
         polycentric      0           14          113         127
         Total 2010       4          207          148         359
```

```
In [41]: print "Table 4"
         tab4 = tab.groupby(level=[0, 2]).sum().unstack().fillna(0)
         tab4['Total 2000'] = tab4.sum(axis=1)
         tab4.loc['Total 2010', :] = tab4.sum(axis=0)
         tab4
```

```
Table 4
```

```
Out[41]: 2010         empty  monocentric  polycentric  Total 2000
         1990
         empty            1           16            2          19
         monocentric      2          156           45         203
         polycentric      1           35          101         137
         Total 2010       4          207          148         359
```

1.5 Spatial analysis of polycentricity

For this section, we also rely on two additional layers. One is the centroid of the MSAs, and is derived from the previous shapefiles by performing a simple GIS operation and projecting the output into the `EPSG:2146`. The second one is an additional shapefile downloaded from NHGIS as well that contains the polygons of the US continental lower states. Since this is very common and is used only for aesthetic purposes, the shapefile is not provided either.

For this illustration, we use only 99 random permutations to build the empirical distribution of both the global and local versions of Moran's I. The results presented in the paper, however, are based on 99,999 and thus are more reliable (although take much longer to run).

```
In [93]: import pysal as ps
         msa_pts_link = '/Users/dani/Desktop/msas_points2163.shp'
         states_link = '/Users/dani/Desktop/states2163.shp'
         years = [1990, 2000, 2010]
         perms = 99
```

```
In [94]: msas = db.groupby(['msa', 'year']).apply(\
                     lambda x: x.groupby('center_id').ngroups).unstack()
         ord = ['m'+i for i in ps.open(msa_pts_link.replace('.shp', '.dbf')).by_col('CBSA')]
         msas = msas.reindex(ord)
```

1.5.1 Moran's I

Moran's I indices that are used to justify further spatial analysis in the paper. The idea is to explore whether the spatial arrangement of polycentricity follows any specific pattern discernible from spatial randomness. Rejecting the null points to such case.

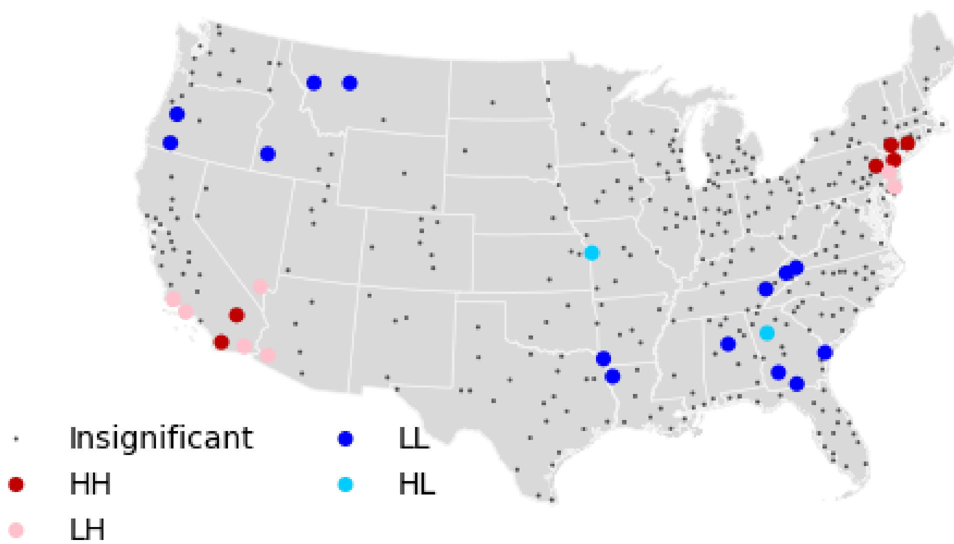
```
In [69]: morans = []
         for k in [9]:
             w = ps.knnW_from_shapefile(msa_pts_link, k=k)
             w.transform = 'R'
             m_90 = ps.Moran(msas[1990].astype(float), w, permutations=perms)
             m_00 = ps.Moran(msas[2000].astype(float), w, permutations=perms)
             m_10 = ps.Moran(msas[2010].astype(float), w, permutations=perms)
             t90_00 = (msas[2000] - msas[1990]).astype(float)
             m_90_00 = ps.Moran(t90_00, w, permutations=perms)
             t00_10 = (msas[2010] - msas[2000]).astype(float)
             m_00_10 = ps.Moran(t00_10, w, permutations=perms)
             out = pd.DataFrame({'I': [m_90.I, m_00.I, m_10.I, m_90_00.I, m_00_10.I], \
                     'p': [m_90.p_sim, m_00.p_sim, m_10.p_sim, m_90_00.p_sim, m_00_10.p_sim], \
                     'var': ['m_90', 'm_00', 'm_10', 'm_90_00', 'm_00_10']})
             out['w'] = 'w' + str(k)
             morans.append(out)
         morans = pd.concat(morans).pivot('var', 'w')
         morans
```

```
Out[69]:                 I     p
         w              w9    w9
         var
         m_00     0.061979  0.03
         m_00_10  0.036066  0.09
         m_10     0.074421  0.01
         m_90     0.036422  0.11
         m_90_00  0.020798  0.12
```

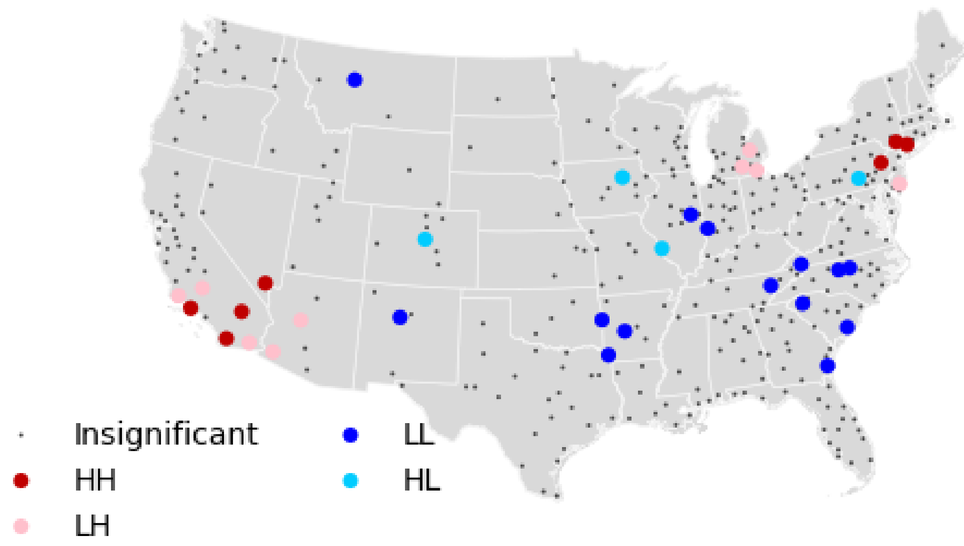
```
In [86]: # Within a loop in case the user wants to explore different values for k
         for k in [9]:
             w = ps.knnW_from_shapefile(msa_pts_link, k=k)
             w.transform = 'R'
             m_90 = ps.Moran_Local(msas[1990].astype(float).values, w, permutations=perms)
             p = tools.plot_lisa(m_90, st=states_link, msa=msa_pts_link, title='Centers in 1990')
             m_00 = ps.Moran_Local(msas[2000].astype(float).values, w, permutations=perms)
             p = tools.plot_lisa(m_00, st=states_link, msa=msa_pts_link, title='Centers in 2000 | Map 1
             m_10 = ps.Moran_Local(msas[2010].astype(float).values, w, permutations=perms)
             p = tools.plot_lisa(m_10, st=states_link, msa=msa_pts_link, title='Centers in 2010')

             t90_00 = (msas[2000] - msas[1990]).astype(float).values
             m_90_00 = ps.Moran_Local(t90_00, w, permutations=perms)
             p = tools.plot_lisa(m_90_00, st=states_link, msa=msa_pts_link, \
                                 title='Change in centers 1990-2000')
             t00_10 = (msas[2010] - msas[2000]).astype(float).values
             m_00_10 = ps.Moran_Local(t00_10, w, permutations=perms)
             p = tools.plot_lisa(m_00_10, st=states_link, msa=msa_pts_link,
                                 title='Change in centers 2000-2010 | Map 2')
```

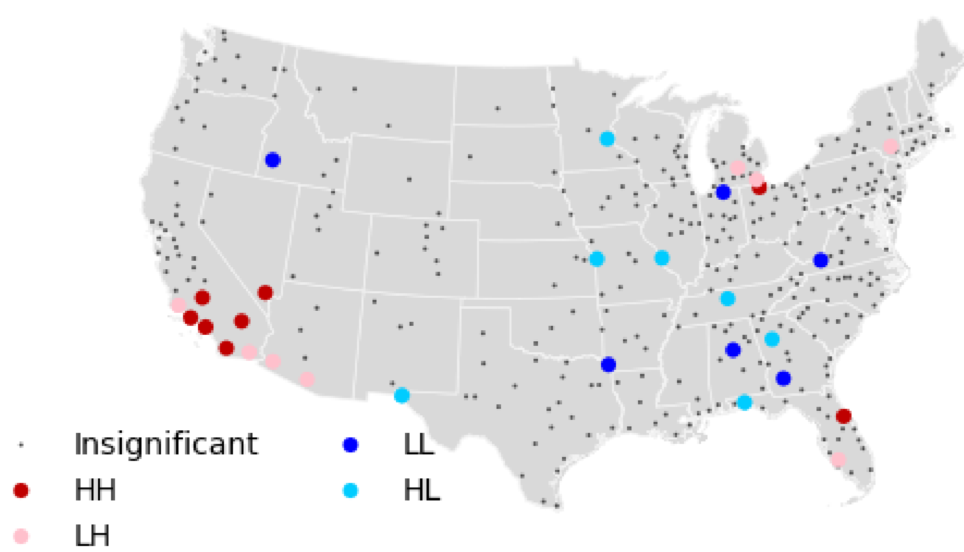
Centers in 1990

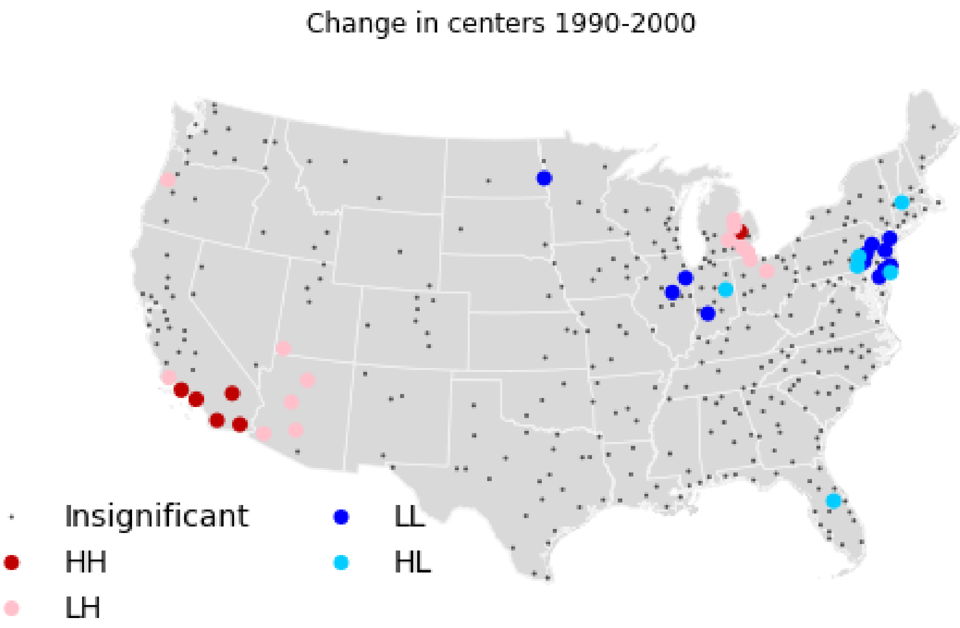


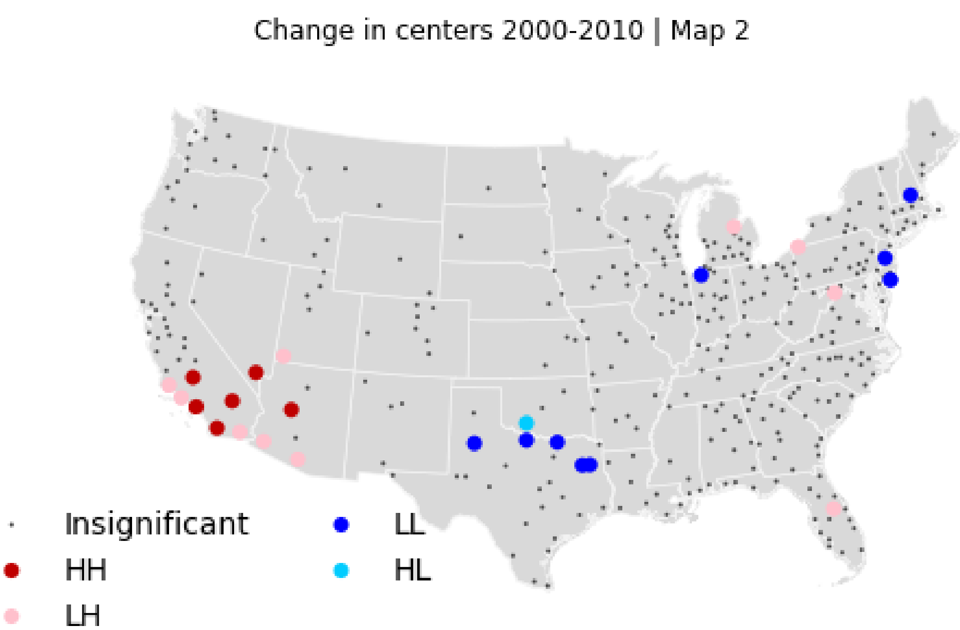
Centers in 2000 | Map 1



Centers in 2010







1.6 City Characterization

Results from the random labeling analysis performed in Section 6 and presented in Tables 5 to 8 of the paper. This basically calculates average values for several variables by type of MSA (no centers, monocentric, polycentric) and tests for statistically significant differences between the averages by using the random labeling technique, borrowed from Rey & Sastré-Gutiérrez (2010). The variables employed are: total population, employment density, income per capita and percentage of people below the poverty line.

Population, income and poverty are also obtained from NHGIS and not redistributed in this context. Employment and density are calculated from the previous data shown in the sections above.

In [121]:
```
pop00F='/Users/dani/AAA/LargeData/T-CentersData/attributes/5-pop/pop2000/'
pop00 = pd.concat([tools.load_soc_ec(pop00F+l) for l in os.listdir(pop00F)])
pop00 = pop00.groupby('msa').sum()

sec00F='/Users/dani/AAA/LargeData/T-CentersData/attributes/7-socEc/socEc2000/'
sec00 = pd.concat([tools.load_soc_ec(sec00F+l) for l in os.listdir(sec00F)])
sec00 = sec00.groupby('msa').sum().drop('incpc', axis=1)

msas_soec = db.groupby(['msa', 'year']).apply(\
            lambda x: x.groupby('center_id').ngroups)\
            .apply(tools._monopoly).unstack()
msas_soec = msas_soec.join(pop00).join(sec00)
msas_soec = msas_soec.join(db[db['year']==2000][['emp', 'Shape_area', 'msa']]\
        .groupby('msa').sum())
msas_soec['emp_dens'] = msas_soec['emp'] * 1. / msas_soec['Shape_area']
msas_soec['inc_pc'] = msas_soec['inc'] * 1. / msas_soec['pop']
msas_soec['pct_below'] = msas_soec['below'] * 100. / msas_soec['pop']
msas_soec = msas_soec[[1990, 2000, 2010, \
        'pop', 'emp_dens', 'inc_pc', 'pct_below']]
```

In [133]:
```
perms = 99
rl90_00 = tools.do_rl(msas_soec, [1990, 2000], perms)
for var in rl90_00:
    print "\n\t%s"%var
    print rl90_00[var].unstack().fillna('')

print '------------------------------------------------------------------'
rl_tables = []
rl00_10 = tools.do_rl(msas_soec, [2000, 2010], perms)
for var in rl00_10:
    print "\n\t%s"%var
    tab = rl00_10[var].unstack().fillna('')
    print tab
    rl_tables.append(tab)
```

```
pop
2000              empty       monocentric       polycentric
1990
empty        57961.0-*    123688.117647-*           79551.0
monocentric    71914.0  188404.046512-**     416521.833333
polycentric                 359553.609756   1749223.21875+***


        emp_dens
2000                  empty       monocentric       polycentric
1990
empty        3.97835490525  13.8418248027-**     41.5310305712
monocentric   1.7953228977  23.1552069292-**     32.0401867937
polycentric                   33.7103582425  78.0635013324+***


        inc_pc
```

```
2000                   empty       monocentric       polycentric
1990
empty          18261.7035593  17865.5425507-**     21530.0851026
monocentric  13672.9440721-**  19173.5165033-**     20090.7586838
polycentric                     19209.1533279  21906.4143172+**

        pct_below
2000                empty      monocentric       polycentric
1990
empty        13.1122651438  14.233278484+**     8.09417857726
monocentric  14.5312456545    12.5869946497     12.4074469974
polycentric                    12.295737511  11.1312509008-**
-------------------------------------------------------------------

        pop
2010                empty       monocentric       polycentric
2000
empty              57961.0           71914.0
monocentric  122379.666667  197135.020833-**     315223.685714
polycentric                    473461.142857  1538691.84956+**

        emp_dens
2010                empty       monocentric      polycentric
2000
empty        3.97835490525      1.7953228977
monocentric  24.2420604204  22.4362925013-**    34.8467702828
polycentric                    28.1182516111  71.709533095+**

        inc_pc
2010                empty       monocentric       polycentric
2000
empty        18261.7035593   13672.9440721-*
monocentric  18383.7643691  18922.0857024-**     20026.9314404
polycentric                    20818.9988839  21555.7755371+**

        pct_below
2010                empty       monocentric       polycentric
2000
empty        13.1122651438     14.5312456545
monocentric  11.0085750881  12.8765604742+**     11.5922490179
polycentric                    12.0246560865  11.3324999094-**
```

These tables can be presented in a more pleasant way, adding the global averages as well the way they are shown in the paper:

```
In [151]: print "Table 5: Size"
          print "Global average: %.1f"%msas_soec['pop'].mean()
          rl_tables[0]
```

```
Table 5: Size
Global average: 640335.4
```

```
Out[151]: 2010                 empty       monocentric       polycentric
          2000
          empty              57961.0           71914.0
```

```
monocentric  122379.666667  197135.020833-**     315223.685714
polycentric                    473461.142857  1538691.84956+**
```

```
In [149]: print "Table 6: Density"
          print "Global average: %.1f"%msas_soec['emp_dens'].mean()
          rl_tables[1]
```

```
Table 6: Density
Global average: 39.3
```

```
Out[149]: 2010                 empty       monocentric      polycentric
          2000
          empty        3.97835490525      1.7953228977
          monocentric  24.2420604204  22.4362925013-**    34.8467702828
          polycentric                    28.1182516111  71.709533095+**
```

```
In [150]: print "Table 7: Income per capita"
          print "Global average: %.1f"%msas_soec['inc_pc'].mean()
          rl_tables[2]
```

```
Table 7: Income per capita
Global average: 19911.8
```

```
Out[150]: 2010                 empty       monocentric       polycentric
          2000
          empty        18261.7035593   13672.9440721-*
          monocentric  18383.7643691  18922.0857024-**     20026.9314404
          polycentric                    20818.9988839  21555.7755371+**
```

```
In [152]: print "Table 8: Poverty (in %)"
          print "Global average: %.1f"%msas_soec['pct_below'].mean()
          rl_tables[3]
```

```
Table 8: Poverty (in %)
Global average: 12.2
```

```
Out[152]: 2010                 empty       monocentric       polycentric
          2000
          empty        13.1122651438     14.5312456545
          monocentric  11.0085750881  12.8765604742+**     11.5922490179
          polycentric                    12.0246560865  11.3324999094-**
```