In [1]:

```
#import the relevant liabaries

import geopandas as gpd
import pandas as pd
from shapely.geometry import Point, LineString, Polygon
from sklearn import cluster
import matplotlib.pyplot as plt
import numpy as np
import pysal
from pysal.lib import weights
from pysal.explore import esda
from esda.moran import Moran,Moran_Local
import splot
from splot.esda import moran_scatterplot, plot_moran, lisa_cluster
import seaborn as sns
```

In [2]:

```
#loading the airbnb_vienna_csv file from the local desktop
vienna_airbnb = pd.read_csv('/Users/michael/Desktop/tomslee_airbnb_vienna_0123_2015-
```

In [3]:

```
#printing the first 5 rows
vienna_airbnb.head()
```

Out[3]:

	room_id	host_id	room_type	district	district-name	neighbourhood_group	reviews	review_scc
0	278286	1452720	Private room	9	Alsergrund	905	48	
1	546999	2074463	Private room	9	Alsergrund	902	7	
2	5514700	22072627	Private room	9	Alsergrund	904	5	
3	6527073	34136313	Private room	9	Alsergrund	904	3	
4	7154476	37468348	Private room	9	Alsergrund	905	4	

In [4]:

```
#creating a point geometry from the longitude and latitude columns
geometry = [Point(xy) for xy in zip(vienna_airbnb['longitude'], vienna_airbnb['latit
# initialize the coordinate reference system EPSG:4326
crs = {'init': 'epsg:4326'}
#creating the geopandas Geodataframe
vienna_gdf = gpd.GeoDataFrame(vienna_airbnb, crs=crs, geometry=geometry)
```

```
/opt/anaconda3/envs/savi/lib/python3.8/site-packages/pyproj/crs/crs.p
y:53: FutureWarning: '+init=<authority>:<code>' syntax is deprecated.
'<authority>:<code>' is the preferred initialization method. When maki
ng the change, be mindful of axis order changes: https://pyproj4.githu
b.io/pyproj/stable/gotchas.html#axis-order-changes-in-proj-6 (https://
pyproj4.github.io/pyproj/stable/gotchas.html#axis-order-changes-in-pro
j-6)
  return _prepare_from_string(" ".join(pjargs))
```

In [5]:

```
#Print the last 5 rows
vienna_gdf.tail()
```

Out[5]:

	room_id	host_id	room_type	district	district-name	neighbourhood_group	reviews	review_s
5337	3092333	9800003	Entire home/apt	23	Liesing	2306	0	
5338	100023	2300124	Entire home/apt	23	Liesing	2306	2	
5339	4000234	500023	Entire home/apt	11	Simmering	1108	6	
5340	4500032	4350003	Entire home/apt	11	Simmering	1108	3	
5341	394235	352353	Private room	11	Simmering	1108	13	

5 rows × 21 columns

In [6]:

```
#creating a shapefile on the deskotp with our new geodataframe
vienna_gdf.to_file('/Users/michael/Desktop/Airbnb_Vienna.shp', driver='ESRI Shapefil
```

In [7]:

```
#Grouping a second dataframe with the neighbourhood group and calculating the mean p
a = vienna_gdf
a1 = a.groupby('neighbourhood_group')
a2 = a1['price'].mean()
a2
```

Out[7]:

```
neighbourhood_group
101     121.175000
102     163.190476
103     179.416667
104     194.941176
105     127.344828
           ...
2315     96.000000
2316     56.000000
2317     47.000000
2318     72.000000
2319     56.000000
Name: price, Length: 248, dtype: float64
```

In [8]:

```
#Grouping a second dataframe with the neighbourhood group and calculating the mediar
b = vienna_gdf
b1 = b.groupby('neighbourhood_group')
b2 = b1['price'].median()
b2
```

Out[8]:

```
neighbourhood_group
101     112.0
102     113.0
103     141.5
104     112.0
105     112.0
        ...
2315     96.0
2316     56.0
2317     47.0
2318     72.0
2319     56.0
Name: price, Length: 248, dtype: float64
```

In [9]:

```
#Merging the two grouped dataframes with the vienna_gdf
vienna_gdf = vienna_gdf.merge(a2, left_on='neighbourhood_group', right_on='neighbour
vienna_gdf = vienna_gdf.merge(b2, left_on='neighbourhood_group', right_on='neighbour
```

In [10]:

```
#Showing the merged dataframe (price_x for median price/price_y for average price)
vienna_gdf.head()
```

Out[10]:

	room_id	host_id	room_type	district	district-name	neighbourhood_group	reviews	review_scc
0	278286	1452720	Private room	9	Alsergrund	905	48	
1	7154476	37468348	Private room	9	Alsergrund	905	4	
2	1502484	8031874	Private room	9	Alsergrund	905	47	
3	3871678	8031874	Private room	9	Alsergrund	905	65	
4	6419039	4759856	Private room	9	Alsergrund	905	4	

5 rows × 23 columns

In [11]:

```
#Rename columns price_x as median price for the neighbourhood group, price_y as aver
vienna_gdf.rename(
    columns={'price_x':'median_price_neighb_group'},
    inplace=True
)


vienna_gdf.rename(
  columns={'price_y' : 'avg_price_neighb_group'},
  inplace=True
)
```

In [12]:

```
#Quick data types check
vienna_gdf.dtypes
```

Out[12]:

```
room_id                                 int64
host_id                                 int64
room_type                              object
district                                int64
district-name                          object
neighbourhood_group                     int64
reviews                                 int64
review_scores_rating                  float64
review_scores_overall_satisfaction    float64
review_scores_accuracy                float64
review_scores_cleanliness             float64
review_scores_checkin                 float64
review_scores_communication           float64
review_scores_location                float64
accommodates                          float64
bedrooms                              float64
median_price_neighb_group               int64
minstay                               float64
latitude                              float64
longitude                             float64
geometry                             geometry
avg_price_neighb_group                float64
price                                 float64
dtype: object
```

In [13]:

```
#Grouping again for the districts to get the median and average price
a3 = vienna_gdf.groupby('district')
a4 = a3['price'].mean()
a5 = a3['price'].median()
```

In [14]:

```
a4
```

Out[14]:

```
district
1     122.462898
2      69.035533
3      71.840426
4      68.681979
5      63.854795
6      71.274448
7      70.291284
8      67.062802
9      62.622283
10     67.577114
11     48.000000
12     60.471831
13     65.844156
14     62.285714
15     62.654434
16     56.060748
17     52.953757
18     56.893855
19     62.552000
20     65.946237
21     68.986486
22     58.893130
23     74.708333
Name: price, dtype: float64
```

In [15]:

```
#Merging the two grouped dataframes with the vienna_gdf
vienna_gdf = vienna_gdf.merge(a4, left_on='district', right_on='district')
vienna_gdf = vienna_gdf.merge(a5, left_on='district', right_on='district')
```

In [16]:

```
vienna_gdf
```

Out[16]:

	room_id	host_id	room_type	district	district-name	neighbourhood_group	reviews	review_
0	278286	1452720	Private room	9	Alsergrund	905	48	
1	7154476	37468348	Private room	9	Alsergrund	905	4	
2	1502484	8031874	Private room	9	Alsergrund	905	47	
3	3871678	8031874	Private room	9	Alsergrund	905	65	
4	6419039	4759856	Private room	9	Alsergrund	905	4	
...	...	...	...	...	...	...	...	
5337	66435	90834	Entire home/apt	11	Simmering	1112	27	
5338	8097431	8274114	Entire home/apt	11	Simmering	1112	0	
5339	4000234	500023	Entire home/apt	11	Simmering	1108	6	
5340	4500032	4350003	Entire home/apt	11	Simmering	1108	3	
5341	394235	352353	Private room	11	Simmering	1108	13	

5342 rows × 25 columns

In [17]:

```
#Rename columns price_x as median price for the district, price_y as average price i
vienna_gdf.rename(
  columns={'price_x' : 'median_price_district'},
  inplace=True
)

vienna_gdf.rename(
  columns={'price_y' : 'avg_price_district'},
  inplace=True
)
```

In [18]:

```
vienna_gdf
```

Out[18]:

	room_id	host_id	room_type	district	district-name	neighbourhood_group	reviews	review_
0	278286	1452720	Private room	9	Alsergrund	905	48	
1	7154476	37468348	Private room	9	Alsergrund	905	4	
2	1502484	8031874	Private room	9	Alsergrund	905	47	
3	3871678	8031874	Private room	9	Alsergrund	905	65	
4	6419039	4759856	Private room	9	Alsergrund	905	4	
...	...	...	...	...	...	...	...	
5337	66435	90834	Entire home/apt	11	Simmering	1112	27	
5338	8097431	8274114	Entire home/apt	11	Simmering	1112	0	
5339	4000234	500023	Entire home/apt	11	Simmering	1108	6	
5340	4500032	4350003	Entire home/apt	11	Simmering	1108	3	
5341	394235	352353	Private room	11	Simmering	1108	13	

5342 rows × 25 columns

In [19]:

```
#Read in Vienna districts shapefile
districts_gdf = gpd.read_file("/Users/michael/Desktop/Vienna.shp")
```

In [20]:

```
districts_gdf
```

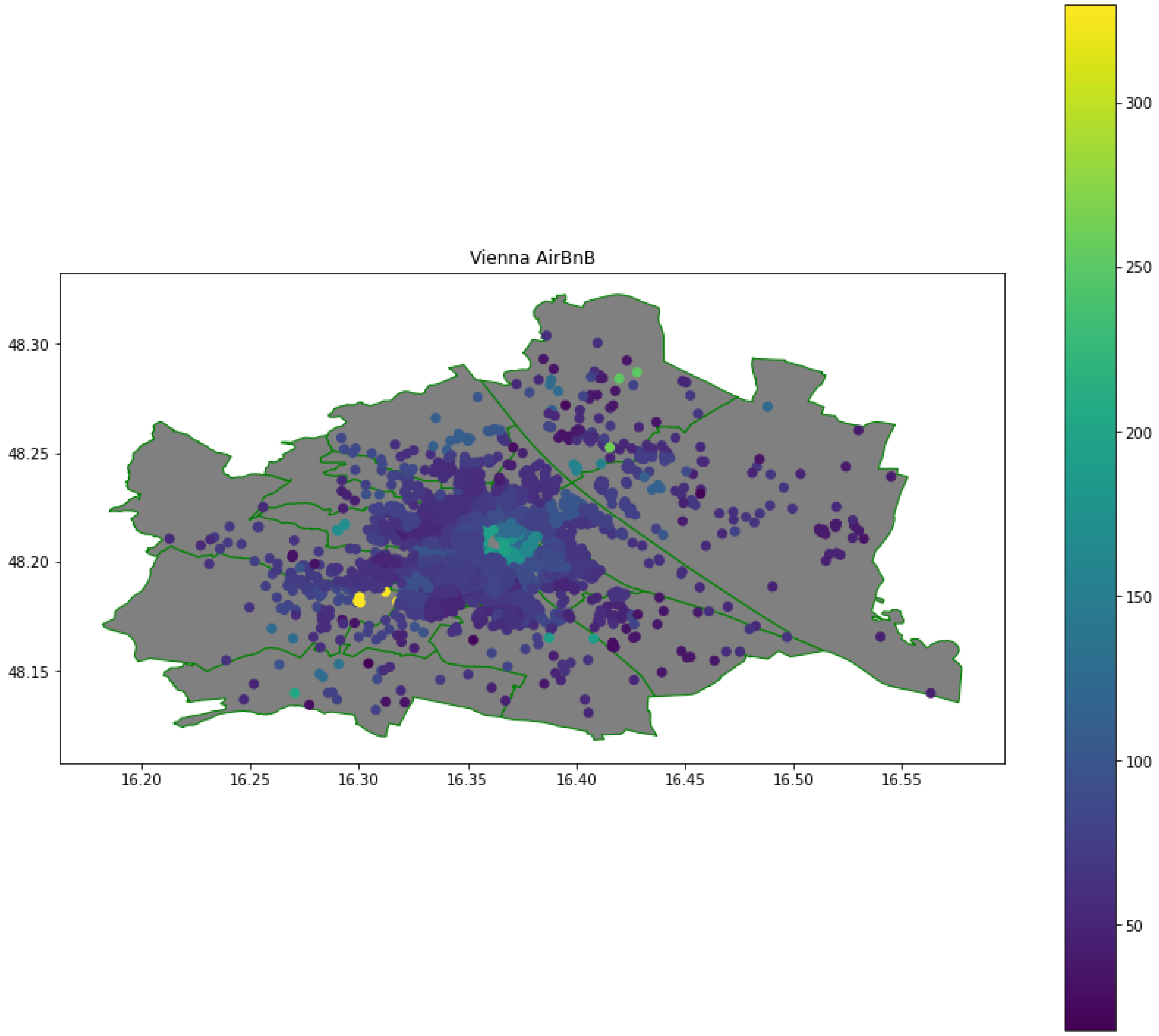
Out[20]:

	district-n	district	geometry
0	Leopoldstadt	2	POLYGON ((16.38484 48.22616, 16.38495 48.22622...
1	Landstrasse	3	POLYGON ((16.38681 48.21271, 16.38683 48.21271...
2	Innere Stadt	1	POLYGON ((16.36497 48.21590, 16.36498 48.21590...
3	Brigittenau	20	POLYGON ((16.38595 48.24764, 16.38611 48.24748...
4	Floridsdorf	21	POLYGON ((16.37817 48.28858, 16.37819 48.28859...
5	Donaustadt	22	POLYGON ((16.48378 48.17615, 16.48358 48.17628...
6	Liesing	23	POLYGON ((16.33924 48.15405, 16.33948 48.15388...
7	Alsergrund	9	POLYGON ((16.34255 48.21837, 16.34259 48.21847...
8	Penzing	14	POLYGON ((16.27508 48.21508, 16.27512 48.21507...
9	Mariahilf	6	POLYGON ((16.34200 48.19634, 16.34424 48.19671...
10	Neubau	7	POLYGON ((16.35825 48.20511, 16.35830 48.20508...
11	Simmering	11	POLYGON ((16.40375 48.18527, 16.40375 48.18527...
12	Favoriten	10	POLYGON ((16.37081 48.14898, 16.37042 48.14908...
13	Hietzing	13	POLYGON ((16.27916 48.16268, 16.27693 48.16020...
14	Meidling	12	POLYGON ((16.33729 48.17093, 16.33729 48.17093...
15	Rudolfsheim-Fuenfhaus	15	POLYGON ((16.32531 48.20531, 16.32534 48.20530...
16	Margareten	5	POLYGON ((16.36476 48.18798, 16.36545 48.18728...
17	Josefstadt	8	POLYGON ((16.33903 48.21106, 16.33904 48.21119...
18	Wieden	4	POLYGON ((16.37505 48.19815, 16.37505 48.19814...
19	Hernals	17	POLYGON ((16.31112 48.22277, 16.31097 48.22278...
20	Ottakring	16	POLYGON ((16.32645 48.20513, 16.32534 48.20530...
21	Doebling	19	POLYGON ((16.30836 48.27243, 16.30908 48.27278...
22	Waehring	18	POLYGON ((16.31557 48.23254, 16.31554 48.23253...

In [21]:

```
#Plotting the Vienna AirBnB prices and the districts geodataframe in the background
fig, ax = plt.subplots(figsize=(12,10))
districts_gdf.plot(ax=ax, facecolor='grey', edgecolor='green')
vienna_gdf.plot(column="avg_price_neighb_group", ax=ax, legend=True)

plt.title("Vienna AirBnB")
plt.tight_layout()
plt.show()
```



In [22]:

```
#Calculating Queen contiguity spatial weights (spatial leg standardize the rows and
w = weights.Queen.from_dataframe(vienna_gdf, idVariable="room_id" )
w.transform = "R"
vienna_gdf["w_price"] = weights.lag_spatial(w, vienna_gdf["avg_price_neighb_group"])
vienna_gdf.head()
```

Out[22]:

	room_id	host_id	room_type	district	district-name	neighbourhood_group	reviews	review_scc
0	278286	1452720	Private room	9	Alsergrund	905	48	
1	7154476	37468348	Private room	9	Alsergrund	905	4	
2	1502484	8031874	Private room	9	Alsergrund	905	47	
3	3871678	8031874	Private room	9	Alsergrund	905	65	
4	6419039	4759856	Private room	9	Alsergrund	905	4	

5 rows × 26 columns

In [23]:

```
#Calculating the global spatial autocorrelation to find the overall pattern in the c
y = vienna_gdf["avg_price_neighb_group"]
moran = Moran(y, w)
moran.I
```

Out[23]:

```
0.013145239031757582
```

In [24]:

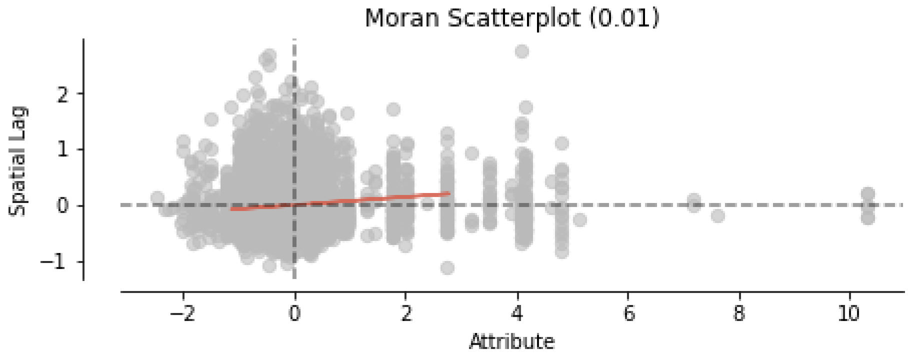
```
#check if the p-value of the global spatial autocorrelation is (reliable) significar
moran.p_sim
```

Out[24]:

```
0.056
```

In [25]:

```
#Plotting Moran's I scatterplot to visualize the global spatial autocorrelation
fig, ax = moran_scatterplot(moran, aspect_equal=True)
plt.show()
```

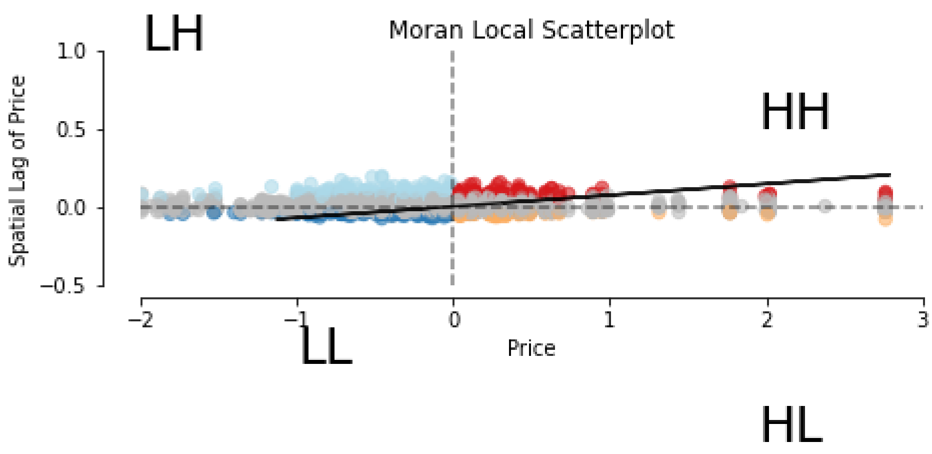


In [26]:

```
m_local = Moran_Local(y, w)
```

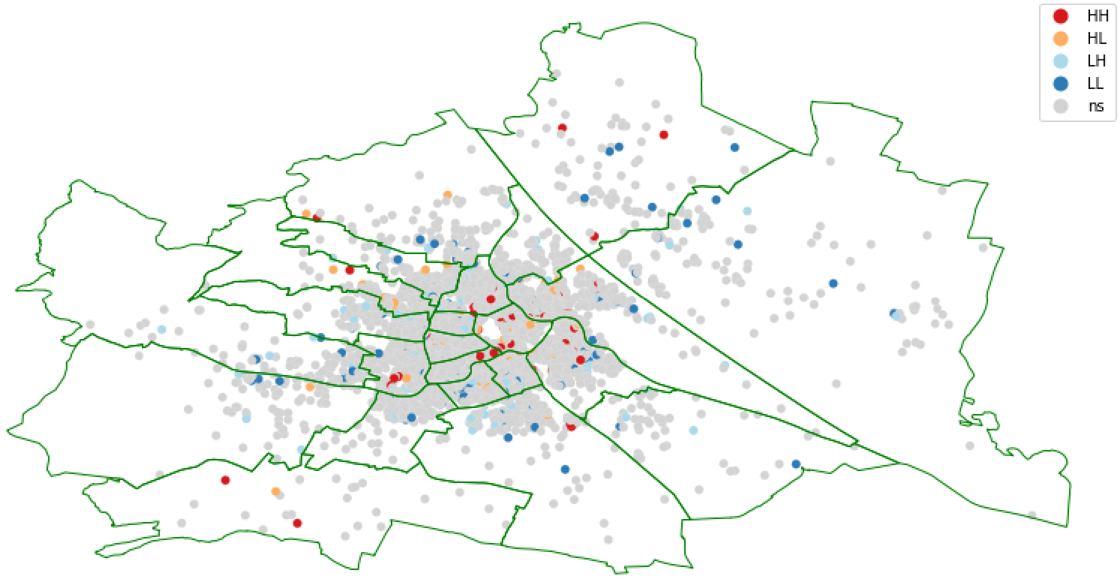
In [27]:

```
#Plotting the Moran Local Scatterplot
fig, ax = moran_scatterplot(m_local, p=0.05)
ax.set_xlabel('Price')
ax.set_ylabel('Spatial Lag of Price')
plt.ylim((-0.5,1))
plt.xlim((-2,3))
plt.text(1.95, 0.5, "HH", fontsize=25)
plt.text(1.95, -1.5, "HL", fontsize=25)
plt.text(-2, 1, "LH", fontsize=25)
plt.text(-1, -1, "LL", fontsize=25)
plt.show()
```



In [28]:

```
#plotting the LISA cluster
fig, ax = plt.subplots(figsize=(14,12))
lisa_cluster(m_local, vienna_gdf, p=0.05, figsize = (16,12),ax=ax)
districts_gdf.plot(ax=ax, facecolor='None', edgecolor='green')
plt.show()
```



In [29]:

```
#read in json file for the neighbourhood_group geometries
airbnb_vienna = gpd.read_file("/Users/michael/Desktop/ZAEHLBEZIRKOGD.json")
```

In [30]:

```
#Quick check of the coordinate reference system
airbnb_vienna.crs
```

Out[30]:

```
<Geographic 2D CRS: EPSG:4326>
Name: WGS 84
Axis Info [ellipsoidal]:
- Lat[north]: Geodetic latitude (degree)
- Lon[east]: Geodetic longitude (degree)
Area of Use:
- name: World
- bounds: (-180.0, -90.0, 180.0, 90.0)
Datum: World Geodetic System 1984
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

In [31]:

```
#using only the selected columns for the new geodataframe
airbnb_new = airbnb_vienna[['BEZNR','ZBEZ','geometry']]
```

In [32]:

```
#Renaming the columns
airbnb_new.rename(
  columns={'BEZNR' : 'district'},
  inplace=True
)

airbnb_new.rename(
  columns={'ZBEZ' : 'neighbourhood_group'},
  inplace=True
)
```

```
/opt/anaconda3/envs/savi/lib/python3.8/site-packages/pandas/core/fram
e.py:4125: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas
-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
 (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  return super().rename(
```

In [33]:

```
airbnb_new
```

Out[33]:

	district	neighbourhood_group	geometry
0	21	2129	POLYGON ((16.39317 48.28030, 16.39322 48.28032...
1	21	2101	POLYGON ((16.40456 48.30195, 16.40440 48.30084...
2	14	1404	POLYGON ((16.29923 48.19271, 16.29967 48.19269...
3	10	1012	POLYGON ((16.34805 48.16615, 16.34844 48.16676...
4	21	2121	POLYGON ((16.40342 48.26006, 16.40362 48.26015...
...	...	...	...
245	22	2207	POLYGON ((16.49017 48.25612, 16.49101 48.25743...
246	22	2231	POLYGON ((16.46116 48.22709, 16.46160 48.22770...
247	20	2006	POLYGON ((16.37046 48.23554, 16.37256 48.23570...
248	10	1014	POLYGON ((16.38276 48.14955, 16.38267 48.14986...
249	13	1304	POLYGON ((16.26413 48.18302, 16.26455 48.18305...

250 rows × 3 columns

In [34]:

```
#Creating a subset of the vienna geodataframe, which include all ratings, prices, ne
vienna_gdf_2 = vienna_gdf[['neighbourhood_group','room_id','review_scores_rating','r
```

In [35]:

```
vienna_gdf_2
```

Out[35]:

	neighbourhood_group	room_id	review_scores_rating	review_scores_overall_satisfaction	re
0	905	278286	2.2	4.8	
1	905	7154476	2.9	3.8	
2	905	1502484	5.0	4.7	
3	905	3871678	5.0	3.5	
4	905	6419039	3.2	4.8	
...	...	...	...	...	
5337	1112	66435	2.4	3.5	
5338	1112	8097431	3.5	3.5	
5339	1108	4000234	3.4	3.6	
5340	1108	4500032	4.3	4.8	
5341	1108	394235	3.3	4.1	

5342 rows × 15 columns

In [36]:

```
#Changing the neighbourhood_group in the airbnb_new dataframe to the type integer th
airbnb_new['neighbourhood_group']=airbnb_new['neighbourhood_group'].astype(int)
```

```
<ipython-input-36-2cbba555b7dd>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas
-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
 (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  airbnb_new['neighbourhood_group']=airbnb_new['neighbourhood_group'].
astype(int)
```

In [37]:

```
#checking the dtypes, the neighbourood_group type has changed from object to intege
airbnb_new.dtypes
```

Out[37]:

```
district                  int64
neighbourhood_group       int64
geometry               geometry
dtype: object
```

In [38]:

```
#Matching both dataframes
airbnb_neighb_gdf = airbnb_new.merge(vienna_gdf_2, left_on='neighbourhood_group', ri
```

In [39]:

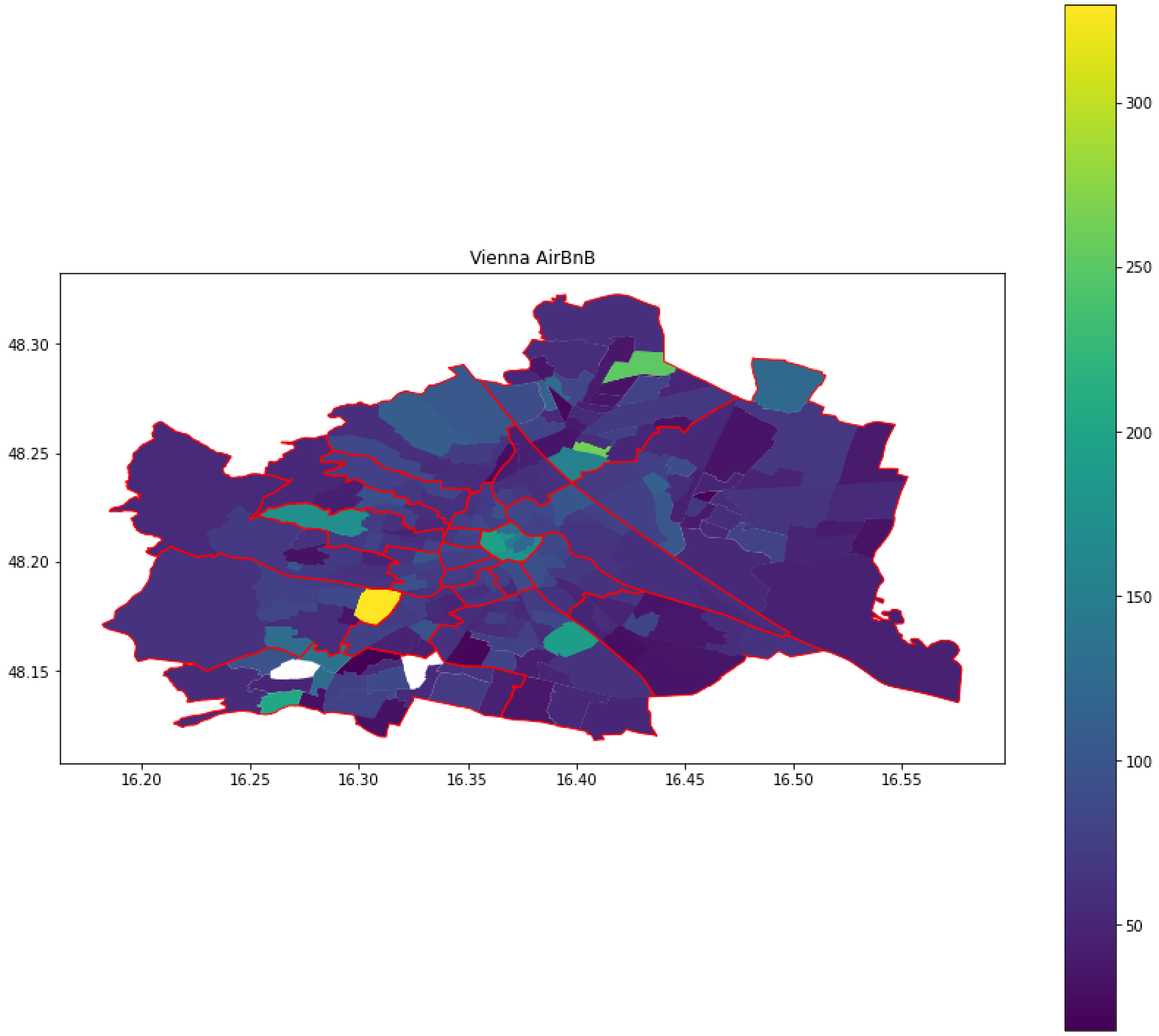
```
#checking the coordinate reference system
airbnb_neighb_gdf.crs
```

Out[39]:

```
<Geographic 2D CRS: EPSG:4326>
Name: WGS 84
Axis Info [ellipsoidal]:
- Lat[north]: Geodetic latitude (degree)
- Lon[east]: Geodetic longitude (degree)
Area of Use:
- name: World
- bounds: (-180.0, -90.0, 180.0, 90.0)
Datum: World Geodetic System 1984
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

In [127]:

```
#Plotting the Vienna AirBnB prices and the districts geodataframe
fig, ax = plt.subplots(figsize=(12,10))
airbnb_neighb_gdf.plot(column="avg_price_neighb_group", ax=ax, legend=True)
districts_gdf.plot(ax=ax, facecolor='None', edgecolor='red')
plt.title("Vienna AirBnB")
plt.tight_layout()
plt.show()
```



In [41]:

```
#Calculating Queen contiguity spatial weights (spatial leg standardize the rows and
w = weights.Queen.from_dataframe(airbnb_neighb_gdf, idVariable="room_id" )
w.transform = "R"
airbnb_neighb_gdf["w_price"] = weights.lag_spatial(w, airbnb_neighb_gdf["avg_price_r
```

In [42]:

```
#Calculating the global spatial autocorrelation to find the overall pattern in the c
y = airbnb_neighb_gdf["avg_price_neighb_group"]
moran = Moran(y, w)
moran.I
```

Out[42]:

```
0.002222789620975046
```

In [43]:

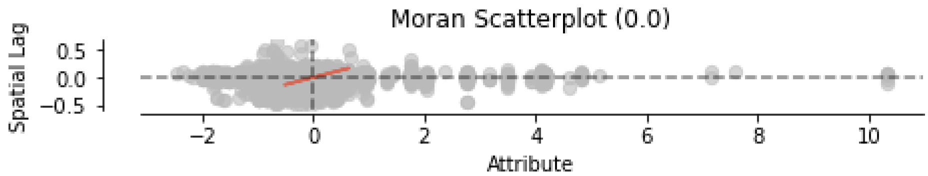
```
#check if the p-value of the global spatial autocorrelation is (reliable) significar
moran.p_sim
```

Out[43]:

```
0.073
```

In [44]:

```
#Plotting Moran's I scatterplot to visualize the global spatial autocorrelation
fig, ax = moran_scatterplot(moran, aspect_equal=True)
plt.show()
```

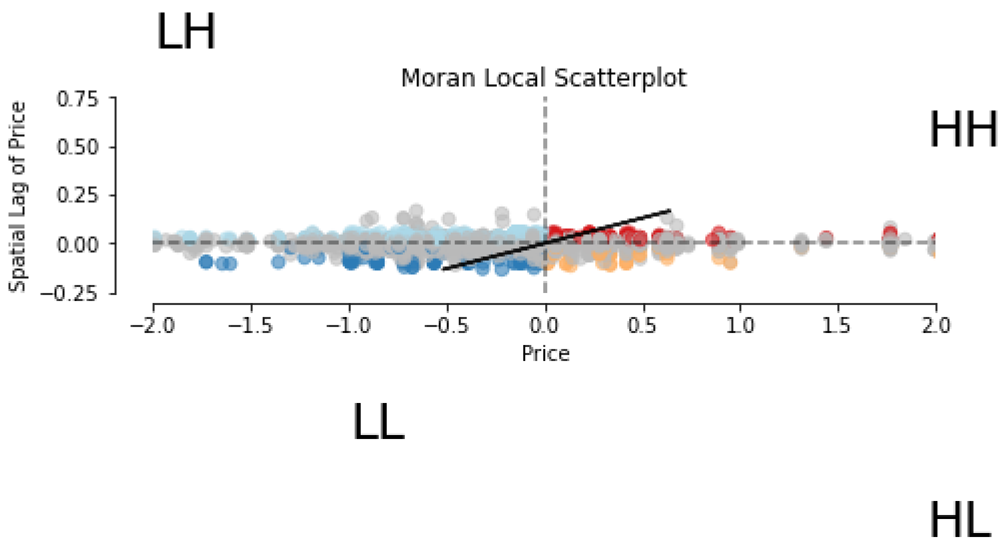


In [45]:

```
#Calculating Morans Local Autocorrelation (LISA)
m_local = Moran_Local(y, w)
```

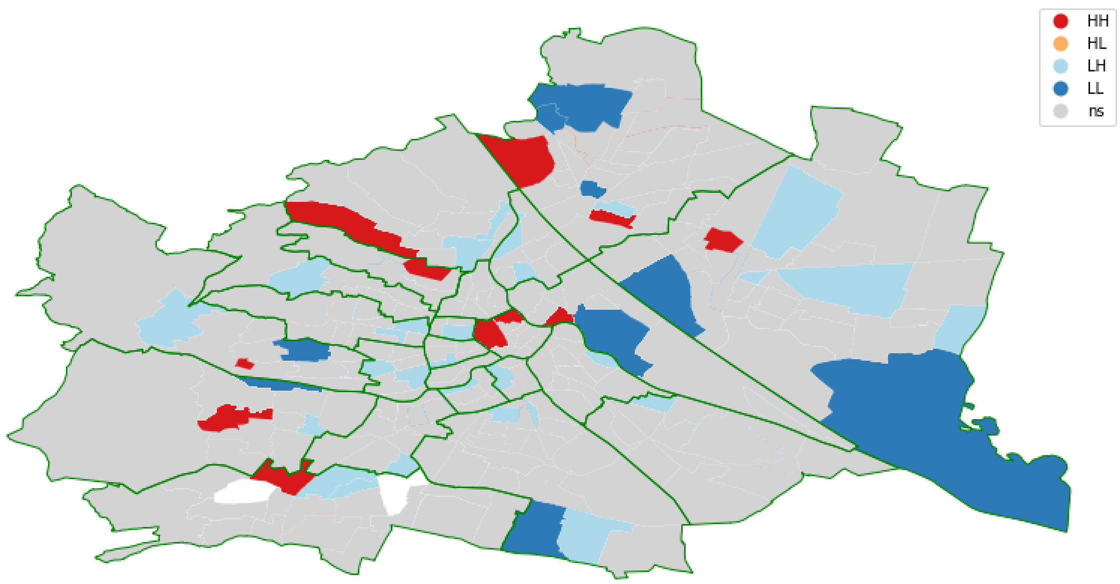
In [46]:

```
#Plotting the Moran Local Scatterplot
fig, ax = moran_scatterplot(m_local, p=0.05)
ax.set_xlabel('Price')
ax.set_ylabel('Spatial Lag of Price')
plt.ylim((-0.25,0.75))
plt.xlim((-2,2))
plt.text(1.95, 0.5, "HH", fontsize=25)
plt.text(1.95, -1.5, "HL", fontsize=25)
plt.text(-2, 1, "LH", fontsize=25)
plt.text(-1, -1, "LL", fontsize=25)
plt.show()
```



In [47]:

```
#Plotting the LISA cluster
fig, ax = plt.subplots(figsize=(14,12))
lisa_cluster(m_local, airbnb_neighb_gdf, p=0.05, figsize = (16,12),ax=ax)
districts_gdf.plot(ax=ax, facecolor='None', edgecolor='green')
plt.show()
```

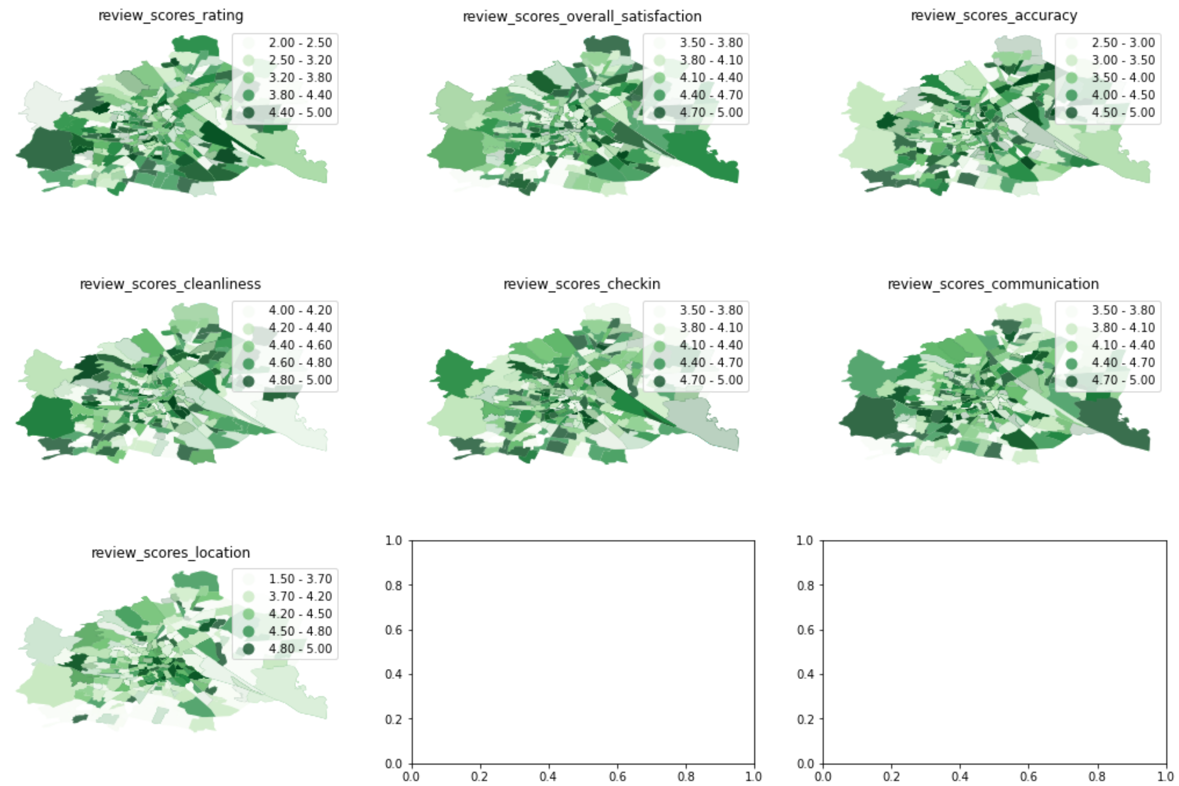


In [48]:

```
#creating a rating list which helps to analyze the reviews
ratings = ['review_scores_rating','review_scores_overall_satisfaction','review_score
```

In [49]:

```
#Plotting all review values
f, axs = plt.subplots(nrows=3, ncols=3, figsize=(18, 12))
# Create figure and axes (this time it's 9, arranged 3 by 3) f, axs = plt.subplots(r
# Make the axes accessible with single indexing
axs = axs.flatten()
        # Start the loop over all the variables of interest
for i, col in enumerate(ratings):
# select the axis where the map will go
    ax = axs[i]
# Plot the map
    airbnb_neighb_gdf.plot(column=col, ax=ax, legend=True,scheme='Quantiles', \
    linewidth=0, cmap='Greens', alpha=0.75) # Remove axis clutter
    ax.set_axis_off()
# Set the axis title to the name of variable being plotted
    ax.set_title(col)
        # Display the figure
plt.show()
```



In [82]:

```
#Creating a K-means cluster for analysing the ratings
kmeans5 = cluster.KMeans(n_clusters=5)
```

In [83]:

```
kmeans5
```

Out[83]:

```
KMeans(n_clusters=5)
```

In [84]:

```
#Creating K-means cluster for all ratings
k5cls = kmeans5.fit(airbnb_neighb_gdf[ratings])
```

In [85]:

```
#Showing the labels
k5cls.labels_
```

Out[85]:

```
array([0, 3, 2, ..., 0, 4, 1], dtype=int32)
```

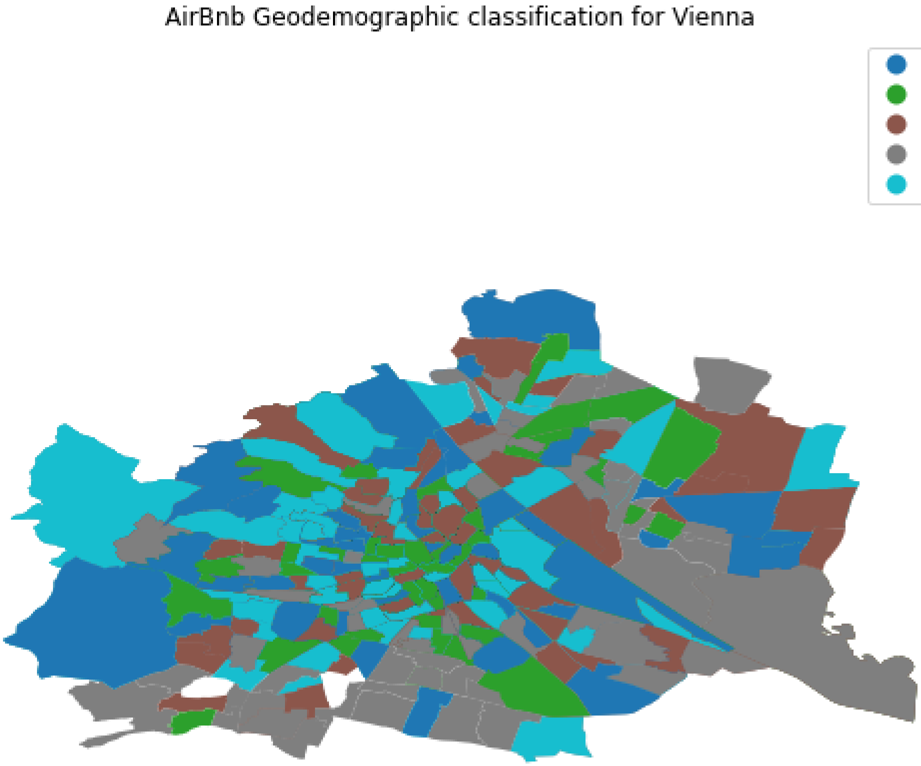
In [86]:

```
airbnb_neighb_gdf['k5cls'] = k5cls.labels_
```

In [90]:

```
#Plotting the Vienna Map with the k-mean clusters
# Setup figure and ax
f, ax = plt.subplots(1, figsize=(9, 9))
# Plot unique values choropleth including a legend and with no boundary lines
airbnb_neighb_gdf.plot(column='k5cls', categorical=True, legend=True, linewidth=0, a

# Remove axis
ax.set_axis_off()
# Keep axes proportionate
plt.axis('equal')
# Add title
plt.title('AirBnb Geodemographic classification for Vienna')
# Display the map
plt.show()
```



In [92]:

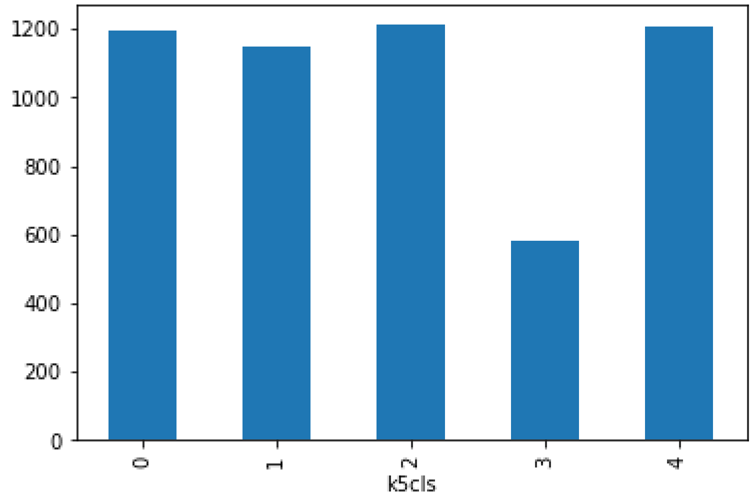
```
#Showing the culster size
k5sizes = airbnb_neighb_gdf.groupby('k5cls').size()
k5sizes
```

Out[92]:

```
k5cls
0    1193
1    1150
2    1211
3     582
4    1206
dtype: int64
```

In [93]:

```
#creating a bar plot for all clusters
_ = k5sizes.plot.bar()
```



In [114]:

```
#Creating the ratings mean for all culsters
k5means = airbnb_neighb_gdf.groupby('k5cls')[ratings].mean()
# Show the table transposed (so it's not too wide)
k5means.T
```

Out[114]:

k5cls	0	1	2	3	4
review_scores_rating	4.252054	4.298783	2.672337	3.735567	2.657877
review_scores_overall_satisfaction	4.268148	4.243217	4.252601	4.199313	4.277363
review_scores_accuracy	3.060520	4.390609	4.427250	3.920790	3.097264
review_scores_cleanliness	4.494384	4.490435	4.483402	4.502062	4.507463
review_scores_checkin	4.228919	4.287130	4.258299	4.285052	4.241128
review_scores_communication	4.237217	4.294261	4.272915	4.237285	4.261774
review_scores_location	4.332858	4.442870	4.349216	2.924742	4.295274

In [115]:

```
# Calculate the summary by group
k5desc = airbnb_neighb_gdf.groupby('k5cls')[ratings].describe()
# Show the table
k5desc
```

Out[115]:

	review_scores_rating								review_scores_overall_satisfactio	
	count	**mean**	**std**	**min**	**25%**	**50%**	**75%**	**max**	**count**	**mean**
k5cls										
0	1193.0	4.252054	0.458621	3.5	3.9	4.30	4.6	5.0	1193.0	4.26814
1	1150.0	4.298783	0.446978	3.5	3.9	4.30	4.7	5.0	1150.0	4.24321
2	1211.0	2.672337	0.438841	2.0	2.3	2.70	3.1	3.5	1211.0	4.25260
3	582.0	3.735567	0.691818	2.0	3.3	3.75	4.3	5.0	582.0	4.19931
4	1206.0	2.657877	0.431575	2.0	2.3	2.60	3.0	3.4	1206.0	4.27736

5 rows × 56 columns

In [121]:

```
 # Name (index) the rows after the category they belong
to_plot = airbnb_neighb_gdf.set_index('k5cls')
# Subset to keep only variables used in K-means clustering
to_plot = to_plot[ratings]
# Display top of the table
to_plot
```

Out[121]:

	review_scores_rating	review_scores_overall_satisfaction	review_scores_accuracy	review_sc
k5cls				
0	4.6	5.0	2.7	
3	4.1	3.5	4.6	
2	3.4	4.4	4.8	
3	4.3	3.8	4.8	
0	4.4	4.9	2.5	
...	...	...	...	
3	2.8	4.3	4.5	
0	4.3	4.0	2.5	
0	4.1	4.5	3.6	
4	3.3	3.6	2.7	
1	5.0	4.3	4.7	

5342 rows × 7 columns

In [122]:

```
#tidy up the table into more useful dataframe
to_plot = to_plot.stack()
to_plot
```

Out[122]:

```
k5cls
0      review_scores_rating                    4.6
       review_scores_overall_satisfaction      5.0
       review_scores_accuracy                  2.7
       review_scores_cleanliness               4.7
       review_scores_checkin                   4.6
                                              ...
1      review_scores_accuracy                  4.7
       review_scores_cleanliness               4.6
       review_scores_checkin                   4.2
       review_scores_communication             4.6
       review_scores_location                  4.4
Length: 37394, dtype: float64
```

In [123]:

```
# reindexing the table
to_plot = to_plot.reset_index()
to_plot.head()
```

Out[123]:

	k5cls	level_1	0
0	0	review_scores_rating	4.6
1	0	review_scores_overall_satisfaction	5.0
2	0	review_scores_accuracy	2.7
3	0	review_scores_cleanliness	4.7
4	0	review_scores_checkin	4.6

In [124]:

```
#Renaming the columns of the reidexed table
to_plot = to_plot.rename(columns={'level_1': 'Rating', 0: 'Values'})
to_plot.head()
```

Out[124]:

	k5cls	Rating	Values
0	0	review_scores_rating	4.6
1	0	review_scores_overall_satisfaction	5.0
2	0	review_scores_accuracy	2.7
3	0	review_scores_cleanliness	4.7
4	0	review_scores_checkin	4.6

In [ ]:

```

```

In [ ]:

```

```