

# Data Interpretation and Writing Exercise (PHL)

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This is a short exercise, based on an unorganized xlsx file containing a relatively small proportion of information regarding a variety of variables related to housing information on four Indianapolis Neighborhoods. The first part of the code is employed to standardize the data structure and making it a workable dataframe, while the second part is a series of visualizations to explore the actual tendencies we can see among these neighborhoods. The third part is an interpretation based on the visualizations.

**Stage 1) Pre-Processing: building working and replicable data for academic research**

```
[1]: import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

file_path = r"C:\Users\pedro\Documents\Data Analysis Work\Job_
↳Exercise\Interpretation and writing exercise for candidates (1).xlsx"
Datex = pd.read_excel(file_path, header=1)

def remove_total(cell):
    if isinstance(cell, str):
        return cell.replace(' Total', '')
    return cell

Datex = Datex.applymap(remove_total)
Datex = Datex[~Datex.apply(lambda row:
                            row.astype(str).str.contains('Source:').any() or
                            row.dropna().empty or
                            any(any(word in str(cell) for cell in row) for word_
↳in ["Housing Cost", "Housing Market"])),
                  axis=1)]

Datex = Datex.reset_index(drop=True)
```

```
[2]: def transform_df(df, start_row, end_row):
    new_df = df.iloc[start_row:end_row]
    columns_to_drop = new_df.columns[12:21]
    new_df = new_df.drop(columns=columns_to_drop)

    vertical_df = new_df.transpose()
    vertical_df = vertical_df.fillna("Year")
    vertical_df.columns = vertical_df.iloc[0]
    vertical_df = vertical_df[1:]
    vertical_df.reset_index(drop=True, inplace=True)
    vertical_df = vertical_df.rename_axis(columns=None)

    # Correcting some of the headers
    vertical_df = vertical_df.rename(columns={'Mapleton-Fall Creak': 'Mapleton_
    ↪Fall Creak', 'St. Clair': 'St. Clair Place'})
    return vertical_df

med_sales_pri_df = transform_df(Datex, 53, 59)
num_home_s_df = transform_df(Datex, 60, 66)
```

```
[3]: def nuanced_df(df, start_row, end_row):
    new_df = df.iloc[start_row:end_row]
    columns_to_drop = new_df.columns[6:21]
    polished_df = new_df.drop(columns=columns_to_drop)
    polished_df = polished_df.fillna("Year")
    polished_df.columns = polished_df.iloc[0]
    polished_df = polished_df[1:]
    polished_df.reset_index(drop=True, inplace=True)
    polished_df = polished_df.rename_axis(columns=None)
    return polished_df

mortgage_loan_app_df = nuanced_df(Datex, 29, 36)
res_buil_per_df = nuanced_df(Datex, 37, 44)
med_a_val_df = nuanced_df(Datex, 45, 52)
```

```
[4]: resDatex = pd.concat([Datex.iloc[0:28], Datex.iloc[66:]], ignore_index=True)
selected_data = resDatex.iloc[20:29, 0:11]
header_texts = selected_data.iloc[0, [1, 3, 5, 7, 9]].tolist()
new_column_labels = ["Year"] + header_texts

dataframes = []
for i in range(2):
    cols = [0] + [j for j in range(1 + i, 11, 2)]
    df = selected_data.iloc[:, cols]
    df = df.iloc[2:]
    df.columns = new_column_labels
    df.reset_index(drop=True, inplace=True)
```

```

dataframes.append(df)

med_mon_mort_df, med_mon_rent_df = dataframes

```

```

[5]: def process_dataframe(data):
    data.columns = data.iloc[0]
    data = data[1:]
    data = data.drop(data.index[1])

    header_texts = data.iloc[0, [1, 4, 7, 10, 13]].tolist()
    new_column_labels = ["Year"] + header_texts

    df = {}
    for i in range(1, 4):
        df[i] = data.iloc[:, [0, i + 0, i + 3, i + 6, i + 9, i + 12]]
        df[i] = df[i].drop(df[i].index[0])
        df[i].reset_index(drop=True, inplace=True)
        df[i].columns = new_column_labels
    return df[1], df[2], df[3]

selected_data_v2 = resDatex.iloc[15:19, 0:16]

cb_h_nm_df, cb_h_wm_df, cb_rent_df = process_dataframe(selected_data_v2)

```

```

[6]: new_data = resDatex.iloc[7:15]
header_texts = new_data.iloc[0, [1, 5, 9, 13, 17]].tolist()
new_column_labels = ["Year"] + header_texts

dataframes = []
for i in range(4):
    cols = [0] + [j+1 for j in range(i, 20, 4)]
    df = new_data.iloc[:, cols]

    df = df.replace('**', np.nan)

    df[df.columns[1]] = pd.to_numeric(df[df.columns[1]], errors='coerce') / 100

    df = df.iloc[2:]
    df.columns = new_column_labels
    df.reset_index(drop=True, inplace=True)
    dataframes.append(df)

asian_ho_df, afr_ho_df, lat_ho_df, white_ho_df = dataframes

```

```

[7]: last_data = resDatex.iloc[1:6, 1:21].drop(resDatex.index[2])
last_data = last_data.reset_index(drop=True)
last_data = last_data.drop(last_data.index[1])

```

```

def process_data(last_data):
    header_texts = last_data.iloc[0, [0, 4, 8, 12, 16]].tolist()
    new_column_labels = header_texts

    df = {}
    for i in range(4):
        columns = [i + j for j in range(0, 19, 4) if i + j < 21]
        df[i] = last_data.iloc[:, columns]
        df[i] = df[i].drop(df[i].index[0])
        df[i].reset_index(drop=True, inplace=True)
        df[i].columns = new_column_labels

    return df[0], df[1], df[2], df[3]

hholds_ten_own, hholds_ten_rent, perc_hholds_ten_own, perc_hholds_ten_rent = \
    process_data(last_data)

hholds_ten_own.iloc[1], hholds_ten_rent.iloc[0] = hholds_ten_rent.iloc[0].\
    copy(), hholds_ten_own.iloc[1].copy()
perc_hholds_ten_own.iloc[1], perc_hholds_ten_rent.iloc[0] = \
    perc_hholds_ten_rent.iloc[0].copy(), perc_hholds_ten_own.iloc[1].copy()

def modify_dataframe(df):
    year_column = pd.DataFrame({'Year': [2012, 2017]})
    df_with_year = pd.concat([year_column, df], axis=1)
    return df_with_year

hholds_ten_own = modify_dataframe(hholds_ten_own)
hholds_ten_rent = modify_dataframe(hholds_ten_rent)
perc_hholds_ten_own = modify_dataframe(perc_hholds_ten_own)
perc_hholds_ten_rent = modify_dataframe(perc_hholds_ten_rent)

```

*All dataframes in long form and ready for time series analysis*

```

[8]: dataframes = [hholds_ten_own, hholds_ten_rent, perc_hholds_ten_own, \
    perc_hholds_ten_rent, asian_ho_df, afr_ho_df, lat_ho_df, white_ho_df, \
    cb_h_nm_df, cb_h_wm_df, cb_rent_df, med_mon_mort_df, med_mon_rent_df, \
    mortgage_loan_app_df, res_buil_per_df, med_a_val_df, med_sales_pri_df, \
    num_home_s_df]

for df in dataframes:
    if 'Year' in df.columns:
        df['Year'] = pd.to_datetime(df['Year'], format='%Y')

print(hholds_ten_own)
print(hholds_ten_rent)

```

```

print(perc_hholds_ten_own)
print(perc_hholds_ten_rent)
print(asian_ho_df)
print(afr_ho_df)
print(lat_ho_df)
print(white_ho_df)
print(cb_h_nm_df)
print(cb_h_wm_df)
print(cb_rent_df)
print(med_mon_mort_df)
print(med_mon_rent_df)
print(mortgage_loan_app_df)
print(res_buil_per_df)
print(med_a_val_df)
print(med_sales_pri_df)
print(num_home_s_df)

```

	Year	Marion County	Crown Hill	Holy Cross	Mapleton	Fall Creek	\
0	2012-01-01	204401	519	685		1359	
1	2017-01-01	198434	555	976		1598	

	St. Clair Place
0	480
1	751

	Year	Marion County	Crown Hill	Holy Cross	Mapleton	Fall Creek	\
0	2012-01-01	155037	1764	1365		3199	
1	2017-01-01	168781	1762	1283		3018	

	St. Clair Place
0	1027
1	1235

	Year	Marion County	Crown Hill	Holy Cross	Mapleton	Fall Creek	\
0	2012-01-01	0.568668	0.227332	0.334146		0.298157	
1	2017-01-01	0.540376	0.239534	0.43205		0.346187	

	St. Clair Place
0	0.318514
1	0.378147

	Year	Marion County	Crown Hill	Holy Cross	Mapleton	Fall Creek	\
0	2012-01-01	0.431332	0.772668	0.665854		0.701843	
1	2017-01-01	0.459624	0.760466	0.56795		0.653813	

	St. Clair Place
0	0.681486
1	0.621853

	Year	Marion County	Crown Hill	Holy Cross	Mapleton	Fall Creek	\
0	2012-01-01	0.453566	0	0		0	
1	2013-01-01	0.434568	0	0.333333		0	

2	2014-01-01	0.457675	0	1	0
3	2015-01-01	0.446326	0	1	0
4	2016-01-01	0.392507	0	0.6	0
5	2017-01-01	0.555920	0	0.611111	0

St. Clair Place

0	NaN
1	NaN
2	NaN
3	1
4	0.466667
5	0.416667

	Year	Marion County	Crown Hill	Holy Cross	Mapleton	Fall Creek	\
0	2012-01-01	0.378957	0.217833	0.072327		0.300362	
1	2013-01-01	0.366115	0.178912	0.069401		0.283486	
2	2014-01-01	0.359220	0.190141	0.079903		0.282676	
3	2015-01-01	0.352226	0.181598	0.071429		0.29519	
4	2016-01-01	0.343028	0.205431	0.151667		0.293333	
5	2017-01-01	0.339403	0.225066	0.141046		0.350245	

St. Clair Place

0	0.084233
1	0.120507
2	0.120968
3	0.040076
4	0.066451
5	0.090038

	Year	Marion County	Crown Hill	Holy Cross	Mapleton	Fall Creek	\
0	2012-01-01	0.657522	0.25679	0.427372		0.315989	
1	2013-01-01	0.651979	0.214286	0.421508		0.307985	
2	2014-01-01	0.645810	0.26555	0.491228		0.324906	
3	2015-01-01	0.635305	0.312044	0.534351		0.346364	
4	2016-01-01	0.631702	0.302564	0.542799		0.352682	
5	2017-01-01	0.637127	0.325153	0.564953		0.377656	

St. Clair Place

0	0.416366
1	0.42809
2	0.464522
3	0.464529
4	0.480806
5	0.502339

	Year	Marion County	Crown Hill	Holy Cross	Mapleton	Fall Creek	\
0	2012-01-01	0.341612	0.674419	0.222222		0.366667	
1	2013-01-01	0.326738	0.6875	0.144928		0.589041	
2	2014-01-01	0.331888	0.693878	0.328244		0.597403	
3	2015-01-01	0.328359	0	0.409091		0.149533	
4	2016-01-01	0.326443	0	0.40678		0.070707	

5	2017-01-01	0.352395	0	0.376147	0.119658
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St. Clair Place

0	0.320988
1	0.306604
2	0.291339
3	0.389105
4	0.375
5	0.424051

	Year	Marion County	Crown Hill	Holy Cross	Mapleton	Fall Creek \
0	2017-01-01	0.13	0.266393	0.264331		0.240642

St. Clair Place

0	0.18
---	------

	Year	Marion County	Crown Hill	Holy Cross	Mapleton	Fall Creek \
0	2017-01-01	0.24	0.234892	0.257991		0.33313

St. Clair Place

0	0.33
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	Year	Marion County	Crown Hill	Holy Cross	Mapleton	Fall Creek \
0	2017-01-01	0.5	0.728682	0.619184		0.658448

St. Clair Place

0	0.6
---	-----

	Year	Marion County	Crown Hill	Holy Cross	Mapleton	Fall Creek \
0	2012-01-01	1172	937.664615	1343		1019.561026
1	2013-01-01	1148	972.482036	1126		1009.761555
2	2014-01-01	1129	830.92429	1142		904.612176
3	2015-01-01	1111	990.182724	1182		960.3878
4	2016-01-01	1111	1020.393939	1114.099275		997.458647
5	2017-01-01	1123	1011.41	1134.936589		1011.220829

St. Clair Place

0	982
1	982
2	848
3	852
4	850
5	907

	Year	Marion County	Crown Hill	Holy Cross	Mapleton	Fall Creek \
0	2012-01-01	751	659.080288	623		714.082287
1	2013-01-01	768	681.540134	641		718.240488
2	2014-01-01	781	690.624771	692		689.11477
3	2015-01-01	788	630.867588	721		710.016728
4	2016-01-01	806	639.299131	749		700.061211
5	2017-01-01	836	661.199773	778.571317		658.203575

St. Clair Place

0	671
1	714
2	711
3	730
4	751
5	791

	Year	Marion County	Crown Hill	Holy Cross	Mapleton	Fall Creek	\
0	2012-01-01	26.236624	32.4	69.2		38.3	
1	2013-01-01	28.36917	27.9	62.5		37.9	
2	2014-01-01	30.322532	36.8	58.7		39.8	
3	2015-01-01	36.263376	58.8	111.5		64.3	
4	2016-01-01	40.753079	76.5	118.3		76.5	
5	2017-01-01	44.172724	100	126.9		91.8	

St. Clair Place

0	41.666667
1	31.944444
2	33.333333
3	73.611111
4	83.333333
5	123.611111

	Year	Marion County	Crown Hill	Holy Cross	Mapleton	Fall Creek	\
0	2012-01-01	11.097826	58.8	60.6		37.8	
1	2013-01-01	9.744565	51.5	60.6		45.4	
2	2014-01-01	11.875	58.8	92.3		40.8	
3	2015-01-01	10.964674	64.7	85.6		37.8	
4	2016-01-01	10.980978	33.8	81.7		33.2	
5	2017-01-01	11.358696	54.4	94.2		55.6	

St. Clair Place

0	77.8
1	43.1
2	76.4
3	106.9
4	80.6
5	112.5

	Year	Marion County	Crown Hill	Holy Cross	Mapleton	Fall Creek	\
0	2012-01-01	91500	51655	56400		63897	
1	2013-01-01	88900	49501	54528		63687	
2	2014-01-01	90400	51109	57768		60461	
3	2015-01-01	93300	51776	60089		61676	
4	2016-01-01	95700	52606	62843		62678	
5	2017-01-01	100200	54871	70077		65832	

St. Clair Place

0	28013
1	31716
2	32267



3 35022  
 4 37467  
 5 44452

	Year	Crown Hill	Holy Cross	Mapleton	Fall Creek	St. Clair	Place \
0	2008-01-01	13412.5	32500		19500		8750
1	2009-01-01	12500	19000		28750		10000
2	2010-01-01	15700	91500		29450		10000
3	2011-01-01	18900	75500		64500		11000
4	2012-01-01	24900	145000		77000		12600
5	2013-01-01	28500	122000		55275		19375
6	2014-01-01	20400	155000		145000		22405
7	2015-01-01	31375	170100		109000		30000
8	2016-01-01	53500	214000		105000		28040
9	2017-01-01	44000	165000		136750		56000
10	2018-01-01	84750	210000		142500		79000

Marion County

0 89000  
 1 89999  
 2 93000  
 3 91000  
 4 97000  
 5 107000  
 6 115500  
 7 121000  
 8 126000  
 9 135000  
 10 148050

	Year	Crown Hill	Holy Cross	Mapleton	Fall Creek	St. Clair	Place \
0	2008-01-01	50	36		137		115
1	2009-01-01	37	42		121		96
2	2010-01-01	27	45		98		76
3	2011-01-01	29	23		82		64
4	2012-01-01	25	37		111		64
5	2013-01-01	32	30		98		56
6	2014-01-01	23	37		93		56
7	2015-01-01	44	44		142		67
8	2016-01-01	40	50		148		64
9	2017-01-01	45	69		166		113
10	2018-01-01	66	56		203		140

Marion County

0 11654  
 1 10457  
 2 9172  
 3 9063  
 4 10527  
 5 12160

6	11796
7	12814
8	14083
9	14875
10	14844

## Stage 2) Data Modelling and Visualization

```
[9]: #Homeownership

#Households by tenure

def plot_time_series(df, ylabel, title, include_marion=True):
    neighborhoods = ['Crown Hill', 'Holy Cross', 'Mapleton Fall Creek', 'St. Clair Place']
    if include_marion:
        neighborhoods.insert(0, 'Marion County')
    df.plot(kind='line', x='Year', y=neighborhoods, figsize=(10, 6),
    title=title)
    plt.xlabel('Year')
    plt.ylabel(ylabel)
    plt.grid(False)
    plt.show()

#Number of owned households
plot_time_series(hholds_ten_own, 'Number of owned households', 'Time Series of
    Number of owned households by Neighborhood')
plot_time_series(hholds_ten_own, 'Number of owned households', 'Time Series of
    Number of owned households by Neighborhood (Excluding Marion County)',
    include_marion=False)

#Number of rented households
plot_time_series(hholds_ten_rent, 'Number of rented households', 'Time Series
    of Number of rented households by Neighborhood')
plot_time_series(hholds_ten_rent, 'Number of rented households', 'Time Series
    of Number of rented households by Neighborhood (Excluding Marion County)',
    include_marion=False)

#Percentage of owned households
plot_time_series(perc_hholds_ten_own, 'Percentage of owned households', 'Time
    Series of Percentage of owned households by Neighborhood')
plot_time_series(perc_hholds_ten_own, 'Percentage of owned households', 'Time
    Series of Percentage of owned households by Neighborhood (Excluding Marion
    County)', include_marion=False)

#Percentage of rented households
```

```

plot_time_series(perc_hholds_ten_rent, 'Percentage of rent households', 'Time_
↳Series of Percentage of rented households by Neighborhood')
plot_time_series(perc_hholds_ten_rent, 'Percentage of rent households', 'Time_
↳Series of Percentage of rented households by Neighborhood (Excluding Marion_
↳County)', include_marion=False)

#Homeownership Rate by Race (Group-Specific)

def plot_homeownership(df, demographic, title):
    df.plot(kind='line', x='Year', y=['Marion County', 'Crown Hill', 'Holy_
↳Cross', 'Mapleton Fall Creek', 'St. Clair Place'], figsize=(10, 6),_
↳title=title)
    plt.xlabel('Year')
    plt.ylabel('Percentage of Home Ownership')
    plt.grid(False)
    plt.show()

plot_homeownership(asian_ho_df, 'Asian', 'Time Series of Asian Homeownership_
↳Rate by Neighborhood')
plot_homeownership(afr_ho_df, 'African-American', 'Time Series of_
↳African-American Homeownership Rate by Neighborhood')
plot_homeownership(lat_ho_df, 'Latina/o', 'Time Series of Latina/o_
↳Homeownership Rate by Neighborhood')
plot_homeownership(white_ho_df, 'Caucasian', 'Time Series of Caucasian_
↳Homeownership Rate by Neighborhood')

#Homeownership Rate by Race (Neighborhood-Specific)

ethnicities = ['Asian', 'African-American', 'Caucasian', 'Latina/o']

dataframes = [asian_ho_df, afr_ho_df, lat_ho_df, white_ho_df]

neighborhoods = ['Marion County', 'Crown Hill', 'Holy Cross', 'Mapleton Fall_
↳Creek', 'St. Clair Place']

fig, axes = plt.subplots(nrows=len(neighborhoods), ncols=1, figsize=(10, 24))

for i, neighborhood in enumerate(neighborhoods):
    ax = axes[i]
    ax.set_title(f'Homeownership Rate by Ethnicity in {neighborhood}')
    ax.set_xlabel('Year')
    ax.set_ylabel('Percentage of Home Ownership')
    ax.grid(False)

    for ethnicity, df in zip(ethnicities, dataframes):
        df.plot(kind='line', x='Year', y=neighborhood, ax=ax, label=ethnicity)

```

```

plt.tight_layout()
plt.legend()
plt.show()

#Homeownership by Race Visualization

fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(15, 10))

axes = axes.flatten()

for i, neighborhood in enumerate(neighborhoods[1:]):
    ax = axes[i]
    ax.set_title(f'Homeownership Rate by Ethnicity in {neighborhood}')
    ax.set_xlabel('Year')
    ax.set_ylabel('Percentage of Home Ownership')
    ax.grid(False)

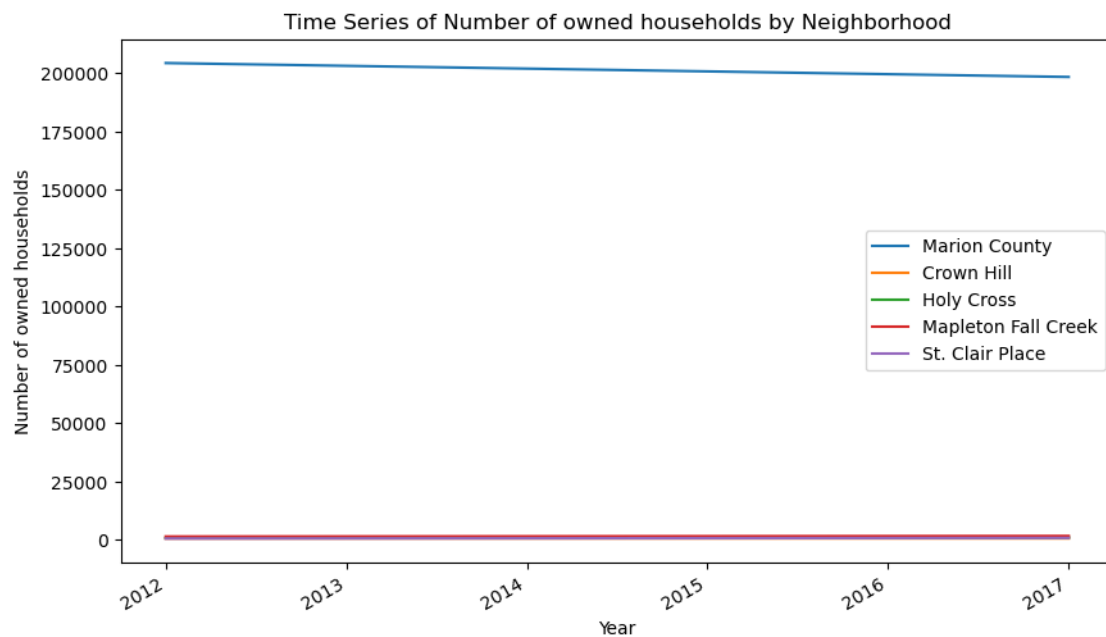
    for ethnicity, df in zip(ethnicities, dataframes):
        df.plot(kind='line', x='Year', y=neighborhood, ax=ax, label=ethnicity)

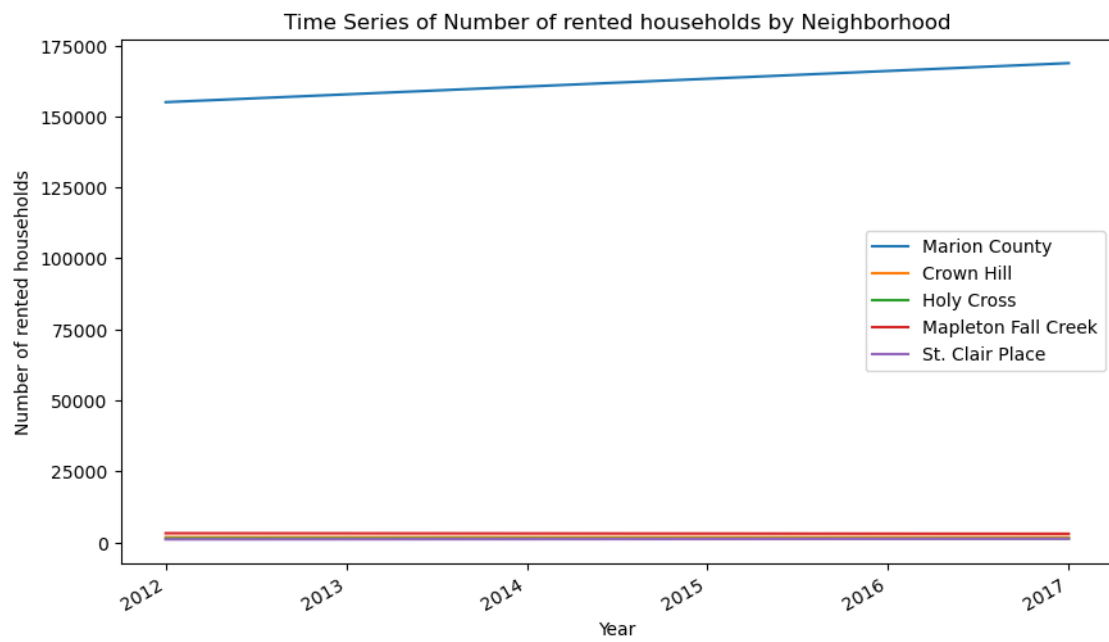
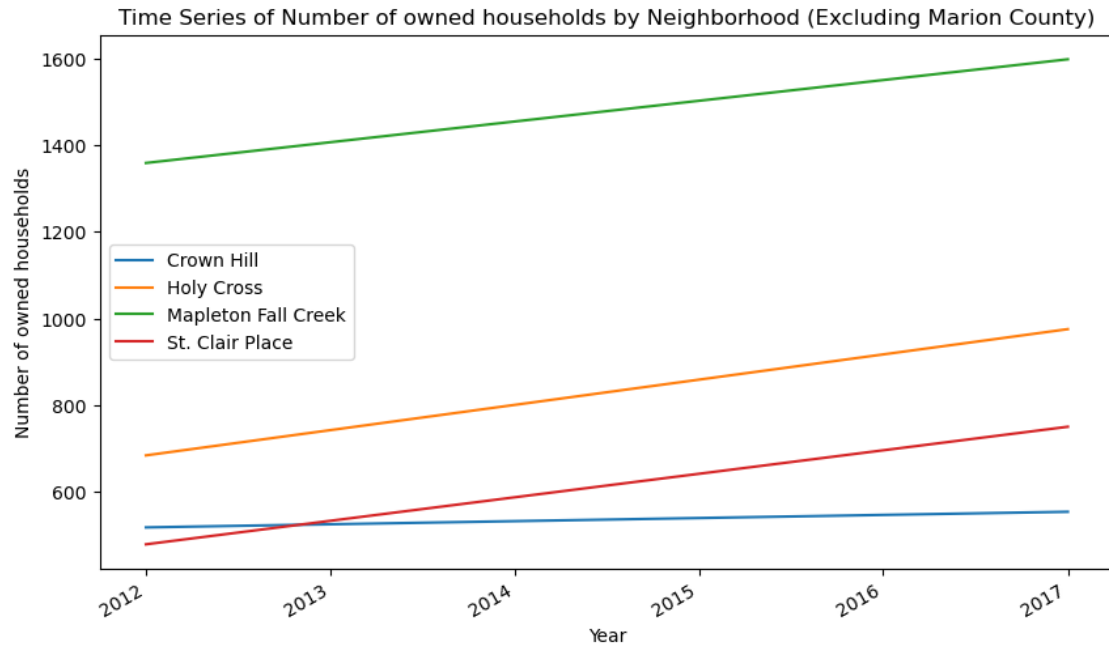
    ax.legend(loc='upper left')

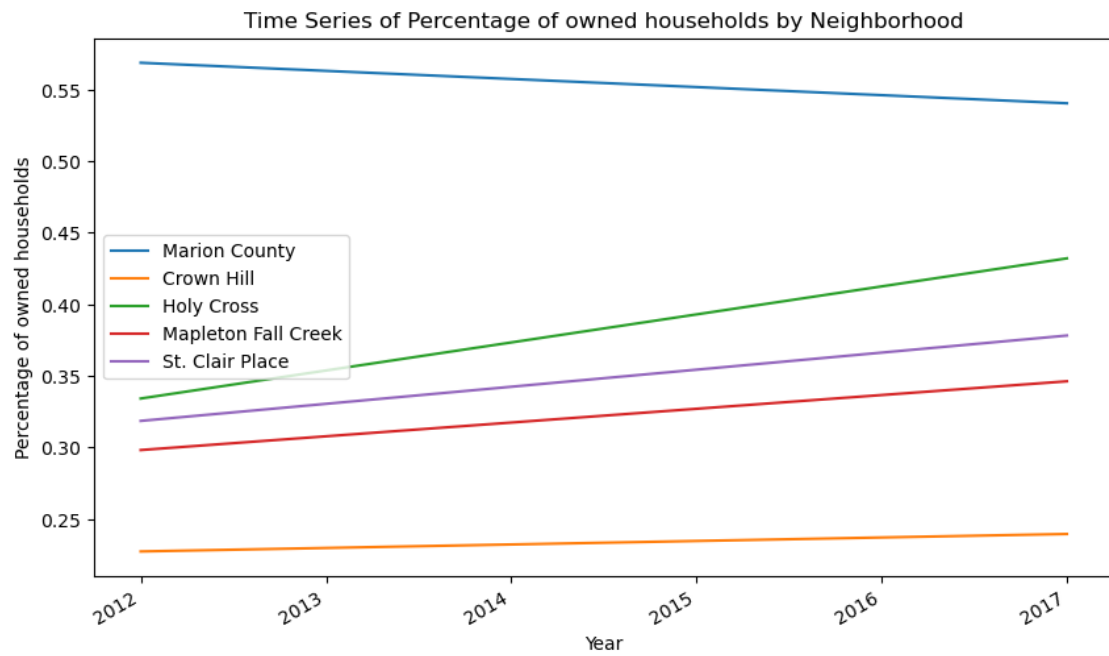
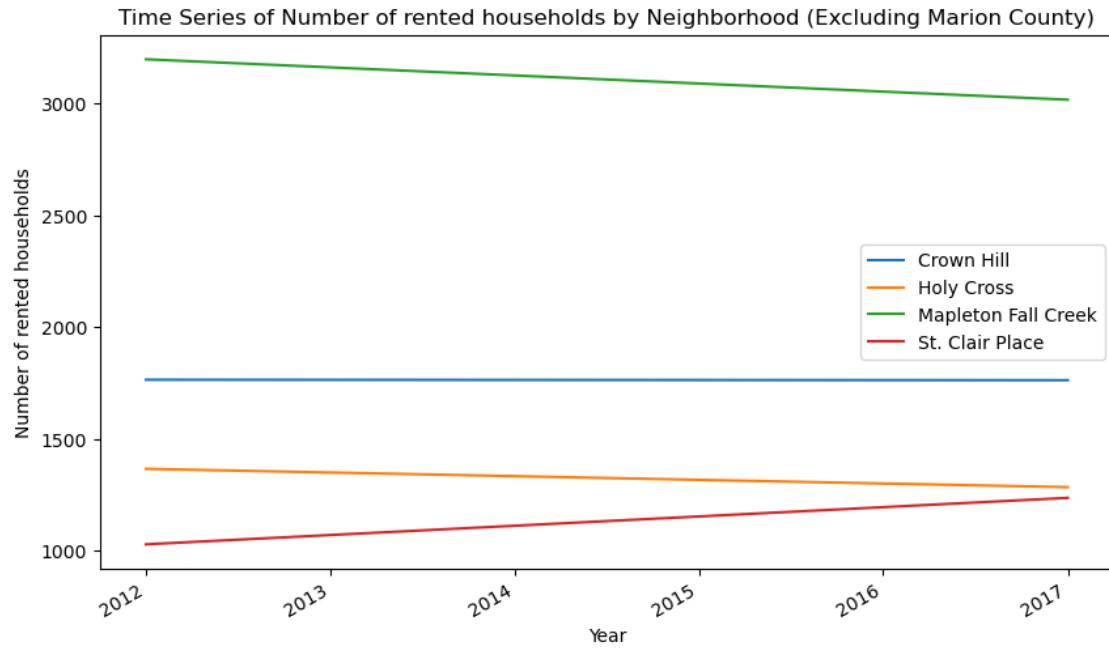
plt.tight_layout()

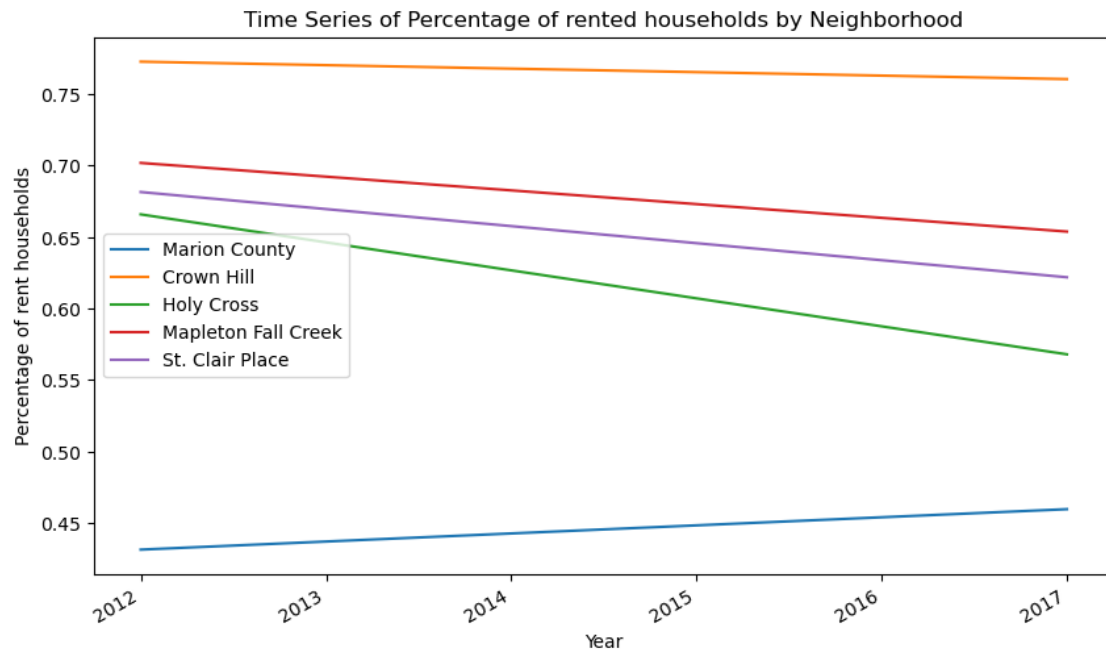
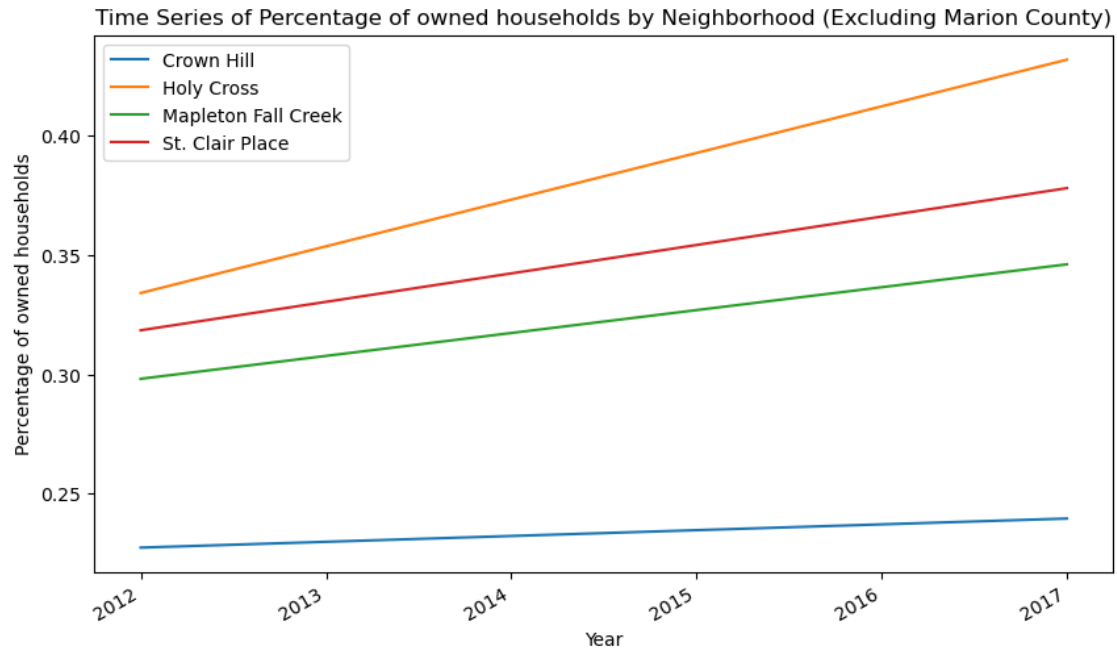
plt.show()

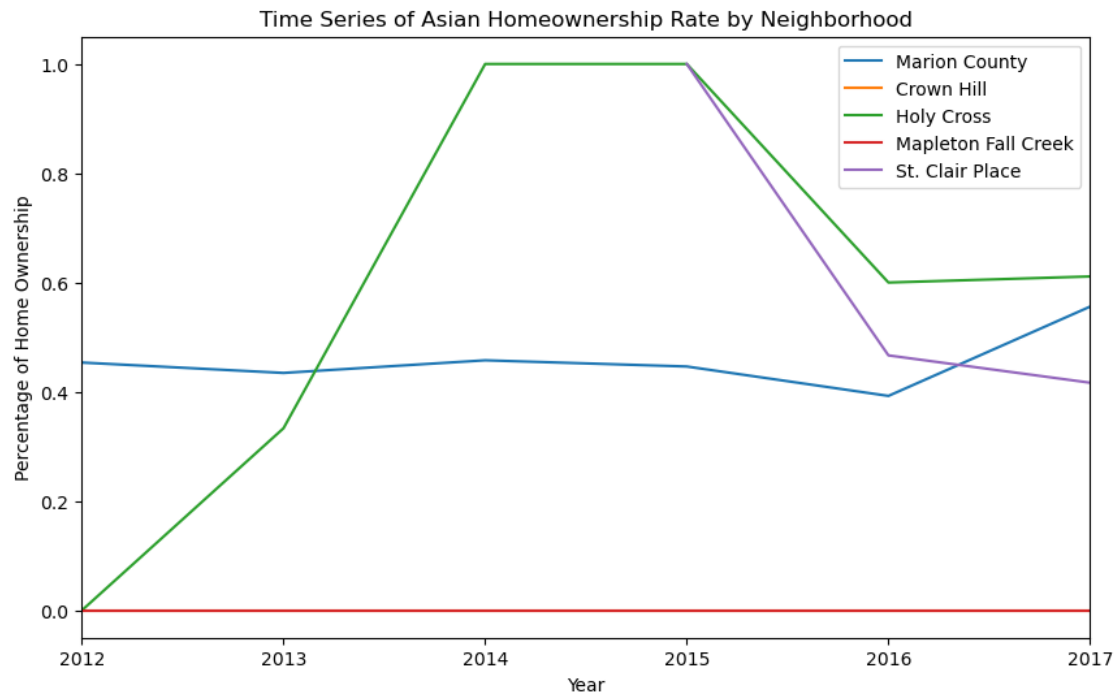
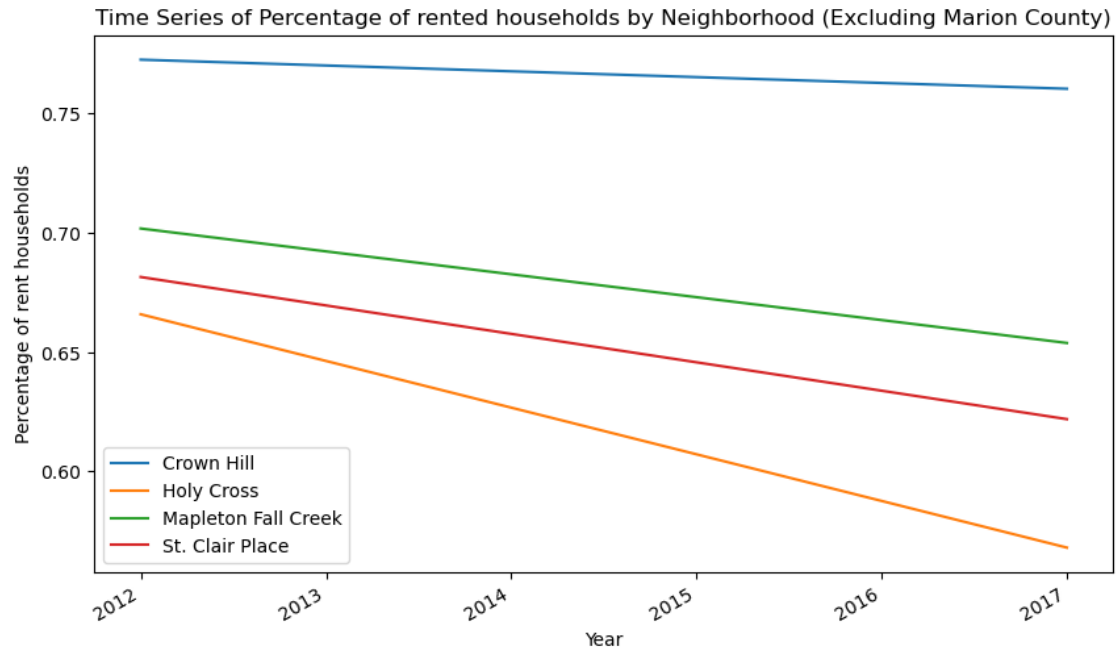
```



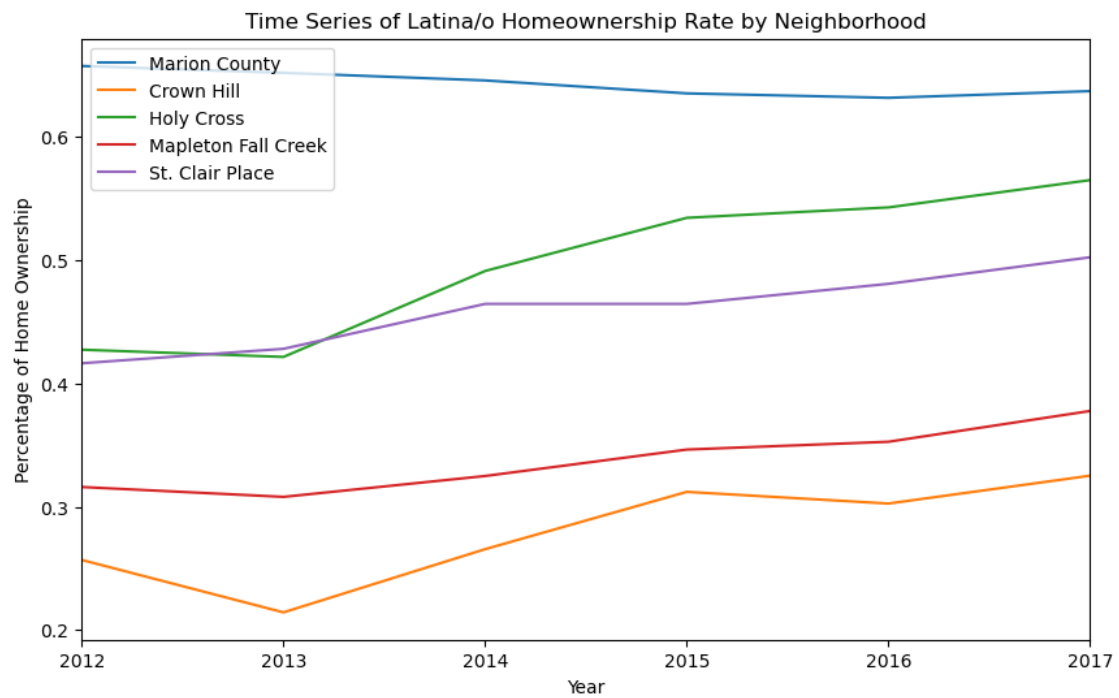
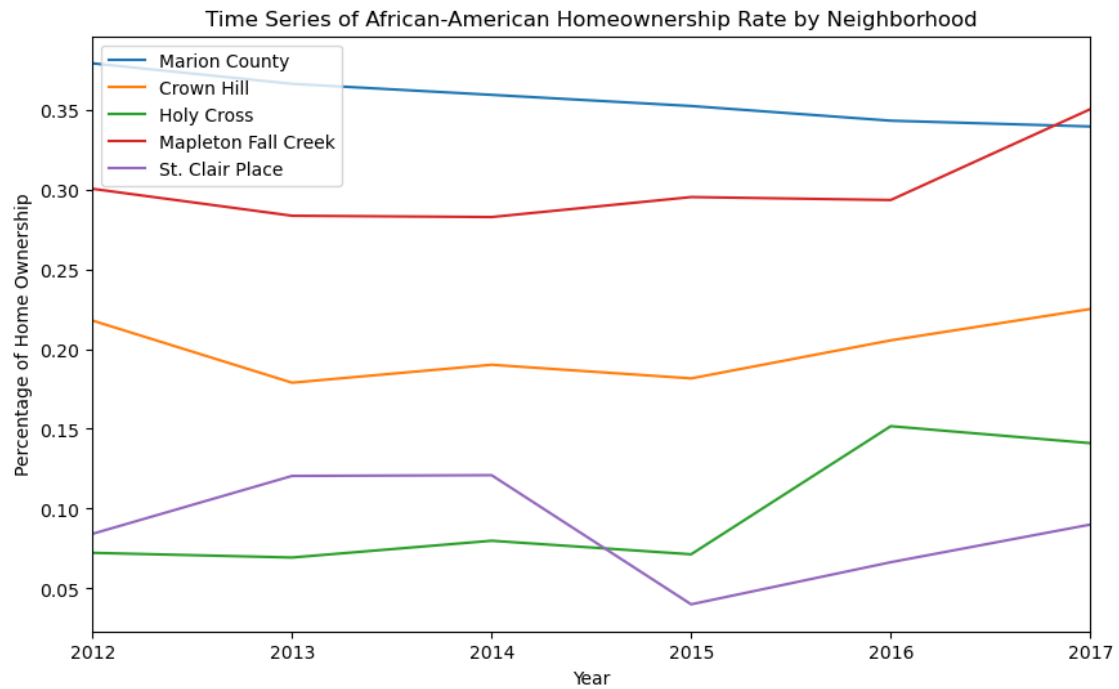


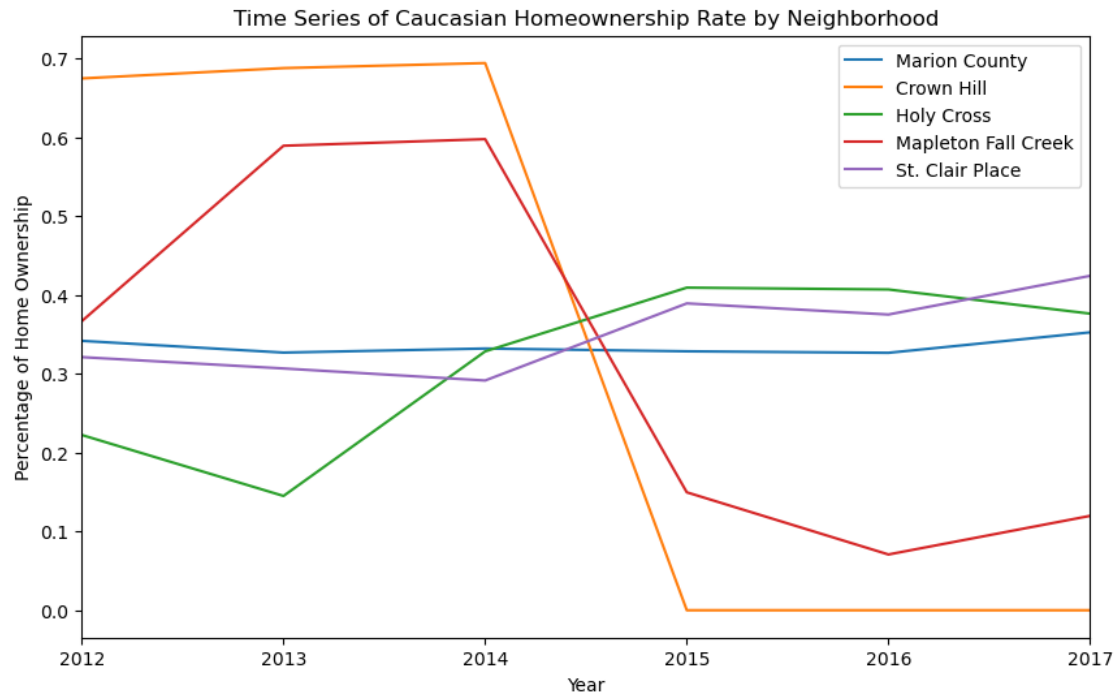


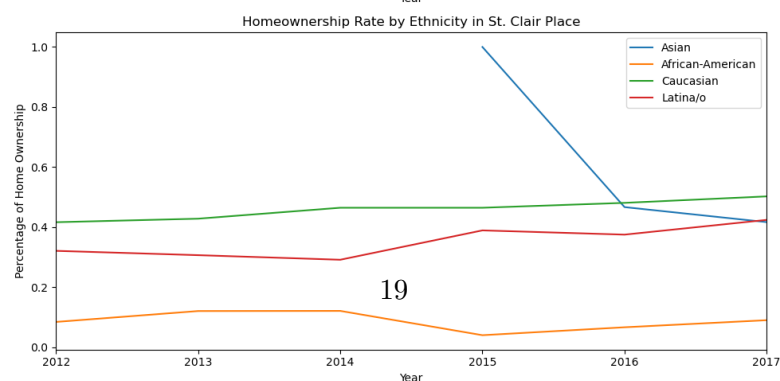
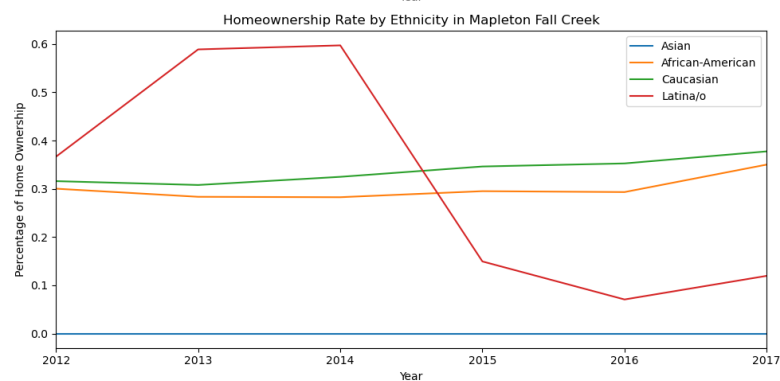
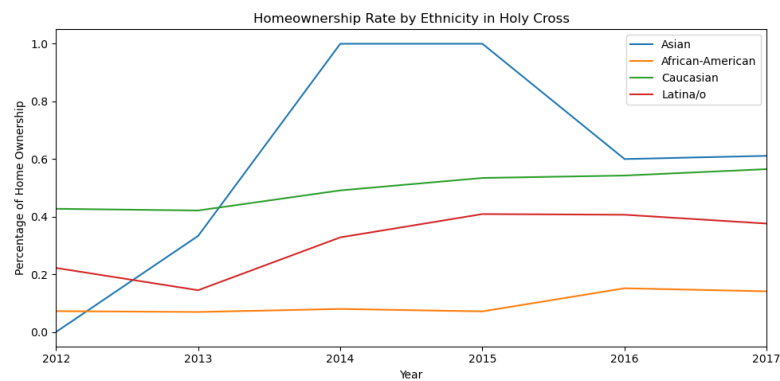
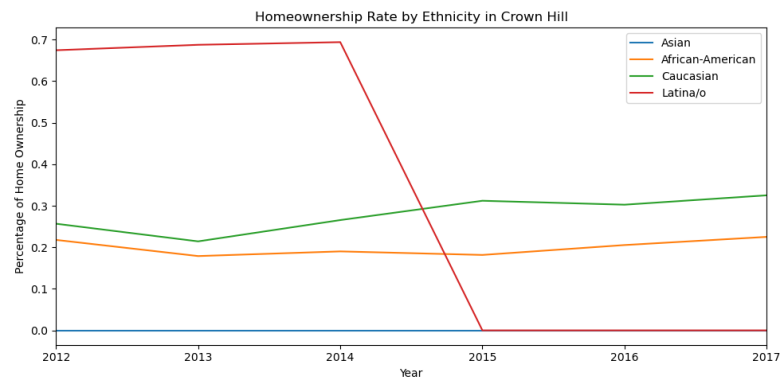
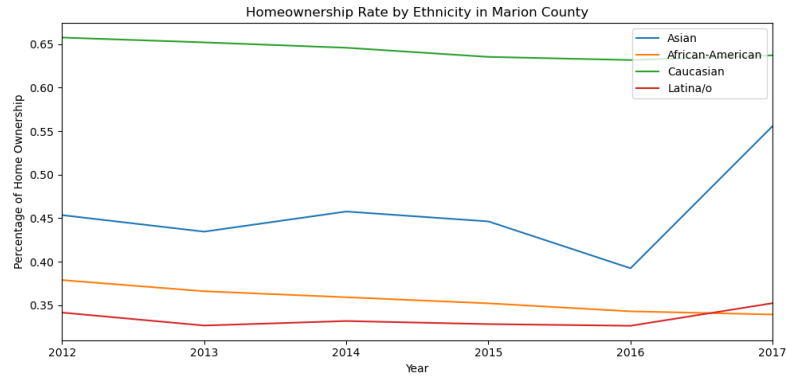


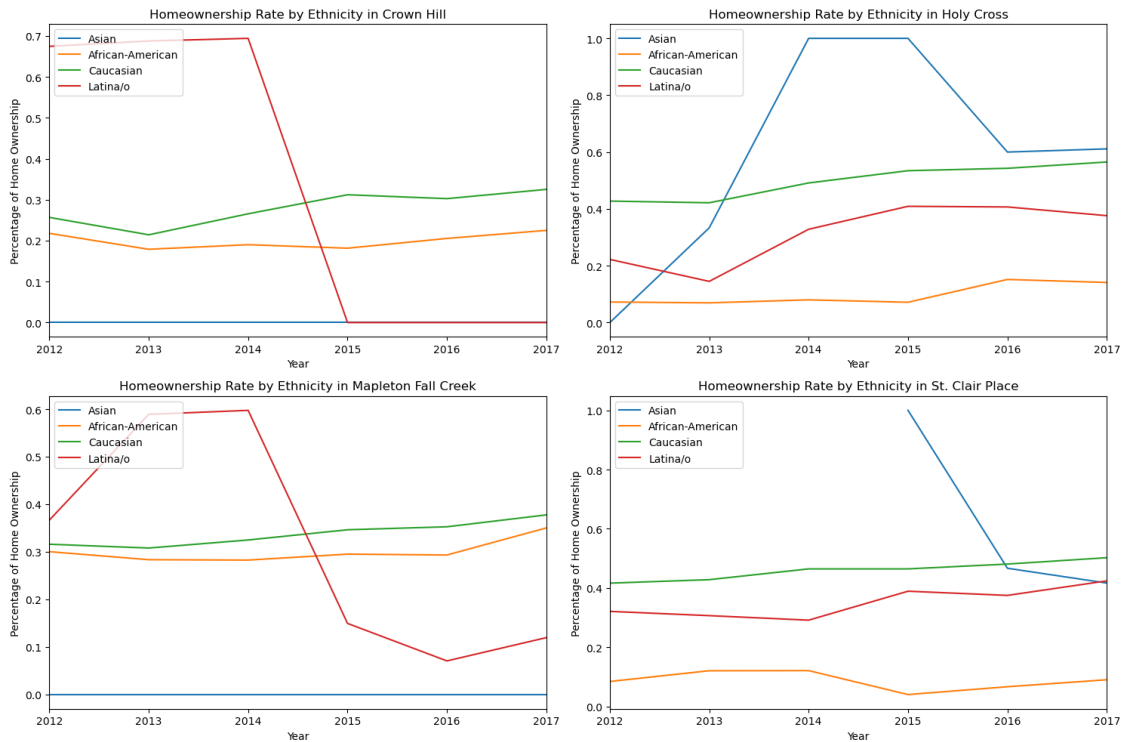












[10]: *#Housing Cost*

*#Cost burden*

```
def plot_scatter(df, ylabel, title):
    df.plot(kind='scatter', x='Year', y='Marion County', figsize=(10, 6),
    ↪title=title)
    df.plot(kind='scatter', x='Year', y='Crown Hill', color='orange', ax=plt.
    ↪gca())
    df.plot(kind='scatter', x='Year', y='Holy Cross', color='green', ax=plt.
    ↪gca())
    df.plot(kind='scatter', x='Year', y='Mapleton Fall Creek', color='blue',
    ↪ax=plt.gca())
    df.plot(kind='scatter', x='Year', y='St. Clair Place', color='red', ax=plt.
    ↪gca())

    plt.xlabel('Year')
    plt.ylabel(ylabel)
    plt.grid(False)
```

```

plt.legend(['Marion County', 'Crown Hill', 'Holy Cross', 'Mapleton Fall_
↳Creek', 'St. Clair Place'])
plt.show()

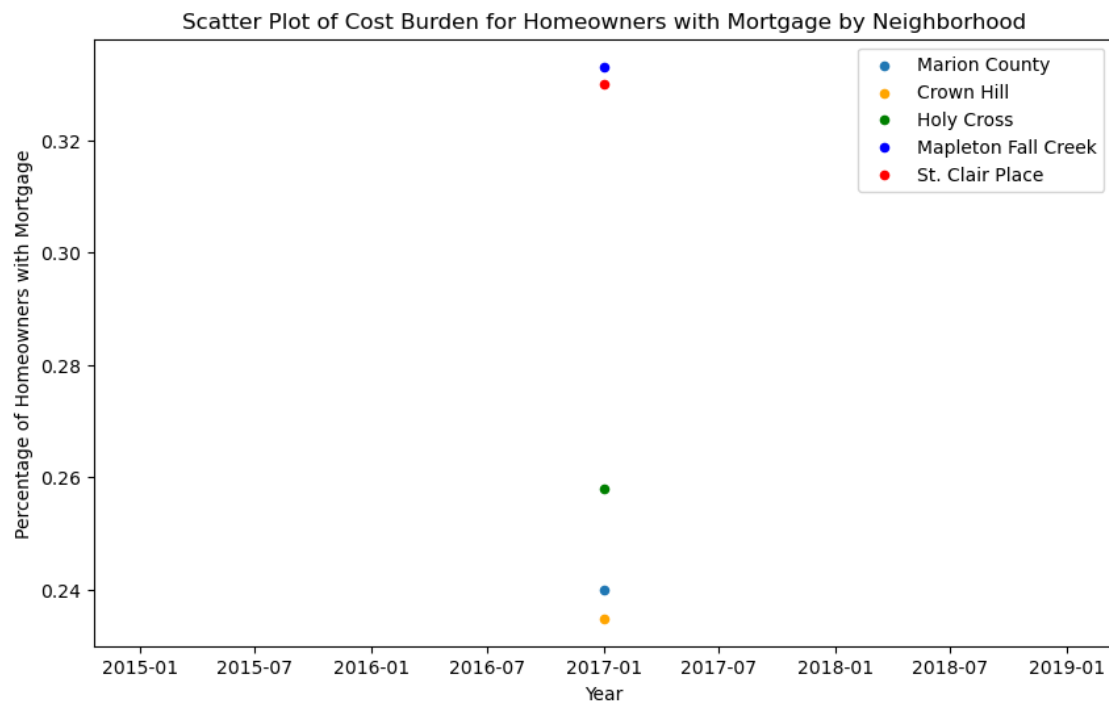
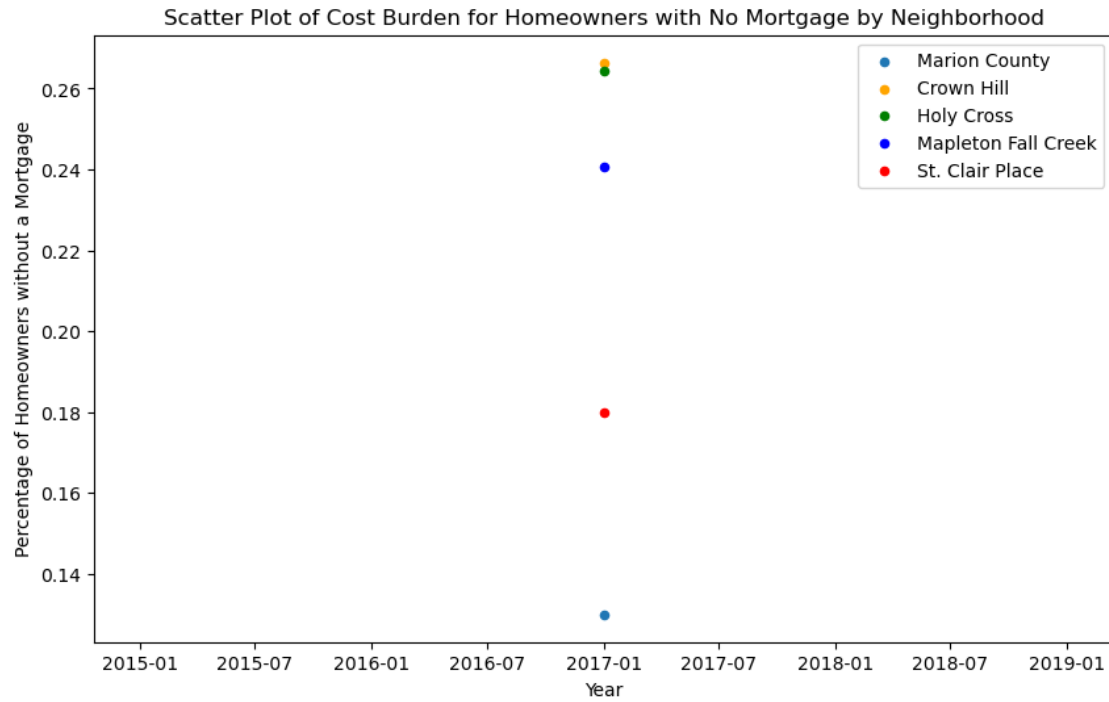
plot_scatter(cb_h_nm_df, 'Percentage of Homeowners without a Mortgage',
↳'Scatter Plot of Cost Burden for Homeowners with No Mortgage by_
↳Neighborhood')
plot_scatter(cb_h_wm_df, 'Percentage of Homeowners with Mortgage', 'Scatter_
↳Plot of Cost Burden for Homeowners with Mortgage by Neighborhood')
plot_scatter(cb_rent_df, 'Percentage of Hold Renters', 'Scatter Plot of Cost_
↳Burden for Renters by Neighborhood')

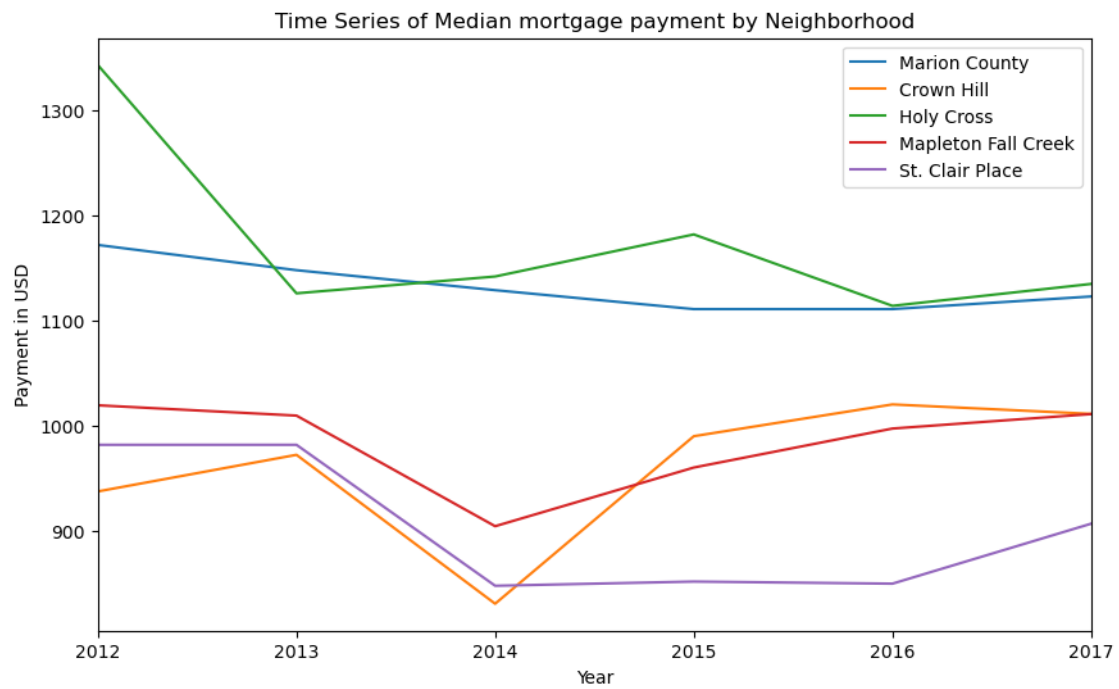
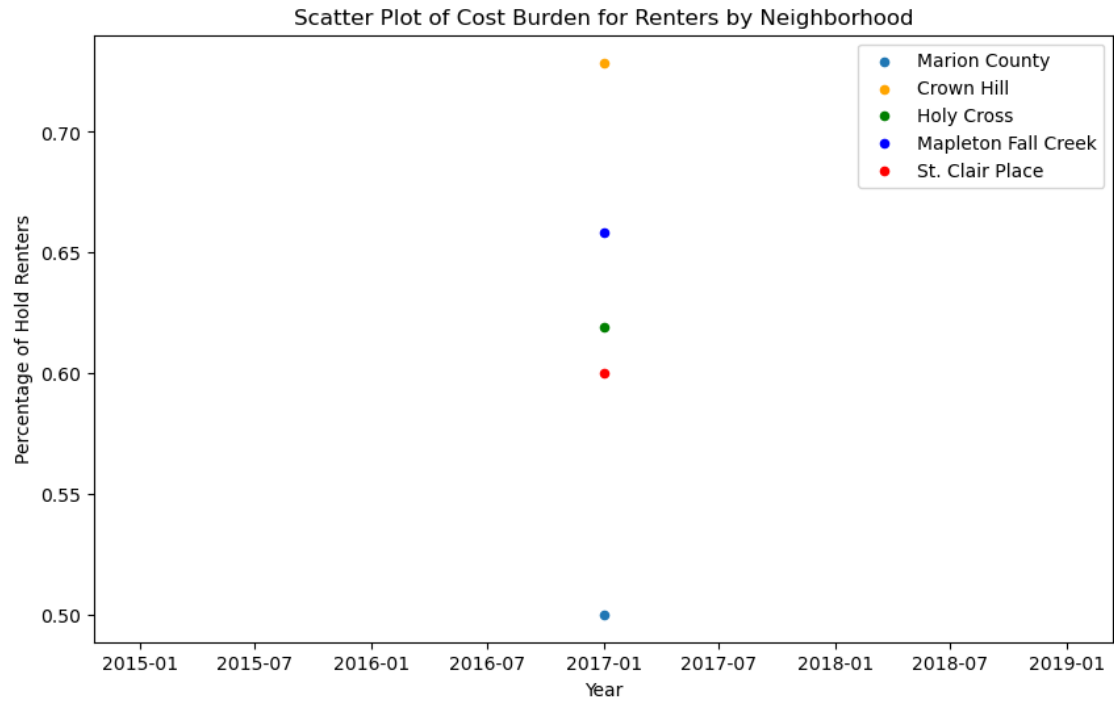
# Median monthly rent and mortgage payment amounts

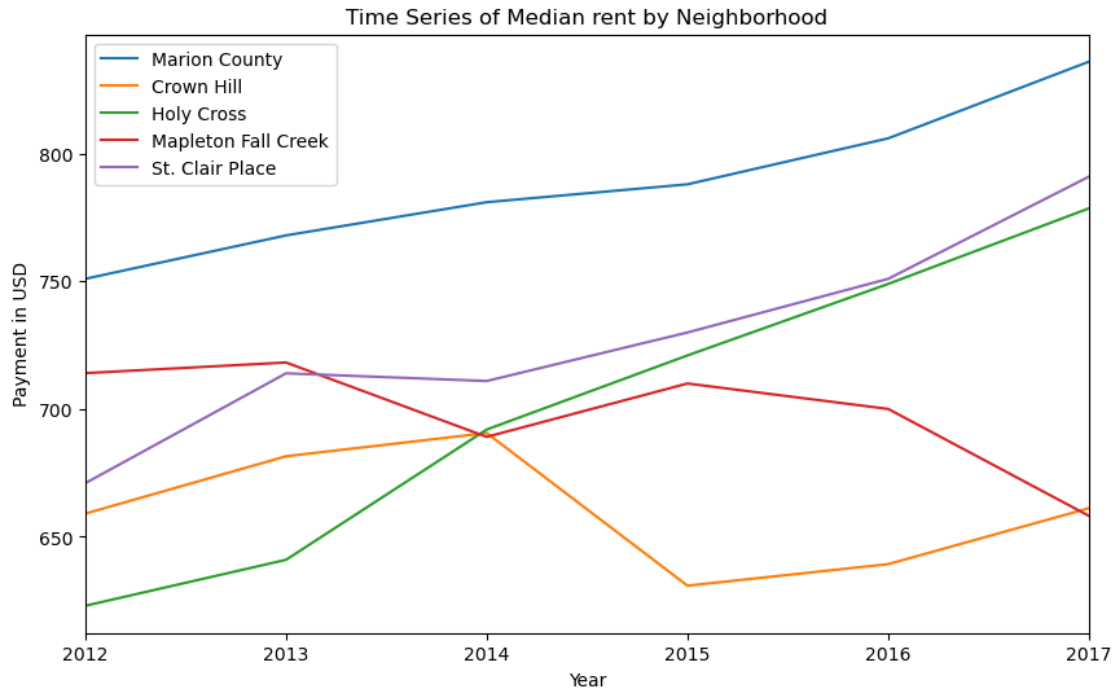
def plot_time_series(df, ylabel, title):
    df.plot(kind='line', x='Year', y=['Marion County', 'Crown Hill', 'Holy_
↳Cross', 'Mapleton Fall Creek', 'St. Clair Place'], figsize=(10, 6),
↳title=title)
    plt.xlabel('Year')
    plt.ylabel(ylabel)
    plt.grid(False)
    plt.show()

plot_time_series(med_mon_mort_df, 'Payment in USD', 'Time Series of Median_
↳mortgage payment by Neighborhood')
plot_time_series(med_mon_rent_df, 'Payment in USD', 'Time Series of Median rent_
↳by Neighborhood')

```







```
[11]: def plot_housing_metric(df, ylabel, title, include_marion=True):
    neighborhoods = ['Marion County', 'Crown Hill', 'Holy Cross', 'Mapleton_
    ↪Fall Creek', 'St. Clair Place']
    if not include_marion:
        neighborhoods.remove('Marion County')
    df.plot(kind='line', x='Year', y=neighborhoods, figsize=(10, 6),
    ↪title=title)
    plt.xlabel('Year')
    plt.ylabel(ylabel)
    plt.grid(False)
    plt.show()

# Mortgage loan applications per sq mile
plot_housing_metric(mortgage_loan_app_df, 'Loan Applications per mi^2', 'Time_
    ↪Series of Mortgage Loan Applications per mi^2 by Neighborhood')

# Residential building permits per square mile
plot_housing_metric(res_buil_per_df, 'Building permits per mi^2', 'Time Series_
    ↪of Residential building permits per mi^2 by Neighborhood')

# Median assessed value
plot_housing_metric(med_a_val_df, 'Price In USD', 'Time Series of Housing_
    ↪Median assessed value by Neighborhood')
```

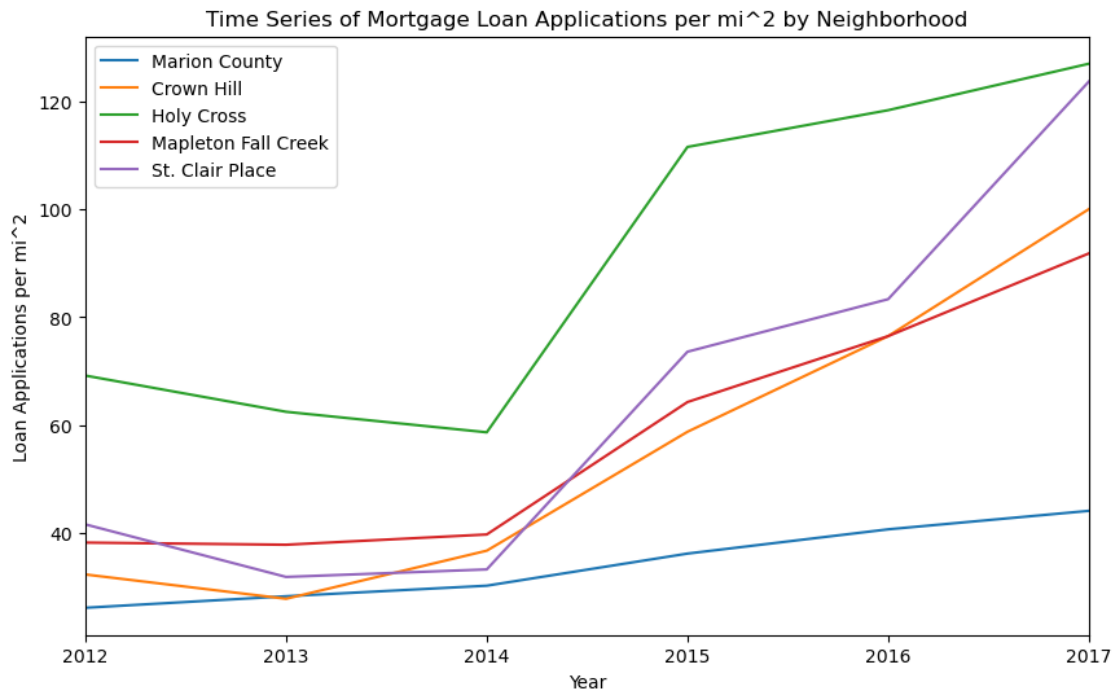


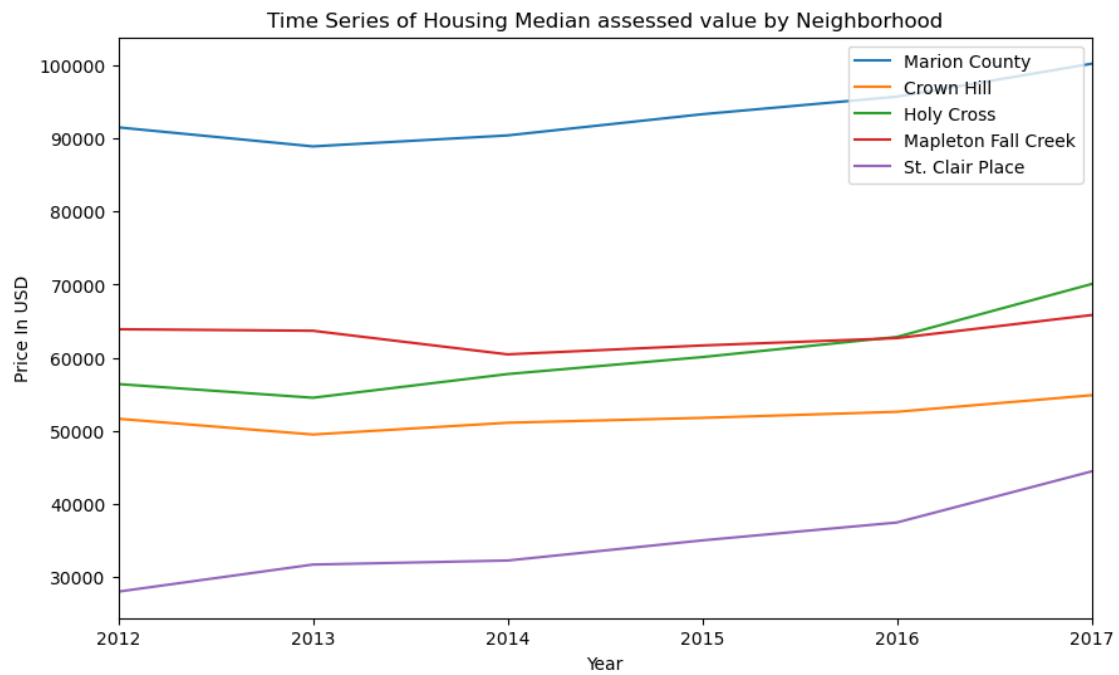
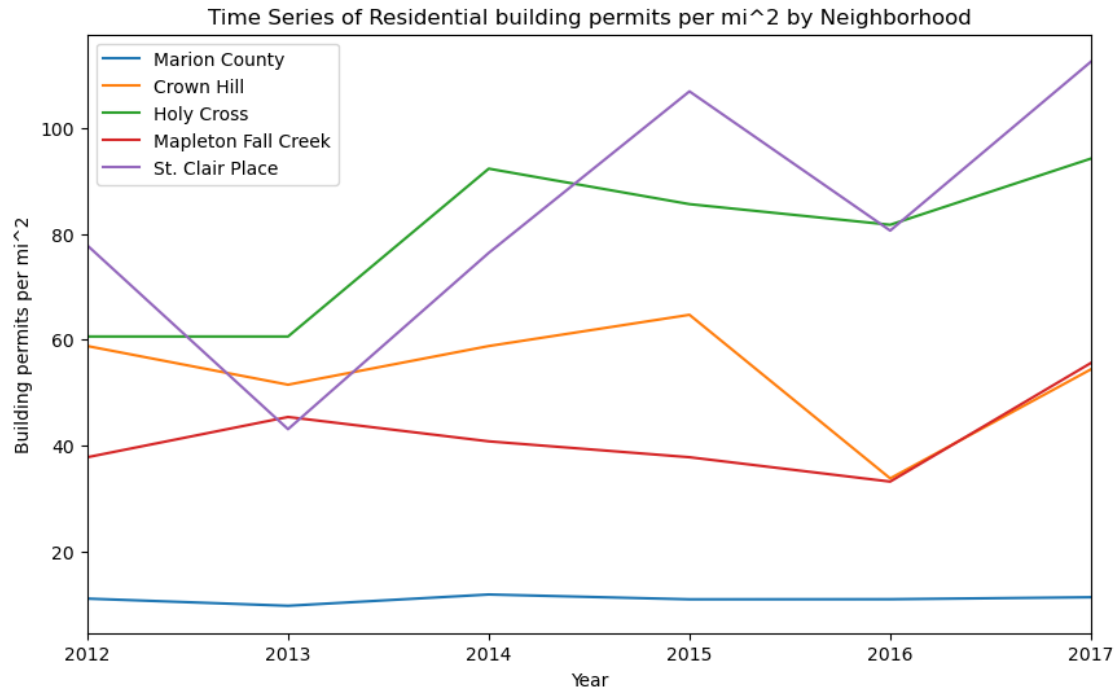
```

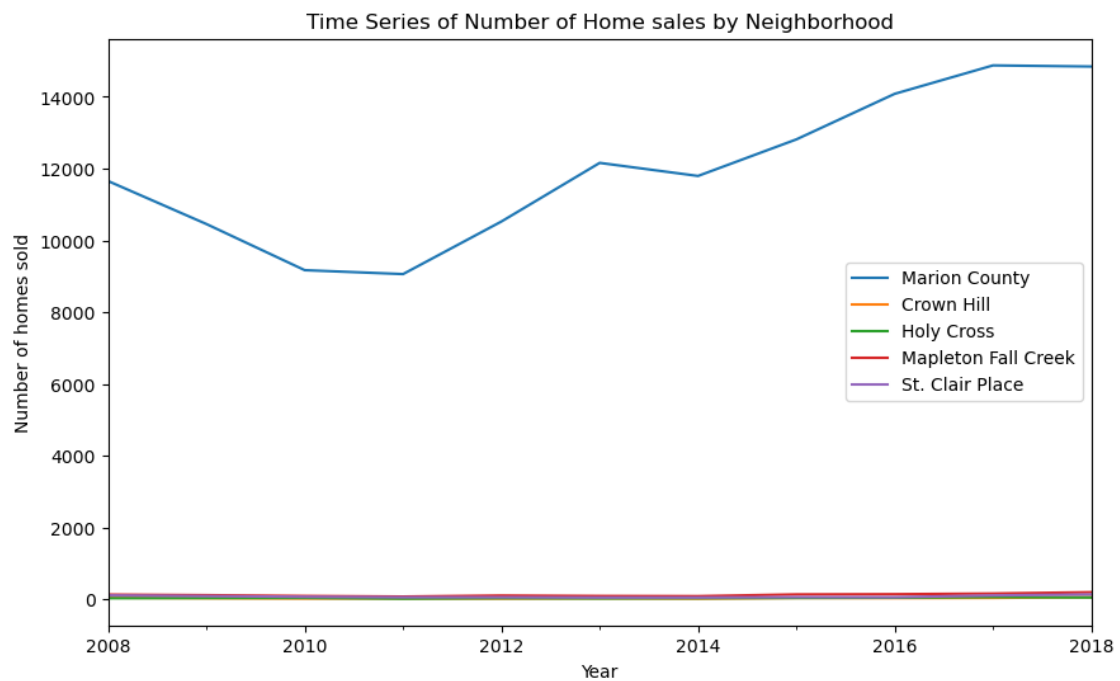
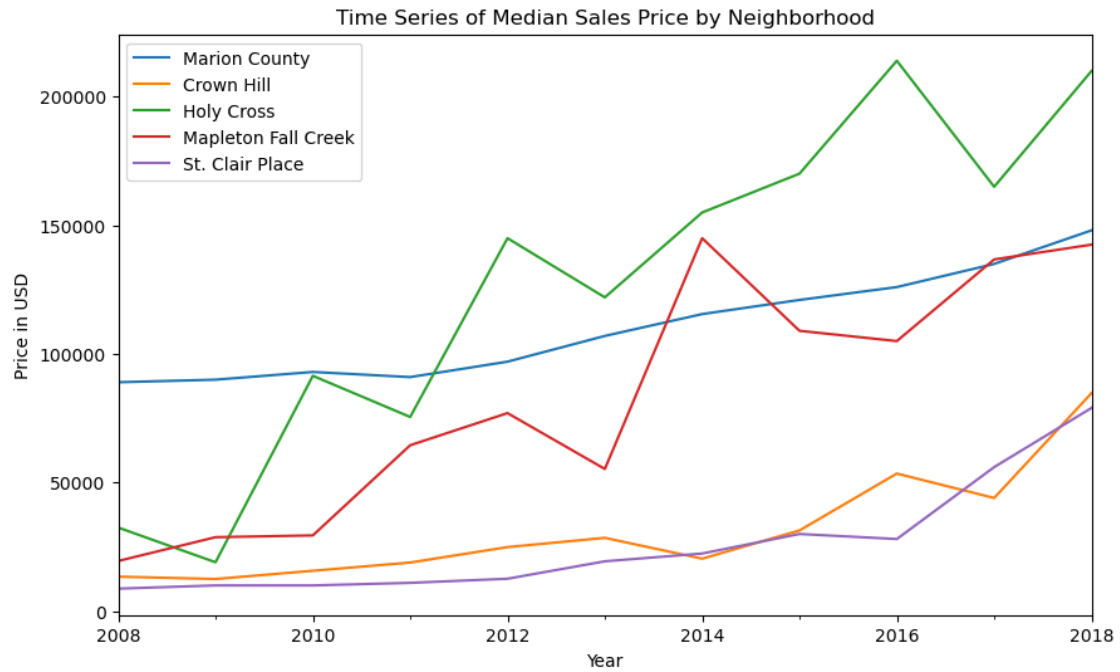
# Median sales price
plot_housing_metric(med_sales_pri_df, 'Price in USD', 'Time Series of Median_
↳Sales Price by Neighborhood')

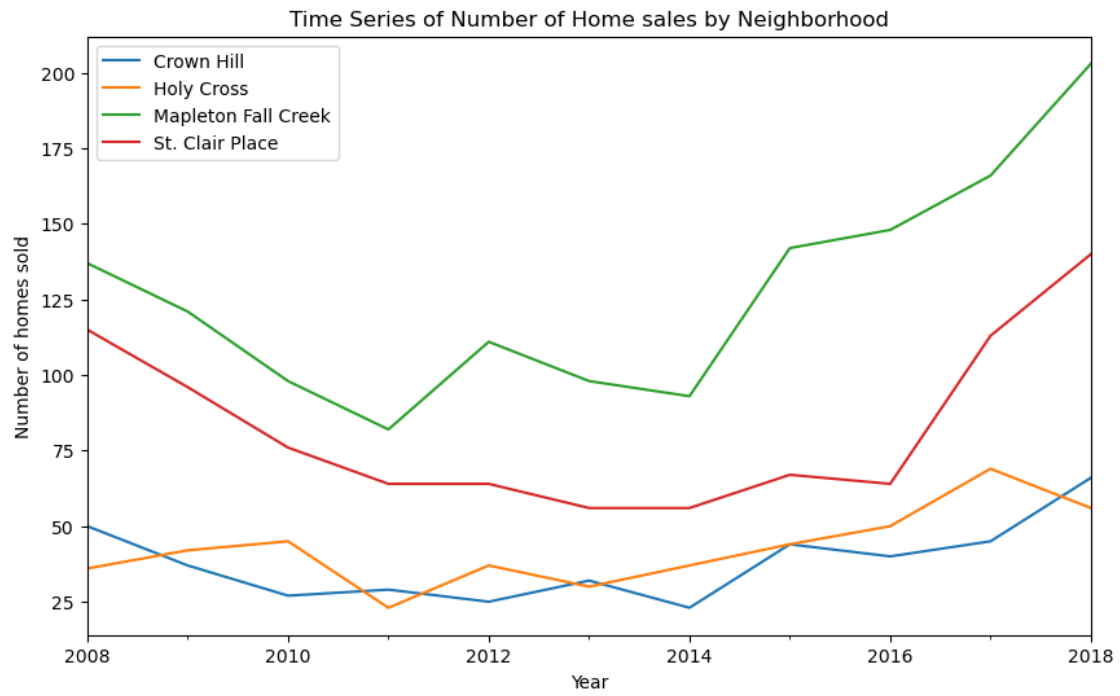
# Number of home sales
plot_housing_metric(num_home_s_df, 'Number of homes sold', 'Time Series of_
↳Number of Home sales by Neighborhood')
plot_housing_metric(num_home_s_df, 'Number of homes sold', 'Time Series of_
↳Number of Home sales by Neighborhood', include_marion=False)

```





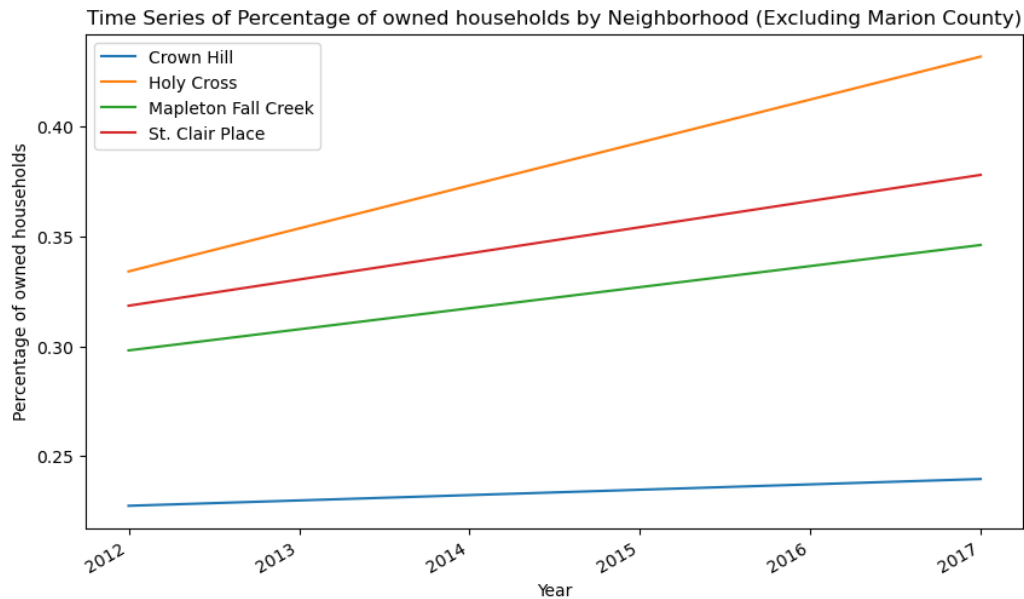




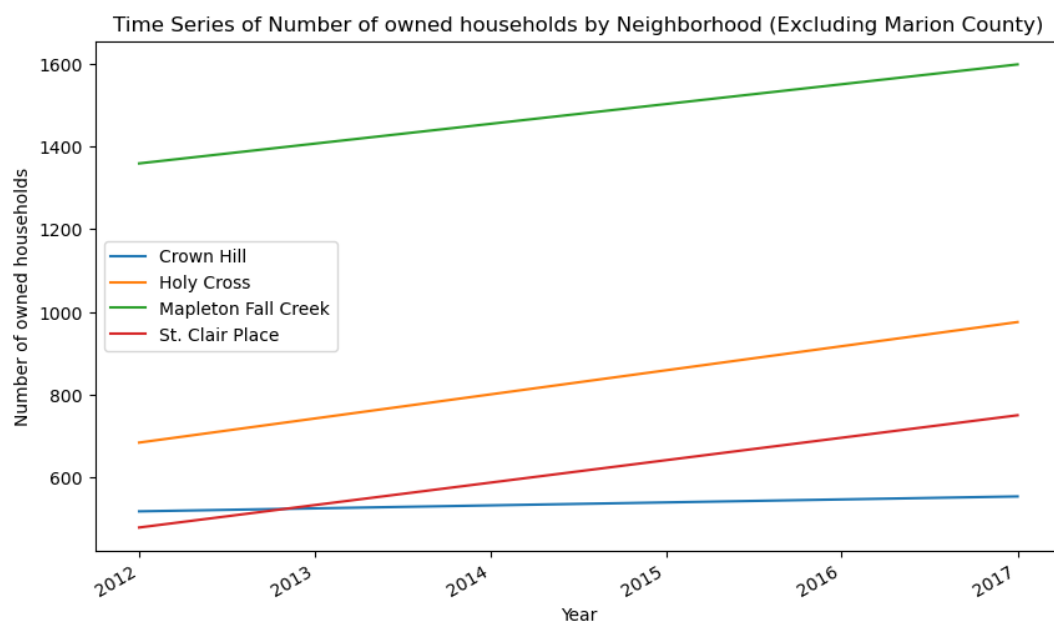
### Stage 3) Interpretations, Analysis and Conclusions

Based on the data, it is possible that increasing building permit issuance in some Indianapolis neighborhoods could have a beneficial impact for its communities.

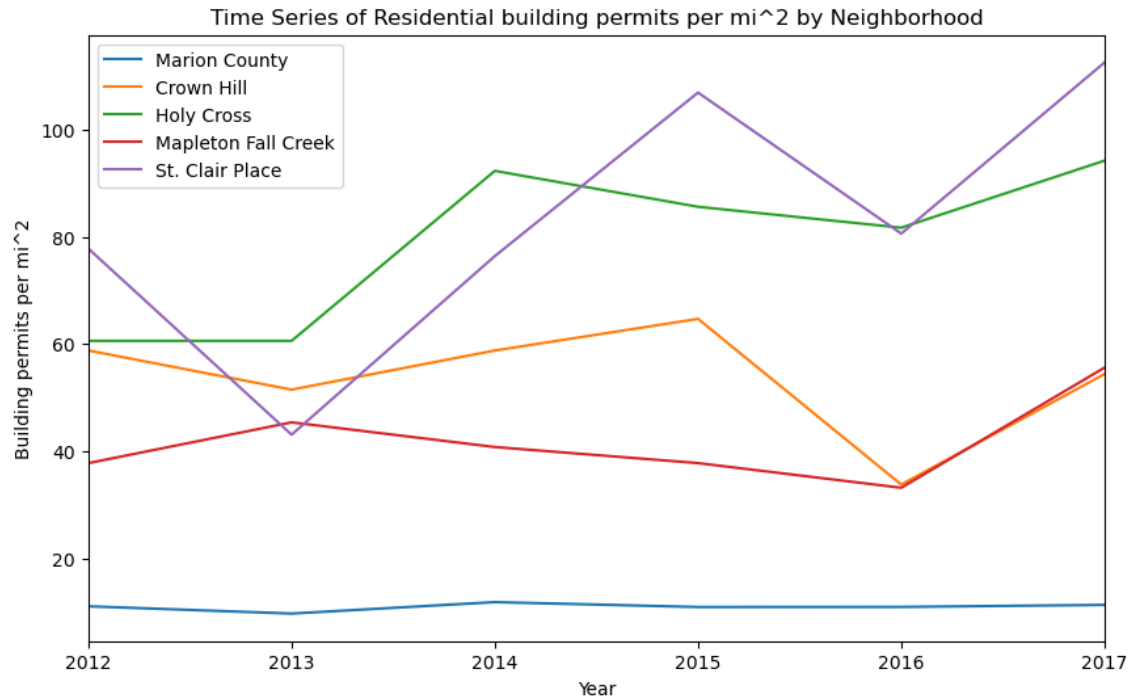
When observing the household ownership trends among some of Indianapolis neighborhoods from 2012 to 2017, it seems that the two neighborhoods from the Eastside area, Holy Cross and St. Clair Place, have had a larger growth (10% and 6%) when compared to two neighborhoods in the Mid-North area, Mapleton Fall Creek and Crown Hill (5% and 1%).



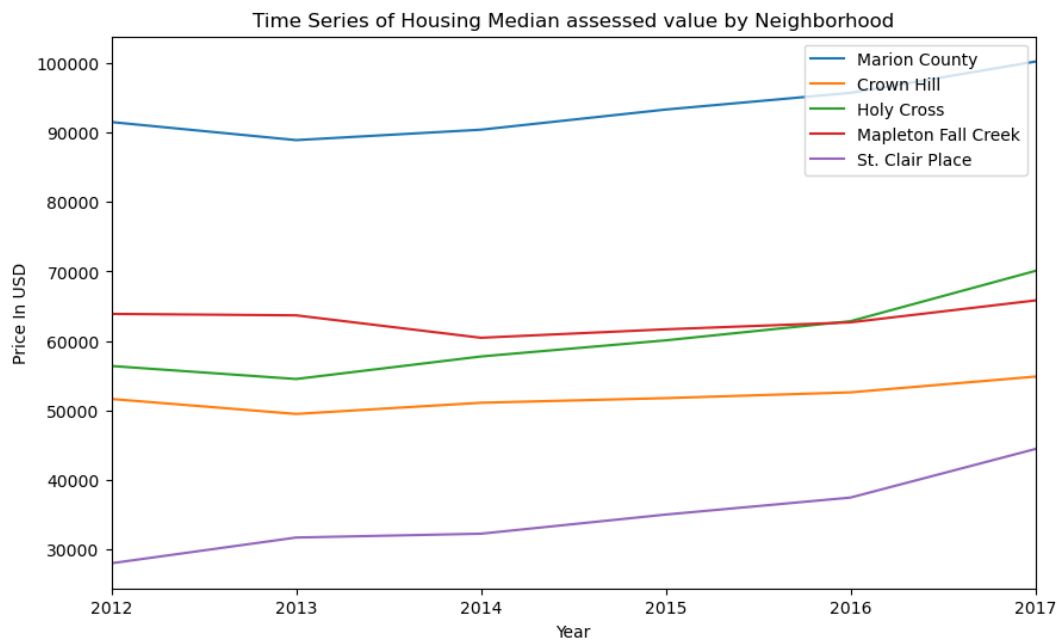
This difference seems real, as the actual numbers of household owners stagnated in Crown Hill (38 increase) and Mapleton Fall Creek had a relatively small growth (239 increase), despite starting with more than double the number of homes to its Eastside counterparts, which both experienced an almost 300 increase during this period.



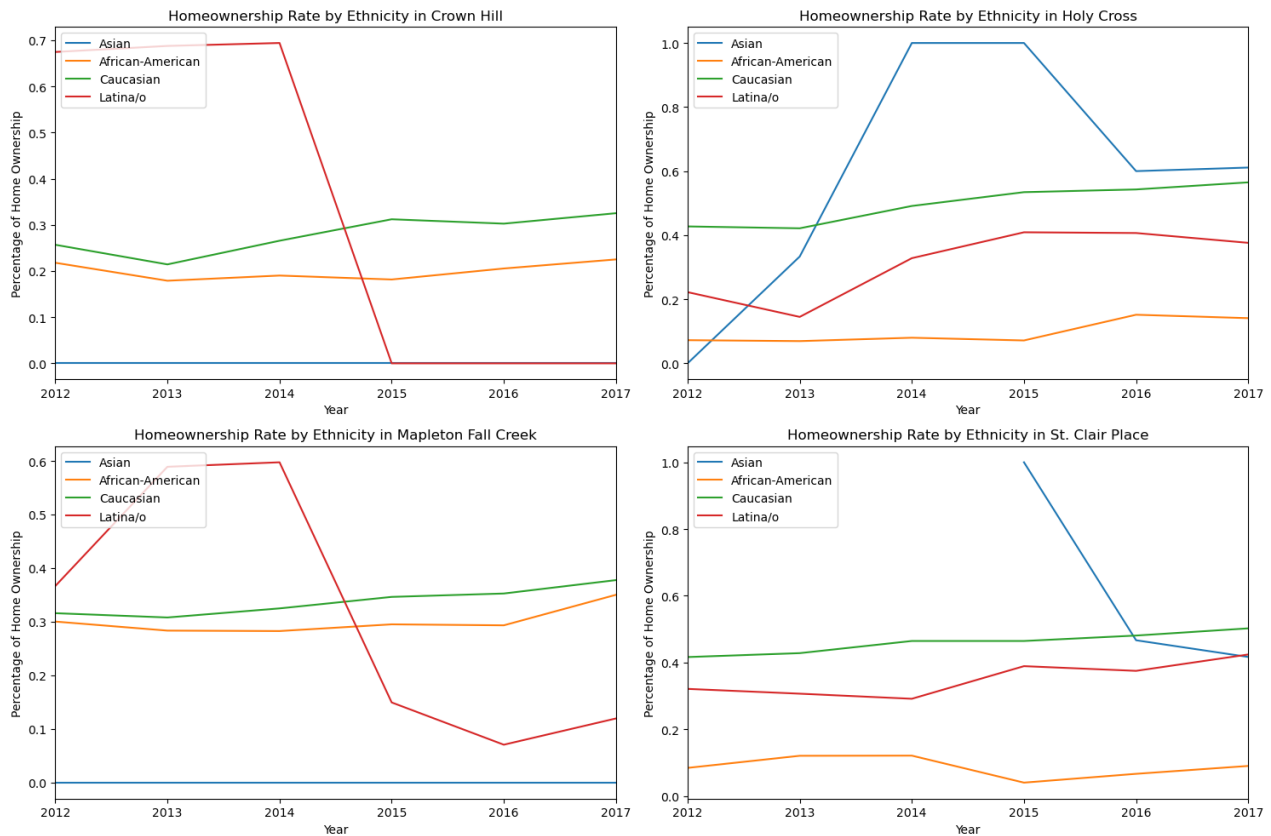
One of the possible variables that could be explaining this difference in trends between these two pairs of neighborhoods could be the unique and prolonged increase of residential building permits issued in these Eastside neighborhoods starting in 2013. More residential building permits result in more households and can allow a locality to meet the housing demands of the population.



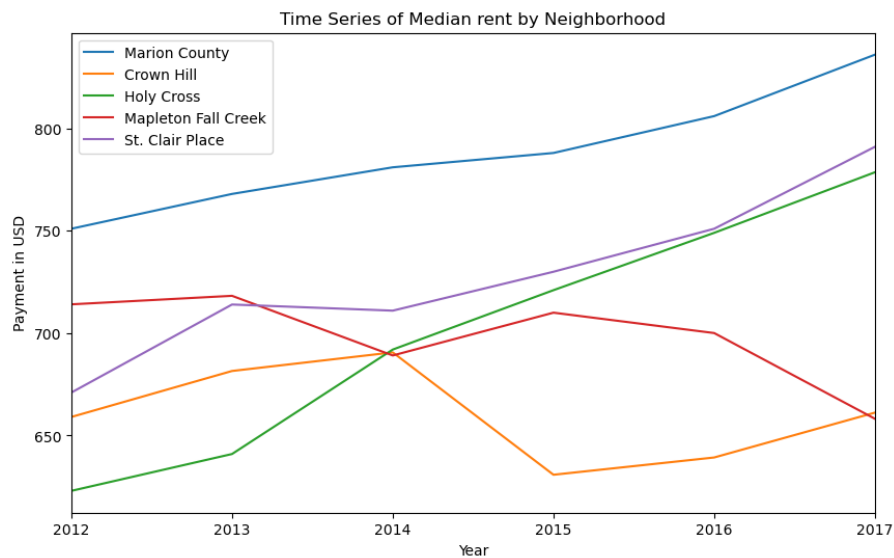
This permit expansion could also be affecting the local median assessed property values, as the Eastside neighborhoods had a noticeably greater growth during this time period.

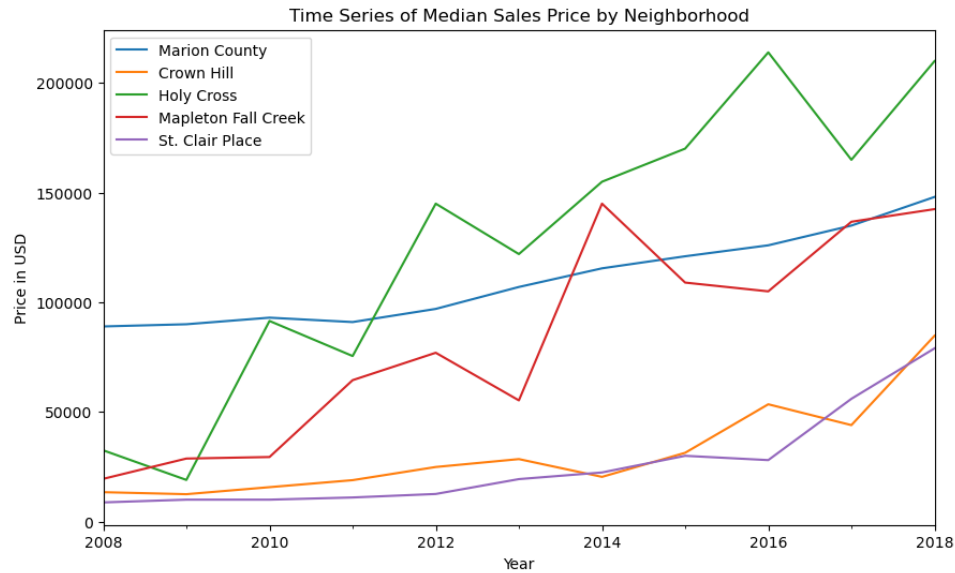


These two Eastside neighborhoods could also be benefiting minorities, as these two localities seem to be experiencing a higher Non-Caucasian homeownership rate during this period.



The increase in building permits could also be beneficial to current homeowners, as the median rent and sales prices of households in these two neighborhoods is greater than the other two.





As a nuance, expanding residential building permits in this locality should be cautious, as intensifying the issuance of these permits also has risks. It could induce an excess supply of real estate in neighborhoods, leading to insurmountable household prices that stagnate sales, followed by an economic downturn due to massive losses from investments.

This was a cursory analysis, as it used only five cases with a few observations (between 1 – 11 for each). For future research, I propose nurturing this data by making a larger database with more variables (median income, number of registered businesses) and cases (neighborhoods) that could allow performing thorough econometric (cointegration tests, difference in difference estimation, fixed effects panel models) and machine learning (K-Nearest Neighbors algorithm) techniques to arrive to robust findings.