data_science_midterm

January 4, 2024

1 CM3005 Data Science Midterm Coursework:

2 Prediction of Future Median Resale Prices - Yearly & Town specific

2.1 Introduction

For this project, I aimed to look into the housing market in Singapore, particularly the resale market. The resale market comprises of previous owners and occupants, selling their properties across Singapore. The prices of these flats are dependent on the type of flat - 1 room, 2 room, 3 room, 4 room, Executive Condominium as well as the location of the home itself.

The Housing & Development Board (**HDB**) oversees the process of selling a flat. Flat owners, who wish to sell their flats, will have to register an Intent to Sell and might be able to grant an Option to Purcahse (**OTP**) to potential buyers. Thereafter, both parties - sellers and buyers will have to sumbmit their respective portions of tthe resale applications. [1]

Objectives

1. Collecting relevant datasets which contribute to the resale prices across Singapore
2. Exploratory Data Analysis of the multiple datasets and the First Normal Form dataframe
3. Multiple Linear Regression to predict the future yearly median and town specific median price

I believe that the linear regression model will be beneficial to those who are looking to purchase homes or wish to better understand the housing market in Singapore. They might be better able to plan their expenses or look into purchasing homes in different towns after looking at the price difference and the prediction of the future.

The results of this project will be able to identify and highlight the different factors that plays a part towards to price change in the resale prices. In addition, it will be able to give us an overall idea on how the much of an impact the different factors are to the yearly prices of the resale flats.

2.2 Dataset Description

In this project, I have used datasets which are in the Comma Separated Value type. I had acquired all datasets from the Department of Statistics Singapore [2] and the Singapore Open Data [3]. There is a total of six datasets that I have utilised in this project. Each dataset contains factors I believed have been and will be instrumental in the prediction of future resale prices of housing flats.

Dataset 1: indicators_of_population.csv - population_df

This dataset was sourced from the Singapore Department of Statistics. This dataset is a Comma Separated Value (CSV) file. I read the file into Jupyter enviroment by using pandas to read the file and convert it into a dataframe. This dataframe had data from the Year 1950 to 2023. However, in order to ensure the consistency across all dataframes used in the project, I dropped columns of data during the pre-processing stage.

Dataset 2: gdp_yearly.csv - gdp_df

This dataset was sourced from the Singapore Department of Statistics. It was a CSV file with several rows of data about the GDP across different sectors that contribute to the economy. To ensure consistency, I dropped rows of data prior to 2007. Thereafter, I looked at which sectors which have the biggest impact and contribution to the housing and resale market.

Dataset 3: average_median_income.csv - household_income_df

This dataset was sourced from the Singapore Department of Statistics. It was a CSV file with information pertaining to the median and average earning across resident household and resident employed households. The data on household income is based on the Annual June Comprehensive Labour Force Surveys conducted by the Ministry of Manpower.

Dataset 4: resale_transactions.csv - transaction_df

This dataset was sourced from the Singapore Department of Statistics. It was a CSV file which had data categorised yearly by each type of flat and how many resale transactions went through. During the pre-processing stage, I restructurd the dateframe and cleaned up the dataframe so that all the data from a particlar years is in a singualr column. I removed the data pertaining to the flat type HUDC, as they have since been privatised and therefore, will no longer be of value to the project. [4]

Dataset 5: MedianResalePricesforRegisteredApplicationsbyTownandFlatType.csv - price_df

This dataset was sourced from the Singapore Open Data. It was a CSV file with information categorised by the quarters in each year documenting the tyope of flat which was sold and the median price it was sold for in the town. To ensure consistency across all the dataframes, I removed the quarter from each year and viewed it as data from the year instead. Thereafter, removed the rows with missing price values. Therafter, I restructured the dataframe and got 2 different dataframes from this dataset - median_price_yearly and town_yearly_median_df.

Dataset 6: Applicationsregisteredforresaleflatsandrentalflats.csv - application_df

This dataset was sourced from Singapore Open Data. It was a CSV file which had data about the number of rental and resale flat applciations which had been registered for a specific year. However, since I decided that the scope of this project would be on resale flats, I removed all the rows which were pertaining to the rental flats.

2.3 Data Preparation Exploratory Data Analysing & Pre-Processing

2.3.1 DataFrame Preparation: population_df

Source: Singapore Department of Statistics

In this dataframe, I analysed all the factors of the population and chose to focus on particular indicators which would best capture the state of the population.

[1]:
```
# Importing relevant libraries and packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import skew
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
```

[2]:
```
# Reading the csv file
# Creating population_df dataframe
population_df = pd.read_csv('hdb_data/indicators_of_population.csv')
```

[3]:
```
# Looking at the top 5 rows of data from the population_df
population_df.head(75)
```

[3]:

	Data Series	Total Population	Resident Population	Singapore Citizen Population	Permanent Resident Population	Non-Resident Population	Total Population Growth
0	2023	5917648	4149253	3610658	538595	1768395	5.0
1	2022	5637022	4073239	3553749	519490		
2	2021	5453566	3986842	3498191	488651		
3	2020	5685807	4044210	3523191	521019		
4	2019	5703569	4026209	3500940	525269		
..	…	…	…	…	…		
69	1954	1248200	na	na	na		
70	1953	1191800	na	na	na		
71	1952	1127000	na	na	na		
72	1951	1068100	na	na	na		
73	1950	1022100	na	na	na		

```
1                    1563783                       3.4
2                    1466724                      -4.1
3                    1641597                      -0.3
4                    1677360                       1.2
..                       …                         …
69                       na                        4.7
70                       na                        5.7
71                       na                        5.5
72                       na                        4.5
73                       na                        4.4

   Resident Population Growth  Population Density   Sex Ratio   …  \
0                         1.9                8058         950  …
1                         2.2                7688         955  …
2                        -1.4                7485         960  …
3                         0.4                7810         957  …
4                         0.8                7866         957  …
..                        …                  …          …  …
69                         na                  na        1138  …
70                         na                  na        1149  …
71                         na                  na        1153  …
72                         na                  na        1159  …
73                         na                  na        1173  …

   Old-Age Support Ratio:Citizens Aged 15-64 Years Per Citizen Aged 65 Years &
Over   \
0                                                  3.5
1                                                  3.6
2                                                  3.8
3                                                  4.1
4                                                  4.3
..                                                 …
69                                                  na
70                                                  na
71                                                  na
72                                                  na
73                                                  na

   Age Dependency Ratio:Citizens Aged Under 15 Years And 65 Years & Over Per
Hundred Citizens Aged 15-64 Years   \
0                                                51.1
1                                                  50
2                                                48.7
3                                                46.8
4                                                45.2
..                                                 …
69                                                  na
```

```
70                                                    na
71                                                    na
72                                                    na
73                                                    na

   Child Dependency Ratio:Citizens Aged Under 15 Years Per Hundred Citizens Aged
15-64 Years   \
0                                                   22.3
1                                                   22.4
2                                                   22.5
3                                                   22.2
4                                                     22
..                                                   …
69                                                    na
70                                                    na
71                                                    na
72                                                    na
73                                                    na

   Old-Age Dependency Ratio:Citizens Aged 65 Years & Over Per Hundred Citizens
Aged 15-64 Years   \
0                                                   28.9
1                                                   27.6
2                                                   26.2
3                                                   24.6
4                                                   23.2
..                                                   …
69                                                    na
70                                                    na
71                                                    na
72                                                    na
73                                                    na

   Old-Age Support Ratio:Citizens Aged 20-64 Years Per Citizen Aged 65 Years &
Over   \
0                                                    3.2
1                                                    3.3
2                                                    3.5
3                                                    3.7
4                                                      4
..                                                   …
69                                                    na
70                                                    na
71                                                    na
72                                                    na
73                                                    na
```

	Age Dependency Ratio:Citizens Aged Under 20 Years And 65 Years & Over Per Hundred Citizens Aged 20-64 Years
0	63.9
1	62.7
2	61.4
3	59.7
4	58.4
..	…
69	na
70	na
71	na
72	na
73	na

	Child Dependency Ratio:Citizens Aged Under 20 Years Per Hundred Citizens Aged 20-64 Years
0	32.6
1	32.8
2	33
3	32.9
4	33.1
..	…
69	na
70	na
71	na
72	na
73	na

	Old-Age Dependency Ratio:Citizens Aged 65 Years & Over Per Hundred Citizens Aged 20-64 Years
0	31.3
1	29.9
2	28.5
3	26.8
4	25.3
..	…
69	na
70	na
71	na
72	na
73	na

	Resident Natural Increase	Rate Of Natural Increase
0	na	na
1	6704	1.6
2	10913	2.7
3	13248	3.3

```
4                        15042                        3.7
..                         …                          …
69                       46239                       37.1
70                       42992                       36.1
71                       39136                       34.7
72                       35735                       33.4
73                       34059                       33.4

[74 rows x 30 columns]
```

[4]:
```
# Dropping entire columns that might not be relevant to the objectives of the␣
 ↪project
population_df.drop(population_df.columns[9:], axis=1, inplace = True)
```

[5]:
```
# Dropping values from the years prior to 2007
# I wanted to keep the years consistent across all dataframes
population_df.drop(population_df.index[17:], axis=0, inplace = True)
```

[6]:
```
# Renamed the column from data series to year
population_df.rename(columns={'Data Series': 'Year'}, inplace = True)
```

[7]:
```
#looking at the population_df again to check if the name has been changed
population_df
```

[7]:
```
    Year  Total Population  Resident Population   \
0   2023           5917648              4149253
1   2022           5637022              4073239
2   2021           5453566              3986842
3   2020           5685807              4044210
4   2019           5703569              4026209
5   2018           5638676              3994283
6   2017           5612253              3965796
7   2016           5607283              3933559
8   2015           5535002              3902690
9   2014           5469724              3870739
10  2013           5399162              3844751
11  2012           5312437              3818205
12  2011           5183688              3789251
13  2010           5076732              3771721
14  2009           4987573              3733876
15  2008           4839396              3642659
16  2007           4588599              3583082

   Singapore Citizen Population  Permanent Resident Population   \
0                       3610658                          538595
1                       3553749                          519490
2                       3498191                          488651
```

3	3523191	521019
4	3500940	525269
5	3471936	522347
6	3439177	526619
7	3408943	524616
8	3375023	527667
9	3343030	527709
10	3313507	531244
11	3285140	533065
12	3257228	532023
13	3230719	541002
14	3200693	533183
15	3164438	478221
16	3133848	449234

	Non-Resident Population	Total Population Growth	\
0	1768395	5.0	
1	1563783	3.4	
2	1466724	-4.1	
3	1641597	-0.3	
4	1677360	1.2	
5	1644393	0.5	
6	1646457	0.1	
7	1673724	1.3	
8	1632312	1.2	
9	1598985	1.3	
10	1554411	1.6	
11	1494232	2.5	
12	1394437	2.1	
13	1305011	1.8	
14	1253697	3.1	
15	1196737	5.5	
16	1005517	4.3	

	Resident Population Growth	Population Density
0	1.9	8058
1	2.2	7688
2	-1.4	7485
3	0.4	7810
4	0.8	7866
5	0.7	7804
6	0.8	7796
7	0.8	7797
8	0.8	7697
9	0.7	7615
10	0.7	7540
11	0.8	7429

```
12                        0.5                7273
13                          1                7146
14                        2.5                7025
15                        1.7                6846
16                        1.6                6552
```

[8]:
```
# Switching the order of the year and the structure of the dataframe itself
population_df = population_df.sort_values(by='Year', ascending=True).
 ↪reset_index(drop=True)
population_df
```

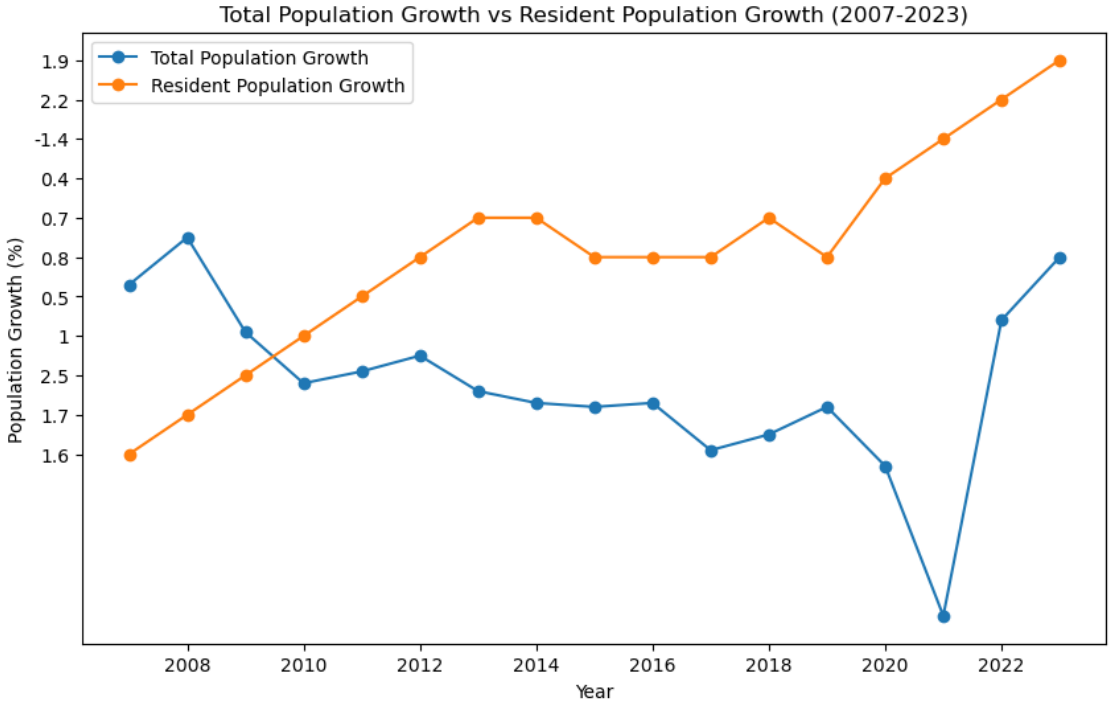
[8]:
```
    Year  Total Population  Resident Population   \
0   2007           4588599              3583082
1   2008           4839396              3642659
2   2009           4987573              3733876
3   2010           5076732              3771721
4   2011           5183688              3789251
5   2012           5312437              3818205
6   2013           5399162              3844751
7   2014           5469724              3870739
8   2015           5535002              3902690
9   2016           5607283              3933559
10  2017           5612253              3965796
11  2018           5638676              3994283
12  2019           5703569              4026209
13  2020           5685807              4044210
14  2021           5453566              3986842
15  2022           5637022              4073239
16  2023           5917648              4149253

   Singapore Citizen Population  Permanent Resident Population   \
0                       3133848                          449234
1                       3164438                          478221
2                       3200693                          533183
3                       3230719                          541002
4                       3257228                          532023
5                       3285140                          533065
6                       3313507                          531244
7                       3343030                          527709
8                       3375023                          527667
9                       3408943                          524616
10                      3439177                          526619
11                      3471936                          522347
12                      3500940                          525269
13                      3523191                          521019
14                      3498191                          488651
15                      3553749                          519490
```

```
16                       3610658                          538595

   Non-Resident Population   Total Population Growth   \
0                  1005517                       4.3
1                  1196737                       5.5
2                  1253697                       3.1
3                  1305011                       1.8
4                  1394437                       2.1
5                  1494232                       2.5
6                  1554411                       1.6
7                  1598985                       1.3
8                  1632312                       1.2
9                  1673724                       1.3
10                 1646457                       0.1
11                 1644393                       0.5
12                 1677360                       1.2
13                 1641597                      -0.3
14                 1466724                      -4.1
15                 1563783                       3.4
16                 1768395                       5.0

   Resident Population Growth  Population Density
0                         1.6                6552
1                         1.7                6846
2                         2.5                7025
3                           1                7146
4                         0.5                7273
5                         0.8                7429
6                         0.7                7540
7                         0.7                7615
8                         0.8                7697
9                         0.8                7797
10                        0.8                7796
11                        0.7                7804
12                        0.8                7866
13                        0.4                7810
14                       -1.4                7485
15                        2.2                7688
16                        1.9                8058
```

[9]:
```
population_df.columns
```

[9]:
```
Index(['Year', 'Total Population ', 'Resident Population ',
       'Singapore Citizen Population ', 'Permanent Resident Population ',
       'Non-Resident Population ', 'Total Population Growth ',
       'Resident Population Growth ', 'Population Density '],
      dtype='object')
```

[10]:
```
# Plotting the data as a line graph
plt.figure(figsize=(10, 6))

# Plotting lines
plt.plot(population_df['Year'], population_df['Total Population Growth '],␣
 ↪marker='o', label='Total Population Growth')
plt.plot(population_df['Year'], population_df['Resident Population Growth '],␣
 ↪marker='o', label='Resident Population Growth')

# Adding labels and title
plt.xlabel('Year')
plt.ylabel('Population Growth (%)')
plt.title('Total Population Growth vs Resident Population Growth (2007-2023)')

# Adding legend to the plot
plt.legend()

# Display the plot
plt.grid(False)
plt.show()
```



Total Population Growth vs Resident Population Growth (2007-2023) Graph

From the line plot, we can see that there has been a steady increase in the resident population growth, however the total popualtion growth has been on a decline. However, we can see that both

the total population growth and the resident population growth took a dip as it was during the Covid19 Pandemic which affected the growth of population. This shows us that there is a ever present and continuous need for housing options for residents as the resident population growth is most likely to increase.

2.3.2 DataFrame Preparation: gdp_df

Source: Singapore Department of Statistics

During the pre-processing stage for this dataframe, I removed data for the years prior to 2007 and focused on particular sectors which directly impact the housing sector in Singapore. In addition, I restructured the dataframe, so that the structure is most compatible in order to be merged with other dataframes.

[11]:
```
# Reading in the gdp_yearly csv file
# Creating a gdp_df which stores relevant values across different sectors
gdp_df = pd.read_csv('hdb_data/gdp_yearly.csv')
gdp_df
```

[11]:

	Data Series	2022	2021	2020	2019	2018	2017	2016	2015	2014	…
0	GDP At Current Market Prices	643545.8	569364.2	480691.2	514066.0	508337.4	474034.1	440754.7	423444.1	398947.9	…
1	Goods Producing Industries	155642.0	138899.6	112345.3	123787.0	129201.3	111601.0	102541.5	102984.3	96557.6	…
2	Manufacturing	131932.6	118345.6								
3	Construction	16796.9	14142.2								
4	Utilities	6731.6	6232.6								
5	Other Goods Industries	180.9	179.2								
6	Services Producing Industries	436069.1	381222.5								
7	Wholesale & Retail Trade	121645.8	107801.2								
8	Wholesale Trade	113921.9	100892.2								
9	Retail Trade	7723.9	6909.0								
10	Transportation & Storage	63568.2	48443.5								
11	Accommodation & Food Services	9318.3	6523.3								
12	Accommodation	4057.9	2279.4								
13	Food & Beverage Services	5260.4	4243.9								
14	Information & Communications	33111.9	29564.2								
15	Finance & Insurance	82394.2	74308.8								
16	Real Estate, Professional Services And Adm…	68880.9	61550.7								
17	Real Estate	17676.6	15515.1								
18	Professional Services	32778.4	29372.6								
19	Administrative & Support Services	18425.9	16663.0								
20	Other Services Industries	57149.8	53030.8								
21	Ownership Of Dwellings	19904.4	18912.9								
22	Gross Value Added At Basic Prices	611615.5	539035.0								
23	Add:Taxes On Products	31930.3	30329.2								

2	94957.7	99693.7	105388.5	88021.9	77026.9	76598.2	71809.7	…
3	11012.7	18054.7	17833.6	17935.1	19760.3	20430.8	19179.9	…
4	6216.8	5873.1	5826.0	5498.1	5615.1	5817.2	5430.2	…
5	158.1	165.5	153.2	145.9	139.2	138.1	137.8	…
6	327389.5	345882.5	334807.1	316123.1	294041.4	278103.0	262844.0	…
7	88967.5	91367.6	89122.5	82138.1	74169.9	65584.5	64724.5	…
8	82773.3	83803.7	81180.2	74360.3	66578.2	58306.1	57829.3	…
9	6194.2	7563.9	7942.3	7777.8	7591.7	7278.4	6895.2	…
10	28812.4	31505.8	30857.5	31589.0	27737.4	30015.0	27092.4	…
11	6560.5	9932.9	9806.9	9349.5	9191.2	8763.1	8666.6	…
12	2465.4	4256.0	4234.5	3891.3	3763.9	3604.7	3640.3	…
13	4095.1	5676.9	5572.4	5458.2	5427.3	5158.4	5026.3	…
14	25723.9	22789.0	20329.1	19142.1	18169.9	16227.4	16196.1	…
15	69816.3	68145.6	62480.8	56785.7	51598.8	49872.2	45966.4	…
16	58982.8	68023.6	69681.2	66738.7	65653.0	62666.4	57533.0	…
17	13610.1	16836.7	16337.3	15686.6	17410.3	18781.5	18962.7	…
18	27230.7	29555.2	26931.7	25911.9	24933.6	24218.6	22104.8	…
19	18142.0	21631.7	26412.2	25140.2	23309.1	19666.3	16465.5	…
20	48526.1	54118.0	52529.1	50380.0	47521.2	44974.4	42665.0	…
21	18785.1	18453.0	17751.0	17436.2	17589.4	18100.1	17797.2	…
22	458519.9	488122.5	481759.4	445160.3	414172.3	399187.4	377198.8	…
23	22171.3	25943.5	26578.0	28873.8	26582.4	24256.7	21749.1	…

	1969	1968	1967	1966	1965	1964	1963	1962	1961	\
0	5081.3	4364.4	3789.9	3356.4	2983.6	2737.2	2809	2529.3	2340.7	
1	1396.4	1174.6	985.4	856.1	752.5	672.9	618.8	535.8	476.9	
2	821.9	659.3	547.8	473	403.9	350.7	328.5	271.4	241.1	
3	285.4	247.4	203.1	176.7	176.6	150.5	127.6	104.4	93.6	
4	146.2	134.8	119.1	96.6	80.4	80.5	71.4	69.2	60	
5	142.9	133.1	115.4	109.8	91.6	91.2	91.3	90.8	82.2	
6	3296.5	2865.7	2517.2	2220.5	1980.7	1848.9	1984.1	1792.1	1671.4	
7	1259.1	1066.2	941.2	795.5	665.6	634.9	795.6	685.4	652.9	
8	na	na	na	na	na	na	na	na	na	
9	na	na	na	na	na	na	na	na	na	
10	459	399.2	342	310.3	294.2	269.7	286.7	280.4	272.8	
11	169.4	151.5	132.7	114.9	105.2	100.8	97.1	91.1	86.5	
12	na	na	na	na	na	na	na	na	na	
13	na	na	na	na	na	na	na	na	na	
14	94.1	87.2	73.7	64.6	59.3	57.4	56.5	54.4	51.3	
15	265.7	211.6	165.5	148.9	130.3	118.3	107.7	97.9	86.5	
16	432.6	372.8	331.6	281.1	261.3	230.1	216.5	199.8	162.3	
17	na	na	na	na	na	na	na	na	na	
18	na	na	na	na	na	na	na	na	na	
19	na	na	na	na	na	na	na	na	na	
20	616.6	577.2	530.5	505.2	464.8	437.7	424	383.1	359.1	
21	123.3	106.1	96.4	90.8	84.1	80.9	78.8	76.3	73.6	
22	4816.2	4146.4	3599	3167.4	2817.3	2602.7	2681.7	2404.2	2221.9	

```
23   265.1     218   190.9     189   166.3   134.5   127.3   125.1   118.8

     1960
0   2157.4
1    432.8
2    228.2
3     67.7
4       57
5     79.9
6   1538.7
7    601.5
8       na
9       na
10   256.3
11    81.5
12      na
13      na
14    50.3
15    71.9
16   146.4
17      na
18      na
19      na
20   330.8
21    68.9
22  2040.4
23     117

[24 rows x 64 columns]
```

[12]:
```
# Dropping entire columns and saving the dataframe
gdp_df.drop(gdp_df.columns[17:], axis=1, inplace = True)

# Making changes to the structure of the gdp_df
# Name change to transposed_df
transposed_df = gdp_df.transpose()

# Set the first row as the header
transposed_df.columns = transposed_df.iloc[0]

# Drop the first row (which is now the header)
transposed_df = transposed_df[1:]

# Reset the index of transposed_df
transposed_df = transposed_df.reset_index()

# Rename the 'index' column to 'Year' in the transposed_df
```

```
transposed_df = transposed_df.rename(columns={'index': 'Year'})

# Display the transposed DataFrame transposed_df
transposed_df
```

[12]:

Data Series	Year	GDP At Current Market Prices	Goods Producing Industries
0	2022	643545.8	155642.0
1	2021	569364.2	138899.6
2	2020	480691.2	112345.3
3	2019	514066.0	123787.0
4	2018	508337.4	129201.3
5	2017	474034.1	111601.0
6	2016	440754.7	102541.5
7	2015	423444.1	102984.3
8	2014	398947.9	96557.6
9	2013	384870.3	90356.4
10	2012	368770.5	92397.2
11	2011	351367.9	88875.7
12	2010	326980.1	87212.2
13	2009	282394.5	76407.5
14	2008	273941.6	72476.1
15	2007	272697.6	77087.9

Data Series	Manufacturing	Construction	Utilities
0	131932.6	16796.9	6731.6
1	118345.6	14142.2	6232.6
2	94957.7	11012.7	6216.8
3	99693.7	18054.7	5873.1
4	105388.5	17833.6	5826.0
5	88021.9	17935.1	5498.1
6	77026.9	19760.3	5615.1
7	76598.2	20430.8	5817.2
8	71809.7	19179.9	5430.2
9	67885.0	17119.7	5219.4
10	70497.2	16422.7	5354.6
11	68806.8	14837.1	5110.2
12	67926.3	14402.7	4765.0
13	57250.9	14989.9	4051.8
14	56392.7	11971.2	3998.7
15	64963.8	8095.8	3911.4

Data Series	Other Goods Industries	Services Producing Industries
0	180.9	436069.1
1	179.2	381222.5
2	158.1	327389.5
3	165.5	345882.5
4	153.2	334807.1

5	145.9	316123.1
6	139.2	294041.4
7	138.1	278103.0
8	137.8	262844.0
9	132.3	255092.1
10	122.7	239471.7
11	121.6	228920.2
12	118.2	210487.7
13	114.9	181693.7
14	113.5	177067.3
15	116.9	172146.6

Data Series	Wholesale & Retail Trade	Wholesale Trade	…	\
0	121645.8	113921.9	…	
1	107801.2	100892.2	…	
2	88967.5	82773.3	…	
3	91367.6	83803.7	…	
4	89122.5	81180.2	…	
5	82138.1	74360.3	…	
6	74169.9	66578.2	…	
7	65584.5	58306.1	…	
8	64724.5	57829.3	…	
9	68495.3	61886.9	…	
10	67637.8	61105.9	…	
11	68009.6	61678.4	…	
12	59177.5	53525.7	…	
13	50395.9	44979.3	…	
14	45086.1	39740.0	…	
15	49097.7	43900.3	…	

Data Series	Information & Communications	Finance & Insurance	\
0	33111.9	82394.2	
1	29564.2	74308.8	
2	25723.9	69816.3	
3	22789.0	68145.6	
4	20329.1	62480.8	
5	19142.1	56785.7	
6	18169.9	51598.8	
7	16227.4	49872.2	
8	16196.1	45966.4	
9	15137.3	42888.3	
10	14011.6	37722.1	
11	12792.4	35298.4	
12	11557.1	33987.9	
13	10699.0	31589.8	
14	9765.6	30190.0	
15	9281.2	29568.6	

Data Series	Real Estate, Professional Services And Administrative & Support Services
0	68880.9
1	61550.7
2	58982.8
3	68023.6
4	69681.2
5	66738.7
6	65653.0
7	62666.4
8	57533.0
9	55306.0
10	50982.6
11	47535.9
12	41994.8
13	35617.1
14	35547.8
15	30506.2

Data Series	Real Estate	Professional Services
0	17676.6	32778.4
1	15515.1	29372.6
2	13610.1	27230.7
3	16836.7	29555.2
4	16337.3	26931.7
5	15686.6	25911.9
6	17410.3	24933.6
7	18781.5	24218.6
8	18962.7	22104.8
9	19243.2	21671.4
10	17078.0	20982.3
11	16127.2	19672.5
12	14034.8	18280.7
13	11027.5	16662.0
14	11362.8	16329.7
15	9360.7	14479.1

Data Series	Administrative & Support Services
0	18425.9
1	16663.0
2	18142.0
3	21631.7
4	26412.2
5	25140.2
6	23309.1
7	19666.3

8	16465.5
9	14391.4
10	12922.3
11	11736.2
12	9679.3
13	7927.6
14	7855.3
15	6666.4

Data Series	Other Services Industries	Ownership Of Dwellings	\
0	57149.8	19904.4	
1	53030.8	18912.9	
2	48526.1	18785.1	
3	54118.0	18453.0	
4	52529.1	17751.0	
5	50380.0	17436.2	
6	47521.2	17589.4	
7	44974.4	18100.1	
8	42665.0	17797.2	
9	40300.2	17251.0	
10	37567.1	15749.3	
11	35896.8	13604.9	
12	32433.5	11347.1	
13	26966.1	10351.7	
14	25945.8	10166.2	
15	24185.3	7943.3	

Data Series	Gross Value Added At Basic Prices	Add:Taxes On Products
0	611615.5	31930.3
1	539035.0	30329.2
2	458519.9	22171.3
3	488122.5	25943.5
4	481759.4	26578.0
5	445160.3	28873.8
6	414172.3	26582.4
7	399187.4	24256.7
8	377198.8	21749.1
9	362699.5	22170.8
10	347618.2	21152.3
11	331400.8	19967.1
12	309047.0	17933.1
13	268452.9	13941.6
14	259709.6	14232.0
15	257177.8	15519.8

[16 rows x 25 columns]

[13]:
```
# Looking at the transposed_df columns
transposed_df.columns
```

[13]:
```
Index(['Year', 'GDP At Current Market Prices', '  Goods Producing Industries',
       '    Manufacturing', '    Construction', '    Utilities',
       '    Other Goods Industries', '  Services Producing Industries',
       '    Wholesale & Retail Trade', '      Wholesale Trade',
       '      Retail Trade', '    Transportation & Storage',
       '    Accommodation & Food Services', '      Accommodation',
       '      Food & Beverage Services', '    Information & Communications',
       '    Finance & Insurance',
       '    Real Estate, Professional Services And Administrative & Support
Services',
       '      Real Estate', '      Professional Services',
       '      Administrative & Support Services',
       '    Other Services Industries', '  Ownership Of Dwellings',
       '  Gross Value Added At Basic Prices', '  Add:Taxes On Products'],
      dtype='object', name='Data Series')
```

[14]:
```
# Displaying the transposed_df
transposed_df
```

[14]:

Data Series	Year	GDP At Current Market Prices	Goods Producing Industries	\
0	2022	643545.8	155642.0	
1	2021	569364.2	138899.6	
2	2020	480691.2	112345.3	
3	2019	514066.0	123787.0	
4	2018	508337.4	129201.3	
5	2017	474034.1	111601.0	
6	2016	440754.7	102541.5	
7	2015	423444.1	102984.3	
8	2014	398947.9	96557.6	
9	2013	384870.3	90356.4	
10	2012	368770.5	92397.2	
11	2011	351367.9	88875.7	
12	2010	326980.1	87212.2	
13	2009	282394.5	76407.5	
14	2008	273941.6	72476.1	
15	2007	272697.6	77087.9	

Data Series	Manufacturing	Construction	Utilities	\
0	131932.6	16796.9	6731.6	
1	118345.6	14142.2	6232.6	
2	94957.7	11012.7	6216.8	
3	99693.7	18054.7	5873.1	
4	105388.5	17833.6	5826.0	
5	88021.9	17935.1	5498.1	

```
6                    77026.9          19760.3        5615.1
7                    76598.2          20430.8        5817.2
8                    71809.7          19179.9        5430.2
9                    67885.0          17119.7        5219.4
10                   70497.2          16422.7        5354.6
11                   68806.8          14837.1        5110.2
12                   67926.3          14402.7        4765.0
13                   57250.9          14989.9        4051.8
14                   56392.7          11971.2        3998.7
15                   64963.8           8095.8        3911.4

Data Series     Other Goods Industries   Services Producing Industries  \
0                                180.9                          436069.1
1                                179.2                          381222.5
2                                158.1                          327389.5
3                                165.5                          345882.5
4                                153.2                          334807.1
5                                145.9                          316123.1
6                                139.2                          294041.4
7                                138.1                          278103.0
8                                137.8                          262844.0
9                                132.3                          255092.1
10                               122.7                          239471.7
11                               121.6                          228920.2
12                               118.2                          210487.7
13                               114.9                          181693.7
14                               113.5                          177067.3
15                               116.9                          172146.6

Data Series     Wholesale & Retail Trade       Wholesale Trade  …  \
0                                121645.8              113921.9  …
1                                107801.2              100892.2  …
2                                 88967.5               82773.3  …
3                                 91367.6               83803.7  …
4                                 89122.5               81180.2  …
5                                 82138.1               74360.3  …
6                                 74169.9               66578.2  …
7                                 65584.5               58306.1  …
8                                 64724.5               57829.3  …
9                                 68495.3               61886.9  …
10                                67637.8               61105.9  …
11                                68009.6               61678.4  …
12                                59177.5               53525.7  …
13                                50395.9               44979.3  …
14                                45086.1               39740.0  …
15                                49097.7               43900.3  …
```

Data Series	Information & Communications	Finance & Insurance
0	33111.9	82394.2
1	29564.2	74308.8
2	25723.9	69816.3
3	22789.0	68145.6
4	20329.1	62480.8
5	19142.1	56785.7
6	18169.9	51598.8
7	16227.4	49872.2
8	16196.1	45966.4
9	15137.3	42888.3
10	14011.6	37722.1
11	12792.4	35298.4
12	11557.1	33987.9
13	10699.0	31589.8
14	9765.6	30190.0
15	9281.2	29568.6

Data Series	Real Estate, Professional Services And Administrative & Support Services
0	68880.9
1	61550.7
2	58982.8
3	68023.6
4	69681.2
5	66738.7
6	65653.0
7	62666.4
8	57533.0
9	55306.0
10	50982.6
11	47535.9
12	41994.8
13	35617.1
14	35547.8
15	30506.2

Data Series	Real Estate	Professional Services
0	17676.6	32778.4
1	15515.1	29372.6
2	13610.1	27230.7
3	16836.7	29555.2
4	16337.3	26931.7
5	15686.6	25911.9
6	17410.3	24933.6
7	18781.5	24218.6
8	18962.7	22104.8

9	19243.2	21671.4
10	17078.0	20982.3
11	16127.2	19672.5
12	14034.8	18280.7
13	11027.5	16662.0
14	11362.8	16329.7
15	9360.7	14479.1

Data Series	Administrative & Support Services
0	18425.9
1	16663.0
2	18142.0
3	21631.7
4	26412.2
5	25140.2
6	23309.1
7	19666.3
8	16465.5
9	14391.4
10	12922.3
11	11736.2
12	9679.3
13	7927.6
14	7855.3
15	6666.4

Data Series	Other Services Industries	Ownership Of Dwellings
0	57149.8	19904.4
1	53030.8	18912.9
2	48526.1	18785.1
3	54118.0	18453.0
4	52529.1	17751.0
5	50380.0	17436.2
6	47521.2	17589.4
7	44974.4	18100.1
8	42665.0	17797.2
9	40300.2	17251.0
10	37567.1	15749.3
11	35896.8	13604.9
12	32433.5	11347.1
13	26966.1	10351.7
14	25945.8	10166.2
15	24185.3	7943.3

Data Series	Gross Value Added At Basic Prices	Add:Taxes On Products
0	611615.5	31930.3
1	539035.0	30329.2

```
2                                   458519.9                    22171.3
3                                   488122.5                    25943.5
4                                   481759.4                    26578.0
5                                   445160.3                    28873.8
6                                   414172.3                    26582.4
7                                   399187.4                    24256.7
8                                   377198.8                    21749.1
9                                   362699.5                    22170.8
10                                  347618.2                    21152.3
11                                  331400.8                    19967.1
12                                  309047.0                    17933.1
13                                  268452.9                    13941.6
14                                  259709.6                    14232.0
15                                  257177.8                    15519.8

[16 rows x 25 columns]
```

[15]:
```
# Remove leading and trailing spaces from column names in transposed_df
transposed_df.columns = transposed_df.columns.str.strip()

# Specifying columns to drop from transposed_df
# I am dropping multiple columns except ones I believe are directly an impact␣
 ↪and result of housing in Singapore
columns_to_drop = [
    'Goods Producing Industries', 'Manufacturing', 'Construction', 'Utilities',
    'Other Goods Industries', 'Services Producing Industries', 'Wholesale &␣
 ↪Retail Trade',
    'Wholesale Trade', 'Retail Trade', 'Transportation & Storage',␣
 ↪'Accommodation & Food Services',
    'Accommodation', 'Food & Beverage Services', 'Information & Communications',
    'Finance & Insurance', 'Real Estate, Professional Services And␣
 ↪Administrative & Support Services',
    'Professional Services', 'Administrative & Support Services', 'Other␣
 ↪Services Industries', 'Add:Taxes On Products', 'Gross Value Added At Basic␣
 ↪Prices']

# Drop the specified columns
gdp_df = transposed_df.drop(columns=columns_to_drop, errors='ignore')
gdp_df.columns.name = None

# Print the gdp_df
gdp_df
```

[15]:
```
    Year GDP At Current Market Prices Real Estate Ownership Of Dwellings
0   2022                     643545.8                  17676.6                  19904.4
1   2021                     569364.2                  15515.1                  18912.9
2   2020                     480691.2                  13610.1                  18785.1
```

3	2019	514066.0	16836.7	18453.0
4	2018	508337.4	16337.3	17751.0
5	2017	474034.1	15686.6	17436.2
6	2016	440754.7	17410.3	17589.4
7	2015	423444.1	18781.5	18100.1
8	2014	398947.9	18962.7	17797.2
9	2013	384870.3	19243.2	17251.0
10	2012	368770.5	17078.0	15749.3
11	2011	351367.9	16127.2	13604.9
12	2010	326980.1	14034.8	11347.1
13	2009	282394.5	11027.5	10351.7
14	2008	273941.6	11362.8	10166.2
15	2007	272697.6	9360.7	7943.3

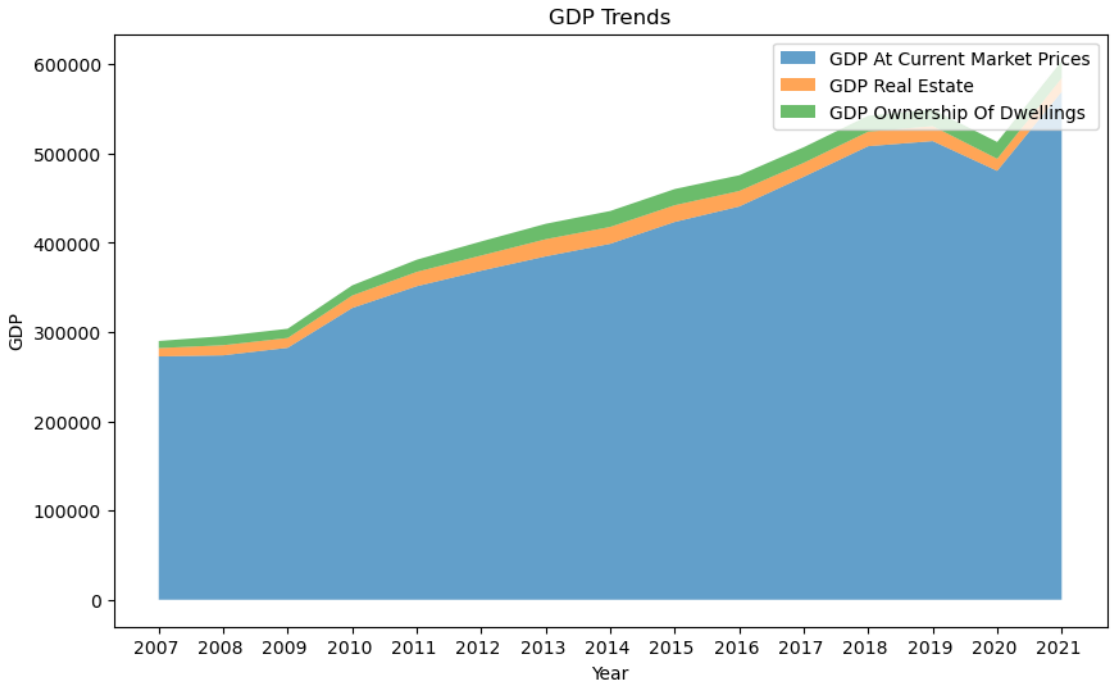
[16]:
```
# Changing the order of the years, 2007 - 2021
# Resetting the index of the gdp_df
gdp_df = gdp_df.sort_values(by='Year', ascending=True).reset_index(drop=True)
gdp_df

#Rename columns Real Estate and Ownership Of Dwellings
gdp_df = gdp_df.rename(columns={'Real Estate':'GDP Real Estate'})
gdp_df = gdp_df.rename(columns={'Ownership Of Dwellings':'GDP Ownership Of␣
 ↪Dwellings'})
gdp_df

#Drop entire rows for year 2022 to ensure consistency across all dateframes
indices_to_drop = [15]
gdp_df = gdp_df.drop(indices_to_drop)

# Display the DataFrame after dropping rows
print("\nAfter dropping rows:")
print(gdp_df)
```

```
After dropping rows:
     Year GDP At Current Market Prices GDP Real Estate  \
0   2007                      272697.6          9360.7
1   2008                      273941.6         11362.8
2   2009                      282394.5         11027.5
3   2010                      326980.1         14034.8
4   2011                      351367.9         16127.2
5   2012                      368770.5         17078.0
6   2013                      384870.3         19243.2
7   2014                      398947.9         18962.7
8   2015                      423444.1         18781.5
9   2016                      440754.7         17410.3
10  2017                      474034.1         15686.6
11  2018                      508337.4         16337.3
```

```
12  2019                      514066.0         16836.7
13  2020                      480691.2         13610.1
14  2021                      569364.2         15515.1

   GDP Ownership Of Dwellings
0                      7943.3
1                     10166.2
2                     10351.7
3                     11347.1
4                     13604.9
5                     15749.3
6                     17251.0
7                     17797.2
8                     18100.1
9                     17589.4
10                    17436.2
11                    17751.0
12                    18453.0
13                    18785.1
14                    18912.9
```

[17]:
```
# Convert columns to numeric type because it was not accepting integers
gdp_df['GDP At Current Market Prices'] = pd.to_numeric(gdp_df['GDP At Current␣
 ↪Market Prices'], errors='coerce')
gdp_df['GDP Real Estate'] = pd.to_numeric(gdp_df['GDP Real Estate'],␣
 ↪errors='coerce')
gdp_df['GDP Ownership Of Dwellings'] = pd.to_numeric(gdp_df['GDP Ownership Of␣
 ↪Dwellings'], errors='coerce')

plt.figure(figsize=(10, 6))

# Plotting the components separately with fill_between
plt.fill_between(gdp_df['Year'], gdp_df['GDP At Current Market Prices'],␣
 ↪label='GDP At Current Market Prices', alpha=0.7)
plt.fill_between(gdp_df['Year'], gdp_df['GDP At Current Market Prices'],␣
 ↪gdp_df['GDP At Current Market Prices'] + gdp_df['GDP Real Estate'],␣
 ↪label='GDP Real Estate', alpha=0.7)
plt.fill_between(gdp_df['Year'], gdp_df['GDP At Current Market Prices'] +␣
 ↪gdp_df['GDP Real Estate'], gdp_df['GDP At Current Market Prices'] +␣
 ↪gdp_df['GDP Real Estate'] + gdp_df['GDP Ownership Of Dwellings'], label='GDP␣
 ↪Ownership Of Dwellings', alpha=0.7)

# Adding labels and title
plt.xlabel('Year')
plt.ylabel('GDP')
plt.title('GDP Trends')
```

```
# Adding legend
plt.legend()

# Display the plot
plt.grid(False)
plt.show()
```



GDP Trends Graph

The graph gives us a visual representation of how the GDP for real estate and ownership of dwellings contribute to the overall GDP at Current Market Prices. Therefore, we can infer that they have a dependent relationship between one another. Thus, if there is reduced interest and participation in purchasing homes, it would affect the GDP Ownership of Dwellings and then consequently the GDP Real Estate and GDP at Current Market Prices.

2.3.3 DataFrame Preparation: household_income_df

Source: Singapore Department of Statistics

[18]:
```
# Reading in the household_income_df csv file
household_income_df = pd.read_csv('hdb_data/average_median_income.csv')
```

[19]:
```
# Printing the dataframes to better understand and analyse the data
household_income_df
```

[19]:

	Year	Resident Households	Resident Employed Households	Average	Median1	\
0	2022	11480	8615	13124	10099	
1	2021	10832	8220	12276	9520	
2	2020	10608	7744	12235	9189	
3	2019	10750	7981	12386	9425	
4	2018	10664	7955	12137	9293	
5	2017	10610	7850	12027	9023	
6	2016	10336	7748	11589	8846	
7	2015	10394	7733	11510	8666	
8	2014	9982	7320	11143	8292	
9	2013	9481	7030	10469	7872	
10	2012	9394	6772	10348	7566	
11	2011	8722	6307	9618	7037	
12	2010	7812	5600	8726	6342	
13	2009	7410	5360	8195	6006	
14	2008	7691	5492	8414	6100	
15	2007	6790	4846	7431	5362	
16	2006	6181	4430	6792	4952	
17	2005	5934	4270	6593	4831	
18	2004	5666	4066	6285	4552	
19	2003	5670	4071	6276	4612	
20	2002	5667	4096	6229	4590	
21	2001	5972	4363	6417	4716	
22	2000	5436	4000	5947	4398	

	Average.1	Median1.1	Unnamed: 7
0	NaN	NaN	NaN
1	NaN	NaN	NaN
2	NaN	NaN	NaN
3	NaN	NaN	NaN
4	NaN	NaN	NaN
5	NaN	NaN	NaN
6	NaN	NaN	NaN
7	NaN	NaN	NaN
8	NaN	NaN	NaN
9	NaN	NaN	NaN
10	NaN	NaN	NaN
11	NaN	NaN	NaN
12	NaN	NaN	NaN
13	NaN	NaN	NaN
14	NaN	NaN	NaN
15	NaN	NaN	NaN
16	NaN	NaN	NaN
17	NaN	NaN	NaN
18	NaN	NaN	NaN
19	NaN	NaN	NaN
20	NaN	NaN	NaN

```
21        NaN         NaN         NaN
22        NaN         NaN         NaN
```

[20]:
```
# Drop the columns as they were irrelevant and save the dataframe
household_income_df.drop(['Average.1', 'Median1.1', 'Unnamed: 7'], axis = 1,␣
 ↪inplace = True)
```

[21]:
```
# Rename the column Median1 to Median
household_income_df = household_income_df.rename(columns={'Median1':'Median␣
 ↪Income'})
household_income_df = household_income_df.rename(columns={'Average':'Average␣
 ↪Income'})
household_income_df
```

[21]:

	Year	Resident Households	Resident Employed Households	Average Income	\
0	2022	11480	8615	13124	
1	2021	10832	8220	12276	
2	2020	10608	7744	12235	
3	2019	10750	7981	12386	
4	2018	10664	7955	12137	
5	2017	10610	7850	12027	
6	2016	10336	7748	11589	
7	2015	10394	7733	11510	
8	2014	9982	7320	11143	
9	2013	9481	7030	10469	
10	2012	9394	6772	10348	
11	2011	8722	6307	9618	
12	2010	7812	5600	8726	
13	2009	7410	5360	8195	
14	2008	7691	5492	8414	
15	2007	6790	4846	7431	
16	2006	6181	4430	6792	
17	2005	5934	4270	6593	
18	2004	5666	4066	6285	
19	2003	5670	4071	6276	
20	2002	5667	4096	6229	
21	2001	5972	4363	6417	
22	2000	5436	4000	5947	

	Median Income
0	10099
1	9520
2	9189
3	9425
4	9293
5	9023
6	8846

```
7            8666
8            8292
9            7872
10           7566
11           7037
12           6342
13           6006
14           6100
15           5362
16           4952
17           4831
18           4552
19           4612
20           4590
21           4716
22           4398
```

[22]:
```
# Changing the order of the years, 2007 - 2021
# Resetting the index of the household_income_df
household_income_df = household_income_df.sort_values(by='Year',␣
 ↪ascending=True).reset_index(drop=True)
household_income_df
```

[22]:

	Year	Resident Households	Resident Employed Households	Average Income	\
0	2000	5436	4000	5947	
1	2001	5972	4363	6417	
2	2002	5667	4096	6229	
3	2003	5670	4071	6276	
4	2004	5666	4066	6285	
5	2005	5934	4270	6593	
6	2006	6181	4430	6792	
7	2007	6790	4846	7431	
8	2008	7691	5492	8414	
9	2009	7410	5360	8195	
10	2010	7812	5600	8726	
11	2011	8722	6307	9618	
12	2012	9394	6772	10348	
13	2013	9481	7030	10469	
14	2014	9982	7320	11143	
15	2015	10394	7733	11510	
16	2016	10336	7748	11589	
17	2017	10610	7850	12027	
18	2018	10664	7955	12137	
19	2019	10750	7981	12386	
20	2020	10608	7744	12235	
21	2021	10832	8220	12276	
22	2022	11480	8615	13124	

```
    Median Income
0            4398
1            4716
2            4590
3            4612
4            4552
5            4831
6            4952
7            5362
8            6100
9            6006
10           6342
11           7037
12           7566
13           7872
14           8292
15           8666
16           8846
17           9023
18           9293
19           9425
20           9189
21           9520
22          10099
```

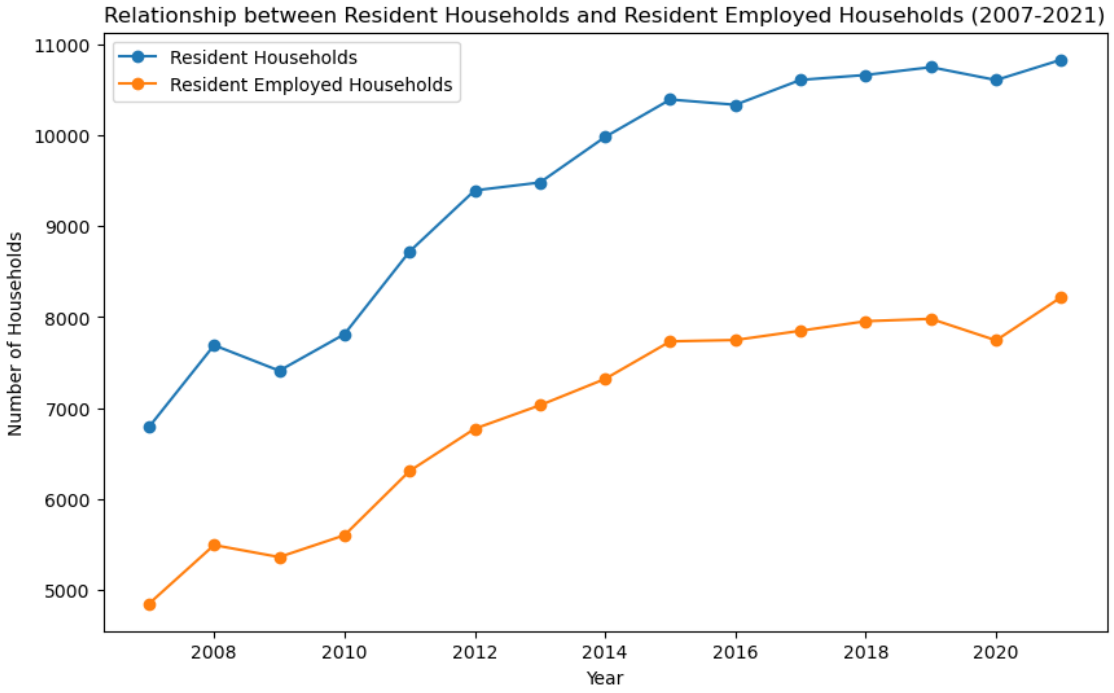
[23]:
```
# Drop multiple rows based on indices (e.g., indices 1 and 3)
indices_to_drop = [0,1,2,3,4,5,6,22]
household_income_df = household_income_df.drop(indices_to_drop)

# Display the household_income_df DataFrame after dropping rows
print("\nAfter dropping rows:")
print(household_income_df)
```

```
After dropping rows:
    Year  Resident Households  Resident Employed Households  Average Income  \
7   2007                 6790                          4846            7431
8   2008                 7691                          5492            8414
9   2009                 7410                          5360            8195
10  2010                 7812                          5600            8726
11  2011                 8722                          6307            9618
12  2012                 9394                          6772           10348
13  2013                 9481                          7030           10469
14  2014                 9982                          7320           11143
15  2015                10394                          7733           11510
16  2016                10336                          7748           11589
17  2017                10610                          7850           12027
```

18	2018	10664	7955	12137
19	2019	10750	7981	12386
20	2020	10608	7744	12235
21	2021	10832	8220	12276

	Median Income
7	5362
8	6100
9	6006
10	6342
11	7037
12	7566
13	7872
14	8292
15	8666
16	8846
17	9023
18	9293
19	9425
20	9189
21	9520

[24]:
```
# line plot for: Relationship between Resident Households and Resident Employed␣
 ↪Households (2007-2021)
plt.figure(figsize=(10, 6))
plt.plot(household_income_df['Year'], household_income_df['Resident␣
 ↪Households'], marker='o', label='Resident Households')
plt.plot(household_income_df['Year'], household_income_df['Resident Employed␣
 ↪Households'], marker='o', label='Resident Employed Households')

# Adding labels and title
plt.xlabel('Year')
plt.ylabel('Number of Households')
plt.title('Relationship between Resident Households and Resident Employed␣
 ↪Households (2007-2021)')

# Adding legend
plt.legend()

# Display the plot
plt.grid(False)
plt.show()
```

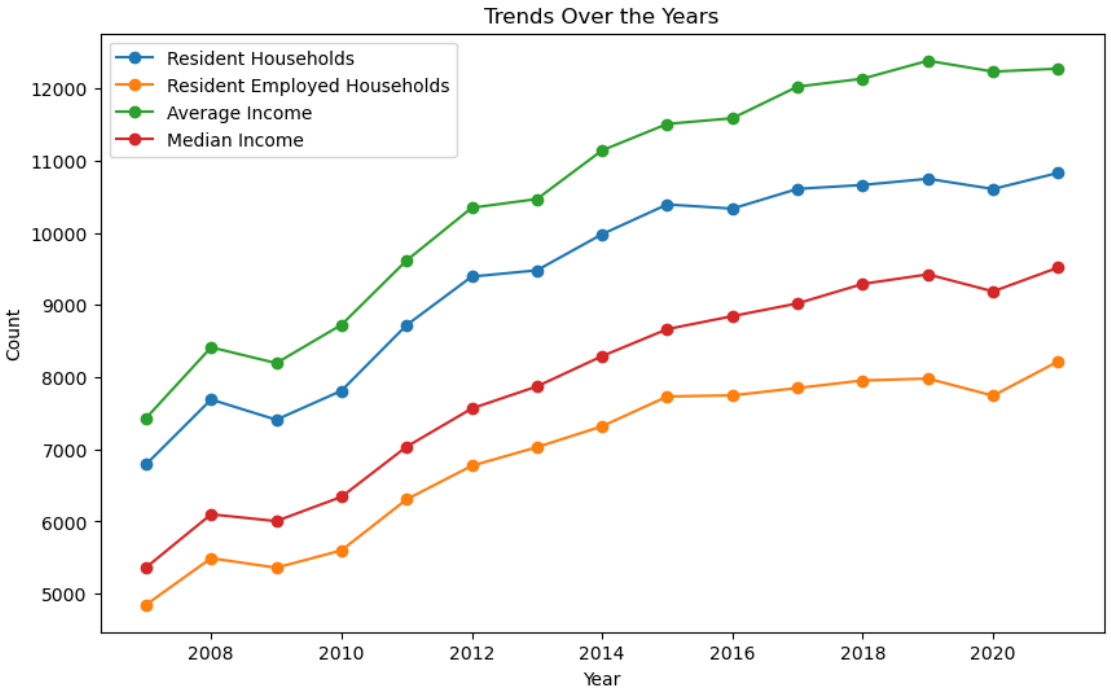


Relationship between Resident Households and Resident Employed Households (2007-2021) Graph

This graphs shows us that there is a high correlation between the number of resident households and the resident employed households. Resident household refers to a household where the household reference person is either a Singapore citizen or permanent resident. A resident employed household refers to a resident household with at least one employed person. Looking at this graph, we can make the inference that as the number of resident households increase, the number of resident employed households increase.

[25]:
```
plt.figure(figsize=(10, 6))

# Time series line plot: Trends over the years
plt.plot(household_income_df['Year'], household_income_df['Resident␣
 ↪Households'], label='Resident Households', marker='o')
plt.plot(household_income_df['Year'], household_income_df['Resident Employed␣
 ↪Households'], label='Resident Employed Households', marker='o')
plt.plot(household_income_df['Year'], household_income_df['Average Income'],␣
 ↪label='Average Income', marker='o')
plt.plot(household_income_df['Year'], household_income_df['Median Income'],␣
 ↪label='Median Income', marker='o')

plt.xlabel('Year')
plt.ylabel('Count')
plt.title('Trends Over the Years')
```

```
plt.legend()
plt.show()
```



The figure Trends Over the Years shows us that there is a upward trend across the different factors; number of resident households, number of resident employed households and the average and median of the income of the household. This shows us that when residents had higher income, they were more likely to purchase a home.

2.3.4 DataFrame Preparation: transaction_df

Source: Singapore Open Data

For this dataframe, I restructured the dataframe and removed data pertaining to the flat type HUDC as it has been privatised and therefore is no longer relevant for the analysis of the resale market. In addition, I grouped all data from the same year together.

[26]:
```
transaction_df = pd.read_csv('hdb_data/resale_transactions.csv')
```

[27]:
```
transaction_df
```

[27]:

	financial_year	flat_type	resale_transactions
0	2006	1 room	22
1	2006	2 room	314
2	2006	3 room	9230
3	2006	4 room	10851
4	2006	5 room	6314

```
..              …                                …                  …
100           2021                           2 room                446
101           2021                           3 room               6747
102           2021                           4 room              12972
103           2021                           5 room               7950
104           2021  Executive and Multi-generation               2247

[105 rows x 3 columns]
```

[28]:
```
#rename the column Median1 to Median
transaction_df = transaction_df.rename(columns={'financial_year':
 ↪'Year','flat_type':'Type','resale_transactions':'No. Transactions'})
transaction_df
```

[28]:
```
     Year                           Type  No. Transactions
0    2006                         1 room                22
1    2006                         2 room               314
2    2006                         3 room              9230
3    2006                         4 room             10851
4    2006                         5 room              6314
..    …                            …                 …
100  2021                         2 room               446
101  2021                         3 room              6747
102  2021                         4 room             12972
103  2021                         5 room              7950
104  2021  Executive and Multi-generation              2247

[105 rows x 3 columns]
```

[29]:
```
transaction_df.head()
```

[29]:
```
   Year    Type  No. Transactions
0  2006  1 room                22
1  2006  2 room               314
2  2006  3 room              9230
3  2006  4 room             10851
4  2006  5 room              6314
```

[30]:
```
transaction_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 105 entries, 0 to 104
Data columns (total 3 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Year              105 non-null    int64
 1   Type              105 non-null    object
 2   No. Transactions  105 non-null    int64
```

```
dtypes: int64(2), object(1)
memory usage: 2.6+ KB
```

[31]:
```
transaction_df.describe()
```

[31]:
```
              Year  No. Transactions
count   105.000000        105.000000
mean   2013.200000       3878.914286
std       4.600167       3910.398064
min    2006.000000          1.000000
25%    2009.000000        269.000000
50%    2013.000000       2211.000000
75%    2017.000000       6791.000000
max    2021.000000      14365.000000
```

[32]:
```
# Checking for missing values in the dateframe
transaction_df.isnull().sum()
```

[32]:
```
Year                0
Type                0
No. Transactions    0
dtype: int64
```

[33]:
```
# Assuming df is your DataFrame
# Pivot the DataFrame
transaction_df = transaction_df.pivot(index='Year', columns='Type', values='No. Transactions').reset_index()

# Rename the columns
transaction_df.columns.name = None  # Remove the 'Type' name from the columns
transaction_df = transaction_df.rename(columns={'1 room': '1_room', '2 room': '2_room', '3 room': '3_room', '4 room': '4_room', '5 room': '5_room', 'Executive and Multi-generation': 'Executive', 'HUDC': 'HUDC',})

# Display the resulting DataFrame
print(transaction_df)
```

```
    Year  1_room  2_room   3_room   4_room   5_room  Executive  HUDC
0   2006    22.0   314.0   9230.0  10851.0   6314.0     2211.0  92.0
1   2007    19.0   269.0   8368.0  10864.0   7447.0     2569.0  76.0
2   2008    17.0   247.0   8295.0  10637.0   7253.0     2058.0  44.0
3   2009    13.0   400.0  10854.0  14365.0  10369.0     3242.0  77.0
4   2010    19.0   530.0   8940.0  10817.0   7274.0     2421.0  60.0
5   2011    14.0   414.0   7230.0   8933.0   5832.0     1874.0  34.0
6   2012    15.0   567.0   6777.0   8747.0   5402.0     2029.0  42.0
7   2013    10.0   581.0   5553.0   6560.0   3549.0     1293.0   6.0
8   2014    19.0   408.0   5472.0   6791.0   3822.0     1160.0   1.0
9   2015     9.0   291.0   5511.0   7857.0   4486.0     1466.0   NaN
```

```
10  2016     7.0   279.0   5509.0   8651.0   4893.0     1555.0   NaN
11  2017    10.0   333.0   5379.0   9154.0   5349.0     1780.0   NaN
12  2018    14.0   392.0   5719.0   9626.0   5854.0     1871.0   NaN
13  2019     8.0   517.0   6023.0  10401.0   6005.0     1818.0   NaN
14  2020    13.0   440.0   6072.0  10941.0   6842.0     2128.0   NaN
15  2021     8.0   446.0   6747.0  12972.0   7950.0     2247.0   NaN
```

[34]:
```
transaction_df['1_room'] = transaction_df['1_room'].round(0)
transaction_df['2_room'] = transaction_df['2_room'].round(0)
transaction_df['3_room'] = transaction_df['3_room'].round(0)
transaction_df['4_room'] = transaction_df['4_room'].round(0)
transaction_df['5_room'] = transaction_df['5_room'].round(0)
transaction_df['Executive'] = transaction_df['Executive'].round(0)
transaction_df['HUDC'] = transaction_df['HUDC'].round(0)

# Print or use transaction_df as needed
print(transaction_df)
```

```
    Year  1_room  2_room   3_room   4_room   5_room  Executive  HUDC
0   2006    22.0   314.0   9230.0  10851.0   6314.0     2211.0  92.0
1   2007    19.0   269.0   8368.0  10864.0   7447.0     2569.0  76.0
2   2008    17.0   247.0   8295.0  10637.0   7253.0     2058.0  44.0
3   2009    13.0   400.0  10854.0  14365.0  10369.0     3242.0  77.0
4   2010    19.0   530.0   8940.0  10817.0   7274.0     2421.0  60.0
5   2011    14.0   414.0   7230.0   8933.0   5832.0     1874.0  34.0
6   2012    15.0   567.0   6777.0   8747.0   5402.0     2029.0  42.0
7   2013    10.0   581.0   5553.0   6560.0   3549.0     1293.0   6.0
8   2014    19.0   408.0   5472.0   6791.0   3822.0     1160.0   1.0
9   2015     9.0   291.0   5511.0   7857.0   4486.0     1466.0   NaN
10  2016     7.0   279.0   5509.0   8651.0   4893.0     1555.0   NaN
11  2017    10.0   333.0   5379.0   9154.0   5349.0     1780.0   NaN
12  2018    14.0   392.0   5719.0   9626.0   5854.0     1871.0   NaN
13  2019     8.0   517.0   6023.0  10401.0   6005.0     1818.0   NaN
14  2020    13.0   440.0   6072.0  10941.0   6842.0     2128.0   NaN
15  2021     8.0   446.0   6747.0  12972.0   7950.0     2247.0   NaN
```

[35]:
```
# Drop multiple rows based on indices (e.g., indices 1 and 3)
indices_to_drop = [0]
transaction_df = transaction_df.drop(indices_to_drop)

# Display the DataFrame after dropping rows
print("\nAfter dropping rows:")
print(transaction_df)
```

```
After dropping rows:
    Year  1_room  2_room   3_room   4_room   5_room  Executive  HUDC
1   2007    19.0   269.0   8368.0  10864.0   7447.0     2569.0  76.0
2   2008    17.0   247.0   8295.0  10637.0   7253.0     2058.0  44.0
```

3	2009	13.0	400.0	10854.0	14365.0	10369.0	3242.0	77.0
4	2010	19.0	530.0	8940.0	10817.0	7274.0	2421.0	60.0
5	2011	14.0	414.0	7230.0	8933.0	5832.0	1874.0	34.0
6	2012	15.0	567.0	6777.0	8747.0	5402.0	2029.0	42.0
7	2013	10.0	581.0	5553.0	6560.0	3549.0	1293.0	6.0
8	2014	19.0	408.0	5472.0	6791.0	3822.0	1160.0	1.0
9	2015	9.0	291.0	5511.0	7857.0	4486.0	1466.0	NaN
10	2016	7.0	279.0	5509.0	8651.0	4893.0	1555.0	NaN
11	2017	10.0	333.0	5379.0	9154.0	5349.0	1780.0	NaN
12	2018	14.0	392.0	5719.0	9626.0	5854.0	1871.0	NaN
13	2019	8.0	517.0	6023.0	10401.0	6005.0	1818.0	NaN
14	2020	13.0	440.0	6072.0	10941.0	6842.0	2128.0	NaN
15	2021	8.0	446.0	6747.0	12972.0	7950.0	2247.0	NaN

[36]:
```
# Drop the 'HUDC' column in place
# The HUDC column was dropped as they are now private developments and␣
 ↪therefore,
# there is no relevant data with resale purchases
transaction_df.drop(columns=['HUDC'], inplace=True)
transaction_df
```

[36]:

	Year	1_room	2_room	3_room	4_room	5_room	Executive
1	2007	19.0	269.0	8368.0	10864.0	7447.0	2569.0
2	2008	17.0	247.0	8295.0	10637.0	7253.0	2058.0
3	2009	13.0	400.0	10854.0	14365.0	10369.0	3242.0
4	2010	19.0	530.0	8940.0	10817.0	7274.0	2421.0
5	2011	14.0	414.0	7230.0	8933.0	5832.0	1874.0
6	2012	15.0	567.0	6777.0	8747.0	5402.0	2029.0
7	2013	10.0	581.0	5553.0	6560.0	3549.0	1293.0
8	2014	19.0	408.0	5472.0	6791.0	3822.0	1160.0
9	2015	9.0	291.0	5511.0	7857.0	4486.0	1466.0
10	2016	7.0	279.0	5509.0	8651.0	4893.0	1555.0
11	2017	10.0	333.0	5379.0	9154.0	5349.0	1780.0
12	2018	14.0	392.0	5719.0	9626.0	5854.0	1871.0
13	2019	8.0	517.0	6023.0	10401.0	6005.0	1818.0
14	2020	13.0	440.0	6072.0	10941.0	6842.0	2128.0
15	2021	8.0	446.0	6747.0	12972.0	7950.0	2247.0

[37]:
```
# Remove ".0" from all columns
transaction_df = transaction_df.applymap(lambda x: int(x) if isinstance(x,␣
 ↪float) and x.is_integer() else x)

# Display the DataFrame after removing ".0"
print("\nAfter removing '.0':")
print(transaction_df)
```

```
After removing '.0':
```

	Year	1_room	2_room	3_room	4_room	5_room	Executive
1	2007	19	269	8368	10864	7447	2569
2	2008	17	247	8295	10637	7253	2058
3	2009	13	400	10854	14365	10369	3242
4	2010	19	530	8940	10817	7274	2421
5	2011	14	414	7230	8933	5832	1874
6	2012	15	567	6777	8747	5402	2029
7	2013	10	581	5553	6560	3549	1293
8	2014	19	408	5472	6791	3822	1160
9	2015	9	291	5511	7857	4486	1466
10	2016	7	279	5509	8651	4893	1555
11	2017	10	333	5379	9154	5349	1780
12	2018	14	392	5719	9626	5854	1871
13	2019	8	517	6023	10401	6005	1818
14	2020	13	440	6072	10941	6842	2128
15	2021	8	446	6747	12972	7950	2247

[38]:
```
print(transaction_df.columns)
```

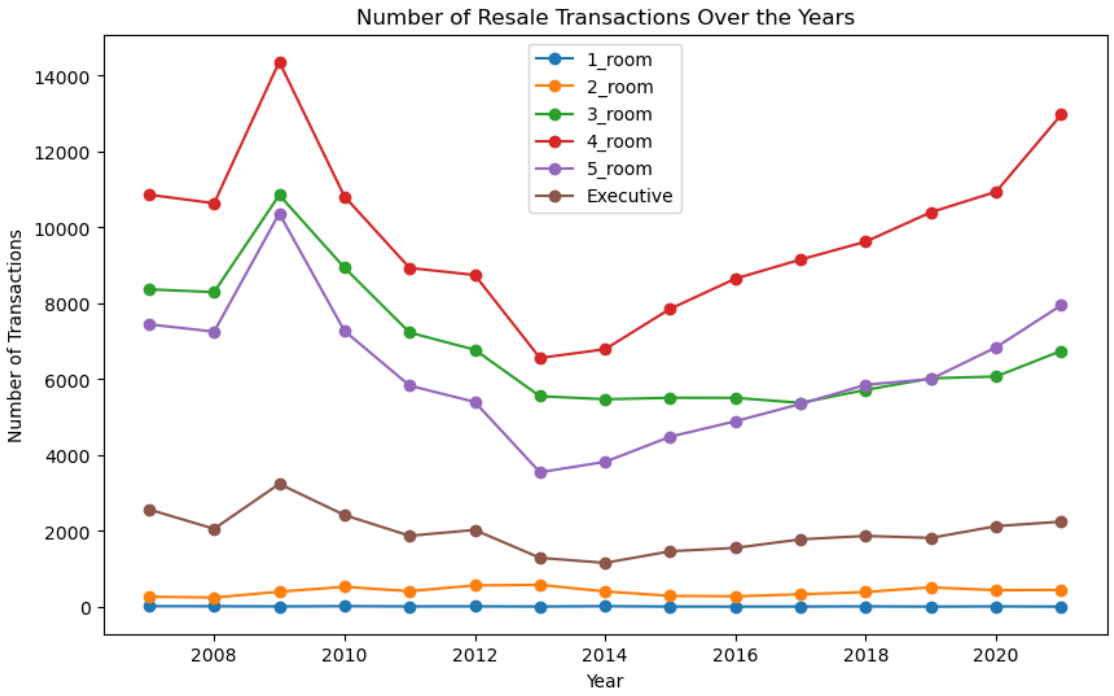
```
Index(['Year', '1_room', '2_room', '3_room', '4_room', '5_room', 'Executive'],
dtype='object')
```

[39]:
```
# Calculate kurtosis for each column
kurtosis_values = transaction_df.kurtosis()

# Print the results
print("Kurtosis for each column:")
print(kurtosis_values)
```

```
Kurtosis for each column:
Year        -1.200000
1_room      -1.313502
2_room      -1.076902
3_room       1.165023
4_room       0.357133
5_room       0.967370
Executive    1.220786
dtype: float64
```

[40]:
```
#Line Plot: Number of transactions over the years
transaction_df = pd.DataFrame(transaction_df)

# Plotting of the line graph
plt.figure(figsize=(10, 6))

for room_type in transaction_df.columns[1:]:
    plt.plot(transaction_df['Year'], transaction_df[room_type],␣
 ↪label=room_type, marker='o')
```

```
plt.title('Number of Resale Transactions Over the Years')
plt.xlabel('Year')
plt.ylabel('Number of Transactions')
plt.legend()
plt.grid(False)
plt.show()
```



Number of Resale Transactions Over the Years Graph

From the graph we can see that ther has been a steady increase in the number of resale transactions for the 5 room, 4 room, 3 room and Executive homes. However, the number of transactions for 1 room and 2 room homes have been stagnant over the years. Therefore, I can make the assumption that the sales for the 5 room, 4 room, 3 room and Executive homes will continue to see an increase over the next few years.

2.3.5 DataFrame Preparation: price_df

Source: Singapore Open Data

For this dataframe, I cleaned by removing rows with NaN values and restructuring the data so that it is consistent by removing the information with regards to the quarter in which it was sold. In addition, I got two dataframes from this dataframe - town_yearly_median_df and median_price_yearly.

[41]:
```
price_df = pd.read_csv('hdb_data/
↪MedianResalePricesforRegisteredApplicationsbyTownandFlatType.csv')
```

[42]:
```
price_df
```

[42]:
```
        quarter        town  flat_type   price
0       2007-Q2  Ang Mo Kio     1-room      na
1       2007-Q2  Ang Mo Kio     2-room       -
2       2007-Q2  Ang Mo Kio     3-room  172000
3       2007-Q2  Ang Mo Kio     4-room  260000
4       2007-Q2  Ang Mo Kio     5-room  372000
…         …          …         …      …
10291   2023-Q3      YISHUN     2-room       -
10292   2023-Q3      YISHUN     3-room  385000
10293   2023-Q3      YISHUN     4-room  500000
10294   2023-Q3      YISHUN     5-room  650000
10295   2023-Q3      YISHUN  Executive       -

[10296 rows x 4 columns]
```

[43]:
```
price_df.head()
```

[43]:
```
    quarter        town flat_type   price
0  2007-Q2  Ang Mo Kio    1-room      na
1  2007-Q2  Ang Mo Kio    2-room       -
2  2007-Q2  Ang Mo Kio    3-room  172000
3  2007-Q2  Ang Mo Kio    4-room  260000
4  2007-Q2  Ang Mo Kio    5-room  372000
```

[44]:
```
price_df.describe()
```

[44]:
```
        quarter        town flat_type  price
count     10296       10296     10296  10098
unique       66          52         6   1261
top     2007-Q2  Ang Mo Kio    1-room      -
freq        156         288      1716   2795
```

[45]:
```
price_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10296 entries, 0 to 10295
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   quarter    10296 non-null  object
 1   town       10296 non-null  object
 2   flat_type  10296 non-null  object
 3   price      10098 non-null  object
```

```
dtypes: object(4)
memory usage: 321.9+ KB
```

[46]:
```
price_df.isnull().sum()
```

[46]:
```
quarter        0
town           0
flat_type      0
price        198
dtype: int64
```

[47]:
```
# Identify and remove rows with '-' or 'na'
price_df = price_df[(price_df != '-') & (price_df != 'na')].dropna()

# Remove additional rows with NA values
price_df.dropna(inplace=True)

# Display the cleaned DataFrame
print(price_df)
```

```
       quarter        town  flat_type   price
2      2007-Q2  Ang Mo Kio     3-room  172000
3      2007-Q2  Ang Mo Kio     4-room  260000
4      2007-Q2  Ang Mo Kio     5-room  372000
8      2007-Q2       Bedok     3-room  172000
9      2007-Q2       Bedok     4-room  224500
…        …          …         …      …
10288  2023-Q3   WOODLANDS     5-room  590000
10289  2023-Q3   WOODLANDS  Executive  802000
10292  2023-Q3      YISHUN     3-room  385000
10293  2023-Q3      YISHUN     4-room  500000
10294  2023-Q3      YISHUN     5-room  650000

[4735 rows x 4 columns]
```

[48]:
```
price_df
```

[48]:
```
       quarter        town  flat_type   price
2      2007-Q2  Ang Mo Kio     3-room  172000
3      2007-Q2  Ang Mo Kio     4-room  260000
4      2007-Q2  Ang Mo Kio     5-room  372000
8      2007-Q2       Bedok     3-room  172000
9      2007-Q2       Bedok     4-room  224500
…        …          …         …      …
10288  2023-Q3   WOODLANDS     5-room  590000
10289  2023-Q3   WOODLANDS  Executive  802000
10292  2023-Q3      YISHUN     3-room  385000
10293  2023-Q3      YISHUN     4-room  500000
```

```
10294  2023-Q3      YISHUN     5-room  650000

[4735 rows x 4 columns]
```

[49]:
```
# Remove the '-Q1', '-Q2', '-Q3', etc., from the 'quarter' column
# I removed it so that it would be easier when merging all the datasets to 1NF
price_df['quarter'] = price_df['quarter'].str.replace('-Q[0-9]', '', regex=True)

# Rename the columns
price_df.rename(columns={'quarter': 'Year', 'town':'Town','flat_type': 'Type',␣
 ↪'price':'Price'}, inplace=True)

# Display the DataFrame after removing the suffixes
price_df
```

[49]:
```
       Year        Town       Type   Price
2      2007  Ang Mo Kio     3-room  172000
3      2007  Ang Mo Kio     4-room  260000
4      2007  Ang Mo Kio     5-room  372000
8      2007       Bedok     3-room  172000
9      2007       Bedok     4-room  224500
…       …          …         …       …
10288  2023   WOODLANDS     5-room  590000
10289  2023   WOODLANDS  Executive  802000
10292  2023      YISHUN     3-room  385000
10293  2023      YISHUN     4-room  500000
10294  2023      YISHUN     5-room  650000

[4735 rows x 4 columns]
```

[50]:
```
# Group by Year and calculate the median Price of the flats
median_price_yearly = price_df.groupby('Year')['Price'].median().reset_index()

# Rename the 'Price' column to 'Median_price'
median_price_yearly = median_price_yearly.rename(columns={'Price':␣
 ↪'yearly_median_price'})

# Display the resulting DataFrame
print(median_price_yearly)
```

```
    Year yearly_median_price
0   2007            293000.0
1   2008            333000.0
2   2009            365000.0
3   2010            410000.0
4   2011            450000.0
5   2012            480000.0
6   2013            482500.0
```

```
7   2014            440000.0
8   2015            425000.0
9   2016            435000.0
10  2017            435000.0
11  2018            436200.0
12  2019            425000.0
13  2020            435000.0
14  2021            515900.0
15  2022            548000.0
16  2023            572000.0
```

[51]:
```
# Drop multiple rows based on indices (e.g., indices 1 and 3)
indices_to_drop = [15,16]
median_price_yearly = median_price_yearly.drop(indices_to_drop)

# Display the DataFrame after dropping rows
print("\nAfter dropping rows:")
print(median_price_yearly)
```

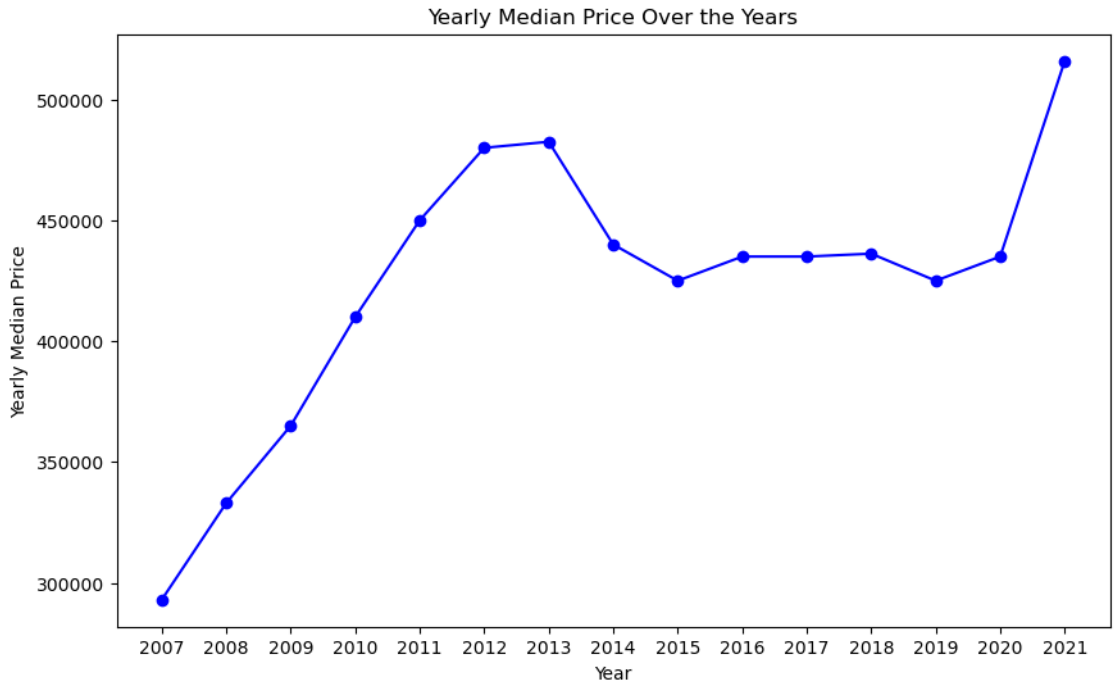
```
After dropping rows:
    Year yearly_median_price
0   2007            293000.0
1   2008            333000.0
2   2009            365000.0
3   2010            410000.0
4   2011            450000.0
5   2012            480000.0
6   2013            482500.0
7   2014            440000.0
8   2015            425000.0
9   2016            435000.0
10  2017            435000.0
11  2018            436200.0
12  2019            425000.0
13  2020            435000.0
14  2021            515900.0
```

[52]:
```
# Remove ".0" from all columns
median_price_yearly = median_price_yearly.applymap(lambda x: int(x) if␣
 ↪isinstance(x, float) and x.is_integer() else x)

# Display the DataFrame after removing ".0"
print("\nAfter removing '.0':")
print(median_price_yearly)
```

```
After removing '.0':
    Year  yearly_median_price
```

0	2007	293000
1	2008	333000
2	2009	365000
3	2010	410000
4	2011	450000
5	2012	480000
6	2013	482500
7	2014	440000
8	2015	425000
9	2016	435000
10	2017	435000
11	2018	436200
12	2019	425000
13	2020	435000
14	2021	515900

[53]:
```
# skewness for the 'yearly_median_price' column in the dataframe
skewness_value = skew(median_price_yearly['yearly_median_price'])

# Plotting
plt.figure(figsize=(10, 6))

# Line plot for 'yearly_median_price'
plt.plot(median_price_yearly['Year'],␣
 ↪median_price_yearly['yearly_median_price'], marker='o', linestyle='-',␣
 ↪color='b')

plt.title('Yearly Median Price Over the Years')
plt.xlabel('Year')
plt.ylabel('Yearly Median Price')
plt.grid(False)
plt.show()

# Print the skewness value
print(f'Skewness: {skewness_value}')
```




```
Skewness: -0.810552934111863
```

Yearly Median Price Over the Years Graph

From the above graph, we have an overview of the median prices of flats over the year. As we can see from the line plot, it hsa a left skewed distribution. The median yearly price has a steady upward from 2007 to 2013 however, there was a decrease in the yearly median price from 2013 to 2015. Thereafter, it has had an overall increase in price. I think it is left skewed as first time home buyers have been more likely to purchase BTO (Built To Order) flats as there are many grants available. In addition, many flats who had a 99 year lease for homes, have a much lower lease which I believe would affect the number of people going through with the purchase of a resale home.

[54]:
```
# I wanted to find the median of each town by each year
# Convert 'Town' column to lowercase
price_df['Town'] = price_df['Town'].str.lower()

# Create a new column for the combination of 'Year' and 'Town'
price_df['Year_Town'] = price_df['Year'].astype(str) + '_' + price_df['Town']

# Create a pivot table to get median prices for each combination of 'Year' and␣
 ↪'Town'
pivot_df = price_df.pivot_table(index=['Year', 'Town'], values='Price',␣
 ↪aggfunc='median')

# Reset the index to make 'Year' and 'Town' regular columns
pivot_df.reset_index(inplace=True)
```

```
# Pivot the table again so that the towns are the columns
town_yearly_median_df = pivot_df.pivot(index='Year', columns='Town',␣
 ↪values='Price')

# Reset the index to make 'Year' a regular column
town_yearly_median_df.reset_index(inplace=True)

# Rename the columns to include '_median' suffix
town_yearly_median_df.columns = [f'{col}_median' if col != 'Year' else col for␣
 ↪col in town_yearly_median_df.columns]

# Print or use final_df as needed
town_yearly_median_df
```

[54]:

	Year	ang mo kio_median	bedok_median	bishan_median	bukit batok_median	\
0	2007	280000.0	257000.0	370250.0	331900.0	
1	2008	327000.0	305000.0	407000.0	333000.0	
2	2009	340000.0	335000.0	412500.0	360000.0	
3	2010	398750.0	384000.0	510000.0	435000.0	
4	2011	434250.0	410500.0	571000.0	424000.0	
5	2012	466500.0	434750.0	527500.0	439250.0	
6	2013	486500.0	452500.0	551500.0	440000.0	
7	2014	451000.0	430000.0	525000.0	418000.0	
8	2015	450000.0	412500.0	535000.0	404500.0	
9	2016	466500.0	410000.0	666000.0	400000.0	
10	2017	462000.0	418000.0	662650.0	395000.0	
11	2018	446000.0	408000.0	660750.0	385000.0	
12	2019	407250.0	387500.0	636750.0	367200.0	
13	2020	405200.0	395000.0	555000.0	375250.0	
14	2021	448000.0	454200.0	678750.0	468000.0	
15	2022	515750.0	477500.0	739700.0	507000.0	
16	2023	538000.0	520500.0	797500.0	592500.0	

	bukit merah_median	bukit panjang_median	central_median	central area_median	\
0	396500.0	249000.0	300000.0	NaN	
1	435550.0	289500.0	310000.0	NaN	
2	457950.0	335650.0	340000.0	NaN	
3	521000.0	372250.0	372500.0	NaN	
4	583750.0	425000.0	418750.0	NaN	
5	606000.0	481800.0	442500.0	NaN	
6	673250.0	485000.0	NaN	NaN	
7	647950.0	409000.0	432500.0	NaN	
8	627500.0	365000.0	839400.0	NaN	
9	617500.0	353300.0	620000.0	NaN	
10	689000.0	415950.0	412500.0	NaN	
11	661250.0	459500.0	850000.0	NaN	

```
12           682000.0             426250.0           NaN           665000.0
13           664700.0             427000.0           NaN           528750.0
14           760000.0             494000.0           NaN           910000.0
15           758000.0             477500.0           NaN           570000.0
16           838000.0             500500.0           NaN           599000.0

   choa chu kang_median  … pasir ris_median punggol_median  \
0              291900.0  …         310000.0       300000.0
1              350400.0  …         370000.0       351000.0
2              358000.0  …         386500.0       388000.0
3              415000.0  …         430250.0       430000.0
4              449250.0  …         486250.0       484500.0
5              485000.0  …         520000.0       523500.0
6              461250.0  …         530750.0       526500.0
7              424250.0  …         502750.0       469000.0
8              415500.0  …         469500.0       438250.0
9              412600.0  …         471200.0       449450.0
10             408000.0  …         475000.0       439200.0
11             394000.0  …         479000.0       438000.0
12             397500.0  …         479500.0       457500.0
13             425000.0  …         497500.0       465000.0
14             481250.0  …         548500.0       493200.0
15             533700.0  …         609500.0       552500.0
16             539500.0  …         650000.0       582900.0

   queenstown_median sembawang_median sengkang_median serangoon_median  \
0           410000.0         292000.0        316000.0         275500.0
1           461500.0         325500.0        371000.0         324500.0
2           461500.0         362000.0        381600.0         345000.0
3           527500.0         415250.0        445000.0         393300.0
4           370000.0         440000.0        494000.0         410000.0
5           513000.0         474000.0        515950.0         473000.0
6           543500.0         491000.0        532000.0         470000.0
7           528250.0         419500.0        470900.0         407500.0
8           517500.0         420000.0        458000.0         388000.0
9           680000.0         415000.0        452500.0         449750.0
10          695000.0         405000.0        439000.0         438850.0
11          707500.0         382000.0        437400.0         470000.0
12          727500.0         392500.0        425000.0         431500.0
13          748000.0         407000.0        455000.0         438000.0
14          790000.0         470900.0        503000.0         524900.0
15          829000.0         534400.0        548000.0         506700.0
16          635000.0         524000.0        580000.0         567000.0

   tampines_median toa payoh_median woodlands_median yishun_median
0         301500.0         337500.0         263000.0      218000.0
1         357000.0         396750.0         298250.0      255500.0
```

```
2         375000.0         405750.0         323000.0      292000.0
3         415000.0         434000.0         360000.0      337000.0
4         461150.0         495250.0         400500.0      377000.0
5         499000.0         548950.0         430000.0      414000.0
6         512100.0         592000.0         441250.0      411000.0
7         457400.0         438250.0         410000.0      368000.0
8         470250.0         491500.0         365000.0      359000.0
9         477500.0         537500.0         390000.0      367000.0
10        477000.0         610000.0         379000.0      356000.0
11        478000.0         580750.0         364000.0      341500.0
12        430000.0         557250.0         366000.0      370000.0
13        435000.0         558000.0         389500.0      389500.0
14        521500.0         617200.0         447500.0      482000.0
15        575750.0         720450.0         512500.0      528250.0
16        617750.0         779000.0         540500.0      485750.0

[17 rows x 27 columns]
```

[55]:
```
# Merge 'central_median' and 'central area_median' columns into a new column␣
 ↪'combined_median'
town_yearly_median_df['combined_median'] =␣
 ↪town_yearly_median_df['central_median'].
 ↪combine_first(town_yearly_median_df['central area_median'])

# Drop the original columns
town_yearly_median_df.drop(['central_median', 'central area_median'], axis=1,␣
 ↪inplace=True)

# Print or use df as needed
print(town_yearly_median_df)
```

```
    Year ang mo kio_median bedok_median bishan_median bukit batok_median  \
0   2007          280000.0     257000.0      370250.0           331900.0
1   2008          327000.0     305000.0      407000.0           333000.0
2   2009          340000.0     335000.0      412500.0           360000.0
3   2010          398750.0     384000.0      510000.0           435000.0
4   2011          434250.0     410500.0      571000.0           424000.0
5   2012          466500.0     434750.0      527500.0           439250.0
6   2013          486500.0     452500.0      551500.0           440000.0
7   2014          451000.0     430000.0      525000.0           418000.0
8   2015          450000.0     412500.0      535000.0           404500.0
9   2016          466500.0     410000.0      666000.0           400000.0
10  2017          462000.0     418000.0      662650.0           395000.0
11  2018          446000.0     408000.0      660750.0           385000.0
12  2019          407250.0     387500.0      636750.0           367200.0
13  2020          405200.0     395000.0      555000.0           375250.0
14  2021          448000.0     454200.0      678750.0           468000.0
```

```
15  2022          515750.0     477500.0      739700.0           507000.0
16  2023          538000.0     520500.0      797500.0           592500.0

   bukit merah_median bukit panjang_median choa chu kang_median  \
0            396500.0             249000.0             291900.0
1            435550.0             289500.0             350400.0
2            457950.0             335650.0             358000.0
3            521000.0             372250.0             415000.0
4            583750.0             425000.0             449250.0
5            606000.0             481800.0             485000.0
6            673250.0             485000.0             461250.0
7            647950.0             409000.0             424250.0
8            627500.0             365000.0             415500.0
9            617500.0             353300.0             412600.0
10           689000.0             415950.0             408000.0
11           661250.0             459500.0             394000.0
12           682000.0             426250.0             397500.0
13           664700.0             427000.0             425000.0
14           760000.0             494000.0             481250.0
15           758000.0             477500.0             533700.0
16           838000.0             500500.0             539500.0

   clementi_median geylang_median  … punggol_median queenstown_median  \
0         302200.0       268250.0  …       300000.0          410000.0
1         351500.0       322500.0  …       351000.0          461500.0
2         388000.0       363000.0  …       388000.0          461500.0
3         432000.0       397500.0  …       430000.0          527500.0
4         420000.0       459750.0  …       484500.0          370000.0
5         438500.0       457000.0  …       523500.0          513000.0
6         390000.0       403650.0  …       526500.0          543500.0
7         435250.0       311500.0  …       469000.0          528250.0
8         428750.0       453000.0  …       438250.0          517500.0
9         422500.0       373750.0  …       449450.0          680000.0
10        432500.0       490000.0  …       439200.0          695000.0
11        504000.0       388900.0  …       438000.0          707500.0
12        387500.0       445500.0  …       457500.0          727500.0
13        497500.0       427500.0  …       465000.0          748000.0
14        673250.0       597500.0  …       493200.0          790000.0
15        564950.0       560000.0  …       552500.0          829000.0
16        597500.0       549000.0  …       582900.0          635000.0

   sembawang_median sengkang_median serangoon_median tampines_median  \
0          292000.0        316000.0         275500.0        301500.0
1          325500.0        371000.0         324500.0        357000.0
2          362000.0        381600.0         345000.0        375000.0
3          415250.0        445000.0         393300.0        415000.0
4          440000.0        494000.0         410000.0        461150.0
5          474000.0        515950.0         473000.0        499000.0
```

```
6          491000.0        532000.0         470000.0        512100.0
7          419500.0        470900.0         407500.0        457400.0
8          420000.0        458000.0         388000.0        470250.0
9          415000.0        452500.0         449750.0        477500.0
10         405000.0        439000.0         438850.0        477000.0
11         382000.0        437400.0         470000.0        478000.0
12         392500.0        425000.0         431500.0        430000.0
13         407000.0        455000.0         438000.0        435000.0
14         470900.0        503000.0         524900.0        521500.0
15         534400.0        548000.0         506700.0        575750.0
16         524000.0        580000.0         567000.0        617750.0

   toa payoh_median woodlands_median yishun_median combined_median
0          337500.0         263000.0      218000.0        300000.0
1          396750.0         298250.0      255500.0        310000.0
2          405750.0         323000.0      292000.0        340000.0
3          434000.0         360000.0      337000.0        372500.0
4          495250.0         400500.0      377000.0        418750.0
5          548950.0         430000.0      414000.0        442500.0
6          592000.0         441250.0      411000.0             NaN
7          438250.0         410000.0      368000.0        432500.0
8          491500.0         365000.0      359000.0        839400.0
9          537500.0         390000.0      367000.0        620000.0
10         610000.0         379000.0      356000.0        412500.0
11         580750.0         364000.0      341500.0        850000.0
12         557250.0         366000.0      370000.0        665000.0
13         558000.0         389500.0      389500.0        528750.0
14         617200.0         447500.0      482000.0        910000.0
15         720450.0         512500.0      528250.0        570000.0
16         779000.0         540500.0      485750.0        599000.0

[17 rows x 26 columns]
```

[56]:
```
town_yearly_median_df.rename(columns={'combined_median': 'central_median'},␣
↪inplace=True)

# Print or use final_df as needed
town_yearly_median_df
```

[56]:
```
    Year ang mo kio_median bedok_median bishan_median bukit batok_median  \
0   2007          280000.0     257000.0      370250.0           331900.0
1   2008          327000.0     305000.0      407000.0           333000.0
2   2009          340000.0     335000.0      412500.0           360000.0
3   2010          398750.0     384000.0      510000.0           435000.0
4   2011          434250.0     410500.0      571000.0           424000.0
5   2012          466500.0     434750.0      527500.0           439250.0
6   2013          486500.0     452500.0      551500.0           440000.0
```

7	2014	451000.0	430000.0	525000.0	418000.0
8	2015	450000.0	412500.0	535000.0	404500.0
9	2016	466500.0	410000.0	666000.0	400000.0
10	2017	462000.0	418000.0	662650.0	395000.0
11	2018	446000.0	408000.0	660750.0	385000.0
12	2019	407250.0	387500.0	636750.0	367200.0
13	2020	405200.0	395000.0	555000.0	375250.0
14	2021	448000.0	454200.0	678750.0	468000.0
15	2022	515750.0	477500.0	739700.0	507000.0
16	2023	538000.0	520500.0	797500.0	592500.0

	bukit merah_median	bukit panjang_median	choa chu kang_median	\
0	396500.0	249000.0	291900.0	
1	435550.0	289500.0	350400.0	
2	457950.0	335650.0	358000.0	
3	521000.0	372250.0	415000.0	
4	583750.0	425000.0	449250.0	
5	606000.0	481800.0	485000.0	
6	673250.0	485000.0	461250.0	
7	647950.0	409000.0	424250.0	
8	627500.0	365000.0	415500.0	
9	617500.0	353300.0	412600.0	
10	689000.0	415950.0	408000.0	
11	661250.0	459500.0	394000.0	
12	682000.0	426250.0	397500.0	
13	664700.0	427000.0	425000.0	
14	760000.0	494000.0	481250.0	
15	758000.0	477500.0	533700.0	
16	838000.0	500500.0	539500.0	

	clementi_median	geylang_median	…	punggol_median	queenstown_median	\
0	302200.0	268250.0	…	300000.0	410000.0	
1	351500.0	322500.0	…	351000.0	461500.0	
2	388000.0	363000.0	…	388000.0	461500.0	
3	432000.0	397500.0	…	430000.0	527500.0	
4	420000.0	459750.0	…	484500.0	370000.0	
5	438500.0	457000.0	…	523500.0	513000.0	
6	390000.0	403650.0	…	526500.0	543500.0	
7	435250.0	311500.0	…	469000.0	528250.0	
8	428750.0	453000.0	…	438250.0	517500.0	
9	422500.0	373750.0	…	449450.0	680000.0	
10	432500.0	490000.0	…	439200.0	695000.0	
11	504000.0	388900.0	…	438000.0	707500.0	
12	387500.0	445500.0	…	457500.0	727500.0	
13	497500.0	427500.0	…	465000.0	748000.0	
14	673250.0	597500.0	…	493200.0	790000.0	
15	564950.0	560000.0	…	552500.0	829000.0	

```
16        597500.0       549000.0  …       582900.0          635000.0

   sembawang_median sengkang_median serangoon_median tampines_median  \
0          292000.0        316000.0         275500.0        301500.0
1          325500.0        371000.0         324500.0        357000.0
2          362000.0        381600.0         345000.0        375000.0
3          415250.0        445000.0         393300.0        415000.0
4          440000.0        494000.0         410000.0        461150.0
5          474000.0        515950.0         473000.0        499000.0
6          491000.0        532000.0         470000.0        512100.0
7          419500.0        470900.0         407500.0        457400.0
8          420000.0        458000.0         388000.0        470250.0
9          415000.0        452500.0         449750.0        477500.0
10         405000.0        439000.0         438850.0        477000.0
11         382000.0        437400.0         470000.0        478000.0
12         392500.0        425000.0         431500.0        430000.0
13         407000.0        455000.0         438000.0        435000.0
14         470900.0        503000.0         524900.0        521500.0
15         534400.0        548000.0         506700.0        575750.0
16         524000.0        580000.0         567000.0        617750.0

   toa payoh_median woodlands_median yishun_median central_median
0          337500.0         263000.0      218000.0       300000.0
1          396750.0         298250.0      255500.0       310000.0
2          405750.0         323000.0      292000.0       340000.0
3          434000.0         360000.0      337000.0       372500.0
4          495250.0         400500.0      377000.0       418750.0
5          548950.0         430000.0      414000.0       442500.0
6          592000.0         441250.0      411000.0            NaN
7          438250.0         410000.0      368000.0       432500.0
8          491500.0         365000.0      359000.0       839400.0
9          537500.0         390000.0      367000.0       620000.0
10         610000.0         379000.0      356000.0       412500.0
11         580750.0         364000.0      341500.0       850000.0
12         557250.0         366000.0      370000.0       665000.0
13         558000.0         389500.0      389500.0       528750.0
14         617200.0         447500.0      482000.0       910000.0
15         720450.0         512500.0      528250.0       570000.0
16         779000.0         540500.0      485750.0       599000.0

[17 rows x 26 columns]
```

[57]:
```
# Drop multiple rows based on indices (e.g., indices 1 and 3)
indices_to_drop = [15,16]
town_yearly_median_df = town_yearly_median_df.drop(indices_to_drop)

# Display the DataFrame after dropping rows
```

```
print("\nAfter dropping rows:")
print(town_yearly_median_df)
```

```
After dropping rows:
    Year ang mo kio_median bedok_median bishan_median bukit batok_median  \
0   2007          280000.0     257000.0      370250.0           331900.0
1   2008          327000.0     305000.0      407000.0           333000.0
2   2009          340000.0     335000.0      412500.0           360000.0
3   2010          398750.0     384000.0      510000.0           435000.0
4   2011          434250.0     410500.0      571000.0           424000.0
5   2012          466500.0     434750.0      527500.0           439250.0
6   2013          486500.0     452500.0      551500.0           440000.0
7   2014          451000.0     430000.0      525000.0           418000.0
8   2015          450000.0     412500.0      535000.0           404500.0
9   2016          466500.0     410000.0      666000.0           400000.0
10  2017          462000.0     418000.0      662650.0           395000.0
11  2018          446000.0     408000.0      660750.0           385000.0
12  2019          407250.0     387500.0      636750.0           367200.0
13  2020          405200.0     395000.0      555000.0           375250.0
14  2021          448000.0     454200.0      678750.0           468000.0

   bukit merah_median bukit panjang_median choa chu kang_median  \
0           396500.0             249000.0            291900.0
1           435550.0             289500.0            350400.0
2           457950.0             335650.0            358000.0
3           521000.0             372250.0            415000.0
4           583750.0             425000.0            449250.0
5           606000.0             481800.0            485000.0
6           673250.0             485000.0            461250.0
7           647950.0             409000.0            424250.0
8           627500.0             365000.0            415500.0
9           617500.0             353300.0            412600.0
10          689000.0             415950.0            408000.0
11          661250.0             459500.0            394000.0
12          682000.0             426250.0            397500.0
13          664700.0             427000.0            425000.0
14          760000.0             494000.0            481250.0

   clementi_median geylang_median  … punggol_median queenstown_median  \
0         302200.0       268250.0  …       300000.0          410000.0
1         351500.0       322500.0  …       351000.0          461500.0
2         388000.0       363000.0  …       388000.0          461500.0
3         432000.0       397500.0  …       430000.0          527500.0
4         420000.0       459750.0  …       484500.0          370000.0
5         438500.0       457000.0  …       523500.0          513000.0
6         390000.0       403650.0  …       526500.0          543500.0
7         435250.0       311500.0  …       469000.0          528250.0
```

```
8         428750.0       453000.0  …       438250.0          517500.0
9         422500.0       373750.0  …       449450.0          680000.0
10        432500.0       490000.0  …       439200.0          695000.0
11        504000.0       388900.0  …       438000.0          707500.0
12        387500.0       445500.0  …       457500.0          727500.0
13        497500.0       427500.0  …       465000.0          748000.0
14        673250.0       597500.0  …       493200.0          790000.0

   sembawang_median sengkang_median serangoon_median tampines_median  \
0          292000.0        316000.0         275500.0        301500.0
1          325500.0        371000.0         324500.0        357000.0
2          362000.0        381600.0         345000.0        375000.0
3          415250.0        445000.0         393300.0        415000.0
4          440000.0        494000.0         410000.0        461150.0
5          474000.0        515950.0         473000.0        499000.0
6          491000.0        532000.0         470000.0        512100.0
7          419500.0        470900.0         407500.0        457400.0
8          420000.0        458000.0         388000.0        470250.0
9          415000.0        452500.0         449750.0        477500.0
10         405000.0        439000.0         438850.0        477000.0
11         382000.0        437400.0         470000.0        478000.0
12         392500.0        425000.0         431500.0        430000.0
13         407000.0        455000.0         438000.0        435000.0
14         470900.0        503000.0         524900.0        521500.0

   toa payoh_median woodlands_median yishun_median central_median
0          337500.0         263000.0      218000.0       300000.0
1          396750.0         298250.0      255500.0       310000.0
2          405750.0         323000.0      292000.0       340000.0
3          434000.0         360000.0      337000.0       372500.0
4          495250.0         400500.0      377000.0       418750.0
5          548950.0         430000.0      414000.0       442500.0
6          592000.0         441250.0      411000.0            NaN
7          438250.0         410000.0      368000.0       432500.0
8          491500.0         365000.0      359000.0       839400.0
9          537500.0         390000.0      367000.0       620000.0
10         610000.0         379000.0      356000.0       412500.0
11         580750.0         364000.0      341500.0       850000.0
12         557250.0         366000.0      370000.0       665000.0
13         558000.0         389500.0      389500.0       528750.0
14         617200.0         447500.0      482000.0       910000.0

[15 rows x 26 columns]
```

[58]:
```
# Remove ".0" from all columns
town_yearly_median_df = town_yearly_median_df.applymap(lambda x: int(x) if␣
 ↪isinstance(x, float) and x.is_integer() else x)
```

```
# Display the DataFrame after removing ".0" from all the town columns
print("\nAfter removing '.0':")
print(town_yearly_median_df)

# there was a row with a NaN value so i used interpolate
# Instead of having 0 or dropping the entire value, i made a decision to use␣
 ↪interpolate
town_yearly_median_df = town_yearly_median_df.interpolate()
print("\nAfter the interpolation:")
print(town_yearly_median_df)
```

```
After removing '.0':
    Year  ang mo kio_median  bedok_median  bishan_median  bukit batok_median  \
0   2007             280000        257000         370250              331900
1   2008             327000        305000         407000              333000
2   2009             340000        335000         412500              360000
3   2010             398750        384000         510000              435000
4   2011             434250        410500         571000              424000
5   2012             466500        434750         527500              439250
6   2013             486500        452500         551500              440000
7   2014             451000        430000         525000              418000
8   2015             450000        412500         535000              404500
9   2016             466500        410000         666000              400000
10  2017             462000        418000         662650              395000
11  2018             446000        408000         660750              385000
12  2019             407250        387500         636750              367200
13  2020             405200        395000         555000              375250
14  2021             448000        454200         678750              468000

    bukit merah_median  bukit panjang_median  choa chu kang_median  \
0               396500                249000                291900
1               435550                289500                350400
2               457950                335650                358000
3               521000                372250                415000
4               583750                425000                449250
5               606000                481800                485000
6               673250                485000                461250
7               647950                409000                424250
8               627500                365000                415500
9               617500                353300                412600
10              689000                415950                408000
11              661250                459500                394000
12              682000                426250                397500
13              664700                427000                425000
14              760000                494000                481250
```

	clementi_median	geylang_median	…	punggol_median	queenstown_median	\
0	302200	268250	…	300000	410000	
1	351500	322500	…	351000	461500	
2	388000	363000	…	388000	461500	
3	432000	397500	…	430000	527500	
4	420000	459750	…	484500	370000	
5	438500	457000	…	523500	513000	
6	390000	403650	…	526500	543500	
7	435250	311500	…	469000	528250	
8	428750	453000	…	438250	517500	
9	422500	373750	…	449450	680000	
10	432500	490000	…	439200	695000	
11	504000	388900	…	438000	707500	
12	387500	445500	…	457500	727500	
13	497500	427500	…	465000	748000	
14	673250	597500	…	493200	790000	

	sembawang_median	sengkang_median	serangoon_median	tampines_median	\
0	292000	316000	275500	301500	
1	325500	371000	324500	357000	
2	362000	381600	345000	375000	
3	415250	445000	393300	415000	
4	440000	494000	410000	461150	
5	474000	515950	473000	499000	
6	491000	532000	470000	512100	
7	419500	470900	407500	457400	
8	420000	458000	388000	470250	
9	415000	452500	449750	477500	
10	405000	439000	438850	477000	
11	382000	437400	470000	478000	
12	392500	425000	431500	430000	
13	407000	455000	438000	435000	
14	470900	503000	524900	521500	

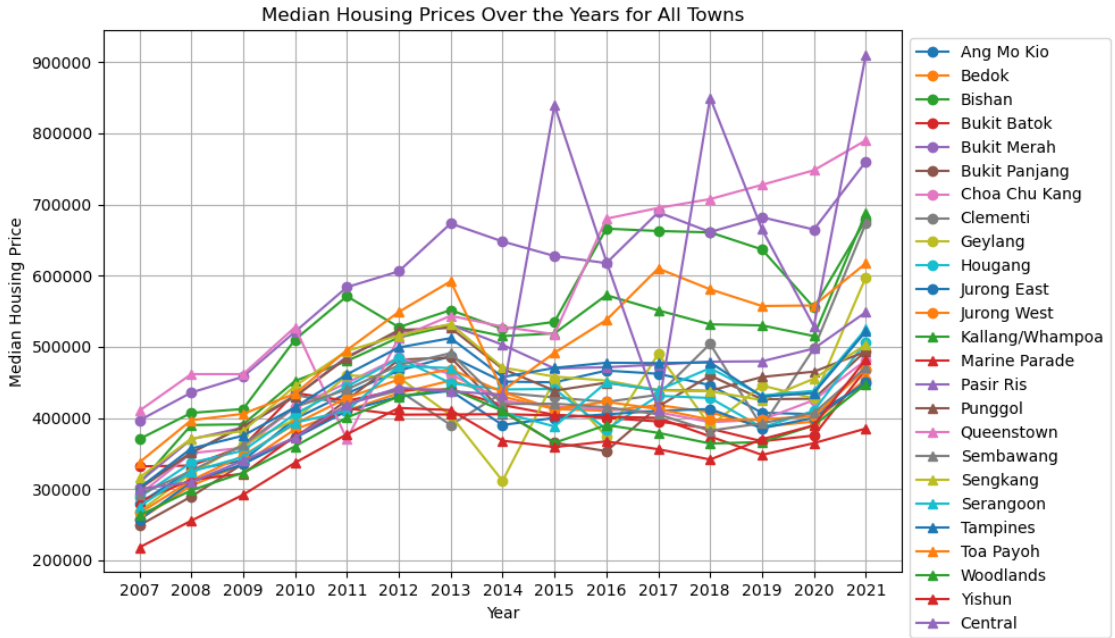
	toa payoh_median	woodlands_median	yishun_median	central_median
0	337500	263000	218000	300000.0
1	396750	298250	255500	310000.0
2	405750	323000	292000	340000.0
3	434000	360000	337000	372500.0
4	495250	400500	377000	418750.0
5	548950	430000	414000	442500.0
6	592000	441250	411000	NaN
7	438250	410000	368000	432500.0
8	491500	365000	359000	839400.0
9	537500	390000	367000	620000.0
10	610000	379000	356000	412500.0
11	580750	364000	341500	850000.0
12	557250	366000	370000	665000.0

```
13            558000            389500         389500        528750.0
14            617200            447500         482000        910000.0

[15 rows x 26 columns]

After the interpolation:
    Year  ang mo kio_median  bedok_median  bishan_median  bukit batok_median  \
0   2007             280000        257000         370250              331900
1   2008             327000        305000         407000              333000
2   2009             340000        335000         412500              360000
3   2010             398750        384000         510000              435000
4   2011             434250        410500         571000              424000
5   2012             466500        434750         527500              439250
6   2013             486500        452500         551500              440000
7   2014             451000        430000         525000              418000
8   2015             450000        412500         535000              404500
9   2016             466500        410000         666000              400000
10  2017             462000        418000         662650              395000
11  2018             446000        408000         660750              385000
12  2019             407250        387500         636750              367200
13  2020             405200        395000         555000              375250
14  2021             448000        454200         678750              468000

    bukit merah_median  bukit panjang_median  choa chu kang_median  \
0               396500                249000                291900
1               435550                289500                350400
2               457950                335650                358000
3               521000                372250                415000
4               583750                425000                449250
5               606000                481800                485000
6               673250                485000                461250
7               647950                409000                424250
8               627500                365000                415500
9               617500                353300                412600
10              689000                415950                408000
11              661250                459500                394000
12              682000                426250                397500
13              664700                427000                425000
14              760000                494000                481250

    clementi_median  geylang_median  …  punggol_median  queenstown_median  \
0            302200          268250  …          300000             410000
1            351500          322500  …          351000             461500
2            388000          363000  …          388000             461500
3            432000          397500  …          430000             527500
4            420000          459750  …          484500             370000
5            438500          457000  …          523500             513000
6            390000          403650  …          526500             543500
```

```
7            435250          311500  …          469000             528250
8            428750          453000  …          438250             517500
9            422500          373750  …          449450             680000
10           432500          490000  …          439200             695000
11           504000          388900  …          438000             707500
12           387500          445500  …          457500             727500
13           497500          427500  …          465000             748000
14           673250          597500  …          493200             790000

    sembawang_median  sengkang_median  serangoon_median  tampines_median  \
0             292000           316000            275500           301500
1             325500           371000            324500           357000
2             362000           381600            345000           375000
3             415250           445000            393300           415000
4             440000           494000            410000           461150
5             474000           515950            473000           499000
6             491000           532000            470000           512100
7             419500           470900            407500           457400
8             420000           458000            388000           470250
9             415000           452500            449750           477500
10            405000           439000            438850           477000
11            382000           437400            470000           478000
12            392500           425000            431500           430000
13            407000           455000            438000           435000
14            470900           503000            524900           521500

    toa payoh_median  woodlands_median  yishun_median  central_median
0             337500            263000         218000        300000.0
1             396750            298250         255500        310000.0
2             405750            323000         292000        340000.0
3             434000            360000         337000        372500.0
4             495250            400500         377000        418750.0
5             548950            430000         414000        442500.0
6             592000            441250         411000        437500.0
7             438250            410000         368000        432500.0
8             491500            365000         359000        839400.0
9             537500            390000         367000        620000.0
10            610000            379000         356000        412500.0
11            580750            364000         341500        850000.0
12            557250            366000         370000        665000.0
13            558000            389500         389500        528750.0
14            617200            447500         482000        910000.0

[15 rows x 26 columns]
```

[59]:
```
plt.figure(figsize=(10, 6))
```

```
# Plotting the median housing prices for the first group of towns (circles)
for i, column in enumerate(town_yearly_median_df.columns[1:
 ↪len(town_yearly_median_df.columns)//2]):  # Exclude the 'Year' column
    plt.plot(town_yearly_median_df['Year'], town_yearly_median_df[column],␣
 ↪label=column.replace('_median', '').title(), marker='o', linestyle='-')

# Plotting the median housing prices for the second group of towns (triangles)
for i, column in enumerate(town_yearly_median_df.
 ↪columns[len(town_yearly_median_df.columns)//2:]):  # Exclude the 'Year'␣
 ↪column
    plt.plot(town_yearly_median_df['Year'], town_yearly_median_df[column],␣
 ↪label=column.replace('_median', '').title(), marker='^', linestyle='-')

plt.xlabel('Year')
plt.ylabel('Median Housing Price')
plt.title('Median Housing Prices Over the Years for All Towns')
plt.legend(loc='upper left', bbox_to_anchor=(1, 1))  # Place legend outside the␣
 ↪plot for better visibility
plt.grid(True)

# Display plot
plt.tight_layout()
plt.show()
```



Median Housing Prices Over the Years for All Towns Graph

Looking at the graph, there is an overall uptrend in the median prices across all towns over the years. However, the median prices of specific town such as the Bukit Merah and Geylang towns fluctuate the most over the years.

2.3.6 DataFrame Preparation: application_df

Source: Singapore Open Data

During the pre-processing stage, I removed all rows pertaining to rental flats as it was not part of this projects scope.

[60]:
```
application_df = pd.read_csv('hdb_data/
↪Applicationsregisteredforresaleflatsandrentalflats.csv')
```

[61]:
```
application_df
```

[61]:

	financial_year	type	applications_registered
0	2007	resale	29612
1	2007	rental	5970
2	2008	resale	28551
3	2008	rental	3695
4	2009	resale	39320
5	2009	rental	2681
6	2010	resale	30061
7	2010	rental	2736
8	2011	resale	24331
9	2011	rental	4918
10	2012	resale	23579
11	2012	rental	4886
12	2013	resale	17552
13	2013	rental	4612
14	2014	resale	17673
15	2014	rental	4001
16	2015	resale	19620
17	2015	rental	4309
18	2016	resale	20894
19	2016	rental	4336
20	2017	resale	22005
21	2017	rental	4753
22	2018	resale	23476
23	2018	rental	4770
24	2019	resale	24772
25	2019	rental	6356
26	2020	resale	26436
27	2020	rental	9184
28	2021	resale	30370
29	2021	rental	9780
30	2022	resale	27941

```
31           2022  rental                    5996
```

[62]:
```
application_df = application_df[application_df['type'] != 'rental']

# Display the modified DataFrame application_df
print(application_df)
```

```
    financial_year    type  applications_registered
0             2007  resale                    29612
2             2008  resale                    28551
4             2009  resale                    39320
6             2010  resale                    30061
8             2011  resale                    24331
10            2012  resale                    23579
12            2013  resale                    17552
14            2014  resale                    17673
16            2015  resale                    19620
18            2016  resale                    20894
20            2017  resale                    22005
22            2018  resale                    23476
24            2019  resale                    24772
26            2020  resale                    26436
28            2021  resale                    30370
30            2022  resale                    27941
```

[63]:
```
# renaming the columns
application_df = application_df.rename(columns={'financial_year': 'Year',␣
↪'applications_registered': 'no_resale_applications'})

# Display application_df
print(application_df)
```

```
    Year    type  no_resale_applications
0   2007  resale                   29612
2   2008  resale                   28551
4   2009  resale                   39320
6   2010  resale                   30061
8   2011  resale                   24331
10  2012  resale                   23579
12  2013  resale                   17552
14  2014  resale                   17673
16  2015  resale                   19620
18  2016  resale                   20894
20  2017  resale                   22005
22  2018  resale                   23476
24  2019  resale                   24772
26  2020  resale                   26436
28  2021  resale                   30370
```

```
30  2022  resale                   27941
```

[64]:
```
# Drop the 'type' column in place
application_df.drop(columns=['type'], inplace=True)
```

[65]:
```
application_df
```

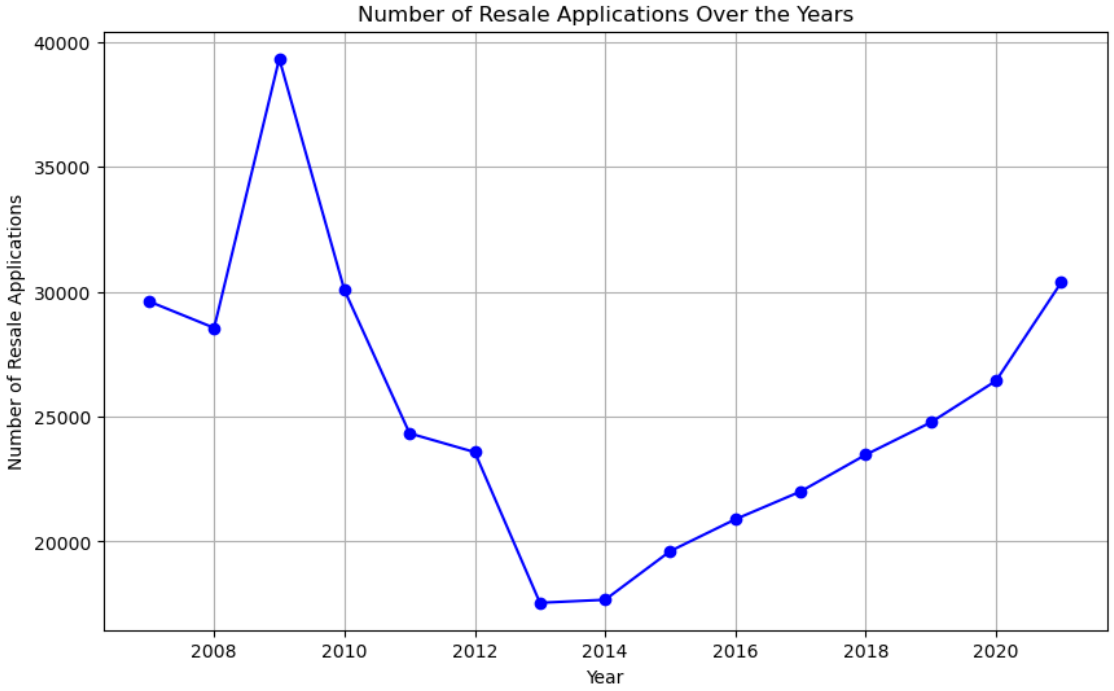
[65]:
```
    Year  no_resale_applications
0   2007                   29612
2   2008                   28551
4   2009                   39320
6   2010                   30061
8   2011                   24331
10  2012                   23579
12  2013                   17552
14  2014                   17673
16  2015                   19620
18  2016                   20894
20  2017                   22005
22  2018                   23476
24  2019                   24772
26  2020                   26436
28  2021                   30370
30  2022                   27941
```

[66]:
```
# Drop multiple rows based on indices (e.g., indices 1 and 3)
indices_to_drop = [30]
application_df = application_df.drop(indices_to_drop)

# Display the DataFrame application_df after dropping rows
print("\nAfter dropping rows:")
print(application_df)
```

```
After dropping rows:
    Year  no_resale_applications
0   2007                   29612
2   2008                   28551
4   2009                   39320
6   2010                   30061
8   2011                   24331
10  2012                   23579
12  2013                   17552
14  2014                   17673
16  2015                   19620
18  2016                   20894
20  2017                   22005
22  2018                   23476
```

24	2019	24772
26	2020	26436
28	2021	30370

[67]:
```
application_df = pd.DataFrame(application_df)

# Plotting
plt.figure(figsize=(10, 6))

plt.plot(application_df['Year'], application_df['no_resale_applications'],␣
 ↪marker='o', linestyle='-', color='b')

plt.title('Number of Resale Applications Over the Years')
plt.xlabel('Year')
plt.ylabel('Number of Resale Applications')
plt.grid(True)
plt.show()
```



Number of Resale Applications Over the Years Graph

The number of reslae applications that have been submitted over the years has been on a upward trend over the last few years from 2013. Therefore, we can assume that it will continue to increase unless there is a major disruption in the housing market.

2.3.7 3.7 DataFrame Preparation: Merging Dataframes - First Normal Form

In this portion of the project, I will be merging all the different dataframes that have been restructured and pre-processed to get a First Normal Form for this dataframe.

[68]:
```
# Merging 2 dataeframes: population_df household_income_df
merge1_df = pd.merge(population_df, household_income_df, on='Year', how='right')

# Print the new dataframe out merge1_df
merge1_df
```

[68]:

	Year	Total Population	Resident Population	Singapore Citizen Population	Permanent Resident Population	Non-Resident Population	Total Population Growth
0	2007	4588599	3583082	3133848	449234	1005517	4.3
1	2008	4839396	3642659	3164438	478221	1196737	5.5
2	2009	4987573	3733876	3200693	533183		
3	2010	5076732	3771721	3230719	541002		
4	2011	5183688	3789251	3257228	532023		
5	2012	5312437	3818205	3285140	533065		
6	2013	5399162	3844751	3313507	531244		
7	2014	5469724	3870739	3343030	527709		
8	2015	5535002	3902690	3375023	527667		
9	2016	5607283	3933559	3408943	524616		
10	2017	5612253	3965796	3439177	526619		
11	2018	5638676	3994283	3471936	522347		
12	2019	5703569	4026209	3500940	525269		
13	2020	5685807	4044210	3523191	521019		
14	2021	5453566	3986842	3498191	488651		

2	1253697	3.1
3	1305011	1.8
4	1394437	2.1
5	1494232	2.5
6	1554411	1.6
7	1598985	1.3
8	1632312	1.2
9	1673724	1.3
10	1646457	0.1
11	1644393	0.5
12	1677360	1.2
13	1641597	-0.3
14	1466724	-4.1

	Resident Population Growth	Population Density	Resident Households	\
0	1.6	6552	6790	
1	1.7	6846	7691	
2	2.5	7025	7410	
3	1	7146	7812	
4	0.5	7273	8722	
5	0.8	7429	9394	
6	0.7	7540	9481	
7	0.7	7615	9982	
8	0.8	7697	10394	
9	0.8	7797	10336	
10	0.8	7796	10610	
11	0.7	7804	10664	
12	0.8	7866	10750	
13	0.4	7810	10608	
14	-1.4	7485	10832	

	Resident Employed Households	Average Income	Median Income
0	4846	7431	5362
1	5492	8414	6100
2	5360	8195	6006
3	5600	8726	6342
4	6307	9618	7037
5	6772	10348	7566
6	7030	10469	7872
7	7320	11143	8292
8	7733	11510	8666
9	7748	11589	8846
10	7850	12027	9023
11	7955	12137	9293
12	7981	12386	9425
13	7744	12235	9189
14	8220	12276	9520

[69]:
```
# Merging 2 dataeframes: merge1_df application_df
merge2_df = pd.merge(merge1_df, application_df, on='Year', how='right')
merge2_df
```

[69]:

	Year	Total Population	Resident Population	\
0	2007	4588599	3583082	
1	2008	4839396	3642659	
2	2009	4987573	3733876	
3	2010	5076732	3771721	
4	2011	5183688	3789251	
5	2012	5312437	3818205	
6	2013	5399162	3844751	
7	2014	5469724	3870739	
8	2015	5535002	3902690	
9	2016	5607283	3933559	
10	2017	5612253	3965796	
11	2018	5638676	3994283	
12	2019	5703569	4026209	
13	2020	5685807	4044210	
14	2021	5453566	3986842	

	Singapore Citizen Population	Permanent Resident Population	\
0	3133848	449234	
1	3164438	478221	
2	3200693	533183	
3	3230719	541002	
4	3257228	532023	
5	3285140	533065	
6	3313507	531244	
7	3343030	527709	
8	3375023	527667	
9	3408943	524616	
10	3439177	526619	
11	3471936	522347	
12	3500940	525269	
13	3523191	521019	
14	3498191	488651	

	Non-Resident Population	Total Population Growth	\
0	1005517	4.3	
1	1196737	5.5	
2	1253697	3.1	
3	1305011	1.8	
4	1394437	2.1	
5	1494232	2.5	
6	1554411	1.6	
7	1598985	1.3	

8	1632312	1.2
9	1673724	1.3
10	1646457	0.1
11	1644393	0.5
12	1677360	1.2
13	1641597	-0.3
14	1466724	-4.1

	Resident Population Growth	Population Density	Resident Households
0	1.6	6552	6790
1	1.7	6846	7691
2	2.5	7025	7410
3	1	7146	7812
4	0.5	7273	8722
5	0.8	7429	9394
6	0.7	7540	9481
7	0.7	7615	9982
8	0.8	7697	10394
9	0.8	7797	10336
10	0.8	7796	10610
11	0.7	7804	10664
12	0.8	7866	10750
13	0.4	7810	10608
14	-1.4	7485	10832

	Resident Employed Households	Average Income	Median Income
0	4846	7431	5362
1	5492	8414	6100
2	5360	8195	6006
3	5600	8726	6342
4	6307	9618	7037
5	6772	10348	7566
6	7030	10469	7872
7	7320	11143	8292
8	7733	11510	8666
9	7748	11589	8846
10	7850	12027	9023
11	7955	12137	9293
12	7981	12386	9425
13	7744	12235	9189
14	8220	12276	9520

	no_resale_applications
0	29612
1	28551
2	39320
3	30061

```
4                    24331
5                    23579
6                    17552
7                    17673
8                    19620
9                    20894
10                   22005
11                   23476
12                   24772
13                   26436
14                   30370
```

[70]:
```
# Merge of population_df, household_income_df and application_df and␣
 ↪transaction_df
merge3_df = pd.merge(merge2_df, transaction_df, on='Year', how='right')
merge3_df
```

[70]:
```
    Year  Total Population  Resident Population   \
0   2007           4588599              3583082
1   2008           4839396              3642659
2   2009           4987573              3733876
3   2010           5076732              3771721
4   2011           5183688              3789251
5   2012           5312437              3818205
6   2013           5399162              3844751
7   2014           5469724              3870739
8   2015           5535002              3902690
9   2016           5607283              3933559
10  2017           5612253              3965796
11  2018           5638676              3994283
12  2019           5703569              4026209
13  2020           5685807              4044210
14  2021           5453566              3986842

   Singapore Citizen Population  Permanent Resident Population   \
0                       3133848                          449234
1                       3164438                          478221
2                       3200693                          533183
3                       3230719                          541002
4                       3257228                          532023
5                       3285140                          533065
6                       3313507                          531244
7                       3343030                          527709
8                       3375023                          527667
9                       3408943                          524616
10                      3439177                          526619
11                      3471936                          522347
```

12	3500940	525269
13	3523191	521019
14	3498191	488651

	Non-Resident Population	Total Population Growth
0	1005517	4.3
1	1196737	5.5
2	1253697	3.1
3	1305011	1.8
4	1394437	2.1
5	1494232	2.5
6	1554411	1.6
7	1598985	1.3
8	1632312	1.2
9	1673724	1.3
10	1646457	0.1
11	1644393	0.5
12	1677360	1.2
13	1641597	-0.3
14	1466724	-4.1

	Resident Population Growth	Population Density	Resident Households
0	1.6	6552	6790
1	1.7	6846	7691
2	2.5	7025	7410
3	1	7146	7812
4	0.5	7273	8722
5	0.8	7429	9394
6	0.7	7540	9481
7	0.7	7615	9982
8	0.8	7697	10394
9	0.8	7797	10336
10	0.8	7796	10610
11	0.7	7804	10664
12	0.8	7866	10750
13	0.4	7810	10608
14	-1.4	7485	10832

	Resident Employed Households	Average Income	Median Income
0	4846	7431	5362
1	5492	8414	6100
2	5360	8195	6006
3	5600	8726	6342
4	6307	9618	7037
5	6772	10348	7566
6	7030	10469	7872
7	7320	11143	8292

```
8                          7733           11510           8666
9                          7748           11589           8846
10                         7850           12027           9023
11                         7955           12137           9293
12                         7981           12386           9425
13                         7744           12235           9189
14                         8220           12276           9520
```

```
    no_resale_applications  1_room  2_room  3_room  4_room  5_room  Executive
0                    29612      19     269    8368   10864    7447       2569
1                    28551      17     247    8295   10637    7253       2058
2                    39320      13     400   10854   14365   10369       3242
3                    30061      19     530    8940   10817    7274       2421
4                    24331      14     414    7230    8933    5832       1874
5                    23579      15     567    6777    8747    5402       2029
6                    17552      10     581    5553    6560    3549       1293
7                    17673      19     408    5472    6791    3822       1160
8                    19620       9     291    5511    7857    4486       1466
9                    20894       7     279    5509    8651    4893       1555
10                   22005      10     333    5379    9154    5349       1780
11                   23476      14     392    5719    9626    5854       1871
12                   24772       8     517    6023   10401    6005       1818
13                   26436      13     440    6072   10941    6842       2128
14                   30370       8     446    6747   12972    7950       2247
```

[71]:
```
# Changing data type so I can merge the dataframes together
merge3_df['Year'] = merge3_df['Year'].astype(int)
median_price_yearly['Year'] = median_price_yearly['Year'].astype(int)

# Merging of the dataframes
merge4_df = pd.merge(merge3_df, median_price_yearly, on='Year', how='right')
merge4_df
```

[71]:
```
    Year  Total Population  Resident Population   \
0   2007           4588599              3583082
1   2008           4839396              3642659
2   2009           4987573              3733876
3   2010           5076732              3771721
4   2011           5183688              3789251
5   2012           5312437              3818205
6   2013           5399162              3844751
7   2014           5469724              3870739
8   2015           5535002              3902690
9   2016           5607283              3933559
10  2017           5612253              3965796
11  2018           5638676              3994283
12  2019           5703569              4026209
```

```
13  2020            5685807              4044210
14  2021            5453566              3986842

   Singapore Citizen Population  Permanent Resident Population   \
0                       3133848                         449234
1                       3164438                         478221
2                       3200693                         533183
3                       3230719                         541002
4                       3257228                         532023
5                       3285140                         533065
6                       3313507                         531244
7                       3343030                         527709
8                       3375023                         527667
9                       3408943                         524616
10                      3439177                         526619
11                      3471936                         522347
12                      3500940                         525269
13                      3523191                         521019
14                      3498191                         488651

   Non-Resident Population   Total Population Growth   \
0                   1005517                       4.3
1                   1196737                       5.5
2                   1253697                       3.1
3                   1305011                       1.8
4                   1394437                       2.1
5                   1494232                       2.5
6                   1554411                       1.6
7                   1598985                       1.3
8                   1632312                       1.2
9                   1673724                       1.3
10                  1646457                       0.1
11                  1644393                       0.5
12                  1677360                       1.2
13                  1641597                      -0.3
14                  1466724                      -4.1

   Resident Population Growth  Population Density   Resident Households  …  \
0                         1.6                6552                  6790  …
1                         1.7                6846                  7691  …
2                         2.5                7025                  7410  …
3                           1                7146                  7812  …
4                         0.5                7273                  8722  …
5                         0.8                7429                  9394  …
6                         0.7                7540                  9481  …
7                         0.7                7615                  9982  …
8                         0.8                7697                 10394  …
```

```
9                        0.8                7797                 10336  …
10                       0.8                7796                 10610  …
11                       0.7                7804                 10664  …
12                       0.8                7866                 10750  …
13                       0.4                7810                 10608  …
14                      -1.4                7485                 10832  …

    Average Income  Median Income  no_resale_applications  1_room  2_room  \
0             7431           5362                   29612      19     269
1             8414           6100                   28551      17     247
2             8195           6006                   39320      13     400
3             8726           6342                   30061      19     530
4             9618           7037                   24331      14     414
5            10348           7566                   23579      15     567
6            10469           7872                   17552      10     581
7            11143           8292                   17673      19     408
8            11510           8666                   19620       9     291
9            11589           8846                   20894       7     279
10           12027           9023                   22005      10     333
11           12137           9293                   23476      14     392
12           12386           9425                   24772       8     517
13           12235           9189                   26436      13     440
14           12276           9520                   30370       8     446

    3_room  4_room  5_room  Executive  yearly_median_price
0     8368   10864    7447       2569               293000
1     8295   10637    7253       2058               333000
2    10854   14365   10369       3242               365000
3     8940   10817    7274       2421               410000
4     7230    8933    5832       1874               450000
5     6777    8747    5402       2029               480000
6     5553    6560    3549       1293               482500
7     5472    6791    3822       1160               440000
8     5511    7857    4486       1466               425000
9     5509    8651    4893       1555               435000
10    5379    9154    5349       1780               435000
11    5719    9626    5854       1871               436200
12    6023   10401    6005       1818               425000
13    6072   10941    6842       2128               435000
14    6747   12972    7950       2247               515900

[15 rows x 21 columns]
```

[72]:
```
# changing data type so I can merge the dataframes together
merge4_df['Year'] = merge4_df['Year'].astype(int)
town_yearly_median_df['Year'] = town_yearly_median_df['Year'].astype(int)
```

```
merge5_df = pd.merge(merge4_df, town_yearly_median_df, on='Year', how='right')
merge5_df
```

[72]:

	Year	Total Population	Resident Population	Singapore Citizen Population	Permanent Resident Population	Non-Resident Population	Total Population Growth
0	2007	4588599	3583082	3133848	449234	1005517	4.3
1	2008	4839396	3642659	3164438	478221	1196737	5.5
2	2009	4987573	3733876	3200693	533183	1253697	3.1
3	2010	5076732	3771721	3230719	541002	1305011	1.8
4	2011	5183688	3789251	3257228	532023	1394437	2.1
5	2012	5312437	3818205	3285140	533065	1494232	2.5
6	2013	5399162	3844751	3313507	531244	1554411	1.6
7	2014	5469724	3870739	3343030	527709	1598985	1.3
8	2015	5535002	3902690	3375023	527667	1632312	1.2
9	2016	5607283	3933559	3408943	524616		
10	2017	5612253	3965796	3439177	526619		
11	2018	5638676	3994283	3471936	522347		
12	2019	5703569	4026209	3500940	525269		
13	2020	5685807	4044210	3523191	521019		
14	2021	5453566	3986842	3498191	488651		

```
9                   1673724                        1.3
10                  1646457                        0.1
11                  1644393                        0.5
12                  1677360                        1.2
13                  1641597                       -0.3
14                  1466724                       -4.1

   Resident Population Growth  Population Density   Resident Households  …  \
0                         1.6                6552                 6790  …
1                         1.7                6846                 7691  …
2                         2.5                7025                 7410  …
3                           1                7146                 7812  …
4                         0.5                7273                 8722  …
5                         0.8                7429                 9394  …
6                         0.7                7540                 9481  …
7                         0.7                7615                 9982  …
8                         0.8                7697                10394  …
9                         0.8                7797                10336  …
10                        0.8                7796                10610  …
11                        0.7                7804                10664  …
12                        0.8                7866                10750  …
13                        0.4                7810                10608  …
14                       -1.4                7485                10832  …

    punggol_median  queenstown_median  sembawang_median  sengkang_median  \
0           300000             410000            292000           316000
1           351000             461500            325500           371000
2           388000             461500            362000           381600
3           430000             527500            415250           445000
4           484500             370000            440000           494000
5           523500             513000            474000           515950
6           526500             543500            491000           532000
7           469000             528250            419500           470900
8           438250             517500            420000           458000
9           449450             680000            415000           452500
10          439200             695000            405000           439000
11          438000             707500            382000           437400
12          457500             727500            392500           425000
13          465000             748000            407000           455000
14          493200             790000            470900           503000

    serangoon_median  tampines_median  toa payoh_median  woodlands_median  \
0             275500           301500            337500            263000
1             324500           357000            396750            298250
2             345000           375000            405750            323000
3             393300           415000            434000            360000
4             410000           461150            495250            400500
```

```
5              473000          499000          548950          430000
6              470000          512100          592000          441250
7              407500          457400          438250          410000
8              388000          470250          491500          365000
9              449750          477500          537500          390000
10             438850          477000          610000          379000
11             470000          478000          580750          364000
12             431500          430000          557250          366000
13             438000          435000          558000          389500
14             524900          521500          617200          447500

    yishun_median  central_median
0          218000        300000.0
1          255500        310000.0
2          292000        340000.0
3          337000        372500.0
4          377000        418750.0
5          414000        442500.0
6          411000        437500.0
7          368000        432500.0
8          359000        839400.0
9          367000        620000.0
10         356000        412500.0
11         341500        850000.0
12         370000        665000.0
13         389500        528750.0
14         482000        910000.0

[15 rows x 46 columns]
```

[73]:
```
# changing data type so I can merge the dataframes together
merge5_df['Year'] = merge5_df['Year'].astype(int)
gdp_df['Year'] = gdp_df['Year'].astype(int)

merge6_df = pd.merge(merge5_df, gdp_df, on='Year', how='right')
merge6_df
```

[73]:
```
    Year  Total Population  Resident Population   \
0   2007           4588599              3583082
1   2008           4839396              3642659
2   2009           4987573              3733876
3   2010           5076732              3771721
4   2011           5183688              3789251
5   2012           5312437              3818205
6   2013           5399162              3844751
7   2014           5469724              3870739
8   2015           5535002              3902690
```

```
9   2016            5607283              3933559
10  2017            5612253              3965796
11  2018            5638676              3994283
12  2019            5703569              4026209
13  2020            5685807              4044210
14  2021            5453566              3986842

   Singapore Citizen Population  Permanent Resident Population   \
0                       3133848                         449234
1                       3164438                         478221
2                       3200693                         533183
3                       3230719                         541002
4                       3257228                         532023
5                       3285140                         533065
6                       3313507                         531244
7                       3343030                         527709
8                       3375023                         527667
9                       3408943                         524616
10                      3439177                         526619
11                      3471936                         522347
12                      3500940                         525269
13                      3523191                         521019
14                      3498191                         488651

   Non-Resident Population   Total Population Growth   \
0                   1005517                       4.3
1                   1196737                       5.5
2                   1253697                       3.1
3                   1305011                       1.8
4                   1394437                       2.1
5                   1494232                       2.5
6                   1554411                       1.6
7                   1598985                       1.3
8                   1632312                       1.2
9                   1673724                       1.3
10                  1646457                       0.1
11                  1644393                       0.5
12                  1677360                       1.2
13                  1641597                      -0.3
14                  1466724                      -4.1

   Resident Population Growth  Population Density   Resident Households  …  \
0                         1.6                6552                 6790  …
1                         1.7                6846                 7691  …
2                         2.5                7025                 7410  …
3                           1                7146                 7812  …
4                         0.5                7273                 8722  …
```

5	0.8	7429	9394	…
6	0.7	7540	9481	…
7	0.7	7615	9982	…
8	0.8	7697	10394	…
9	0.8	7797	10336	…
10	0.8	7796	10610	…
11	0.7	7804	10664	…
12	0.8	7866	10750	…
13	0.4	7810	10608	…
14	-1.4	7485	10832	…

	sengkang_median	serangoon_median	tampines_median	toa payoh_median	\
0	316000	275500	301500	337500	
1	371000	324500	357000	396750	
2	381600	345000	375000	405750	
3	445000	393300	415000	434000	
4	494000	410000	461150	495250	
5	515950	473000	499000	548950	
6	532000	470000	512100	592000	
7	470900	407500	457400	438250	
8	458000	388000	470250	491500	
9	452500	449750	477500	537500	
10	439000	438850	477000	610000	
11	437400	470000	478000	580750	
12	425000	431500	430000	557250	
13	455000	438000	435000	558000	
14	503000	524900	521500	617200	

	woodlands_median	yishun_median	central_median	\
0	263000	218000	300000.0	
1	298250	255500	310000.0	
2	323000	292000	340000.0	
3	360000	337000	372500.0	
4	400500	377000	418750.0	
5	430000	414000	442500.0	
6	441250	411000	437500.0	
7	410000	368000	432500.0	
8	365000	359000	839400.0	
9	390000	367000	620000.0	
10	379000	356000	412500.0	
11	364000	341500	850000.0	
12	366000	370000	665000.0	
13	389500	389500	528750.0	
14	447500	482000	910000.0	

	GDP At Current Market Prices	GDP Real Estate	GDP Ownership Of Dwellings
0	272697.6	9360.7	7943.3

```
1                       273941.6          11362.8                       10166.2
2                       282394.5          11027.5                       10351.7
3                       326980.1          14034.8                       11347.1
4                       351367.9          16127.2                       13604.9
5                       368770.5          17078.0                       15749.3
6                       384870.3          19243.2                       17251.0
7                       398947.9          18962.7                       17797.2
8                       423444.1          18781.5                       18100.1
9                       440754.7          17410.3                       17589.4
10                      474034.1          15686.6                       17436.2
11                      508337.4          16337.3                       17751.0
12                      514066.0          16836.7                       18453.0
13                      480691.2          13610.1                       18785.1
14                      569364.2          15515.1                       18912.9

[15 rows x 49 columns]
```

[74]:
```
merge6_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15 entries, 0 to 14
Data columns (total 49 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   Year                            15 non-null     int32
 1   Total Population                15 non-null     int64
 2   Resident Population             15 non-null     object
 3   Singapore Citizen Population    15 non-null     object
 4   Permanent Resident Population   15 non-null     object
 5   Non-Resident Population         15 non-null     object
 6   Total Population Growth         15 non-null     float64
 7   Resident Population Growth      15 non-null     object
 8   Population Density              15 non-null     object
 9   Resident Households             15 non-null     int64
 10  Resident Employed Households    15 non-null     int64
 11  Average Income                  15 non-null     int64
 12  Median Income                   15 non-null     int64
 13  no_resale_applications          15 non-null     int64
 14  1_room                          15 non-null     int64
 15  2_room                          15 non-null     int64
 16  3_room                          15 non-null     int64
 17  4_room                          15 non-null     int64
 18  5_room                          15 non-null     int64
 19  Executive                       15 non-null     int64
 20  yearly_median_price             15 non-null     int64
 21  ang mo kio_median               15 non-null     int64
 22  bedok_median                    15 non-null     int64
 23  bishan_median                   15 non-null     int64
```

```
 24  bukit batok_median              15 non-null     int64
 25  bukit merah_median              15 non-null     int64
 26  bukit panjang_median            15 non-null     int64
 27  choa chu kang_median            15 non-null     int64
 28  clementi_median                 15 non-null     int64
 29  geylang_median                  15 non-null     int64
 30  hougang_median                  15 non-null     int64
 31  jurong east_median              15 non-null     int64
 32  jurong west_median              15 non-null     int64
 33  kallang/whampoa_median          15 non-null     int64
 34  marine parade_median            15 non-null     float64
 35  pasir ris_median                15 non-null     int64
 36  punggol_median                  15 non-null     int64
 37  queenstown_median               15 non-null     int64
 38  sembawang_median                15 non-null     int64
 39  sengkang_median                 15 non-null     int64
 40  serangoon_median                15 non-null     int64
 41  tampines_median                 15 non-null     int64
 42  toa payoh_median                15 non-null     int64
 43  woodlands_median                15 non-null     int64
 44  yishun_median                   15 non-null     int64
 45  central_median                  15 non-null     float64
 46  GDP At Current Market Prices    15 non-null     float64
 47  GDP Real Estate                 15 non-null     float64
 48  GDP Ownership Of Dwellings      15 non-null     float64
dtypes: float64(6), int32(1), int64(36), object(6)
memory usage: 5.8+ KB
```

[75]:
```
# Changing the data types of multiple columns Resident Population, Singapore␣
 ↪Citizen Population, Permanent Resident Population
# Non-Resident Population, Total Population Growth, Resident Population
# Population Density, marine parade_median, central_median
# GDP At Current Market Prices, GDP Real Estate, GDP Ownership Of Dwellings

merge6_df['Resident Population '] = merge6_df['Resident Population '].
 ↪astype('int64')

merge6_df['Singapore Citizen Population '] = merge6_df['Singapore Citizen␣
 ↪Population '].astype('int64')

merge6_df['Permanent Resident Population '] = merge6_df['Permanent Resident␣
 ↪Population '].astype('int64')

merge6_df['Non-Resident Population '] = merge6_df['Non-Resident Population '].
 ↪astype('int64')
```

```
merge6_df['Total Population Growth '] = merge6_df['Total Population Growth '].
 ↪astype('int64')
merge6_df['Resident Population ']  = merge6_df['Resident Population '].
 ↪astype('int64')



merge6_df['Population Density '] = merge6_df['Population Density '].
 ↪astype('int64')

merge6_df['marine parade_median'] = merge6_df['marine parade_median'].
 ↪astype('int64')

merge6_df['central_median'] = merge6_df['central_median'].astype('int64')
merge6_df['GDP At Current Market Prices']  = merge6_df['GDP At Current Market␣
 ↪Prices'].astype('int64')
merge6_df['GDP Real Estate'] = merge6_df['GDP Real Estate'].astype('int64')
merge6_df[ 'GDP Ownership Of Dwellings']  = merge6_df[ 'GDP Ownership Of␣
 ↪Dwellings'].astype('int64')
```

[76]:
```
# Checking the data types in the merge6_df dataframe
merge6_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15 entries, 0 to 14
Data columns (total 49 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   Year                            15 non-null     int32
 1   Total Population                15 non-null     int64
 2   Resident Population             15 non-null     int64
 3   Singapore Citizen Population    15 non-null     int64
 4   Permanent Resident Population   15 non-null     int64
 5   Non-Resident Population         15 non-null     int64
 6   Total Population Growth         15 non-null     int64
 7   Resident Population Growth      15 non-null     object
 8   Population Density              15 non-null     int64
 9   Resident Households             15 non-null     int64
 10  Resident Employed Households    15 non-null     int64
 11  Average Income                  15 non-null     int64
 12  Median Income                   15 non-null     int64
 13  no_resale_applications          15 non-null     int64
 14  1_room                          15 non-null     int64
 15  2_room                          15 non-null     int64
 16  3_room                          15 non-null     int64
 17  4_room                          15 non-null     int64
 18  5_room                          15 non-null     int64
```

```
 19  Executive                       15 non-null     int64
 20  yearly_median_price             15 non-null     int64
 21  ang mo kio_median               15 non-null     int64
 22  bedok_median                    15 non-null     int64
 23  bishan_median                   15 non-null     int64
 24  bukit batok_median              15 non-null     int64
 25  bukit merah_median              15 non-null     int64
 26  bukit panjang_median            15 non-null     int64
 27  choa chu kang_median            15 non-null     int64
 28  clementi_median                 15 non-null     int64
 29  geylang_median                  15 non-null     int64
 30  hougang_median                  15 non-null     int64
 31  jurong east_median              15 non-null     int64
 32  jurong west_median              15 non-null     int64
 33  kallang/whampoa_median          15 non-null     int64
 34  marine parade_median            15 non-null     int64
 35  pasir ris_median                15 non-null     int64
 36  punggol_median                  15 non-null     int64
 37  queenstown_median               15 non-null     int64
 38  sembawang_median                15 non-null     int64
 39  sengkang_median                 15 non-null     int64
 40  serangoon_median                15 non-null     int64
 41  tampines_median                 15 non-null     int64
 42  toa payoh_median                15 non-null     int64
 43  woodlands_median                15 non-null     int64
 44  yishun_median                   15 non-null     int64
 45  central_median                  15 non-null     int64
 46  GDP At Current Market Prices    15 non-null     int64
 47  GDP Real Estate                 15 non-null     int64
 48  GDP Ownership Of Dwellings      15 non-null     int64
dtypes: int32(1), int64(47), object(1)
memory usage: 5.8+ KB
```

2.3.8 DataFrame Preparation: Feature Engineering - First Normal Form DataFrame

After merging the dataframes, I decided that there were some columns that would not be as heplful in analysing for the linear regression model. Instead, I decided to get columns from the merged dataframe and create new columns which would be more representative of the dataframe.

New columns created in the dataframe: 1. Population Growth Rate - Total Population Growth & Total Population 2. Population Density per Resident Household - Population Density & Resident Households 3. Median Price Change - yearly_median_price 4. GDP per Capita - GDP At Current Market Prices & Total Population

[77]:
```
# Population Growth Rate:
# Adding in Population growth rate.
# This column represents the growth rate which is the chnage in population
```

```
merge6_df['Population Growth Rate'] = (merge6_df['Total Population Growth '] /␣
 ↪merge6_df['Total Population ']) * 100
merge6_df
```

[77]:

	Year	Total Population	Resident Population	Singapore Citizen Population	Permanent Resident Population	Non-Resident Population	Total Population Growth
0	2007	4588599	3583082	3133848	449234	1005517	4
1	2008	4839396	3642659	3164438	478221	1196737	5
2	2009	4987573	3733876	3200693	533183	1253697	3
3	2010	5076732	3771721	3230719	541002	1305011	1
4	2011	5183688	3789251	3257228	532023	1394437	2
5	2012	5312437	3818205	3285140	533065	1494232	2
6	2013	5399162	3844751	3313507	531244	1554411	1
7	2014	5469724	3870739	3343030	527709	1598985	1
8	2015	5535002	3902690	3375023	527667		
9	2016	5607283	3933559	3408943	524616		
10	2017	5612253	3965796	3439177	526619		
11	2018	5638676	3994283	3471936	522347		
12	2019	5703569	4026209	3500940	525269		
13	2020	5685807	4044210	3523191	521019		
14	2021	5453566	3986842	3498191	488651		

```
8                    1632312                          1
9                    1673724                          1
10                   1646457                          0
11                   1644393                          0
12                   1677360                          1
13                   1641597                          0
14                   1466724                         -4

   Resident Population Growth   Population Density   Resident Households  …  \
0                         1.6                 6552                 6790  …
1                         1.7                 6846                 7691  …
2                         2.5                 7025                 7410  …
3                           1                 7146                 7812  …
4                         0.5                 7273                 8722  …
5                         0.8                 7429                 9394  …
6                         0.7                 7540                 9481  …
7                         0.7                 7615                 9982  …
8                         0.8                 7697                10394  …
9                         0.8                 7797                10336  …
10                        0.8                 7796                10610  …
11                        0.7                 7804                10664  …
12                        0.8                 7866                10750  …
13                        0.4                 7810                10608  …
14                       -1.4                 7485                10832  …

    serangoon_median  tampines_median  toa payoh_median  woodlands_median  \
0             275500           301500            337500            263000
1             324500           357000            396750            298250
2             345000           375000            405750            323000
3             393300           415000            434000            360000
4             410000           461150            495250            400500
5             473000           499000            548950            430000
6             470000           512100            592000            441250
7             407500           457400            438250            410000
8             388000           470250            491500            365000
9             449750           477500            537500            390000
10            438850           477000            610000            379000
11            470000           478000            580750            364000
12            431500           430000            557250            366000
13            438000           435000            558000            389500
14            524900           521500            617200            447500

    yishun_median  central_median  GDP At Current Market Prices  \
0          218000          300000                         272697
1          255500          310000                         273941
2          292000          340000                         282394
3          337000          372500                         326980
```

```
4          377000          418750                          351367
5          414000          442500                          368770
6          411000          437500                          384870
7          368000          432500                          398947
8          359000          839400                          423444
9          367000          620000                          440754
10         356000          412500                          474034
11         341500          850000                          508337
12         370000          665000                          514066
13         389500          528750                          480691
14         482000          910000                          569364

    GDP Real Estate  GDP Ownership Of Dwellings  Population Growth Rate
0              9360                        7943                0.000087
1             11362                       10166                0.000103
2             11027                       10351                0.000060
3             14034                       11347                0.000020
4             16127                       13604                0.000039
5             17078                       15749                0.000038
6             19243                       17251                0.000019
7             18962                       17797                0.000018
8             18781                       18100                0.000018
9             17410                       17589                0.000018
10            15686                       17436                0.000000
11            16337                       17751                0.000000
12            16836                       18453                0.000018
13            13610                       18785                0.000000
14            15515                       18912               -0.000073

[15 rows x 50 columns]
```

[78]:
```
# Population Density per Resident Household: population density per resident␣
 ↪household.
merge6_df['Population Density per Resident Household'] = merge6_df['Population␣
 ↪Density '] / merge6_df['Resident Households']
merge6_df
```

[78]:
```
    Year  Total Population   Resident Population   \
0   2007            4588599              3583082
1   2008            4839396              3642659
2   2009            4987573              3733876
3   2010            5076732              3771721
4   2011            5183688              3789251
5   2012            5312437              3818205
6   2013            5399162              3844751
7   2014            5469724              3870739
8   2015            5535002              3902690
```

```
9   2016            5607283              3933559
10  2017            5612253              3965796
11  2018            5638676              3994283
12  2019            5703569              4026209
13  2020            5685807              4044210
14  2021            5453566              3986842

    Singapore Citizen Population   Permanent Resident Population   \
0                        3133848                          449234
1                        3164438                          478221
2                        3200693                          533183
3                        3230719                          541002
4                        3257228                          532023
5                        3285140                          533065
6                        3313507                          531244
7                        3343030                          527709
8                        3375023                          527667
9                        3408943                          524616
10                       3439177                          526619
11                       3471936                          522347
12                       3500940                          525269
13                       3523191                          521019
14                       3498191                          488651

    Non-Resident Population   Total Population Growth   \
0                    1005517                         4
1                    1196737                         5
2                    1253697                         3
3                    1305011                         1
4                    1394437                         2
5                    1494232                         2
6                    1554411                         1
7                    1598985                         1
8                    1632312                         1
9                    1673724                         1
10                   1646457                         0
11                   1644393                         0
12                   1677360                         1
13                   1641597                         0
14                   1466724                        -4

   Resident Population Growth   Population Density   Resident Households  …  \
0                         1.6                 6552                 6790  …
1                         1.7                 6846                 7691  …
2                         2.5                 7025                 7410  …
3                           1                 7146                 7812  …
4                         0.5                 7273                 8722  …
```

5	0.8	7429	9394	…
6	0.7	7540	9481	…
7	0.7	7615	9982	…
8	0.8	7697	10394	…
9	0.8	7797	10336	…
10	0.8	7796	10610	…
11	0.7	7804	10664	…
12	0.8	7866	10750	…
13	0.4	7810	10608	…
14	-1.4	7485	10832	…

	tampines_median	toa payoh_median	woodlands_median	yishun_median	\
0	301500	337500	263000	218000	
1	357000	396750	298250	255500	
2	375000	405750	323000	292000	
3	415000	434000	360000	337000	
4	461150	495250	400500	377000	
5	499000	548950	430000	414000	
6	512100	592000	441250	411000	
7	457400	438250	410000	368000	
8	470250	491500	365000	359000	
9	477500	537500	390000	367000	
10	477000	610000	379000	356000	
11	478000	580750	364000	341500	
12	430000	557250	366000	370000	
13	435000	558000	389500	389500	
14	521500	617200	447500	482000	

	central_median	GDP At Current Market Prices	GDP Real Estate	\
0	300000	272697	9360	
1	310000	273941	11362	
2	340000	282394	11027	
3	372500	326980	14034	
4	418750	351367	16127	
5	442500	368770	17078	
6	437500	384870	19243	
7	432500	398947	18962	
8	839400	423444	18781	
9	620000	440754	17410	
10	412500	474034	15686	
11	850000	508337	16337	
12	665000	514066	16836	
13	528750	480691	13610	
14	910000	569364	15515	

	GDP Ownership Of Dwellings	Population Growth Rate	\
0	7943	0.000087	

```
1                         10166                0.000103
2                         10351                0.000060
3                         11347                0.000020
4                         13604                0.000039
5                         15749                0.000038
6                         17251                0.000019
7                         17797                0.000018
8                         18100                0.000018
9                         17589                0.000018
10                        17436                0.000000
11                        17751                0.000000
12                        18453                0.000018
13                        18785                0.000000
14                        18912               -0.000073

    Population Density per Resident Household
0                                    0.964948
1                                    0.890131
2                                    0.948043
3                                    0.914747
4                                    0.833868
5                                    0.790824
6                                    0.795275
7                                    0.762873
8                                    0.740523
9                                    0.754354
10                                   0.734779
11                                   0.731808
12                                   0.731721
13                                   0.736237
14                                   0.691008

[15 rows x 51 columns]
```

[79]:
```
# Median Price Change: representing the change in median prices from the␣
 ↪previous year

merge6_df['Median Price Change Year'] = merge6_df['yearly_median_price'].diff()



# Replace NaN values in Median Price Change Year with 0
merge6_df["Median Price Change Year"] = pd.to_numeric(merge6_df["Median Price␣
 ↪Change Year"], errors="coerce").astype("Int64")
merge6_df["Median Price Change Year"] = merge6_df["Median Price Change Year"].
 ↪fillna(0)
```

```
# Display merge6_df after the conversion
print("\nAfter converting Median Price Change Year:")
print(merge6_df)
```

```
After converting Median Price Change Year:
    Year  Total Population   Resident Population   \
0   2007            4588599               3583082
1   2008            4839396               3642659
2   2009            4987573               3733876
3   2010            5076732               3771721
4   2011            5183688               3789251
5   2012            5312437               3818205
6   2013            5399162               3844751
7   2014            5469724               3870739
8   2015            5535002               3902690
9   2016            5607283               3933559
10  2017            5612253               3965796
11  2018            5638676               3994283
12  2019            5703569               4026209
13  2020            5685807               4044210
14  2021            5453566               3986842

    Singapore Citizen Population   Permanent Resident Population   \
0                        3133848                          449234
1                        3164438                          478221
2                        3200693                          533183
3                        3230719                          541002
4                        3257228                          532023
5                        3285140                          533065
6                        3313507                          531244
7                        3343030                          527709
8                        3375023                          527667
9                        3408943                          524616
10                       3439177                          526619
11                       3471936                          522347
12                       3500940                          525269
13                       3523191                          521019
14                       3498191                          488651

    Non-Resident Population   Total Population Growth   \
0                   1005517                         4
1                   1196737                         5
2                   1253697                         3
3                   1305011                         1
4                   1394437                         2
5                   1494232                         2
6                   1554411                         1
```

7	1598985	1
8	1632312	1
9	1673724	1
10	1646457	0
11	1644393	0
12	1677360	1
13	1641597	0
14	1466724	-4

	Resident Population Growth	Population Density	Resident Households	…	\
0	1.6	6552	6790	…	
1	1.7	6846	7691	…	
2	2.5	7025	7410	…	
3	1	7146	7812	…	
4	0.5	7273	8722	…	
5	0.8	7429	9394	…	
6	0.7	7540	9481	…	
7	0.7	7615	9982	…	
8	0.8	7697	10394	…	
9	0.8	7797	10336	…	
10	0.8	7796	10610	…	
11	0.7	7804	10664	…	
12	0.8	7866	10750	…	
13	0.4	7810	10608	…	
14	-1.4	7485	10832	…	

	toa payoh_median	woodlands_median	yishun_median	central_median	\
0	337500	263000	218000	300000	
1	396750	298250	255500	310000	
2	405750	323000	292000	340000	
3	434000	360000	337000	372500	
4	495250	400500	377000	418750	
5	548950	430000	414000	442500	
6	592000	441250	411000	437500	
7	438250	410000	368000	432500	
8	491500	365000	359000	839400	
9	537500	390000	367000	620000	
10	610000	379000	356000	412500	
11	580750	364000	341500	850000	
12	557250	366000	370000	665000	
13	558000	389500	389500	528750	
14	617200	447500	482000	910000	

	GDP At Current Market Prices	GDP Real Estate	GDP Ownership Of Dwellings	\
0	272697	9360	7943	
1	273941	11362	10166	
2	282394	11027	10351	
3	326980	14034	11347	

```
4                        351367            16127                        13604
5                        368770            17078                        15749
6                        384870            19243                        17251
7                        398947            18962                        17797
8                        423444            18781                        18100
9                        440754            17410                        17589
10                       474034            15686                        17436
11                       508337            16337                        17751
12                       514066            16836                        18453
13                       480691            13610                        18785
14                       569364            15515                        18912

    Population Growth Rate  Population Density per Resident Household  \
0                 0.000087                                   0.964948
1                 0.000103                                   0.890131
2                 0.000060                                   0.948043
3                 0.000020                                   0.914747
4                 0.000039                                   0.833868
5                 0.000038                                   0.790824
6                 0.000019                                   0.795275
7                 0.000018                                   0.762873
8                 0.000018                                   0.740523
9                 0.000018                                   0.754354
10                0.000000                                   0.734779
11                0.000000                                   0.731808
12                0.000018                                   0.731721
13                0.000000                                   0.736237
14               -0.000073                                   0.691008

    Median Price Change Year
0                          0
1                      40000
2                      32000
3                      45000
4                      40000
5                      30000
6                       2500
7                     -42500
8                     -15000
9                      10000
10                         0
11                      1200
12                    -11200
13                     10000
14                     80900

[15 rows x 52 columns]
```

[80]:
```
# GDP per Capita
merge6_df['GDP per Capita'] = merge6_df['GDP At Current Market Prices'] /␣
 ↪merge6_df['Total Population ']
merge6_df
```

[80]:

	Year	Total Population	Resident Population	Singapore Citizen Population	Permanent Resident Population	Non-Resident Population	Total Population Growth
0	2007	4588599	3583082	3133848	449234	1005517	4
1	2008	4839396	3642659	3164438	478221	1196737	5
2	2009	4987573	3733876	3200693	533183	1253697	3
3	2010	5076732	3771721	3230719	541002	1305011	1
4	2011	5183688	3789251	3257228	532023	1394437	2
5	2012	5312437	3818205	3285140	533065	1494232	2
6	2013	5399162	3844751	3313507	531244	1554411	1
7	2014	5469724	3870739	3343030	527709		
8	2015	5535002	3902690	3375023	527667		
9	2016	5607283	3933559	3408943	524616		
10	2017	5612253	3965796	3439177	526619		
11	2018	5638676	3994283	3471936	522347		
12	2019	5703569	4026209	3500940	525269		
13	2020	5685807	4044210	3523191	521019		
14	2021	5453566	3986842	3498191	488651		

```
7                    1598985                          1
8                    1632312                          1
9                    1673724                          1
10                   1646457                          0
11                   1644393                          0
12                   1677360                          1
13                   1641597                          0
14                   1466724                         -4

   Resident Population Growth   Population Density   Resident Households  …  \
0                         1.6                 6552                 6790  …
1                         1.7                 6846                 7691  …
2                         2.5                 7025                 7410  …
3                           1                 7146                 7812  …
4                         0.5                 7273                 8722  …
5                         0.8                 7429                 9394  …
6                         0.7                 7540                 9481  …
7                         0.7                 7615                 9982  …
8                         0.8                 7697                10394  …
9                         0.8                 7797                10336  …
10                        0.8                 7796                10610  …
11                        0.7                 7804                10664  …
12                        0.8                 7866                10750  …
13                        0.4                 7810                10608  …
14                       -1.4                 7485                10832  …

    woodlands_median  yishun_median  central_median  \
0             263000         218000          300000
1             298250         255500          310000
2             323000         292000          340000
3             360000         337000          372500
4             400500         377000          418750
5             430000         414000          442500
6             441250         411000          437500
7             410000         368000          432500
8             365000         359000          839400
9             390000         367000          620000
10            379000         356000          412500
11            364000         341500          850000
12            366000         370000          665000
13            389500         389500          528750
14            447500         482000          910000

    GDP At Current Market Prices  GDP Real Estate  GDP Ownership Of Dwellings  \
0                         272697             9360                        7943
1                         273941            11362                       10166
2                         282394            11027                       10351
```

3	326980	14034	11347
4	351367	16127	13604
5	368770	17078	15749
6	384870	19243	17251
7	398947	18962	17797
8	423444	18781	18100
9	440754	17410	17589
10	474034	15686	17436
11	508337	16337	17751
12	514066	16836	18453
13	480691	13610	18785
14	569364	15515	18912

	Population Growth Rate	Population Density per Resident Household	\
0	0.000087	0.964948	
1	0.000103	0.890131	
2	0.000060	0.948043	
3	0.000020	0.914747	
4	0.000039	0.833868	
5	0.000038	0.790824	
6	0.000019	0.795275	
7	0.000018	0.762873	
8	0.000018	0.740523	
9	0.000018	0.754354	
10	0.000000	0.734779	
11	0.000000	0.731808	
12	0.000018	0.731721	
13	0.000000	0.736237	
14	-0.000073	0.691008	

	Median Price Change Year	GDP per Capita
0	0	0.059429
1	40000	0.056606
2	32000	0.056620
3	45000	0.064408
4	40000	0.067783
5	30000	0.069416
6	2500	0.071283
7	-42500	0.072937
8	-15000	0.076503
9	10000	0.078604
10	0	0.084464
11	1200	0.090152
12	-11200	0.090131
13	10000	0.084542
14	80900	0.104402

```
[15 rows x 53 columns]
```

[81]:
```
merge6_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15 entries, 0 to 14
Data columns (total 53 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   Year                                  15 non-null     int32
 1   Total Population                      15 non-null     int64
 2   Resident Population                   15 non-null     int64
 3   Singapore Citizen Population          15 non-null     int64
 4   Permanent Resident Population         15 non-null     int64
 5   Non-Resident Population               15 non-null     int64
 6   Total Population Growth               15 non-null     int64
 7   Resident Population Growth            15 non-null     object
 8   Population Density                    15 non-null     int64
 9   Resident Households                   15 non-null     int64
 10  Resident Employed Households          15 non-null     int64
 11  Average Income                        15 non-null     int64
 12  Median Income                         15 non-null     int64
 13  no_resale_applications                15 non-null     int64
 14  1_room                                15 non-null     int64
 15  2_room                                15 non-null     int64
 16  3_room                                15 non-null     int64
 17  4_room                                15 non-null     int64
 18  5_room                                15 non-null     int64
 19  Executive                             15 non-null     int64
 20  yearly_median_price                   15 non-null     int64
 21  ang mo kio_median                     15 non-null     int64
 22  bedok_median                          15 non-null     int64
 23  bishan_median                         15 non-null     int64
 24  bukit batok_median                    15 non-null     int64
 25  bukit merah_median                    15 non-null     int64
 26  bukit panjang_median                  15 non-null     int64
 27  choa chu kang_median                  15 non-null     int64
 28  clementi_median                       15 non-null     int64
 29  geylang_median                        15 non-null     int64
 30  hougang_median                        15 non-null     int64
 31  jurong east_median                    15 non-null     int64
 32  jurong west_median                    15 non-null     int64
 33  kallang/whampoa_median                15 non-null     int64
 34  marine parade_median                  15 non-null     int64
 35  pasir ris_median                      15 non-null     int64
 36  punggol_median                        15 non-null     int64
 37  queenstown_median                     15 non-null     int64
 38  sembawang_median                      15 non-null     int64
```

```
 39  sengkang_median                          15 non-null     int64
 40  serangoon_median                         15 non-null     int64
 41  tampines_median                          15 non-null     int64
 42  toa payoh_median                         15 non-null     int64
 43  woodlands_median                         15 non-null     int64
 44  yishun_median                            15 non-null     int64
 45  central_median                           15 non-null     int64
 46  GDP At Current Market Prices             15 non-null     int64
 47  GDP Real Estate                          15 non-null     int64
 48  GDP Ownership Of Dwellings               15 non-null     int64
 49  Population Growth Rate                   15 non-null     float64
 50  Population Density per Resident Household  15 non-null     float64
 51  Median Price Change Year                 15 non-null     Int64
 52  GDP per Capita                           15 non-null     float64
dtypes: Int64(1), float64(3), int32(1), int64(47), object(1)
memory usage: 6.3+ KB
```

2.4 Multiple Linear Regression

In this portion, I want to find the linear regression in two different areas. The reason why I want to look into the correaltions of these 2 topics is so that I am able to get a more in-depth analysis of how the prices will differ in the future. 1. Prediciting the yearly median price for resale flats 2. Predicting each towns' yearly median price for resale flats

[82]:
```
# Trying to find the factors with the highest correlation
# By using corr() I am able to find the correlation between the yearly median␣
 ↪price and other factors
merge6_df.corr()['yearly_median_price']
```

[82]:
```
Year                                  0.667580
Total Population                      0.715791
Resident Population                   0.698723
Singapore Citizen Population          0.642837
Permanent Resident Population         0.551895
Non-Resident Population               0.701012
Total Population Growth              -0.788820
Resident Population Growth           -0.779925
Population Density                    0.700415
Resident Households                   0.735150
Resident Employed Households          0.735028
Average Income                        0.710936
Median Income                         0.706825
no_resale_applications               -0.453906
1_room                               -0.512795
2_room                                0.600214
3_room                               -0.580993
4_room                               -0.318794
5_room                               -0.446492
```

```
Executive                                  -0.475875
yearly_median_price                         1.000000
ang mo kio_median                           0.903728
bedok_median                                0.973125
bishan_median                               0.758171
bukit batok_median                          0.875285
bukit merah_median                          0.883240
bukit panjang_median                        0.937293
choa chu kang_median                        0.959939
clementi_median                             0.725102
geylang_median                              0.762659
hougang_median                              0.949756
jurong east_median                          0.981380
jurong west_median                          0.981188
kallang/whampoa_median                      0.897949
marine parade_median                        0.849356
pasir ris_median                            0.981465
punggol_median                              0.956901
queenstown_median                           0.503882
sembawang_median                            0.946878
sengkang_median                             0.950071
serangoon_median                            0.950485
tampines_median                             0.965318
toa payoh_median                            0.842767
woodlands_median                            0.978405
yishun_median                               0.979007
central_median                              0.538590
GDP At Current Market Prices                0.688524
GDP Real Estate                             0.776580
GDP Ownership Of Dwellings                  0.799991
Population Growth Rate                     -0.817321
Population Density per Resident Household  -0.762845
Median Price Change Year                    0.151970
GDP per Capita                              0.668564
Name: yearly_median_price, dtype: float64
```

2.4.1 Predicting Yearly Median

Predicting Yearly Median: Data Preparation

[83]:
```
print(merge6_df.columns)
```

```
Index(['Year', 'Total Population ', 'Resident Population ',
       'Singapore Citizen Population ', 'Permanent Resident Population ',
       'Non-Resident Population ', 'Total Population Growth ',
       'Resident Population Growth ', 'Population Density ',
       'Resident Households', 'Resident Employed Households', 'Average Income',
       'Median Income', 'no_resale_applications', '1_room', '2_room', '3_room',
       '4_room', '5_room', 'Executive', 'yearly_median_price',
```

```
       'ang mo kio_median', 'bedok_median', 'bishan_median',
       'bukit batok_median', 'bukit merah_median', 'bukit panjang_median',
       'choa chu kang_median', 'clementi_median', 'geylang_median',
       'hougang_median', 'jurong east_median', 'jurong west_median',
       'kallang/whampoa_median', 'marine parade_median', 'pasir ris_median',
       'punggol_median', 'queenstown_median', 'sembawang_median',
       'sengkang_median', 'serangoon_median', 'tampines_median',
       'toa payoh_median', 'woodlands_median', 'yishun_median',
       'central_median', 'GDP At Current Market Prices', 'GDP Real Estate',
       'GDP Ownership Of Dwellings', 'Population Growth Rate',
       'Population Density per Resident Household', 'Median Price Change Year',
       'GDP per Capita'],
      dtype='object')
```

[84]:
```
columns_to_drop = [ 'Total Population ', 'Resident Population ',
                    'Singapore Citizen Population ', 'Permanent Resident␣
 ↪Population ',
                   'Non-Resident Population ', 'Total Population Growth ',
                   'Resident Population Growth ', 'Population Density ',
                   'Resident Households', 'Resident Employed Households',␣
 ↪'Average Income',
                   'Median Income', 'no_resale_applications', '1_room',␣
 ↪'2_room', '3_room',
                   '4_room', '5_room', 'Executive',
                   'GDP At Current Market Prices','Population Growth Rate',
                      'Population Density per Resident Household', 'Median␣
 ↪Price Change Year']
# Drop the specified columns
yearly_prediction_median_df = merge6_df.drop(columns=columns_to_drop, axis=1)

yearly_prediction_median_df
```

[84]:

	Year	yearly_median_price	ang mo kio_median	bedok_median	bishan_median	\
0	2007	293000	280000	257000	370250	
1	2008	333000	327000	305000	407000	
2	2009	365000	340000	335000	412500	
3	2010	410000	398750	384000	510000	
4	2011	450000	434250	410500	571000	
5	2012	480000	466500	434750	527500	
6	2013	482500	486500	452500	551500	
7	2014	440000	451000	430000	525000	
8	2015	425000	450000	412500	535000	
9	2016	435000	466500	410000	666000	
10	2017	435000	462000	418000	662650	
11	2018	436200	446000	408000	660750	
12	2019	425000	407250	387500	636750	
13	2020	435000	405200	395000	555000	

```
14  2021                515900              448000        454200          678750

    bukit batok_median  bukit merah_median  bukit panjang_median  \
0               331900              396500                249000
1               333000              435550                289500
2               360000              457950                335650
3               435000              521000                372250
4               424000              583750                425000
5               439250              606000                481800
6               440000              673250                485000
7               418000              647950                409000
8               404500              627500                365000
9               400000              617500                353300
10              395000              689000                415950
11              385000              661250                459500
12              367200              682000                426250
13              375250              664700                427000
14              468000              760000                494000

    choa chu kang_median  clementi_median  …  sengkang_median  \
0                 291900           302200  …           316000
1                 350400           351500  …           371000
2                 358000           388000  …           381600
3                 415000           432000  …           445000
4                 449250           420000  …           494000
5                 485000           438500  …           515950
6                 461250           390000  …           532000
7                 424250           435250  …           470900
8                 415500           428750  …           458000
9                 412600           422500  …           452500
10                408000           432500  …           439000
11                394000           504000  …           437400
12                397500           387500  …           425000
13                425000           497500  …           455000
14                481250           673250  …           503000

    serangoon_median  tampines_median  toa payoh_median  woodlands_median  \
0             275500           301500            337500            263000
1             324500           357000            396750            298250
2             345000           375000            405750            323000
3             393300           415000            434000            360000
4             410000           461150            495250            400500
5             473000           499000            548950            430000
6             470000           512100            592000            441250
7             407500           457400            438250            410000
8             388000           470250            491500            365000
9             449750           477500            537500            390000
```

```
10            438850           477000           610000           379000
11            470000           478000           580750           364000
12            431500           430000           557250           366000
13            438000           435000           558000           389500
14            524900           521500           617200           447500

    yishun_median  central_median  GDP Real Estate  \
0          218000          300000             9360
1          255500          310000            11362
2          292000          340000            11027
3          337000          372500            14034
4          377000          418750            16127
5          414000          442500            17078
6          411000          437500            19243
7          368000          432500            18962
8          359000          839400            18781
9          367000          620000            17410
10         356000          412500            15686
11         341500          850000            16337
12         370000          665000            16836
13         389500          528750            13610
14         482000          910000            15515

    GDP Ownership Of Dwellings  GDP per Capita
0                         7943        0.059429
1                        10166        0.056606
2                        10351        0.056620
3                        11347        0.064408
4                        13604        0.067783
5                        15749        0.069416
6                        17251        0.071283
7                        17797        0.072937
8                        18100        0.076503
9                        17589        0.078604
10                       17436        0.084464
11                       17751        0.090152
12                       18453        0.090131
13                       18785        0.084542
14                       18912        0.104402

[15 rows x 30 columns]
```

[85]:
```
print(yearly_prediction_median_df.columns)
```

```
Index(['Year', 'yearly_median_price', 'ang mo kio_median', 'bedok_median',
       'bishan_median', 'bukit batok_median', 'bukit merah_median',
       'bukit panjang_median', 'choa chu kang_median', 'clementi_median',
       'geylang_median', 'hougang_median', 'jurong east_median',
```

```
       'jurong west_median', 'kallang/whampoa_median', 'marine parade_median',
       'pasir ris_median', 'punggol_median', 'queenstown_median',
       'sembawang_median', 'sengkang_median', 'serangoon_median',
       'tampines_median', 'toa payoh_median', 'woodlands_median',
       'yishun_median', 'central_median', 'GDP Real Estate',
       'GDP Ownership Of Dwellings', 'GDP per Capita'],
      dtype='object')
```

[86]:
```
#Building our model

train_data = yearly_prediction_median_df[yearly_prediction_median_df["Year"] <␣
↪2018].copy()
test_data = yearly_prediction_median_df[yearly_prediction_median_df["Year"] >=␣
↪2018].copy()
```

[87]:
```
train_data.shape
```

[87]:
```
(11, 30)
```

[88]:
```
test_data.shape
```

[88]:
```
(4, 30)
```

[89]:
```
reg = LinearRegression()
```

[90]:
```
predictors =['ang mo kio_median', 'bedok_median',
       'bishan_median', 'bukit batok_median', 'bukit merah_median',
       'bukit panjang_median', 'choa chu kang_median', 'clementi_median',
       'geylang_median', 'hougang_median', 'jurong east_median',
       'jurong west_median', 'kallang/whampoa_median', 'marine parade_median',
       'pasir ris_median', 'punggol_median', 'queenstown_median',
       'sembawang_median', 'sengkang_median', 'serangoon_median',
       'tampines_median', 'toa payoh_median', 'woodlands_median',
       'yishun_median', 'central_median', 'GDP Real Estate',
       'GDP Ownership Of Dwellings', 'GDP per Capita']
target = "yearly_median_price"
```

[91]:
```
reg.fit(train_data[predictors], train_data["yearly_median_price"])
```

[91]:
```
LinearRegression()
```

[92]:
```
# Creating predictions using the predictors that I have idenitifed
predictions = reg.predict(test_data[predictors])
```

[93]:
```
# A new column predictions_yearly_median
test_data["predictions_yearly_median"] = predictions
```

[94]:
```
# Displaying the test that I have run and looking at the predictions
test_data
```

[94]:

	Year	yearly_median_price	ang mo kio_median	bedok_median	bishan_median	\
11	2018	436200	446000	408000	660750	
12	2019	425000	407250	387500	636750	
13	2020	435000	405200	395000	555000	
14	2021	515900	448000	454200	678750	

	bukit batok_median	bukit merah_median	bukit panjang_median	\
11	385000	661250	459500	
12	367200	682000	426250	
13	375250	664700	427000	
14	468000	760000	494000	

	choa chu kang_median	clementi_median	…	serangoon_median	\
11	394000	504000	…	470000	
12	397500	387500	…	431500	
13	425000	497500	…	438000	
14	481250	673250	…	524900	

	tampines_median	toa payoh_median	woodlands_median	yishun_median	\
11	478000	580750	364000	341500	
12	430000	557250	366000	370000	
13	435000	558000	389500	389500	
14	521500	617200	447500	482000	

	central_median	GDP Real Estate	GDP Ownership Of Dwellings	\
11	850000	16337	17751	
12	665000	16836	18453	
13	528750	13610	18785	
14	910000	15515	18912	

	GDP per Capita	predictions_yearly_median
11	0.090152	447315.938745
12	0.090131	429611.299081
13	0.084542	439505.250771
14	0.104402	516609.567522

[4 rows x 31 columns]

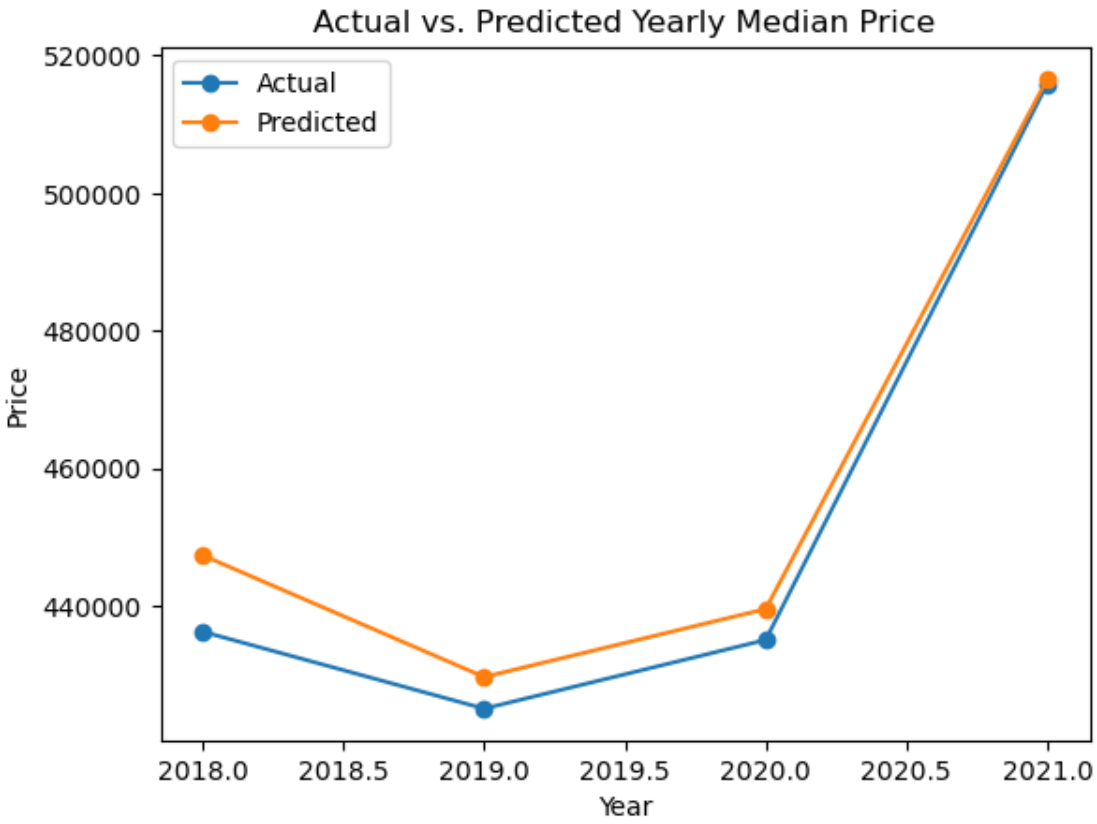
[95]:
```
test_data['predictions_yearly_median'] = test_data['predictions_yearly_median'].
 ↪round().astype(int)
# Display the modified DataFrame
test_data
```

[95]:
```
    Year  yearly_median_price  ang mo kio_median  bedok_median  bishan_median  \
11  2018               436200             446000        408000         660750
12  2019               425000             407250        387500         636750
13  2020               435000             405200        395000         555000
14  2021               515900             448000        454200         678750

    bukit batok_median  bukit merah_median  bukit panjang_median  \
11              385000              661250                459500
12              367200              682000                426250
13              375250              664700                427000
14              468000              760000                494000

    choa chu kang_median  clementi_median  …  serangoon_median  \
11                394000           504000  …            470000
12                397500           387500  …            431500
13                425000           497500  …            438000
14                481250           673250  …            524900

    tampines_median  toa payoh_median  woodlands_median  yishun_median  \
11           478000            580750            364000         341500
12           430000            557250            366000         370000
13           435000            558000            389500         389500
14           521500            617200            447500         482000

    central_median  GDP Real Estate  GDP Ownership Of Dwellings  \
11          850000            16337                       17751
12          665000            16836                       18453
13          528750            13610                       18785
14          910000            15515                       18912

    GDP per Capita  predictions_yearly_median
11        0.090152                     447316
12        0.090131                     429611
13        0.084542                     439505
14        0.104402                     516610

[4 rows x 31 columns]
```

Predicting Yearly Median: Data Visualisation

[96]:
```
test_data.plot(x='Year', y=['yearly_median_price',␣
 ↪'predictions_yearly_median'], kind='line', marker='o')

# Plotting of the line graph Actual vs. Predicted Yearly Median Price
plt.title('Actual vs. Predicted Yearly Median Price')
plt.xlabel('Year')
plt.ylabel('Price')
plt.legend(['Actual', 'Predicted'])
```

```
plt.show()
```



Actual vs. Predicted Yearly Median Price Graph

We can see from the graph, that the model has been successful in predicting the yearly median price. Therefore, we can confirm that the predictors that we have identified does play a significant factor in contributing toward the yearly median prices.

4.1.3 Predicting Yearly Median: Data Evaluation

[97]:
```
merge6_df.describe()["yearly_median_price"]
```

[97]:
```
count        15.000000
mean     424040.000000
std       57051.778487
min      293000.000000
25%      417500.000000
50%      435000.000000
75%      445000.000000
max      515900.000000
Name: yearly_median_price, dtype: float64
```

[98]:
```
mse_error = mean_squared_error(test_data["yearly_median_price"],␣
 ↪test_data["predictions_yearly_median"])
rmse_error = np.sqrt(mse_error)

print("Root Mean Squared Error (RMSE):", rmse_error)
```

```
Root Mean Squared Error (RMSE): 6434.7863600899755
```

Evaluation: Yearly Median Price - Root Mean Squared Error (RMSE)

In order to evaluate the performance of the model to predict the future yearly median prices across all types of flats and towns, I used the Root Mean Squared Error value. I chose to use RMSE as it would take the square root of the averaged squared difference between the actual and predicted yearly median price. Furthermore, it penalises the larger error much heavier than if I were have used the Mean Absolte Error (MAE) as it squares the errors. Looking at the model, the RSME score was 6434.7863600899755 which means that on average, the predictions made by the model was off by approximately $6434. In the context of the housing market, I think that is a relatively good value for the model to have attained.

2.4.2 Multiple Linear Regression: Predicting Town's Yearly Median

Predicting Town's Yearly Media: Data Preparation

[99]:
```
# Predicting each towns median for the future
columns_to_drop = [ 'Total Population ', 'Resident Population ',
       'Singapore Citizen Population ', 'Permanent Resident Population ',
       'Non-Resident Population ', 'Total Population Growth ',
       'Resident Population Growth ', 'Population Density ',
       'Resident Households', 'Resident Employed Households', 'Average Income',
       'Median Income', 'no_resale_applications', '1_room', '2_room', '3_room',
       '4_room', '5_room', 'Executive',
       'GDP At Current Market Prices','Population Growth Rate',
       'Population Density per Resident Household', 'Median Price Change Year']

# Drop the specified columns
town_yearly_prediction_median_df = merge6_df.drop(columns=columns_to_drop,␣
 ↪axis=1)

# Display the modified DataFrame
town_yearly_prediction_median_df
```

[99]:

	Year	yearly_median_price	ang mo kio_median	bedok_median	bishan_median	\
0	2007	293000	280000	257000	370250	
1	2008	333000	327000	305000	407000	
2	2009	365000	340000	335000	412500	
3	2010	410000	398750	384000	510000	
4	2011	450000	434250	410500	571000	
5	2012	480000	466500	434750	527500	
6	2013	482500	486500	452500	551500	
7	2014	440000	451000	430000	525000	

8	2015	425000	450000	412500	535000
9	2016	435000	466500	410000	666000
10	2017	435000	462000	418000	662650
11	2018	436200	446000	408000	660750
12	2019	425000	407250	387500	636750
13	2020	435000	405200	395000	555000
14	2021	515900	448000	454200	678750

	bukit batok_median	bukit merah_median	bukit panjang_median	\
0	331900	396500	249000	
1	333000	435550	289500	
2	360000	457950	335650	
3	435000	521000	372250	
4	424000	583750	425000	
5	439250	606000	481800	
6	440000	673250	485000	
7	418000	647950	409000	
8	404500	627500	365000	
9	400000	617500	353300	
10	395000	689000	415950	
11	385000	661250	459500	
12	367200	682000	426250	
13	375250	664700	427000	
14	468000	760000	494000	

	choa chu kang_median	clementi_median	…	sengkang_median	\
0	291900	302200	…	316000	
1	350400	351500	…	371000	
2	358000	388000	…	381600	
3	415000	432000	…	445000	
4	449250	420000	…	494000	
5	485000	438500	…	515950	
6	461250	390000	…	532000	
7	424250	435250	…	470900	
8	415500	428750	…	458000	
9	412600	422500	…	452500	
10	408000	432500	…	439000	
11	394000	504000	…	437400	
12	397500	387500	…	425000	
13	425000	497500	…	455000	
14	481250	673250	…	503000	

	serangoon_median	tampines_median	toa payoh_median	woodlands_median	\
0	275500	301500	337500	263000	
1	324500	357000	396750	298250	
2	345000	375000	405750	323000	
3	393300	415000	434000	360000	

```
4             410000          461150           495250           400500
5             473000          499000           548950           430000
6             470000          512100           592000           441250
7             407500          457400           438250           410000
8             388000          470250           491500           365000
9             449750          477500           537500           390000
10            438850          477000           610000           379000
11            470000          478000           580750           364000
12            431500          430000           557250           366000
13            438000          435000           558000           389500
14            524900          521500           617200           447500

    yishun_median  central_median  GDP Real Estate  \
0          218000          300000             9360
1          255500          310000            11362
2          292000          340000            11027
3          337000          372500            14034
4          377000          418750            16127
5          414000          442500            17078
6          411000          437500            19243
7          368000          432500            18962
8          359000          839400            18781
9          367000          620000            17410
10         356000          412500            15686
11         341500          850000            16337
12         370000          665000            16836
13         389500          528750            13610
14         482000          910000            15515

    GDP Ownership Of Dwellings  GDP per Capita
0                         7943        0.059429
1                        10166        0.056606
2                        10351        0.056620
3                        11347        0.064408
4                        13604        0.067783
5                        15749        0.069416
6                        17251        0.071283
7                        17797        0.072937
8                        18100        0.076503
9                        17589        0.078604
10                       17436        0.084464
11                       17751        0.090152
12                       18453        0.090131
13                       18785        0.084542
14                       18912        0.104402

[15 rows x 30 columns]
```

[100]:
```
# Building our model
train_data_x =␣
 ↪town_yearly_prediction_median_df[town_yearly_prediction_median_df["Year"] <␣
 ↪2018].copy()

test_data_x =␣
 ↪town_yearly_prediction_median_df[town_yearly_prediction_median_df["Year"] >=␣
 ↪2018].copy()
```

[101]:
```
train_data_x.shape
```

[101]:
```
(11, 30)
```

[102]:
```
test_data_x.shape
```

[102]:
```
(4, 30)
```

[103]:
```
predictors = ['yearly_median_price', 'GDP Real Estate', 'GDP Ownership Of␣
 ↪Dwellings', 'GDP per Capita']

# Initialize a dictionary to store predictions for each town
predictions_dict = {}

# Iterate over each town and make predictions
for town in ["ang mo kio_median", "bedok_median", "bishan_median", "bukit␣
 ↪batok_median", "bukit merah_median",
             "bukit panjang_median", "choa chu kang_median", "clementi_median",␣
 ↪"geylang_median", "hougang_median",
             "jurong east_median", "jurong west_median", "kallang/
 ↪whampoa_median", "marine parade_median",
             "pasir ris_median", "punggol_median", "queenstown_median",␣
 ↪"sembawang_median", "sengkang_median",
             "serangoon_median", "tampines_median", "toa payoh_median",␣
 ↪"woodlands_median", "yishun_median", "central_median"]:

    # Fit the model for the current town
    reg.fit(train_data_x[predictors], train_data_x[town])

    # Make predictions for the years 2018, 2019, 2020, and 2021
    predictions = reg.predict(test_data_x[test_data_x['Year'].isin([2018, 2019,␣
 ↪2020, 2021])][predictors])

    # Store the predictions in the dictionary
    predictions_dict[town + "_prediction"] = predictions

# Add the predicted columns to test_data_x
for key, value in predictions_dict.items():
```

```
    test_data_x[key] = np.nan  # Add new columns with NaN values
    test_data_x.loc[test_data_x['Year'].isin([2018, 2019, 2020, 2021]), key] =␣
 ↪value  # Assign predictions to the correct rows

# Drop additional rows with NaN values
test_data_x = test_data_x.dropna(subset=['ang mo kio_median_prediction'])

# Reset index
test_data_x = test_data_x.reset_index(drop=True)
```

[104]:
```
test_data_x
```

[104]:

	Year	yearly_median_price	ang mo kio_median	bedok_median	bishan_median	\
0	2018	436200	446000	408000	660750	
1	2019	425000	407250	387500	636750	
2	2020	435000	405200	395000	555000	
3	2021	515900	448000	454200	678750	

	bukit batok_median	bukit merah_median	bukit panjang_median	\
0	385000	661250	459500	
1	367200	682000	426250	
2	375250	664700	427000	
3	468000	760000	494000	

	choa chu kang_median	clementi_median	…	punggol_median_prediction	\
0	394000	504000	…	431456.983257	
1	397500	387500	…	418386.614673	
2	425000	497500	…	438258.009006	
3	481250	673250	…	506552.281430	

	queenstown_median_prediction	sembawang_median_prediction	\
0	718585.692187	406074.485186	
1	720913.598156	393867.270520	
2	847755.722152	387387.987370	
3	892702.591778	469458.825097	

	sengkang_median_prediction	serangoon_median_prediction	\
0	437893.730862	443758.558191	
1	427015.882148	429925.903655	
2	407477.038170	478217.393098	
3	491127.210426	559131.872959	

	tampines_median_prediction	toa payoh_median_prediction	\
0	479963.233382	607500.027552	
1	473613.049567	587619.426443	
2	494841.085694	681381.671410	
3	561832.760365	813964.320771	

```
   woodlands_median_prediction  yishun_median_prediction  \
0                 375724.226072             360443.181867
1                 367589.701348             349980.514621
2                 376992.942659             357731.413400
3                 432623.103605             435534.950940

   central_median_prediction
0              537077.438377
1              591508.370451
2              399400.956986
3              375945.792167

[4 rows x 55 columns]
```

[105]:
```
prediction_columns = [col for col in test_data_x.columns if col.
 ↪endswith("_prediction")]

# Round all the prediction columns
test_data_x[prediction_columns] = test_data_x[prediction_columns].round().
 ↪astype(int)

# Display test_data_x
print(test_data_x)
```

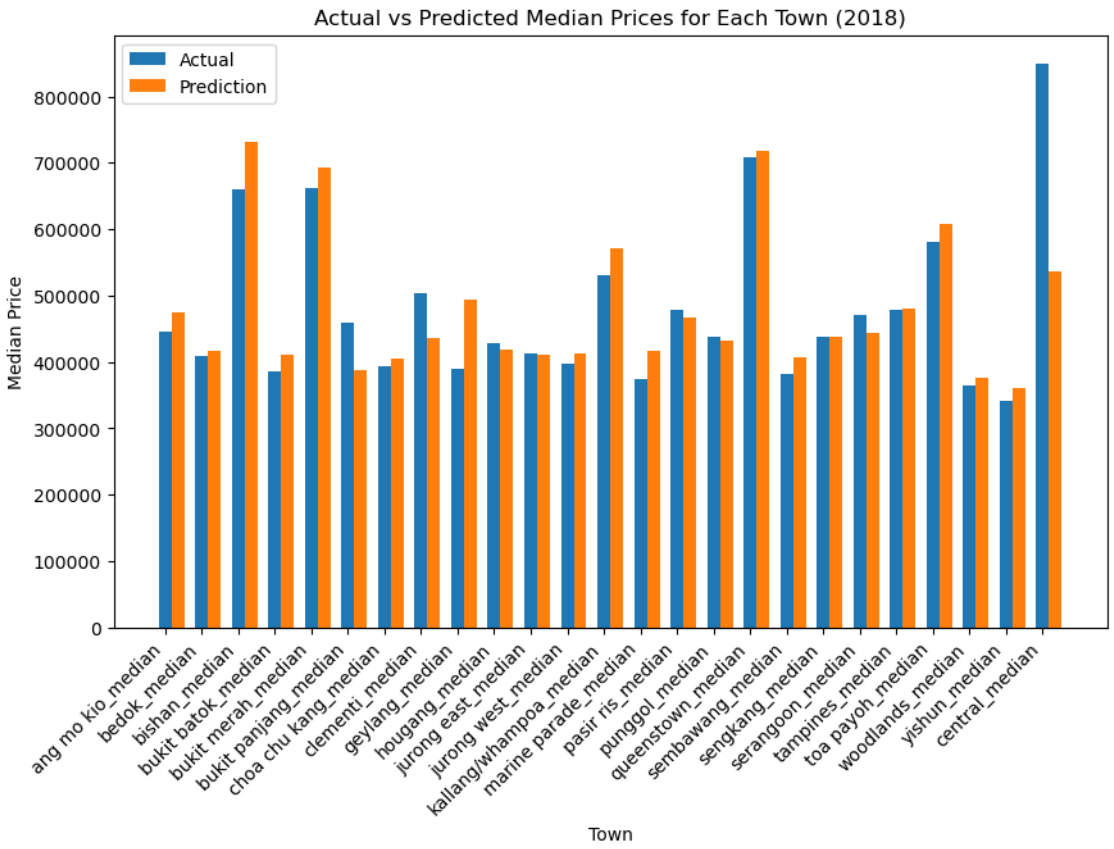
```
   Year  yearly_median_price  ang mo kio_median  bedok_median  bishan_median  \
0  2018               436200             446000        408000         660750
1  2019               425000             407250        387500         636750
2  2020               435000             405200        395000         555000
3  2021               515900             448000        454200         678750

   bukit batok_median  bukit merah_median  bukit panjang_median  \
0              385000              661250                459500
1              367200              682000                426250
2              375250              664700                427000
3              468000              760000                494000

   choa chu kang_median  clementi_median  …  punggol_median_prediction  \
0                394000           504000  …                    431457
1                397500           387500  …                    418387
2                425000           497500  …                    438258
3                481250           673250  …                    506552

   queenstown_median_prediction  sembawang_median_prediction  \
0                        718586                       406074
1                        720914                       393867
2                        847756                       387388
3                        892703                       469459
```

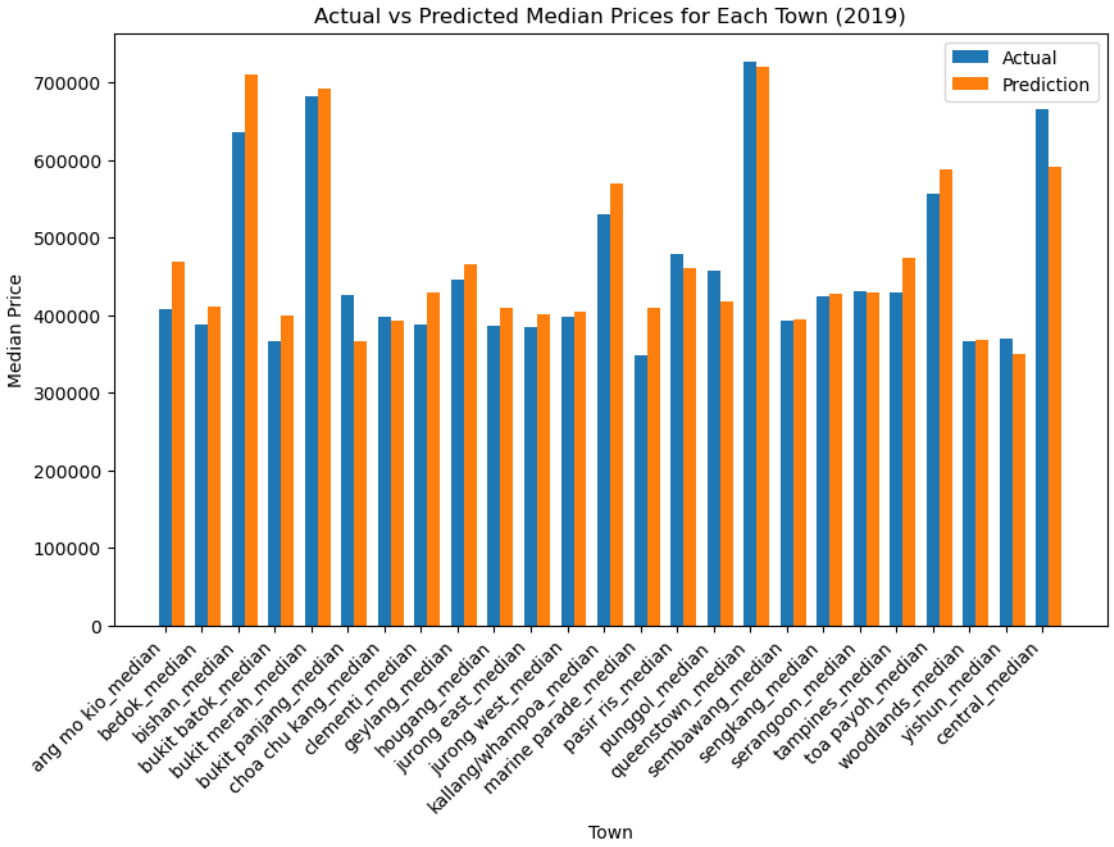
```
   sengkang_median_prediction  serangoon_median_prediction  \
0                      437894                       443759
1                      427016                       429926
2                      407477                       478217
3                      491127                       559132

   tampines_median_prediction  toa payoh_median_prediction  \
0                      479963                       607500
1                      473613                       587619
2                      494841                       681382
3                      561833                       813964

   woodlands_median_prediction  yishun_median_prediction  \
0                       375724                    360443
1                       367590                    349981
2                       376993                    357731
3                       432623                    435535

   central_median_prediction
0                     537077
1                     591508
2                     399401
3                     375946

[4 rows x 55 columns]
```

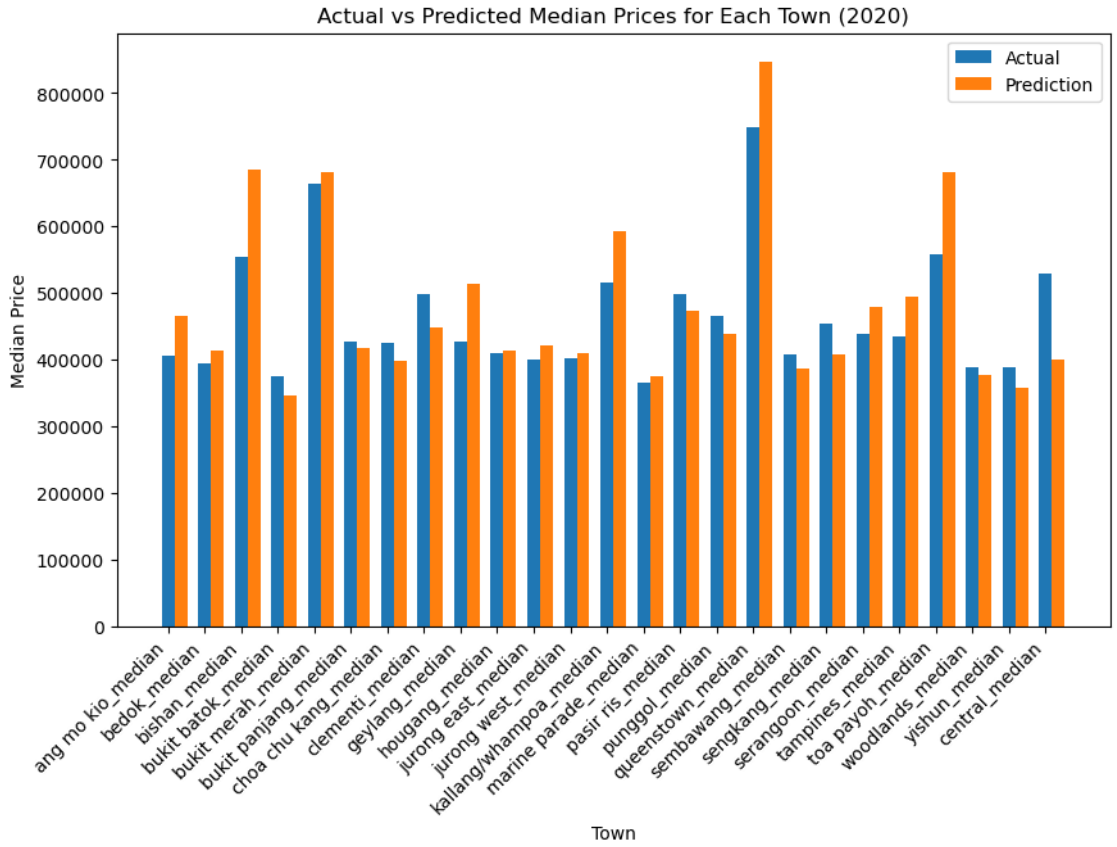
Predicting Town's Yearly Median: Data Visualations

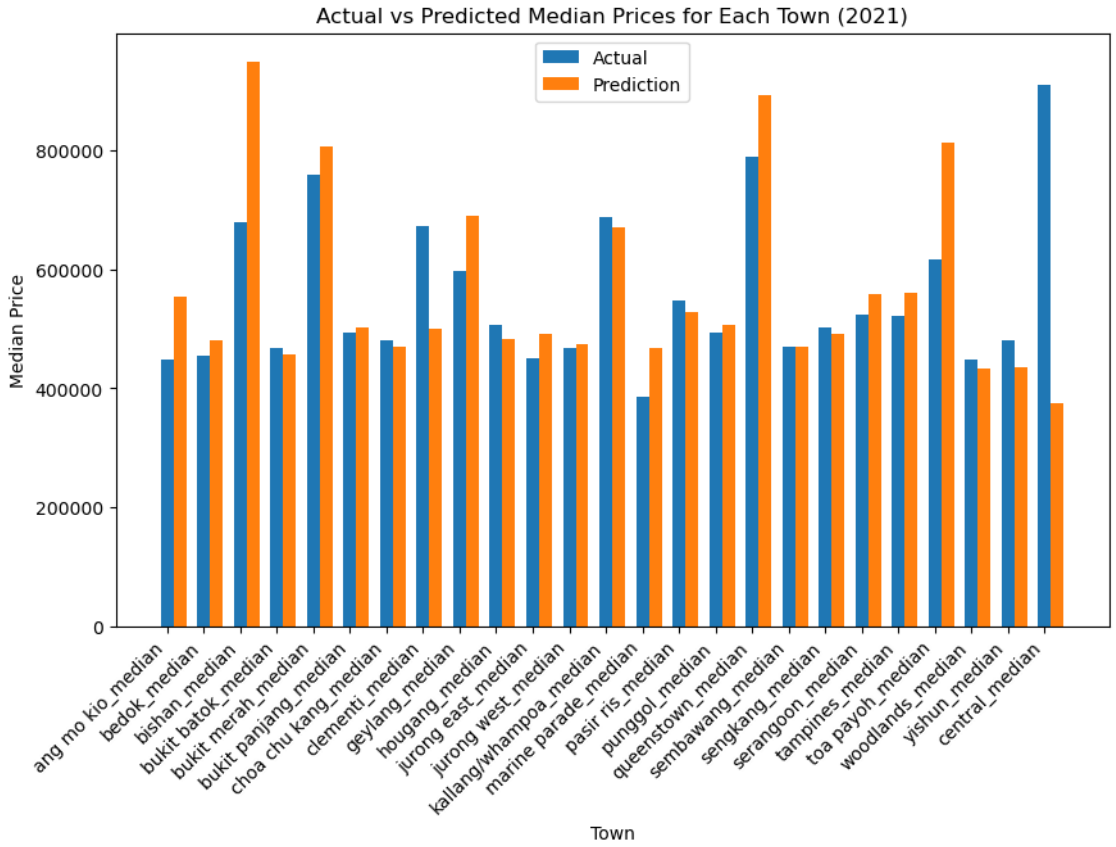
[106]:
```
# Extract relevant columns for plotting
town_columns = ["ang mo kio_median", "bedok_median", "bishan_median", "bukit␣
 ↪batok_median", "bukit merah_median",
                "bukit panjang_median", "choa chu kang_median",␣
 ↪"clementi_median", "geylang_median", "hougang_median",
                "jurong east_median", "jurong west_median", "kallang/
 ↪whampoa_median", "marine parade_median",
                "pasir ris_median", "punggol_median", "queenstown_median",␣
 ↪"sembawang_median", "sengkang_median",
                "serangoon_median", "tampines_median", "toa payoh_median",␣
 ↪"woodlands_median", "yishun_median", "central_median"]

prediction_columns = [col for col in test_data_x.columns if col.
 ↪endswith("_prediction")]

# Prepare data for plotting
years = test_data_x["Year"]

bar_width = 0.35
```

```
bar_positions_actual = np.arange(len(town_columns))
bar_positions_predicted = [pos + bar_width for pos in bar_positions_actual]

# Loop through each year to create grouped bar chart
for i, year in enumerate(years):
    actual_values = test_data_x.loc[test_data_x["Year"] == year, town_columns].
 ↪values.flatten()
    predicted_values = test_data_x.loc[test_data_x["Year"] == year,␣
 ↪prediction_columns].values.flatten()

    plt.figure(figsize=(10, 6))
    plt.bar(bar_positions_actual, actual_values, width=bar_width,␣
 ↪label="Actual")
    plt.bar(bar_positions_predicted, predicted_values, width=bar_width,␣
 ↪label="Prediction")

    plt.title(f"Actual vs Predicted Median Prices for Each Town ({year})")
    plt.xlabel("Town")
    plt.ylabel("Median Price")
    plt.xticks(bar_positions_actual, town_columns, rotation=45, ha="right")
    plt.legend()
    plt.show()
```




Actual vs Predicted Median Prices for Each Town (2019)
Actual
Prediction
Median Price
0
100000
200000
300000
400000
500000
600000
700000
Town
ang mo kio_median
bedok_median
bishan_median
bukit batok_median
bukit merah_median
bukit panjang_median
choa chu kang_median
clementi_median
geylang_median
hougang_median
jurong east_median
jurong west_median
kallang/whampoa_median
marine parade_median
pasir ris_median
punggol_median
queenstown_median
sembawang_median
sengkang_median
serangoon_median
tampines_median
toa payoh_median
woodlands_median
yishun_median
central_median


Actual vs Predicted Median Prices for Each Town (2020)
Actual
Prediction
Median Price
0
100000
200000
300000
400000
500000
600000
700000
800000
ang mo kio_median
bedok_median
bishan_median
bukit batok_median
bukit merah_median
bukit panjang_median
choa chu kang_median
clementi_median
geylang_median
hougang_median
jurong east_median
jurong west_median
kallang/whampoa_median
marine parade_median
pasir ris_median
punggol_median
queenstown_median
sembawang_median
sengkang_median
serangoon_median
tampines_median
toa payoh_median
woodlands_median
yishun_median
central_median
Town

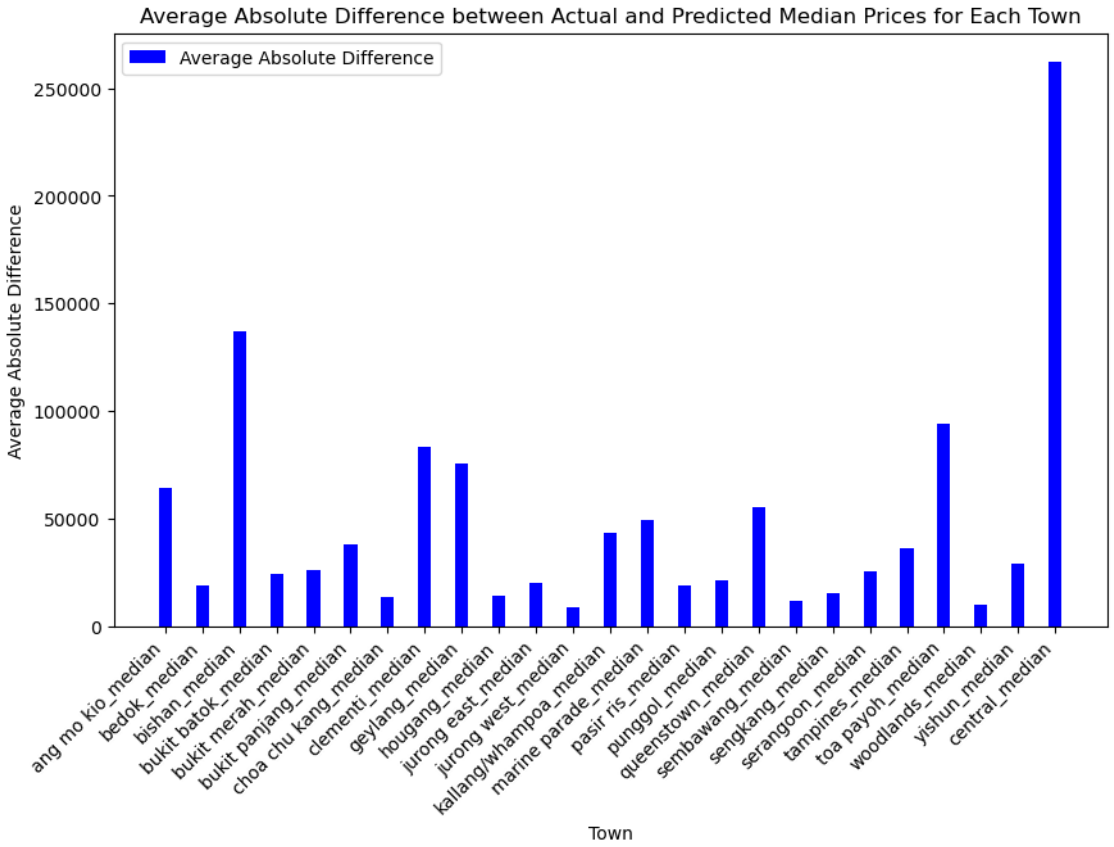


Actual vs Predicted Median Prices for Each Town Graph

I plotted the graph for each year so that it is clear to visualise the difference between each town and their actual and predicted prices. The model has been able to accurately predict the prices for the majority of towns however, there are a few outliers such as Bishan, Central and Toa Payoh.

[107]:
```
# Extract relevant columns for plotting
town_columns = ["ang mo kio_median", "bedok_median", "bishan_median", "bukit␣
↪batok_median", "bukit merah_median",
                "bukit panjang_median", "choa chu kang_median",␣
↪"clementi_median", "geylang_median",
                "hougang_median","jurong east_median", "jurong west_median",␣
↪"kallang/whampoa_median",
                "marine parade_median","pasir ris_median", "punggol_median",␣
↪"queenstown_median",
                "sembawang_median", "sengkang_median", "serangoon_median",␣
↪"tampines_median",
                "toa payoh_median", "woodlands_median", "yishun_median",␣
↪"central_median"]
```

```
prediction_columns = [col for col in test_data_x.columns if col.
 ↪endswith("_prediction")]

# Calculate the absolute differences between actual and predicted values
absolute_differences = np.abs(test_data_x[town_columns].values -␣
 ↪test_data_x[prediction_columns].values)

# Calculate the average absolute difference for each town
average_absolute_difference = np.mean(absolute_differences, axis=0)

# Create a grouped bar chart
plt.figure(figsize=(10, 6))
bar_positions = np.arange(len(town_columns))
bar_width = 0.35

plt.bar(bar_positions, average_absolute_difference, width=bar_width,␣
 ↪label="Average Absolute Difference", color='blue')

plt.title("Average Absolute Difference between Actual and Predicted Median␣
 ↪Prices for Each Town")
plt.xlabel("Town")
plt.ylabel("Average Absolute Difference")
plt.xticks(bar_positions, town_columns, rotation=45, ha="right")
plt.legend()
plt.show()
```



Average Absolute Difference between Actual and Predicted Median Prices for Each Town Graph

From this graph we can see that the model has been relatively sucessfully in predicting each towns median yearly price. However, we can see that the prices for Bishan, Central and Toa Payoh is not the most representative of the actual prices. However, I do think the model has been accurate to a degree as the prices for the years which we covered previously did show that the median prices for Bishan and the Central did fluctuate the most in comparison to the other towns over the years.

Predicting Town's Yearly Median: Data Evaluation

[108]:
```
# Extract relevant columns for calculating RMSE
actual_columns = ["ang mo kio_median", "bedok_median", "bishan_median", "bukit␣
↪batok_median", "bukit merah_median",
                  "bukit panjang_median", "choa chu kang_median",␣
↪"clementi_median", "geylang_median",
                  "hougang_median", "jurong east_median", "jurong west_median",␣
↪"kallang/whampoa_median",
                  "marine parade_median", "pasir ris_median", "punggol_median",␣
↪"queenstown_median",
```

```
                  "sembawang_median", "sengkang_median", "serangoon_median",␣
 ↪"tampines_median",
                  "toa payoh_median", "woodlands_median", "yishun_median",␣
 ↪"central_median"]

predicted_columns = [f"{town}_prediction" for town in town_columns]

# Calculate squared differences
squared_diff = (test_data_x[actual_columns] - test_data_x[predicted_columns])**2

# Calculate mean squared differences for each town
mse_per_town = squared_diff.mean()

# Calculate RMSE for each town
rmse_per_town = np.sqrt(mse_per_town)

# Calculate overall RMSE
overall_rmse = np.sqrt(mean_squared_error(test_data_x[actual_columns],␣
 ↪test_data_x[predicted_columns]))
print("\nRMSE:", overall_rmse)
```

```
RMSE: 85721.92041240093
```

[109]:
```
town_yearly_prediction_median_df.describe()
```

[109]:
```
              Year  yearly_median_price  ang mo kio_median   bedok_median  \
count    15.000000            15.000000           15.00000      15.000000
mean   2014.000000        424040.000000       417930.00000  392930.000000
std       4.472136         57051.778487        59433.45859   54734.703669
min    2007.000000        293000.000000       280000.00000  257000.000000
25%    2010.500000        417500.000000       401975.00000  385750.000000
50%    2014.000000        435000.000000       446000.00000  410000.000000
75%    2017.500000        445000.000000       456500.00000  424000.000000
max    2021.000000        515900.000000       486500.00000  454200.000000

       bishan_median  bukit batok_median  bukit merah_median  \
count       15.00000           15.000000           15.000000
mean    551310.00000       398406.666667       601593.333333
std      99131.14726        40121.907387       104213.775595
min     370250.00000       331900.000000       396500.000000
25%     517500.00000       371225.000000       552375.000000
50%     551500.00000       400000.000000       627500.000000
75%     648750.00000       429500.000000       668975.000000
max     678750.00000       468000.000000       760000.000000

       bukit panjang_median  choa chu kang_median  clementi_median  …  \
```

```
count             15.000000            15.000000        15.000000  …
mean          399213.333333        411260.000000    433563.333333  …
std            71708.635330         50677.528128     83214.682484  …
min           249000.000000        291900.000000    302200.000000  …
25%           359150.000000        395750.000000    389000.000000  …
50%           415950.000000        415000.000000    428750.000000  …
75%           443250.000000        437125.000000    436875.000000  …
max           494000.000000        485000.000000    673250.000000  …

       sengkang_median  serangoon_median  tampines_median  toa payoh_median  \
count        15.000000         15.000000        15.000000         15.000000
mean     446423.333333     415986.666667    444493.333333     506710.000000
std       57298.650154      64302.123012     60915.312603      86521.139448
min      316000.000000     275500.000000    301500.000000     337500.000000
25%      431200.000000     390650.000000    422500.000000     436125.000000
50%      452500.000000     431500.000000    461150.000000     537500.000000
75%      482450.000000     459875.000000    477750.000000     569375.000000
max      532000.000000     524900.000000    521500.000000     617200.000000

       woodlands_median  yishun_median  central_median  GDP Real Estate  \
count         15.000000      15.000000       15.000000        15.000000
mean      375133.333333  355833.333333   525293.333333     15424.533333
std        51173.450380   64425.667763   204001.128206      3003.310718
min       263000.000000  218000.000000   300000.000000      9360.000000
25%       362000.000000  339250.000000   392500.000000     13822.000000
50%       379000.000000  367000.000000   437500.000000     16127.000000
75%       405250.000000  383250.000000   642500.000000     17244.000000
max       447500.000000  482000.000000   910000.000000     19243.000000

       GDP Ownership Of Dwellings  GDP per Capita
count                   15.000000       15.000000
mean                 15415.600000        0.075152
std                   3706.208956        0.013760
min                   7943.000000        0.056606
25%                  12475.500000        0.066095
50%                  17436.000000        0.072937
75%                  17948.500000        0.084503
max                  18912.000000        0.104402

[8 rows x 30 columns]
```

[110]:
```
actual_columns = [ 'ang mo kio_median', 'bedok_median',
                   'bishan_median', 'bukit batok_median', 'bukit merah_median',
                   'bukit panjang_median', 'choa chu kang_median',␣
 ↪'clementi_median',
                   'geylang_median', 'hougang_median', 'jurong east_median',
```

```
                    'jurong west_median', 'kallang/whampoa_median', 'marine␣
 ↪parade_median',
                    'pasir ris_median', 'punggol_median', 'queenstown_median',
                    'sembawang_median', 'sengkang_median', 'serangoon_median',
                    'tampines_median', 'toa payoh_median', 'woodlands_median',
                    'yishun_median', 'central_median']

predicted_columns = ['ang mo kio_median_prediction', 'bedok_median_prediction',
                         'bishan_median_prediction', 'bukit␣
 ↪batok_median_prediction',
                         'bukit merah_median_prediction', 'bukit␣
 ↪panjang_median_prediction',
                         'choa chu kang_median_prediction',␣
 ↪'clementi_median_prediction',
                         'geylang_median_prediction', 'hougang_median_prediction',
                         'jurong east_median_prediction', 'jurong␣
 ↪west_median_prediction',
                         'kallang/whampoa_median_prediction', 'marine␣
 ↪parade_median_prediction',
                         'pasir ris_median_prediction',␣
 ↪'punggol_median_prediction',
                         'queenstown_median_prediction',␣
 ↪'sembawang_median_prediction',
                         'sengkang_median_prediction',␣
 ↪'serangoon_median_prediction',
                         'tampines_median_prediction', 'toa␣
 ↪payoh_median_prediction',
                          'woodlands_median_prediction',␣
 ↪'yishun_median_prediction',
                         'central_median_prediction']

# Calculate MAE for predictions of each town
mae_values = np.abs(test_data_x[actual_columns].values -␣
 ↪test_data_x[predicted_columns].values).mean()

# Print the overall MAE for the predictions of the towns
print("Mean Absolute Error (MAE) for Predictions:", mae_values)
```

```
Mean Absolute Error (MAE) for Predictions: 47919.39
```

[111]:
```
# Calculate MAE for each town
mae_values_per_town = np.abs(test_data_x[actual_columns].values -␣
 ↪test_data_x[predicted_columns].values).mean(axis=0)

# Create a DataFrame mae_df to display the results
mae_df = pd.DataFrame({'Town': actual_columns, 'MAE': mae_values_per_town})
```

```
# Print or display the MAE values for each town
print(mae_df)
```

```
                     Town        MAE
0        ang mo kio_median   64105.25
1             bedok_median   18974.25
2            bishan_median  136763.75
3       bukit batok_median   24001.25
4       bukit merah_median   26231.50
5     bukit panjang_median   37864.50
6     choa chu kang_median   13414.50
7          clementi_median   83288.00
8           geylang_median   75785.25
9           hougang_median   14394.75
10      jurong east_median   20253.50
11      jurong west_median    8976.75
12  kallang/whampoa_median   43573.50
13    marine parade_median   49520.50
14        pasir ris_median   19019.50
15          punggol_median   21437.50
16       queenstown_median   55032.75
17        sembawang_median   11623.50
18         sengkang_median   15476.50
19        serangoon_median   25566.00
20         tampines_median   36437.50
21        toa payoh_median   94316.25
22        woodlands_median   10174.50
23           yishun_median   29299.00
24          central_median  262454.50
```

[112]:
```
standard_deviation_values = np.std(test_data_x[predicted_columns], axis=0)

# Print the standard deviation values for each column
for column, std_value in zip(predicted_columns, standard_deviation_values):
    print(f"Standard Deviation of {column}: {std_value}")
```

```
Standard Deviation of ang mo kio_median_prediction: 36491.34716186154
Standard Deviation of bedok_median_prediction: 28840.16478259963
Standard Deviation of bishan_median_prediction: 105559.48031175362
Standard Deviation of bukit batok_median_prediction: 39495.342727814124
Standard Deviation of bukit merah_median_prediction: 51913.42326893884
Standard Deviation of bukit panjang_median_prediction: 52202.57807330975
Standard Deviation of choa chu kang_median_prediction: 31239.1548101097
Standard Deviation of clementi_median_prediction: 27547.87053476185
Standard Deviation of geylang_median_prediction: 88023.17108686497
Standard Deviation of hougang_median_prediction: 30460.3023325032
Standard Deviation of jurong east_median_prediction: 35652.03884071709
Standard Deviation of jurong west_median_prediction: 28597.339993214402
```

```
Standard Deviation of kallang/whampoa_median_prediction: 41081.7867734596
Standard Deviation of marine parade_median_prediction: 32880.940851046216
Standard Deviation of pasir ris_median_prediction: 26675.971814537515
Standard Deviation of punggol_median_prediction: 34176.31839812475
Standard Deviation of queenstown_median_prediction: 76904.00853783566
Standard Deviation of sembawang_median_prediction: 32603.309471585857
Standard Deviation of sengkang_median_prediction: 30990.515085264393
Standard Deviation of serangoon_median_prediction: 50164.15747573161
Standard Deviation of tampines_median_prediction: 35076.433267223736
Standard Deviation of toa payoh_median_prediction: 88770.32629875538
Standard Deviation of woodlands_median_prediction: 25881.548586782825
Standard Deviation of yishun_median_prediction: 34630.756456508425
Standard Deviation of central_median_prediction: 90761.64739855706
```

Evaluation: Towns Yearly Median - Mean Absolute Error (MAE)

In order to evaluate the performance of the model to predict the future towns' yearly median across all flat types, I used the Mean Absolute Error (MAE) to find how effective the model has been in predicting each towns' yearly median price in comparison to the actual towns' median prices. From the results, we can observe that the accuracy of the predictions varies across the towns. For example, the towns Bukit Merah and Choa Chu Kang have relatively low MAE values. Therefore, implying that the model has been able to predict the towns' median prices and it aligns closely to the actual median prices. However, for the towns Bishan and the Central, there is a relatively higher MAE value, which suggests that the models' predictions exhibits larger absolute errors. Overall, the comparison of MAE values across the towns allows for much more targeted refinement of the model which will improve the prediction accuracy.

2.5 Conclusion

From the obtained results of both models, predicting the yearly median prices and the towns' median yearly prices, it can be concluded that the machine learning multiple linear regression model was successful in both scenarios. The prediction of the yearly median prices demonstrated a high level of accuracy, closely aligning with the actual yearly median values. This success can be attributed to the significant impact of the identified factors, including GDP, population, and the number of transactions, which played a pivotal role in training the model.

However, when predicting the towns' yearly median prices, the model exhibited success for most towns but faced challenges in accurately forecasting a few. This discrepancy may stem from insufficient historical data for certain towns, particularly over an extended period. It is essential to acknowledge that factors beyond those considered in this project, such as unforeseen events like a pandemic or upcoming government projects, could influence town-specific median prices. For instance, the addition of a new Mass Rapid Transport (MRT) line through the Central area could significantly impact property prices in specific towns. [5] To enhance the model's accuracy, future iterations could incorporate additional variables, including upcoming developmental projects and external events. This would provide a more comprehensive understanding of the dynamic factors influencing town-specific median prices.

The predictive models generated from this project can offer valuable insights for individuals interested in purchasing resale properties, especially those seeking to compare prices across different towns. Given the desirability of resale markets in well-established and matured estates in Singapore,

these models can aid potential buyers in making informed decisions.

Moreover, the developed solution has the potential to be adapted for predicting prices in other real estate markets, such as rental prices in new building projects. By extending the model's application to diverse scenarios, it can serve as a valuable tool for individuals and organizations involved in real estate planning, investment, and decision-making.

2.6 References

[1] https://www.hdb.gov.sg/business/estate-agents-and-salespersons/buying-a-resale-flat/procedures

[2] https://www.singstat.gov.sg/find-data

[3] https://beta.data.gov.sg.

[4] https://www.nlb.gov.sg/main/article-detail?cmsuuid=d66bfa02-aef8-44a1-a07f-9e1d79a084e1#:~:text=The%20Housing%20and%20Urban%20Development,could%20not%20afford%20private%2

[5] https://www.lta.gov.sg/content/ltagov/en/upcoming_projects/rail_expansion/cross_island_line.html