```
#I defined all the necessary
libraries that I will be using in
my whole analysis .

import plotly.express as px
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from matplotlib.colors import ListedColormap from
matplotlib import cm
```

Analysing Barcelona's Rent Market between 2014-2022 :

A chronic and unfolding rental crisis has plagued Barcelona, one of the most dynamic and socially diverse cities in Europe, in recent decades. It's clear that there is a big demand for the housing more than the available apartments in the market and this is because of diffrent domestic and external factors This rental crisis has grown to become a signiAcant concern for residents, businesses, and policymakers, necessitating urgent analysis and resolution. Most importantly, it's not diCcult to read the patterns and shapes behind the scenes as rental prices keep evolving.

For this analysis, I will be using a dataset containing rent prices across Barcelona from 2014 to 2022. The data covers 10 districts and 73 neighborhoods, offering a detailed view of the rental market over an 8-year period. By examining this data, I aim to uncover insights that can help stakeholders navigate the complexities of the rental market.

Real estate investors, housing industry businesses, and property managers form the greatest number of observers for this report. In making signiAcant judgements, either for speculation use, property evaluations, or interpreting the advancement of the market, such organizations require notice of advertise trends. In displaying a more sophisticated image of the factors that play a role in the price variation of leasing in Barcelona, I aim to give realistic bits of information which can harmonize decision-making in the presence of a stubborn lease crisis.

```
#data_url = "https://www.kaggle.com/code/marshuu/barcelona-rent-prices-2014-202
dataset = 'https://storage.googleapis.com/kagglesdsdata/datasets/2664235/456586
df = pd.read_csv(dataset, skiprows=9, sep =",") df.head()
```

	2014	1	Eixample	la Nova Esquerra de l'Eixample	average rent (euro/month)	716.13
0	2014	1	Eixample	Sant Antoni	average rent (euro/month)	693.43
1	2014	1	Sants-Montjuic	el Poble Sec	average rent (euro/month)	568.00
2	2014	1	Sants-Montjuic	la Marina de Port	average rent (euro/month)	553.55

Next steps: View recommended plots New interactive sheet

Data processing and cleansing

```
data = pd.read_csv(dataset, header=0)  # check the name of my columns
print(data.columns) data.rename(columns={'incorrect_column_name':
'Year'}, inplace=True)
```

```
Index(['Year', 'Trimester', 'District', 'Neighbourhood', 'Average _rent',
       'Price'],
dtype='object') df.describe(),
df.info() # This step is to check
the statistics of my data set
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4613 entries, 0 to 4612 Data
columns (total 6 columns):
      #    Column                          Non-Null Count   Dtype
     ---   ------                          --------------   -----
     0    2014                            4613 non-null    int64
     1    1                               4613 non-null    int64
     2    Eixample                        4613 non-null    object
     3    la Nova Esquerra de l'Eixample  4613 non-null    object
     4    average rent (euro/month)       4613 non-null    object  5    716.13
          4613 non-null    float64
     dtypes: float64(1), int64(2), object(3)
     memory usage: 216.4+ KB
```

```
(              2014            1       716.13
count  4613.000000  4613.000000  4613.000000
mean   2017.752872     2.443312   415.884598
std       2.459660     1.115649   443.088224
min    2014.000000     1.000000     3.180000
25%    2016.000000     1.000000    12.100000
 50%    2018.000000     2.000000    20.330000
75%    2020.000000     3.000000   777.210000
max    2022.000000     4.000000  2034.000000,
None)
```

Before visualizing the dataset and starting to work with it , it is crucial to inspect its structure and get the statistical summary to identify potential issues. By using 'df.info()' and 'df.describe()' , I examined the data types, missing values, and overall distribution. I noticed that some column names are unclear, and the dataset contains numerical values stored as objects, which could affect calculations.
It's also more diCcult to work with the column names effectively because they appear to be formatted wrongly. The format of the dataset also neeed to be change in order to make the visualisations more organised and smooth .

```
unique_neighborhoods = data['Neighbourhood'].unique()
print(unique_neighborhoods)

unique_district = data['District'].unique() print(unique_district)
```

```
['el Raval' 'Gothic Quarter' 'la Barceloneta'
 'Sant Pere, Santa Caterina i la Ribera' 'Fort Pienc' 'Sagrada Familia'
     "la Dreta de l'Eixample" "l'Antiga Esquerra de l'Eixample"
     "la Nova Esquerra de l'Eixample" 'Sant Antoni' 'el Poble Sec'
     'la Marina de Port' 'la Font de la Guatlla' 'Hostafrancs' 'la Bordeta'
     'Sants - Badal' 'Sants' 'les Corts' 'la Maternitat i Sant Ramon'
     'Pedralbes' 'Vallvidrera, el Tibidabo i les Planes' 'Sarria'
     'les Tres Torres' 'Sant Gervasi - la Bonanova' 'Sant Gervasi - Galvany'
     'el Putxet i el Farro' 'Vallcarca i els Penitents' 'el Coll' 'la Salut'
     'la Vila de Gracia' "el Camp d'en Grassot i Gracia Nova"
     'el Baix Guinardo' 'Can Baro' 'el Guinardo' "la Font d'en Fargues"
     'el Carmel' 'la Teixonera' 'Sant Genis dels Agudells' 'Montbau'
     "la Vall d'Hebron" 'Horta' 'Vilapicina i la Torre Llobeta' 'Porta'
     'el Turo de la Peira' 'Can Peguera' 'la Guineueta' 'Canyelles'
     'les Roquetes' 'Verdun' 'la Prosperitat' 'la Trinitat Nova'
     'Ciutat Meridiana' 'la Trinitat Vella' 'el Bon Pastor' 'Sant Andreu'
     'la Sagrera' 'el Congres i els Indians' 'Navas'
     "el Camp de l'Arpa del Clot" 'el Clot'
     'el Parc i la Llacuna del Poblenou' 'la Vila Olimpica del Poblenou'
     'el Poblenou' 'Diagonal Mar i el Front Maritim del Poblenou'
     'el Besos i el Maresme' 'Provencals del Poblenou'
     'Sant Marti de Provencals' 'la Verneda i la Pau' 'Torre Baro'
    'Baro de Viver' 'la Marina del Prat Vermell' 'Vallbona' 'la Clota'
     'la Sagrada Familia' 'Sant Martíide Provencals']
```

```
['Ciutat Vella' 'Eixample' 'Sants-Montjuic' 'Les Corts'
 'Sarria-Sant Gervasi' 'Gracia' 'Horta-Guinardo' 'Nou Barris'
 'Sant Andreu' 'Sant Marti']
```

```
# Here I converted the datatype of the column to the right format
df= pd.read_csv(dataset) df['Year'] = df['Year'].astype(int)
df['Trimester'] = df['Trimester'].astype(int)
df['Price'] = pd.to_numeric(df['Price'], errors='coerce') print(data.dtypes)
```

```
Year              int64
Trimester         int64
    District          object
    Neighbourhood     object
    Average _rent     object
    Price            float64
    dtype: object
```

```
data = data.drop_duplicates() #for any duplicates data we will eliminate it so
```

```
#check if there is any null values in these columns since we are mainly going t
print(data[['Neighbourhood', 'Price']].isnull().sum())
```

```
Neighbourhood    0 Price
    0 dtype: int64
```

```
data = data.rename(columns={"Average _rent": "Average_rent"}) # this is just to
# filtering
rent_per_month = data[data["Average_rent"] == "average rent (euro/month)"]
rent_per_sqm = data[data["Average_rent"] == "average rent per surface (euro/m2)

# Calculating the avrege rent per month and the average rent per meter square
avg_rent_per_month = rent_per_month.groupby("Year")["Price"].mean().round(2)
avg_rent_per_sqm = rent_per_sqm.groupby("Year")["Price"].mean().round(2)

# Convert results into DataFrames avg_rent_per_month =
avg_rent_per_month.reset_index().rename(columns={"Price": avg_rent_per_sqm =
avg_rent_per_sqm.reset_index().rename(columns={"Price": "Avg

# Merge both DataFrames into a new dataframe called avg_df avg_df =
pd.merge(avg_rent_per_month, avg_rent_per_sqm, on="Year")
print(avg_df)
```

```
   Year  Avg_Rent_Monthly  Avg_Rent_Sqm
0  2014            661.64          9.73
1  2015            695.24         10.45
2  2016            750.96         11.49
```

```
3  2017           829.38        12.64
4  2018           874.05        12.82
5  2019           923.32        13.37
6  2020           915.92        13.32
7  2021           871.59        12.72
8  2022           922.55        13.35
```

I noticed that in the column "Average_rent" there are 2 diffrenet kinds of imputs "average rent (euro/month)" and "average rent per surface (euro/m2)", so i tried to sperate them in diffrent columns and add it the dataframe for more clearty .

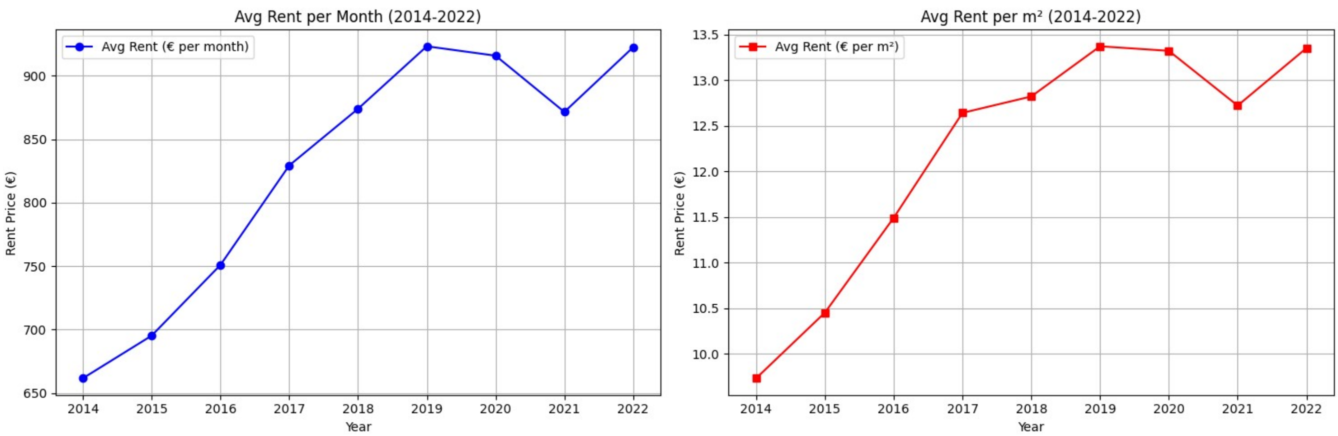
one more thing is that the average price was not calculated, so I caluculated it and put it in the right column

```
#creating the new data frame with caluclateed avg rent

# Define the years we want to compute the average rent for years
= range(2014, 2023)

# Lists to store results
rent_per_month = []
rent_per_sqm = []

# Loop through each year and compute the averages for both rent per month and p
for year in years:     # Rent per month
    y_month = data[(data['Year'] == year) & (data['Average_rent'] == 'average r
rent_per_month.append(round(y_month, 2))

    # Rent per square meter
    y_meter = data[(data['Year'] == year) & (data['Average_rent'] == 'average r
rent_per_sqm.append(round(y_meter, 2))

# Create a DataFrame to store the results
rent_per_year = pd.DataFrame({
    'Year': years,
    'Rent_per_Month': rent_per_month,
'Rent_per_Sqm': rent_per_sqm
})

# Display the DataFrame print(rent_per_year)
```

```
   Year  Rent_per_Month  Rent_per_Sqm
0  2014          661.64          9.73
1  2015          695.24         10.45
2  2016          750.96         11.49
```

```
3  2017          829.38          12.64
4  2018          874.05          12.82
5  2019          923.32          13.37
6  2020          915.92          13.32
7  2021          871.59          12.72
8  2022          922.55          13.35
```

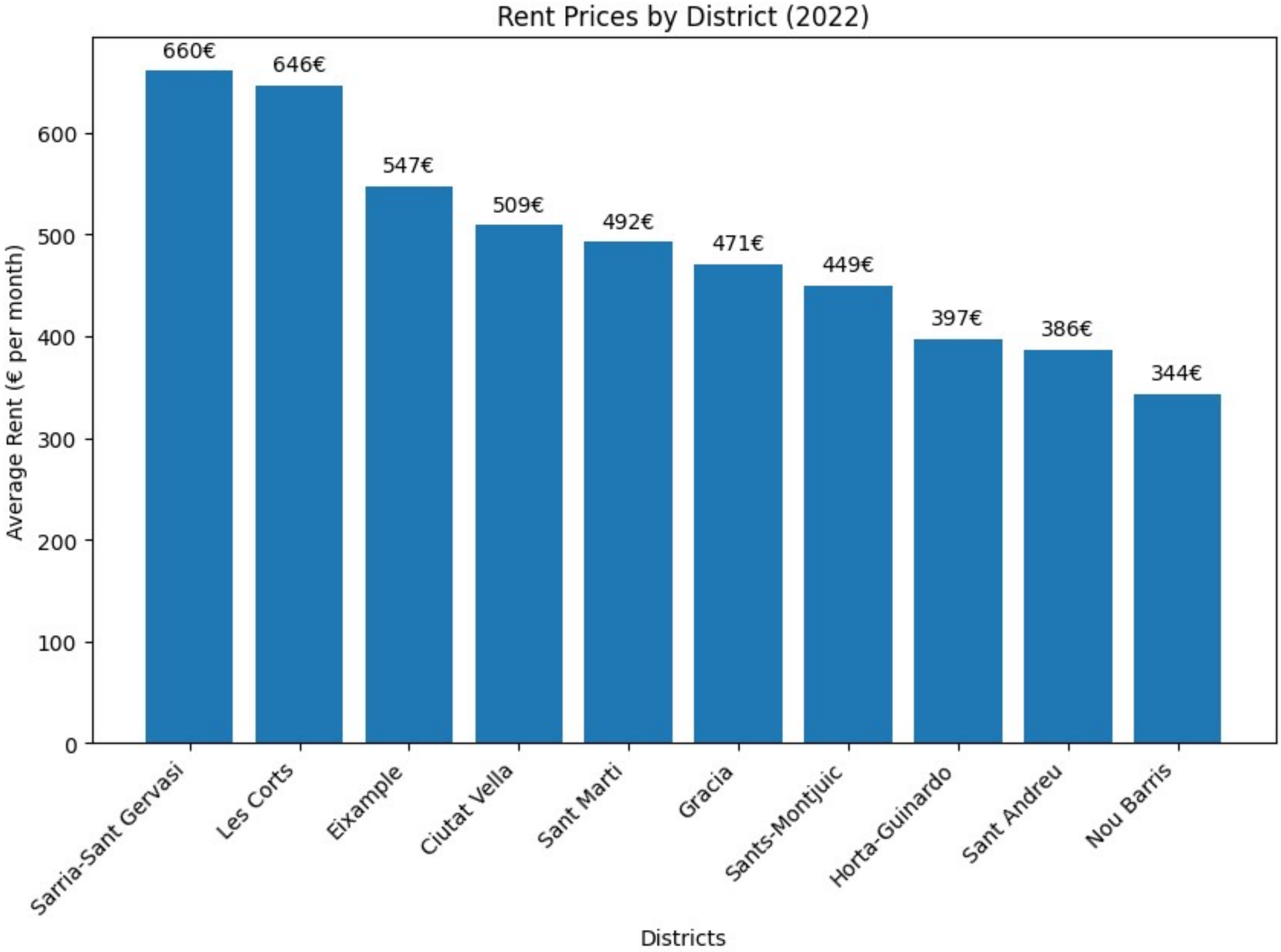
```
# 1-Line chart: Rent Prices over time (2014-2022) fig,

axes = plt.subplots(1, 2, figsize=(15, 5))

# Plot for Rent per Month
axes[0].plot(rent_per_year["Year"], rent_per_year["Rent_per_Month"], marker='o'
axes[0].set_xlabel("Year") axes[0].set_ylabel("Rent
Price (€)")
axes[0].set_title("Avg Rent per Month (2014-2022)")
axes[0].grid(True)
axes[0].legend()

# Plot for Rent per Square Meter
axes[1].plot(rent_per_year["Year"], rent_per_year["Rent_per_Sqm"], marker='s',
axes[1].set_xlabel("Year") axes[1].set_ylabel("Rent
Price (€)")
axes[1].set_title("Avg Rent per m² (2014-2022)")
axes[1].grid(True)
axes[1].legend()


plt.tight_layout()
plt.show()
```



This line chart shows how rent Prices have changed ! signiAcally over the years 2014-2022 .

Rent has gone up signiAcantly in Barcelona, particularly in 2019. This is to be expected because the epidemic of Covid-19 led to the prices of most commodities and services going up (Rexhepi et al.). The rent per square meter went up from arround €10 to €13.4 from the year 2014 to 2019, which indicates a rising trend in the rent prices per square metre. After 2019 and up to 2021, there was a slight drop in both averagee rent per month and rent per square meter, but an increase was noted in 2022. This is a sign that even as the rental charges rose, residents were not always getting extra space relative to what they were paying. This is a major challenge for many people looking for budget-friendly accommodation. This Zuctuations in rental charges can be due to the pandemic, which greatly shifted the property market. As evidenced by capital cities such as Berlin, this information can assist policymakers in understanding the plight of the renters and come up with measures, for example, rent control, to reduce the housing expenses.

```
# 2-Bar chart : Rent Prices by distict 2022 the most recent affordability

#first we have to filter the data for 2022

data_2022 = df[df['Year'] == 2022] # from the dataset get only the values for 2

district_rent_2022 = data_2022.groupby('District')['Price'].mean().sort_values(

fig, ax = plt.subplots(figsize=(10, 6))

#create the bars of the bar chart
bars = ax.bar(
    district_rent_2022.index,
district_rent_2022.values,
    color='#1f77b4'  # I used this blue color for the bar chart
)

ax.set_xlabel('Districts')
ax.set_ylabel('Average Rent (€ per month)') ax.set_title('Rent
Prices by District (2022)') plt.xticks(rotation=45,
ha='right')


for bar in bars: # here for each bar I added the respective value of the rent f
yval = bar.get_height()
    ax.text(bar.get_x() + bar.get_width()/2, yval + 10 , f'{yval:.0f}€', ha='ce

#show the visualisation
plt.show()
plt.tight_layout()
plt.show()
```




```
<Figure size 640x480 with 0 Axes>
```

Why the rent prices differ ?

The bar chart indicates that Sarria-Sant Gervasi is the most expensive neighborhood in Barcelona, with prices over €650 per month. Being the city's most central neighborhood (localbarcelona.com,2024), it makes perfect sense. The upper-class families also prefer to reside in this neighborhood because it contains better parks, schools, and a wealthier way of life. The variation between the most expensive and least expensive regions is around €250, so even the less expensive regions are not that dissimilar in cost.

Moreover, the rent increases are concentrated in certain areas of the city instead of being dispersed, and thereby makes housing in these spots unaffordable to locals. Since lowincome individuals can be pushed to reside on the periphery of the city, the imbalance also presents housing access problems. It catalyzes the broader challenge of escalating rental cost in Barcelona, and it is thus critical to review policies that tackle supply and price regulation of housing.

```
# 3- Heatmap:  average rent prices per month in districts
```

```
# Filter data to include only the columns we need from the original dataframe
heatmap_data = data[['Year', 'District', 'Price']]

# Pivot the data so that 'Year' is on rows, 'District' is on columns, and 'Pric
heatmap_data_pivot = heatmap_data.pivot_table(index='Year', columns='District',

# Plot the heatmap using Seaborn plt.figure(figsize=(14,
8))
sns.heatmap(heatmap_data_pivot, annot=True, cmap='YlGnBu', fmt='.1f', cbar_kws=
plt.title('Average Rent Prices by District and Year (2014-2022)')
plt.ylabel('Year')
plt.xlabel('District')
plt.xticks(rotation=45, ha='right')
plt.tight_layout() plt.show()
```

How does the price allocation among districs, throught the years look like ?

The heatmap illustrates the average monthly rent price evolution of the districts in Barcelona between 2014 and 2022. It can be seen from the heatmap that rents have been increasing consistently over time in nearly all the districts, but with some increasing more than others. The "Ciutat Viella" neighborhood has changed the most from light to dark colors, showing that there was a very high growth in rent between 2014 and 2022. Every neighborhood has experienced a rise in rent prices in general, showing the housing affordability crisis around and in Barcelona once again.

```
 #color map for the districts pastel_colors = ['#FAD02E', '#F28D35', '#D83367',

'#F07C69', '#81D8D0', '#A9C9B

# create a list with all the 10 districts of barcelona - the same names that ar
district_list = ['Ciutat Vella','Eixample','Sants-Montjuic','Les Corts',
 'Sarria-Sant Gervasi', 'Gracia' , 'Horta-Guinardo', 'Nou Barris' ,
 'Sant Andreu' , 'Sant Marti']

# This codition check if there are enough colors in the color list to get assig
if len(district_list) > len(pastel_colors):     pastel_colors = pastel_colors *
(len(district_list) // len(pastel_colors))

# create the fixed district color map
district_color_map = {district: pastel_colors[i] for i, district in enumerate(d

# Here I just printed the results of my color map to check if there is any erro
print(district_color_map)
```

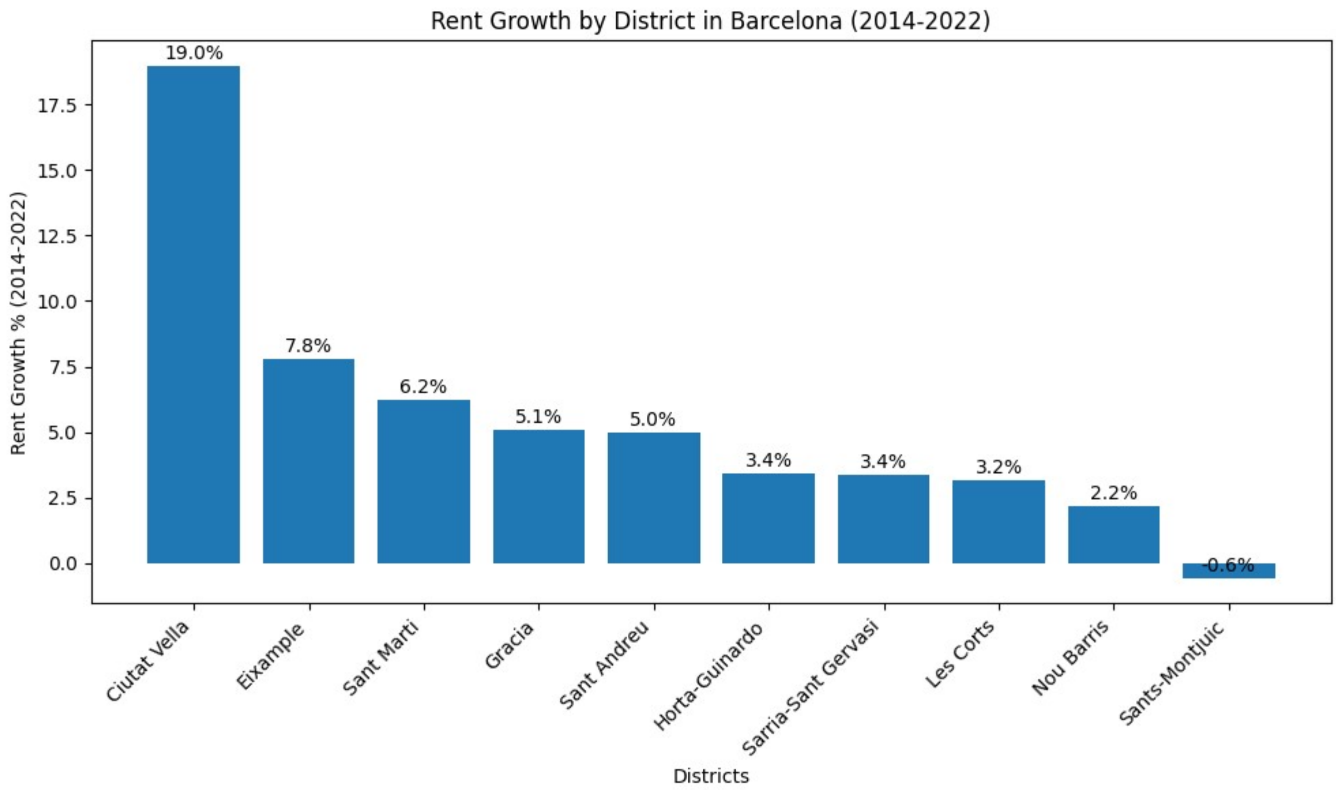
```
{'Ciutat Vella': '#FAD02E', 'Eixample': '#F28D35', 'Sants-Montjuic': '#D833
```

why we created a district color map

In the upcoming visualisations we will focus more about districts and their neigherhoods' insights. So for a better and more organised visalisations , I created this district color map so all the district have the same color in all the visualisation -when needed- so we can identify them more easily , especially that they are 10 different districts .

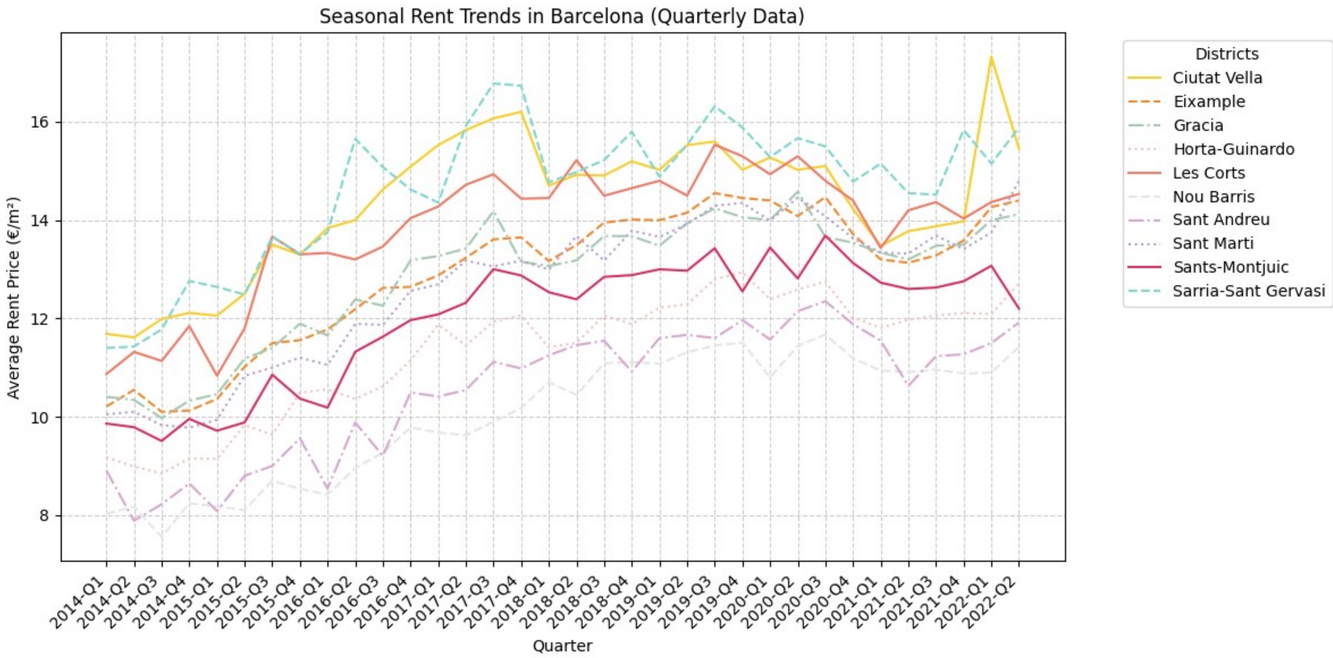
```
#4-bar chart : Rent Growth by District in Barcelona (2014-2022)

#this is a bar chart to show the growth in the price per meter square for the d
# and it will also highlights which distric had the most growth in rent prices #
Filter the data for rent prices per square meter
rent_per_sqm_data = data[data['Average_rent'] == 'average rent per surface (eur
```

```
# Calculate the average rent per square meter by district and year
district_rent_by_year = rent_per_sqm_data.groupby(['District', 'Year'])['Price'

# Pivot the data to have districts as rows and years as columns
rent_pivot = district_rent_by_year.pivot(index='District', columns='Year', valu

# Calculate the rent growth percentage
rent_growth = rent_pivot.pct_change(axis='columns') * 100 rent_growth
= rent_growth.iloc[:, -1]  # Select the last year (2022)

# Sort districts by rent growth percentage
sorted_rent_growth = rent_growth.sort_values(ascending=False)

# Plot the bar chart
fig, ax = plt.subplots(figsize=(10, 6))

bars = ax.bar(sorted_rent_growth.index, sorted_rent_growth.values,
              color='#1f77b4') # I did not used the district color map here bec



ax.set_xlabel('Districts')
ax.set_ylabel('Rent Growth % (2014-2022)')
ax.set_title('Rent Growth by District in Barcelona (2014-2022)')

plt.xticks(rotation=45, ha='right') # Add percentages in to of

the bars

for bar in bars:     yval =
bar.get_height()
    ax.text(bar.get_x() + bar.get_width()/2, yval + 0.1 , f'{yval:.1f}%',
ha='center', va='bottom', fontsize=10)

plt.tight_layout()
plt.show()
```




```
#5- Line chart : Seasonal Trends in Rent Price


# from the trimester and year columns i have in my data set i created a new col
data['Quarter'] = data['Year'].astype(str) + '-Q' + data['Trimester'].astype(st

# Filter the data  for rent per square meter
rent_per_sqm_data = data[data['Average_rent'] == 'average rent per surface (eur

# Group by District and Quarter, then calculate the mean rent price
quarterly_rent_trends = rent_per_sqm_data.groupby(['District', 'Quarter'])['Pri

# convert the grouped data into a pivot table for the plot
quarterly_pivot = quarterly_rent_trends.pivot(index='Quarter', columns='Distric
# create the line plot
```

```
fig = plt.subplots(figsize=(12, 6))
line_styles = ['-', '--', '-.', ':']# for each district use a diffrent line sty
for i, district in enumerate(quarterly_pivot.columns):
  # each district will have its assigned color in the color map that I
#created earlier and have a diffrent line style ( the line styles are assigne
    plt.plot(quarterly_pivot.index, quarterly_pivot[district],
label=district, color=district_color_map[district],
linestyle=line_styles[i % len(line_styles)])



plt.xlabel('Quarter')
plt.ylabel('Average Rent Price (€/m²)')
plt.title('Seasonal Rent Trends in Barcelona (Quarterly Data)')
plt.xticks(rotation=45 , ha='right')
plt.legend(title='Districts', bbox_to_anchor=(1.05, 1), loc='upper left')

# Add gridlines to be able to read the values clearly plt.grid(True,
linestyle='--', alpha=0.6)



plt.tight_layout()
plt.show()
```



How does rent act by seasons ?

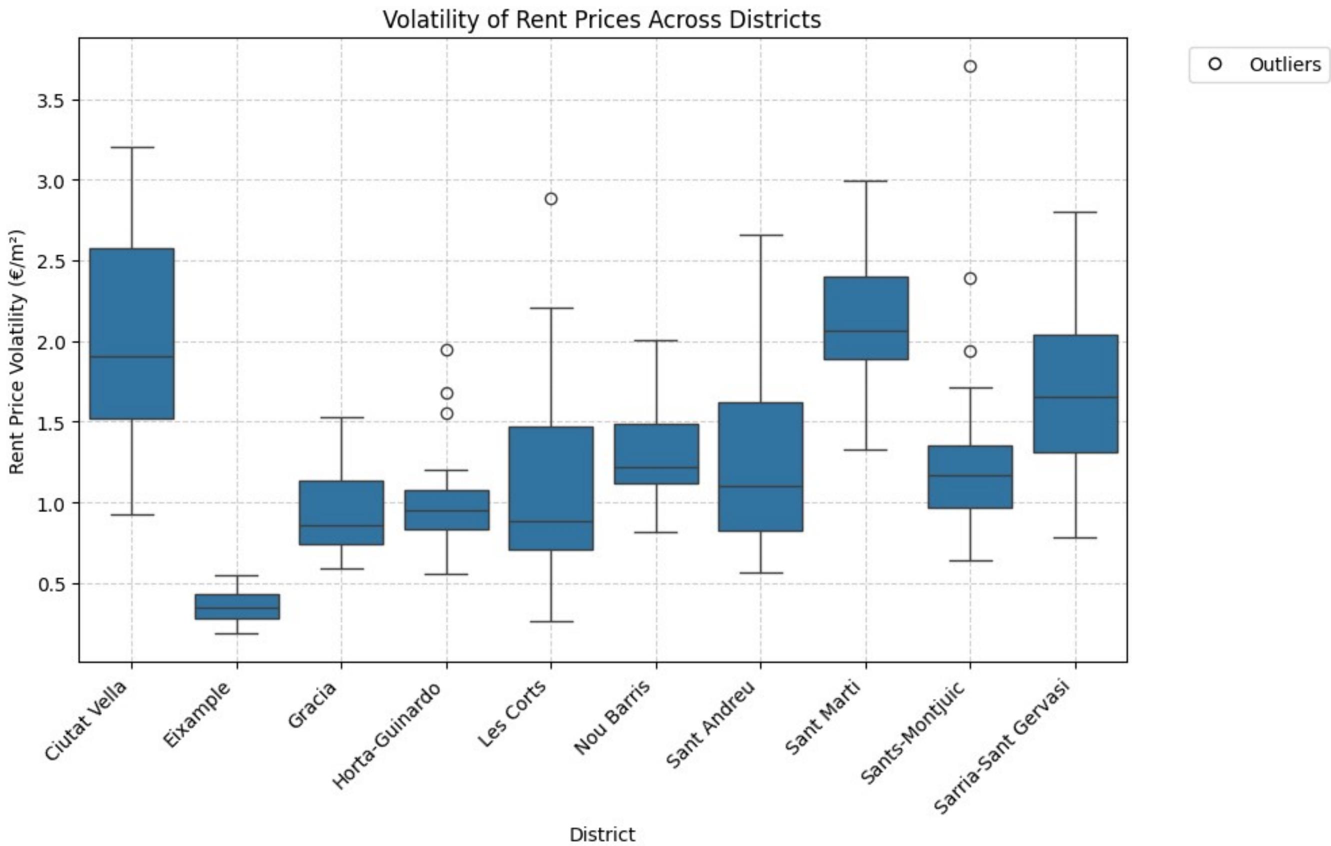
while there are dramatic Zuctuations between quarters in this line chart , we can notice that the level of rent has gone up during the years . We can see that Ciutat Viella experienced the largest rent increase, with average rent per square metre increasing from 14 EUR to nearly 18 EUR in a single quarter from 2021-Q4 to 2022-Q1. This is perhaps because of the increased demand for housing within this central, tourist-Alled area (Kley and Stenpaß ,2020), possibly driven by a post-pandemic surge (COVID-2019) in both tourism and housing demand as companies and people returned to the city. Conversely, the Garcia district's average rent per square metre fell the most, from 17 EUR in 2017-Q4 to 15 EUR in 2018-Q1, perhaps indicating short-term oversupply or changing demand away from this district because of issues such as infrastructure construction.

Between Q4 of 2018 and Q2 of 2022, average rents rose in all districts. But the most volatile prices were those of Gracia, Sant-Andreu, and Les Corts, where lines that were continuously going up and down. We also can see that Sant Martí experienced the least Zuctuations, the rent prices in this district were more stable over time. This makes so much sens since Sant Martí is the residential quarter of the city, its bucked away for the tourist center and offers more affrodable choices to residents .(Parrilla-González et al. ,2020).

This graph is helpful for stakeholders and potential renters to better understand the timing of rent price increases and anticipate future market movements, which is crucial in solving the ongoing rent crisis in Barcelona.

```
#6- Box plot : Volatility of rent prices across districts

# Filter the data for rent per square meter
rent_per_sqm_data = data[data['Average_rent'] == 'average rent per surface (eur

# Group by District and Quarter, then calculate the standard deviation to get t
volatility_data = rent_per_sqm_data.groupby(['District', 'Quarter'])['Price'].s



# visualise box plots plt.figure(figsize=(10,
6))
sns.boxplot(x='District', y='Price', data=volatility_data)

outlier_legend = plt.Line2D([0], [0], marker='o', color='w', markerfacecolor='w
plt.legend(handles=[outlier_legend], bbox_to_anchor=(1.05, 1), loc='upper left'

plt.xlabel('District')
plt.ylabel('Rent Price Volatility (€/m²)')
```

```
plt.title('Volatility of Rent Prices Across Districts') plt.xticks(rotation=45,
ha='right')

plt.grid(True, linestyle='--', alpha=0.6) # the grids here serve to show exactl
plt.show()
```

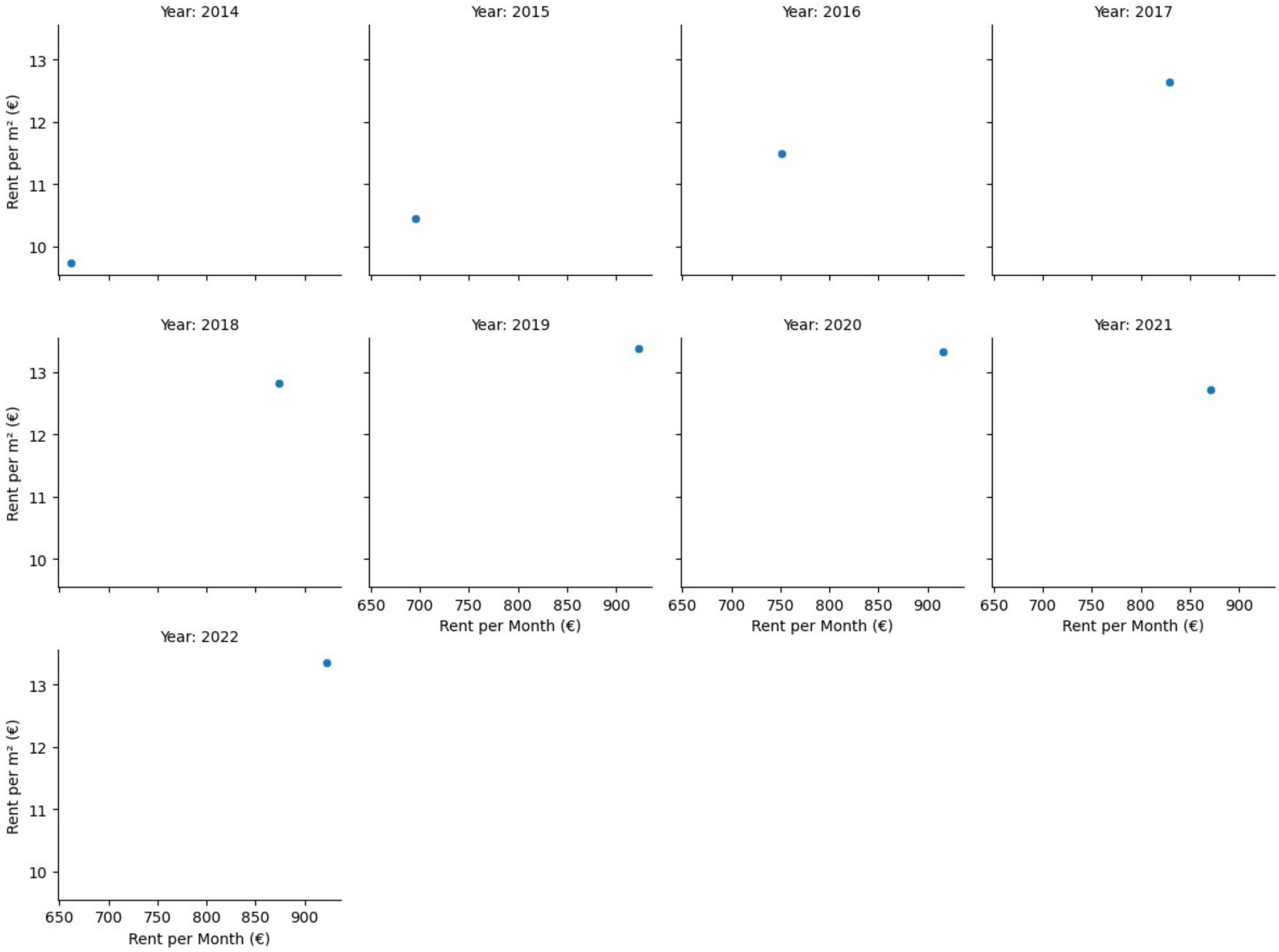


How can volatility anlysis helps identify the districts affordability ?

From this boxplot graph we can see clearly how the rental prices in Barcelona's various districts shifted from 2014 to 2022. This deviation in prices is called volatility ; the higher the volatility, the more drastically the prices have changed from year to year, and the lower the volatility, the more consistently the prices have remained. As we can see, Neighborhoods like Ciutat Vella, Sant Martí, and Sarrià-Sant Gervasi had very unstable rent prices it's mostly because of the less stable and more dynamic rental market in these areas. Eixample, Gràcia, and Horta-Guinardó had extremely low volatility as their relative boxes were smaller , indicating more stable and orderly rent tendencies. Tenants may want to live in low-volatility areas to avoid exaggerate rent increases , while investors may be drawn to high-volatility areas in the hope of higher returns with higher risk. This volatility analysis is useful to both renters and investors. Moreover, a picture of rent distribution by districts can inform urban planning and policy interventions intended to enhance affordability and market stability within the city.(Jones et al. ,2005)

```
#7-facet grid :Correlation Between Average Rent & Rent per m² (Scatter Plot)
```

```
# Create a FacetGrid by year
g = sns.FacetGrid(rent_per_year, col="Year", col_wrap=4, height=3)
g.map(sns.scatterplot, 'Rent_per_Month', 'Rent_per_Sqm')

# Add titles and labels
g.set_axis_labels('Rent per Month (€)', 'Rent per m² (€)')
g.set_titles('Year: {col_name}')
plt.tight_layout() plt.show()
```

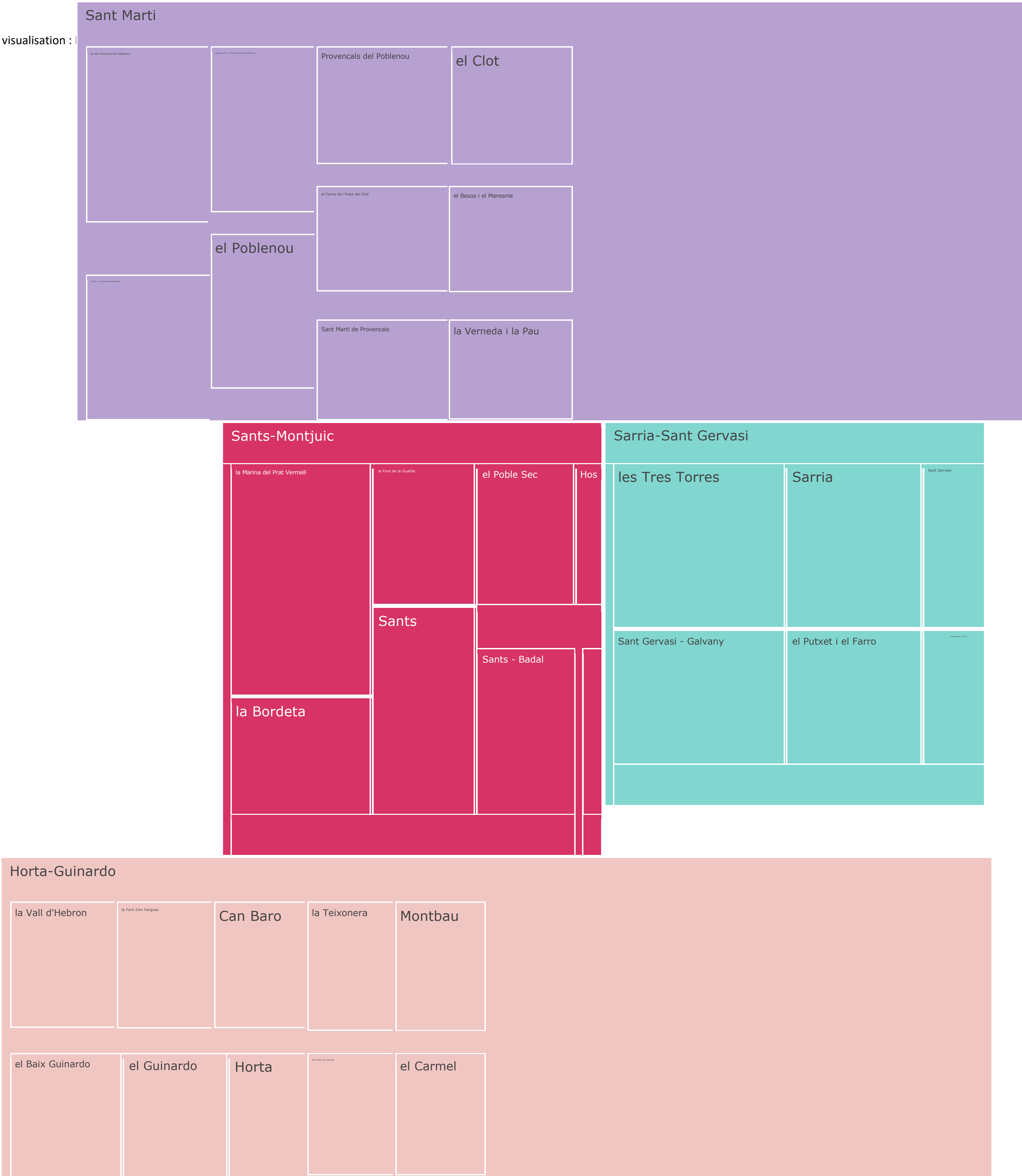


What is the relationship between the price of the rent per month and the rent per meter square ?

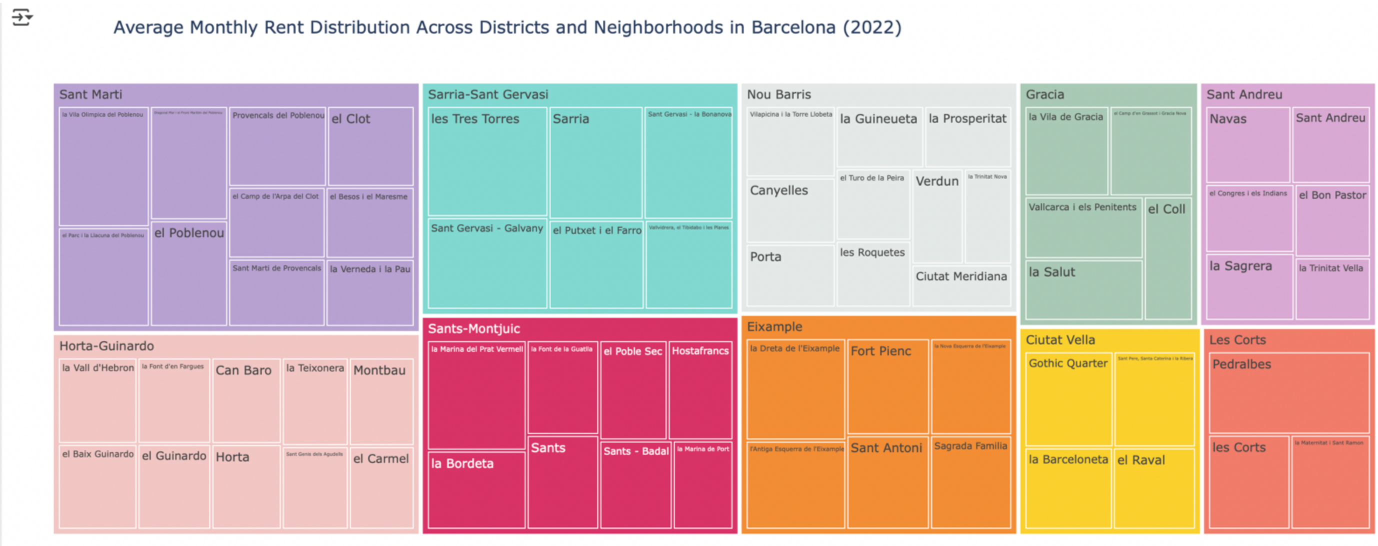
This facet grid scatter plot illustrates the yearly relationship between the rent per square meter and average monthly rent in Barcelona for the years 2014 to 2022. I selected this visualisation because it breaks down the data into easy side-by-side comparisons on a yearby-year basis, which is helpful in identifying temporal trends in barcelona real estate market . Even though each plot of the annual sums only has a single point, the grid format graphically holds the linear rising trend for both variables (Avg rent and rent per sqm) to demonstrate that cost per square meter rises with monthly rents which means that tenants are paying more every year for the same appartement size. This is interesting because it shows that rent inZation is impacting cost eCciency of living space as well as overall price, which is important to renters who must optimize value and to urban planners and lawmakers interested in housing affordability and density.

```
#8- treemap : Overview of the average rent prices across all Barcelona's neigbe

data_2022 = data[data['Year'] == 2022] # get all the data related to the yaer 2

# AGroup the data by district and neighbourhood
aggregated_data = data_2022.groupby(['District', 'Neighbourhood'], as_index=Fal
    'Price': 'mean'  # Calculate the mean rent price per neighborhood })

# Rename 'Price' to 'Avg_Rent_Per_Month' for clarity
aggregated_data = aggregated_data.rename(columns={'Price': 'Avg_Rent_Per_Month'


# Using the new data that we got , we create the treemap plot using the libralr
fig = px.treemap(     aggregated_data,
    path=['District', 'Neighbourhood'],  # Hierarchical structure : each distri
values='Avg_Rent_Per_Month',  # Size of the box based on Avg Rent per Month
color='District',  # Color of theneighbourhood based on the district
hover_data=['Avg_Rent_Per_Month'],
    color_discrete_map=district_color_map,  # Apply the district color map
title="Average Monthly Rent Distribution Across Districts and Neighborhoods
)


fig.update_layout(
    margin=dict(t=50, l=0, r=0, b=0),  # Adjust margins for better appearance
showlegend=False
)


fig.show()
```

Average Monthly Rent Distribution Across Districts and Neighborho data visualisation : l



ʻʻ I uploaded a screenshot from my code for this visualisation because it was cotted when converted to PDFʼʼ



What makes this treemap important ?

The treemap chart provides a systematic and detailed picture of the average monthly rent prices in Barcelona's districts and its relative neighborhoods during 2022. I used this particular chart type Because it is capable of displaying hierarchical data in a compact and easily comprehensible manner enabling it to make easy comparison at both the global and micro levels by displaying the data from district (parent) to neighborhood (child). The block size in each of them shows the average rent for each neighborhood, and districts are divided by the district color map. Geographic clustering and relative rents can be visually and easily identiAed by this dual encoding.

Even more interestingly, the treemap shows a number of important insights . High-end housing concentrations are characterized by the fact that some neighborhoods within a variety of districts, such as **Sant Martí** and **Sarrià-Sant Gervasi**, possess rates of renting that are much higher. In contrast, smaller, lower-priced blocks prevail in areas such as **HortaGuinardó** and **Nou Barris**, which point to rental markets overall that are more modestly priced. Furthermore, the treemap detects intra-district heterogeneity, highlighting speciAc neighbourhoods in otherwise affordable districts with much higher average rents—a subtlety perhaps lost on district aggregations.

To political parties interested in correcting spatial imbalances, passing speciAc rent control regulations, or seeking where to invest, this degree of precision is invaluable.

Conclusion and Discussion :

In this explanatory data analysis pipeline , the rental market in Barcelona was examined between the years 2014 and 2022. Through eight speciAc visualisations such as line charts, bar graphs, a heatmap, box plots, scatter plots, and a treemap, the study identiAed spatial as well as temporal patterns and trends in the rental price. The objective of the choice of each visualisation was to signify price behavior, seasonal variation, temporal evolution, and spatial variability at the district and neighborhood scales.

One of the greatest assets of this pipeline is that it delivers complex, multi-dimensional information in an understandable and useful form. The analysis is made understandable to technical and non-technical readers thats because I used visualizations that differentiate time-based trends, geographic heterogeneity, and intra-city disparity. Further, the embedding of granular views such as neighborhood-level treemaps and aggregated views like districtlevel bar charts allowed both macro and micro-level insights into the rental market.

However , The analysis is not without its limitations. First, the data only includes averaged or aggregated rent values, not by type of property, Zat size, or on speciAc terms of lease. Second, some visualisations like (scatter plots for each year) utilize only a small number of annual aggregated data points, which will weaken their statistical power and interpretability. In addition, it is harder to put rent changes into context using external supply-side or demandside forces when there are missing demographic, tourism, or economic data. For this , I had to do my own research about it .

Notwithstanding these limitations, the information obtained has several important implications for the business side of the housing industry. Most neighborhoods experienced stable long-term rises in rents, based on the Agures, whereas other areas, such as Sant Martí and Sarrià-Sant Gervasi, experienced considerably greater rent inZation. Seasonal analysis detected that rents rose signiAcantly over the summer, suggesting that tourism and shortterm rentals may have played a role. A leading indicator for localised investment and intervention policies, the treemap visualisation revealed intra-district differences by picking out neighbourhoods in affordable districts that have seen a steep increase in price.

From a business point of view, these results suggest both opportunities and risks. Highvolatility neighborhoods may be lucrative in the short term for real estate investors and developers but introduce more unpredictability. Areas with stable but low rental increase, however, can be safer and more desirable places to invest for the long term. Property managers can also use this information to vary pricing strategies according to seasonal

Zuctuations. Finally, housing policy groups might use these Andings to determine the most needy neighborhoods and communities that require rental subsidies and affordability initiatives.

Data-driven guidance for investors interested in Barcelona Real Estate:

1. Invest in development, low-volatility submarkets like Eixample and Gràcia, with consistently rising rents. (Jones et al. , 2005)
2. Switch pricing models or rental offerings to track and predict peak seasonality of demand, particularly during summer seasons.(Azevedo,2022)
3. Invest in purchasing and developing low-cost neighborhoods in high-growth districts prior to prices having completely caught up with whole-district averages.
4. To counter affordability concerns and retain long-term residents, call for policy priority in high-volatility neighborhoods like Ciutat Vella and Sant Martí.

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Github link :

https://github.com/khadijayadi/khadijayadi/blob/main/data_visualisation_Barcelona_rent_market_2014_2022_-2.ipynb

Gisma University of Applied Sciences

Assessment Submission Form

Student Number (If this is group work, please include the student numbers of all group participants)	GH1025231
Assessment Title	Analysing Barcelona's Rent Market between 2014–2022
Module Code	B106
Module Title	Data Visualisation (WS1224)
Module Tutor	Mehran Monavari
Date Submitted	27/03/2025

Declaration of Authorship

I declare that all material in this assessment is my own work except where there is clear acknowledgement and appropriate reference to the work of others.

I fully understand that the unacknowledged inclusion of another person's writings or ideas or works in this work may be considered plagiarism and that, should a formal investigation process confirms the allegation, I would be subject to the penalties associated with plagiarism, asper GISMA Business School, University of Applied Sciences' regulations for academic misconduct.

Signed……khadija ayadi ………………………………………… Date ……………………27/03/2025………………………