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In [1]:
```
#@title Helper Functions and Imports

from pydrive2.auth import GoogleAuth
from google.colab import drive
from pydrive2.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
import pandas as pd
import seaborn as sns
from matplotlib import pyplot as plt
import matplotlib as mpl
import numpy as np
from scipy.stats import pearsonr, spearmanr

# Some visual settings
sns.set()
mpl.rcParams['xtick.labelsize'] = 12
mpl.rcParams['ytick.labelsize'] = 12
mpl.rcParams['axes.labelsize'] = 14

RENT_ID = '1R6v2uHpFyNb1z2DT0M_JHTUE3PHFFYmu'
SOCIORANK_ID = '1gc57mT5zgIb-XeVsMfCphnWTRz1-dmLj'

def load_df(drive_id, **load_kwargs):
  auth.authenticate_user()
  gauth = GoogleAuth()
  gauth.credentials = GoogleCredentials.get_application_default()
  drive = GoogleDrive(gauth)
  download = drive.CreateFile({'id': drive_id})
  filename = '{}.csv'.format(drive_id)
  download.GetContentFile(filename)
  return pd.read_csv(filename, **load_kwargs)
```

Introduction to Data Science - Lab #2

Exploratory Data Analysis

Case Study: Rental Listings in Jerusalem

In this lab we will practice our exploratory data analysis skills using real data!

We will explore data of rental pricings in Jersualem. The dataset consists of listings published in https://www.komo.co.il/ during the summer of 2022.

We will use two python packages for visualizing the data: `matplotlib` (and specifically its submodule `pyplot` imported here as `plt`) and `seaborn` (imported as `sns`). Seaborn is a package that "wraps" matplotlib and introduces more convenient functions for quickly creating standard visualizations based on dataframes.

Please **breifly** go over this quick start guide to matplotlib, the first seaborn introduction page until the "Multivariate views on complex datasets" section (not included), and the second introduction page until the "Combining multiple views on the data" section.

In [2]:
```
#@title Loading the dataset
rent_df = load_df(RENT_ID)[['propertyID','neighborhood','monthlyRate','mefarsem',
                            'rooms','floor','area','entry','description','numFloors']]
rent_df = rent_df.drop_duplicates(subset='propertyID').reset_index(drop=True)
rent_df_backup_for_exercise = rent_df.copy()
clean_df_area_filtered = None
clean_df = None
```

Let's print a random sample:

In [3]:
```
np.random.seed(2)
rent_df.sample(5)
```

Out[3]:

	propertyID	neighborhood	monthlyRate	mefarsem	rooms	floor	area	entry	description	numFloors
403	3981729	גבעת מרדכי	4500.0	private	3.0	6.0	62.0	10/08/2022	דירה יפה, נקיה, ומשופצת לאחרונה. מתאים למשפחות...	8.0
457	3991612	קריית משה	3000.0	private	3.5	3.0	NaN	NaN	במחיר חסר תקדים! דירה בת 3.5 חדרים. ברחוב שושנ...	4.0
500	3976987	הגבעה הצרפתית	7800.0	private	4.0	11.0	118.0	10/08/2022	בבניין שתי מעליות, מעלית שבת. חניון תת קרקעי ע...	13.0
84	3985356	גילה	3600.0	private	2.0	1.0	60.0	10/08/2022	מקום מדהים ,קומה ראשונה,תחנת אוטובוס,גני ילדים...	1.0
109	3994714	קריית יובל	3500.0	private	2.0	1.0	55.0	10/08/2022	להשכרה דירת 3 חדרים שהפכו אותה ל2 חדרים, עם סל...	4.0

And print some summary statistics:

In [4]:
```
rent_df.describe(include='all')
```

Out[4]:

	propertyID	neighborhood	monthlyRate	mefarsem	rooms	floor	area	entry	description	numFloors
count	6.120000e+02	612	612.000000	612	612.000000	611.000000	295.000000	292	596	610.000000
unique	NaN	54	NaN	2	NaN	NaN	NaN	17	578	NaN
top	NaN	קריית יובל	NaN	private	NaN	NaN	NaN	10/08/2022	להשכרה, דירה, קומה ראשונה, בירושלים	NaN
freq	NaN	66	NaN	600	NaN	NaN	NaN	259	8	NaN
mean	3.981582e+06	NaN	4717.393791	NaN	2.927288	1.916530	87.664407	NaN	NaN	3.908197
std	6.525543e+04	NaN	2195.215139	NaN	1.007350	1.581006	277.004591	NaN	NaN	1.978065
min	2.494041e+06	NaN	0.000000	NaN	1.000000	-2.000000	1.000000	NaN	NaN	1.000000
25%	3.981694e+06	NaN	3500.000000	NaN	2.000000	1.000000	42.000000	NaN	NaN	3.000000
50%	3.987901e+06	NaN	4400.000000	NaN	3.000000	2.000000	60.000000	NaN	NaN	4.000000
75%	3.992605e+06	NaN	5800.000000	NaN	3.500000	3.000000	85.000000	NaN	NaN	4.000000
max	3.995088e+06	NaN	17000.000000	NaN	6.000000	11.000000	4554.000000	NaN	NaN	15.000000

The variables we will focus on are:

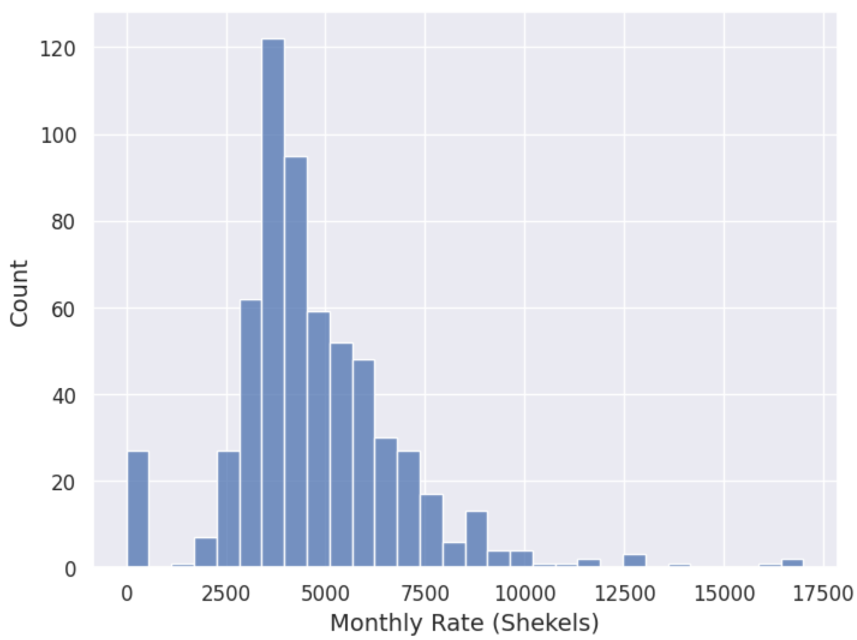
1. neighborhood: The hebrew name of the neighborhood in jerusalem where the listing is located
2. monthlyRate: The monthly rate (שכר דירה) in shekels
3. rooms: The number of rooms in the apartment
4. floor: The floor in which the apartment is located
5. area: The area of the apartment in squared meters
6. numFloors: The total number of floors in the building

What is the distribution of prices in this dataset?

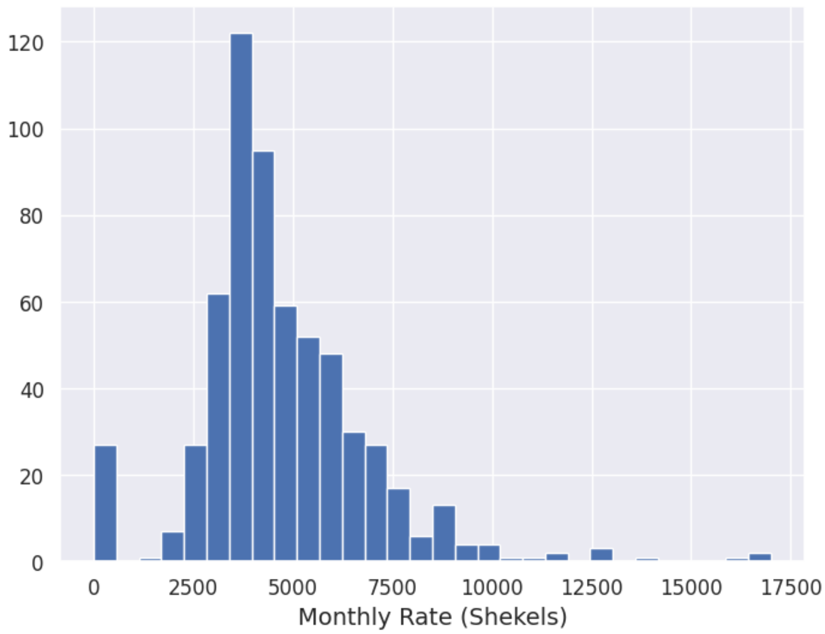
Q: Plot a histogram with 30 bins of the monthly rates in this dataset:

In [4]:

In [5]:
```
# @title Solution 1
plt.figure(figsize=(8,6))
sns.histplot(rent_df['monthlyRate'], bins=30)
plt.xlabel("Monthly Rate (Shekels)");
```



In [6]:
```
# @title Solution 2
rent_df["monthlyRate"].hist(bins=30, figsize=(8,6))
plt.xlabel("Monthly Rate (Shekels)");
```



We see that the prices distribution peaks around ~3500 Shekels and that it is right skewed, as there are some very expensive apartments. We can also see a peak at zero which makes sense as sometimes listings do not include a price. We would want to filter those out when we analyze prices later on.

Q: Print the number of listings that have no monthly rate:

In [7]:
```
# @title Solution
print("Number of apartments without a price: ", rent_df['monthlyRate'].value_counts()[0].round(3))
```

```
Number of apartments without a price:  25
```

We want to remove those listings, but we don't want to lose these entries, as we might want to know how many and what type of outliers we originally removed. So we create another dataframe that has the listings we removed and the reason for removal.

In [8]:
```
outlier_df = pd.DataFrame(columns=rent_df.columns.to_list()+['reason']) # will save the outliers

outliers = rent_df[rent_df['monthlyRate'] <= 0].reset_index(drop=True)
outliers['reason']= "monthlyRate <= 0"
outlier_df = pd.concat([outlier_df, outliers], axis=0, ignore_index=True).drop_duplicates().reset_index(drop=True)
outlier_df.tail()
```

Out[8]:

	propertyID	neighborhood	monthlyRate	mefarsem	rooms	floor	area	entry	description	numFloors	reason
20	3983978	קריית משה	0.0	private	4.0	3.0	100.0	10/08/2022	דירת 4 חדרים - במצב מצויין - שמורה ביותר כולל ...	5.0	monthlyRate <= 0
21	3985184	נווה יעקב	0.0	private	4.0	1.0	68.0	10/08/2022	דירה במצב שמור מאד. ממוזגת, 2 חדרי שירותים (אח...	2.0	monthlyRate <= 0
22	3952750	מוסררה	0.0	private	5.5	1.0	180.0	10/08/2022	להשכרה דירה מפוארת, במרכז העיר מרחק הליכה מהע...	4.0	monthlyRate <= 0
23	3988157	גבעת שאול	0.0	private	5.0	1.0	140.0	10/08/2022	בית פרטי שתי קומות שימש בעבר לגן מתאים לכל מתרה...	2.0	monthlyRate <= 0
24	3981160	גבעת משואה	0.0	private	6.0	-2.0	NaN	NaN	מול נוף עוצר נשימה, 6 חדרים מרווחים, מרפסת 70 ...	5.0	monthlyRate <= 0

We will now remove those listings and save the result to a new variable `clean_df` :

In [9]:
```
clean_df = rent_df[rent_df['monthlyRate'] > 0].reset_index(drop=True)
```

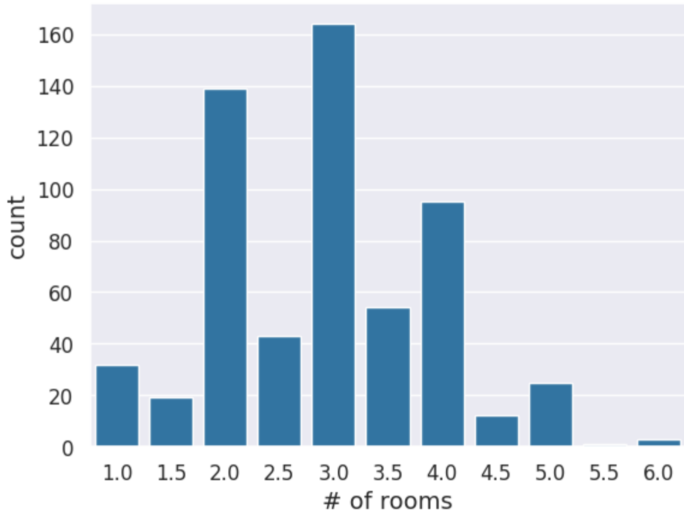
What is the distribution of the number of rooms?

Q: Use `sns.countplot` to compare the counts of listings with different numbers of rooms. Plot all bars in the same color of your choice.

In [9]:

In [10]:
```
# @title Solution
if clean_df is None:
```

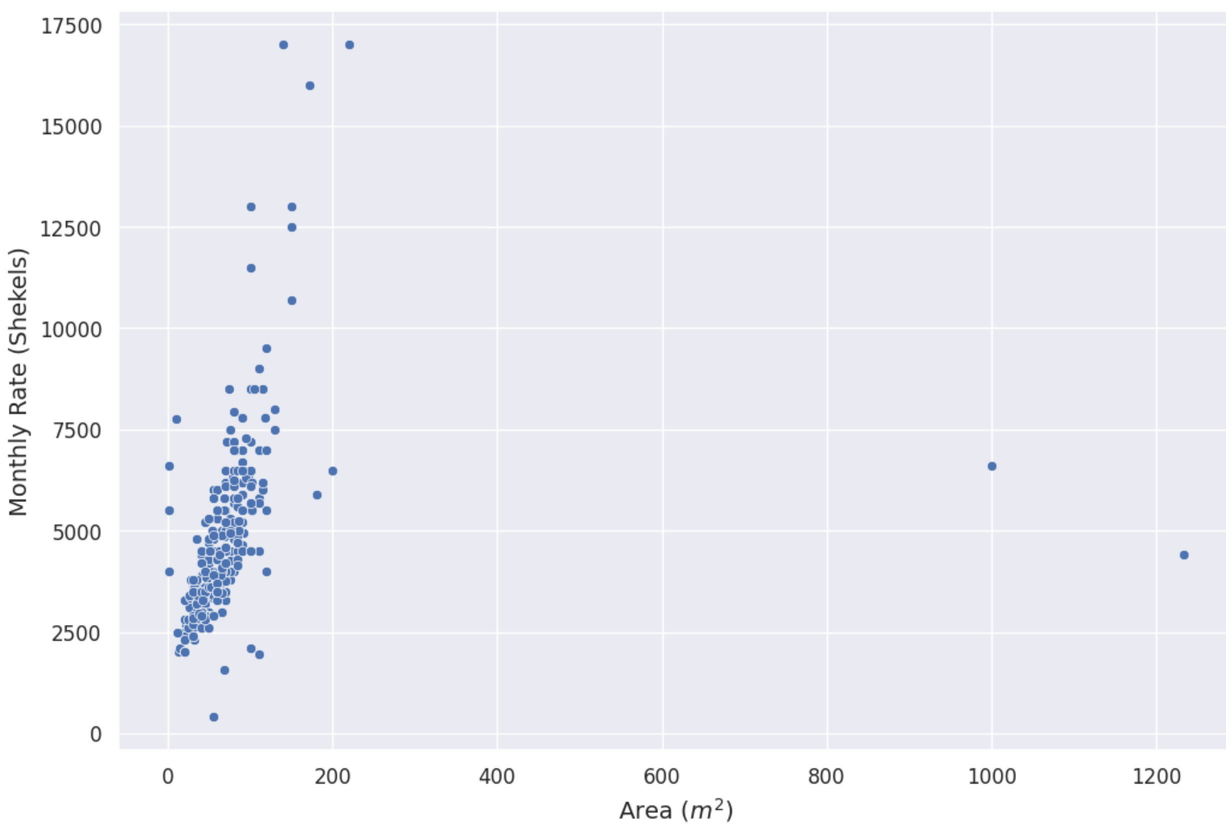
```
    print("Can't run until 'clean_df' is created!")
else:
    sns.countplot(x='rooms', data=clean_df, color='tab:blue')
    plt.xlabel("# of rooms");
```



The distribution peaks at three rooms and we also see that "half rooms" are less common.

Can we see an association between apartment area and price?

In [11]:
```
if clean_df is None:
    print("Can't run until 'clean_df' is created!")
else:
    plt.figure(figsize=(12,8))
    sns.scatterplot(x='area', y='monthlyRate', data=clean_df)
    plt.ylabel("Monthly Rate (Shekels)")
    plt.xlabel("Area ($m^2$)");
```



We see clear outliers here! We know that area is measured in squared meters and it is unlikely that there are any apartments of ~1000m^2.

Let's look at those samples to see if we can understand what happend there:

In [12]:
```
if clean_df is None:
    print("Can't run until 'clean_df' is created!")
else:
```

```
display(clean_df.sort_values('area', ascending=False).head(4))
```

	propertyID	neighborhood	monthlyRate	mefarsem	rooms	floor	area	entry	description	numFloors
185	3964340	תלפיות	4400.0	private	2.0	2.0	1234.0	10/08/2022	NaN	3.0
543	3956561	זכרון משה	6600.0	private	3.5	3.0	1000.0	01/07/2022	דירה מהממת בלב ירושלים. צמודה לרכבת הקלה- תחנת...	3.0
576	3974914	תלפיות	17000.0	private	5.0	3.0	220.0	10/08/2022	... דירת 5 חדרים ענקית ומהממת, בבנין בוטיק ויחודי	4.0
566	3988577	פסגת זאב	6500.0	private	5.5	1.0	200.0	10/08/2022	... דירה בת 5.5 חדרים . בקומה התחתונה סלון , מטבח	3.0

And inspect the description of one of those listings:

In [13]:
```
if clean_df is None:
  print("Can't run until 'clean_df' is created!")
else:
  display(clean_df.at[543,'description'])
```

'דירה מהממת בלב ירושלים. צמודה לרכבת הקלה- תחנת הדוידקה. 3 חדרים ענקיים ולכל חדר מרפסת גדולה. חלל כניסה עם פינת ישיבה. מתאימה מאוד ל- 3 שותפים'

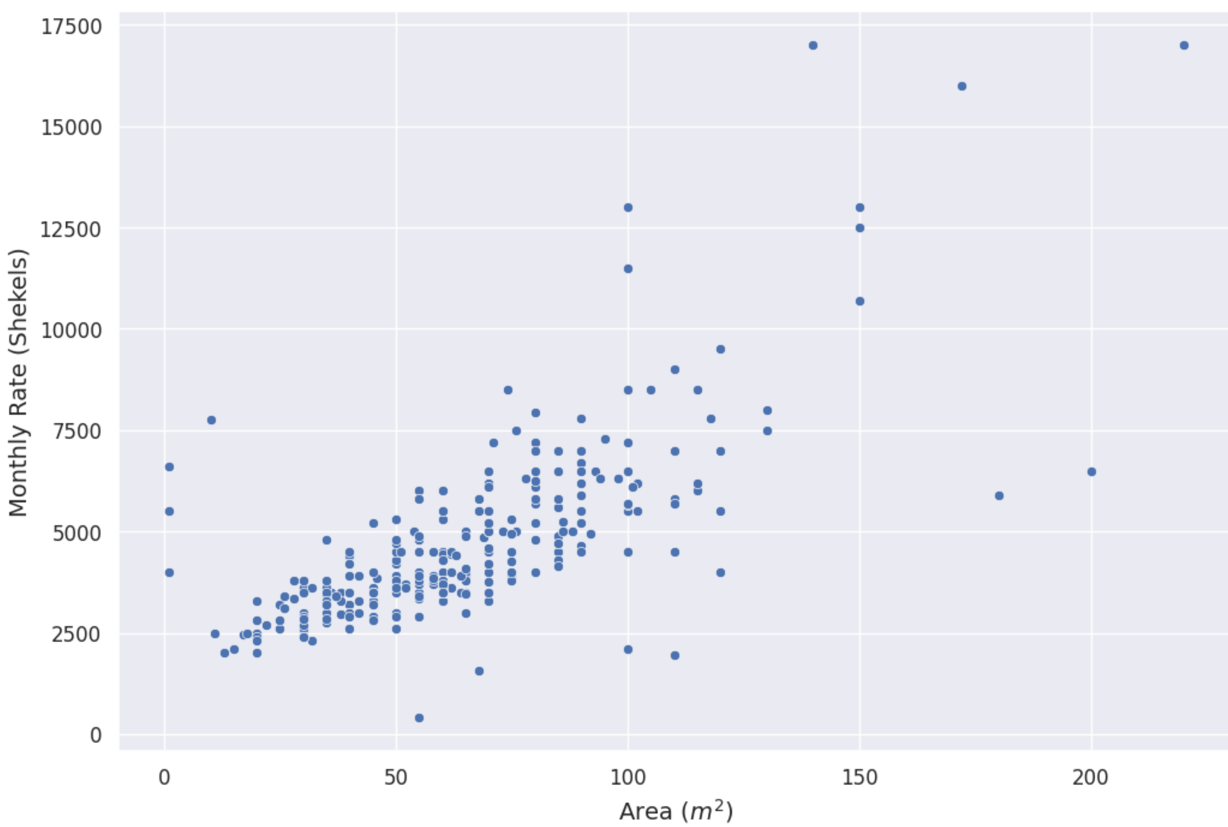
Clearly not a 1000 m^2 apartment...

Q: Save a new dataframe named `clean_df_area_filtered` with all listings with area smaller than 800 m^2. Again, add the removed outliers to the outliers_df dataframe.

Plot again the scatter of area vs. monthly rate after removing the outliers.

In [13]:
```

```

In [14]:
```
# @title Solution
if clean_df is None:
  print("Can't run until 'clean_df' is created!")
elif outlier_df is None:
  print("Can't run until 'outlier_df' is created!")
else:
  # save outliers
  outliers = clean_df[clean_df['area'] >= 800].reset_index(drop=True)
  outliers['reason']= "'area' >= 800"
  outlier_df = pd.concat([outlier_df, outliers], axis=0, ignore_index=True).drop_duplicates().reset_index(drop=True)

  # remove the outliers from the dataset
  clean_df_area_filtered = clean_df[clean_df['area'] < 800].reset_index(drop=True)
  plt.figure(figsize=(12,8))
  sns.scatterplot(x='area', y='monthlyRate', data=clean_df_area_filtered)
  plt.xlabel("Area ($m^2$)")
  plt.ylabel("Monthly Rate (Shekels)");
```



Again, we see some strange behavior of apartments with almost zero area but with a high monthly rate. Let's check them out:

We start with all apartments with an area between 0 to 25 m^2:

In [15]:
```python
# Show all apartments with area between 0 and 25
clean_df_area_filtered[clean_df_area_filtered['area'].between(0,25)]
```

Out[15]:

	propertyID	neighborhood	monthlyRate	mefarsem	rooms	floor	area	entry	description	numFloors
0	3994505	קריית יובל	2000.0	private	1.0	2.0	13.0	10/08/2022	יחידת דיור להשכרה ברחוב הראשי של קריית יובל, ה...	2.0
1	3981298	רחביה	2450.0	private	1.0	1.0	17.0	10/08/2022	דירת יחיד 17 מטר כולל מרפסת קטנה	3.0
3	3993997	בית וגן	2100.0	private	1.0	0.0	15.0	10/08/2022	דירת חדר, כ-15 מ"ר, במיקום מרכזי אך שקט, משופצ...	3.0
5	3993552	הר נוף	2000.0	private	1.0	0.0	20.0	10/08/2022	יחידה משופצת ליחיד או למשרד , מיקום מצוין	4.0
6	3972039	גבעת שאול	2700.0	private	1.0	0.0	22.0	10/08/2022	דירת חדר כחדשה , כניסה נפרדת ללא וועד בית , מו...	1.0
7	3988096	המושבה הגרמנית	2500.0	private	1.0	0.0	18.0	10/08/2022	רלוונטי לנשים בלבד. ללא עישון. ללא חיות מחמד. ...	1.0
8	3992809	נחלאות	3200.0	private	1.0	2.0	25.0	10/08/2022	הדירה המגניבה בנחלאות, מתפנה אחרי תקופה ארוכה ...	2.0
10	3983516	הגבעה הצרפתית	2000.0	private	1.0	2.0	20.0	10/08/2022	דירת חדר קטנה, מסוגננת ונחמדה, מתאימה ליחיד בל...	13.0
12	3987706	נחלאות	2800.0	private	1.0	0.0	20.0	10/08/2022	להשכרה, דירה, בירושלים ברחוב חצור בנחלאות. דיר...	2.0
13	3991842	קטמון הישנה	2500.0	private	1.0	1.0	20.0	10/08/2022	דירת חדר ליחיד באזור יפייפה ושקט בקטמון הישנה....	4.0
14	3992479	קריית יובל	2400.0	private	1.0	1.0	20.0	10/08/2022	דירת חדר חמודה עם גינה קטנה משותפת,מתאים ליחיד...	1.0
15	3974372	תל ארזה	2500.0	private	1.0	0.0	11.0	10/08/2022	להשכרה, דירת חדר , בירושלים	4.0
19	3985106	קטמונים	2300.0	private	1.0	0.0	20.0	10/08/2022	דירת חדר חמודה עם חצר במיקום מרכזי. כמה דק' ה...	3.0
21	3985295	מוסררה	2600.0	private	1.5	0.0	25.0	10/08/2022	אזור חרדי. מיקום מרכזי קרוב להכול. מרוהטת מלא	4.0
27	3982008	קריית יובל	2800.0	private	1.5	0.0	25.0	10/08/2022	הדירה נמצאת ברחוב שקט 7 דקות הליכה מעין כרם יש...	3.0
28	3990245	מחנה יהודה	3300.0	private	1.5	1.0	20.0	10/08/2022	NaN	4.0
79	3992532	רמות	2000.0	private	2.0	0.0	20.0	10/08/2022	דירה חמודה ברמות מגיעה עם מזגן ומכונת כביסה די...	4.0
122	3986473	בית וגן	4000.0	private	2.5	2.0	1.0	10/08/2022	להשכרה, דירה, קומה 2, בירושלים	2.0
197	3984483	ארנונה	6600.0	private	4.0	2.0	1.0	01/09/2022	בשכונת ארנונה, רח' שלום יהודה, דירת 4 חדרים מש...	4.0
234	3985019	פסגת זאב	5500.0	private	4.0	3.0	1.0	10/08/2022	להשכרה 4 חדרים מרווחת עם מרפסת סוכה שטופת שמש ...	4.0
235	3944204	בית הכרם	7750.0	private	4.0	3.0	10.0	01/09/2022	בבניין חדש, מושקעת, מוארת, מאווררת רח' שקט, רח...	5.0
274	3982178	נווה יעקב	5500.0	private	5.0	1.0	1.0	10/08/2022	דירה במצב מעולה!! נוף, מוארת, מאווררת, מרפסת סוכה	4.0

Some make sense and others do not. Let's focus on the expensive ones (between 5,000 and 10,000 shekels):

In [16]:
```python
# Show all apartments with area between 0 and 25 that also have a price between 5000 and 10000
if clean_df_area_filtered is None:
  print("Can't run until 'clean_df_area_filtered' is created!")
else:
  display(clean_df_area_filtered[clean_df_area_filtered['area'].between(0,25) & clean_df_area_filtered['monthlyRate'].between(5000, 10000)])
```

	propertyID	neighborhood	monthlyRate	mefarsem	rooms	floor	area	entry	description	numFloors
197	3984483	ארנונה	6600.0	private	4.0	2.0	1.0	01/09/2022	בשכונת ארנונה, רח' שלום יהודה, דירת 4 חדרים מש...	4.0
234	3985019	פסגת זאב	5500.0	private	4.0	3.0	1.0	10/08/2022	להשכרה 4 חדרים מרווחת עם מרפסת סוכה שטופת שמש ...	4.0
235	3944204	בית הכרם	7750.0	private	4.0	3.0	10.0	01/09/2022	בבניין חדש, מושקעת, מוארת, מאווררת רח' שקט, רח...	5.0
274	3982178	נווה יעקב	5500.0	private	5.0	1.0	1.0	10/08/2022	דירה במצב מעולה!! נוף, מוארת, מאווררת, מרפסת סוכה	4.0

Those are clearly wrong too... Besides that the relationship between the area and the price seems linear. Let's remove these outliers too:

In [17]:
```python
#remove the outliers
if clean_df_area_filtered is None:
  print("Can't run until 'clean_df_area_filtered' is created!")
elif outlier_df is None:
  print("Can't run until 'outlier_df' is created!")
else:
  non_ouliers = clean_df_area_filtered['area'] > 10 # get non outliers series of true/false

  # save outliers
  outliers = clean_df_area_filtered[~non_ouliers].reset_index(drop=True) # get the outliers
  outliers['reason']= "'area' <= 10"
  outlier_df = pd.concat([outlier_df, outliers], axis=0, ignore_index=True).drop_duplicates().reset_index(drop=True)

  # remove them
  clean_df_area_filtered = clean_df_area_filtered[non_ouliers].reset_index(drop=True)
```

Can we see a different pattern for top floor apartments?

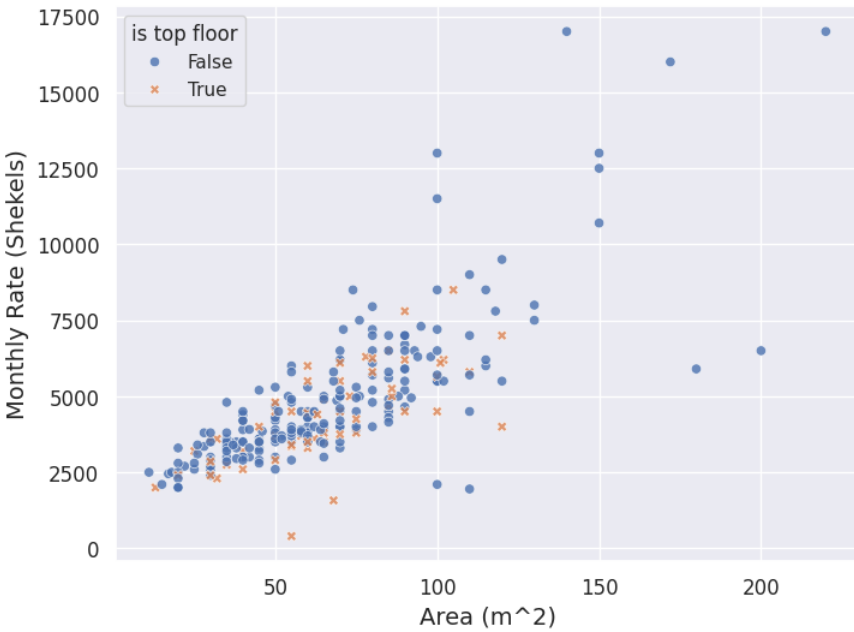
Q: Plot again a scatter of area vs. monthly rate. This time distinguish (by color / marker style or both) between apartments that are in the top floor and the rest of the apartments. (To do that you should create a new column in `clean_df_area_filtered` called `is top floor` and set it to 1 if the apartment is in the top floor and 0 otherwise.)

In [17]:

```
```

In [18]:

```
# @title Solution

if clean_df_area_filtered is None:
  print("Can't run until 'clean_df_area_filtered' is created!")
else:
  clean_df_area_filtered['is top floor'] = clean_df_area_filtered['floor'] == clean_df_area_filtered['numFloors']
  plt.figure(figsize=(8,6))
  sns.scatterplot(x='area', y='monthlyRate', data=clean_df_area_filtered, alpha=0.8, hue='is top floor', style="is top floor");
  plt.xlabel("Area (m^2)")
  plt.ylabel("Monthly Rate (Shekels)");
```



We can take a deeper look on the apartments with the very high monthly rate (to see if those are outliers or not):

In [19]:

```
if clean_df_area_filtered is None:
  print("Can't run until 'clean_df_area_filtered' is created!")
else:
  display(clean_df_area_filtered[clean_df_area_filtered['monthlyRate'] > 11000])
```

	propertyID	neighborhood	monthlyRate	mefarsem	rooms	floor	area	entry	description	numFloors	is top floor
198	3956418	רחביה	13000.0	agent	4.0	1.0	100.0	NaN	Beautifully renovated furnished authentic arab...	3.0	False
236	3985051	טלביה	17000.0	private	4.0	4.0	140.0	10/08/2022	בקינג דיוד רזדנס דירת 4 חדרים להשכרה ללא תיו...	10.0	False
257	3982363	רחביה	16000.0	private	5.0	2.0	172.0	10/08/2022	הזדמנות נדירה!!! ברחוב רד"ק, בנקודה הכי קרובה ...	5.0	False
260	3980016	אבו תור	12500.0	private	5.0	0.0	150.0	10/08/2022	דירת דופלקס ענקית 150 מ"ר עם כניסה נפרדת. הדיר...	4.0	False
263	3994228	בית ישראל	11500.0	private	5.0	1.0	100.0	10/08/2022	דירה ממוקמת בלב ירושלים שכונת בית ישראל, מרפסת...	3.0	False
266	3974914	תלפיות	17000.0	private	5.0	3.0	220.0	10/08/2022	דירת 5 חדרים ענקית ומהממת, בבנין בוטיק ויחודי ...	4.0	False
270	3981999	תלפיות	13000.0	private	5.0	4.0	150.0	10/08/2022	דירת 5 חדרים חדשה! בדירה יש מרפסת מרפסת שירו...	5.0	False

We can see some representation of the more expensive neighborhoods of Jerusalem here.. More on the neighborhoods later on!

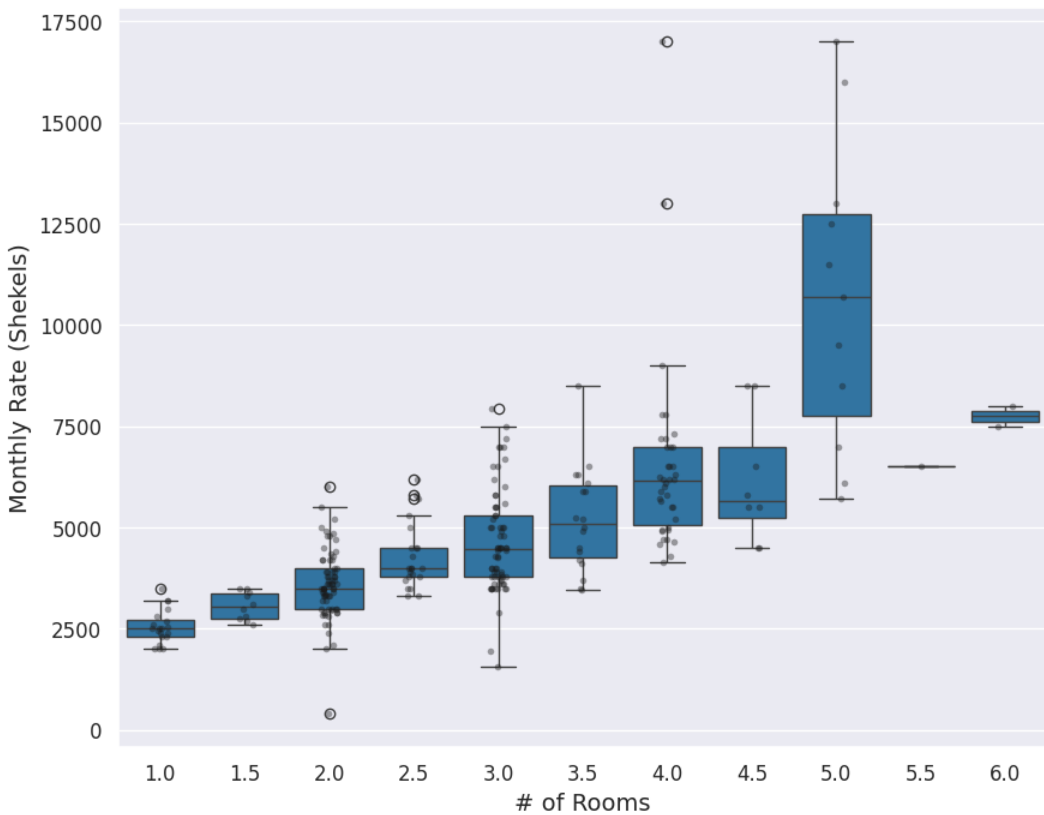
Is there also a relation between the number of rooms and the listing price?

Q: Create a visualization that compares the distribution of prices for different number of rooms. Your visualization should provide information about central tendency (mean/median/mode) and some information about the distribution of individual values around it (standard deviation/interquartile range) for each number of rooms. Also, show the real prices of the listings per number of rooms.

In [20]:

```
# @title Solution
if clean_df_area_filtered is None:
  print("Can't run until 'clean_df_area_filtered' is created!")
else:
  plt.figure(figsize=(10,8))
  sns.boxplot(x='rooms', y='monthlyRate', data=clean_df_area_filtered, color='tab:blue')
  sns.stripplot(x='rooms', y='monthlyRate', alpha=0.4 ,size=4,color='k',data=clean_df_area_filtered)
  plt.xlabel("# of Rooms")
  plt.ylabel("Monthly Rate (Shekels)");
```

```
# Or:
# plt.figure(figsize=(10,8))
# sns.barplot(x='rooms', y='monthlyRate', data=clean_df_area_filtered, color='tab:blue', errorbar=None, estimator='median')
# # Can also use mean but median is more informative in this case as prices are skewed...
# sns.stripplot(x='rooms', y='monthlyRate', alpha=0.4 ,color='k',data=clean_df_area_filtered)
# plt.xlabel("# of Rooms")
# plt.ylabel("Monthly Rate (Shekels)");

#Violin plot completly fails for very small subsets:
# plt.figure(figsize=(10,8))
# sns.violinplot(x='rooms', y='monthlyRate', data=clean_df_area_filtered, color='tab:blue')
# plt.xlabel("# of Rooms")
# plt.ylabel("Monthly Rate (Shekels)");
```



Now that we finished pre-processing the data, we can see the state of our outliers VS the data that remains:

In [21]:
```
if outlier_df is None:
  print("Can't run until 'outlier_df' is created!")
else:
  # describe the outlier data
  display(outlier_df.groupby('reason').describe())
  print(f"Proportion removed: {100*len(outlier_df) / (len(outlier_df)+len(clean_df_area_filtered)):.0f} %")
```

							monthlyRate			rooms	...		area							numFloor	
	count	mean	std	min	25%	50%	75%	max	count	mean	...	75%	max	count	mean	std	min	25%	50%	75%	ma
reason																					
'area' <= 10	5.0	5870.0	1399.821417	4000.0	5500.0	5500.0	6600.0	7750.0	5.0	3.90	...	1.0	10.0	5.0	3.80	1.095445	2.0	4.0	4.0	4.0	5.
'area' >= 800	2.0	5500.0	1555.634919	4400.0	4950.0	5500.0	6050.0	6600.0	2.0	2.75	...	1175.5	1234.0	2.0	3.00	0.000000	3.0	3.0	3.0	3.0	3.
monthlyRate <= 0	25.0	0.0	0.000000	0.0	0.0	0.0	0.0	0.0	25.0	3.28	...	99.0	4554.0	25.0	3.48	2.293469	1.0	2.0	3.0	4.0	11.

3 rows × 40 columns

```
Proportion removed: 10 %
```

Submission Exercises

Part 1: Diving deeper into rental prices

We will create a copy of the dataset and work on that. We want to make sure that we do not modify the original dataset.

In [22]:
```
# @title Part 1 - Create a DataFrame
part1_df = rent_df_backup_for_exercise.copy()
```

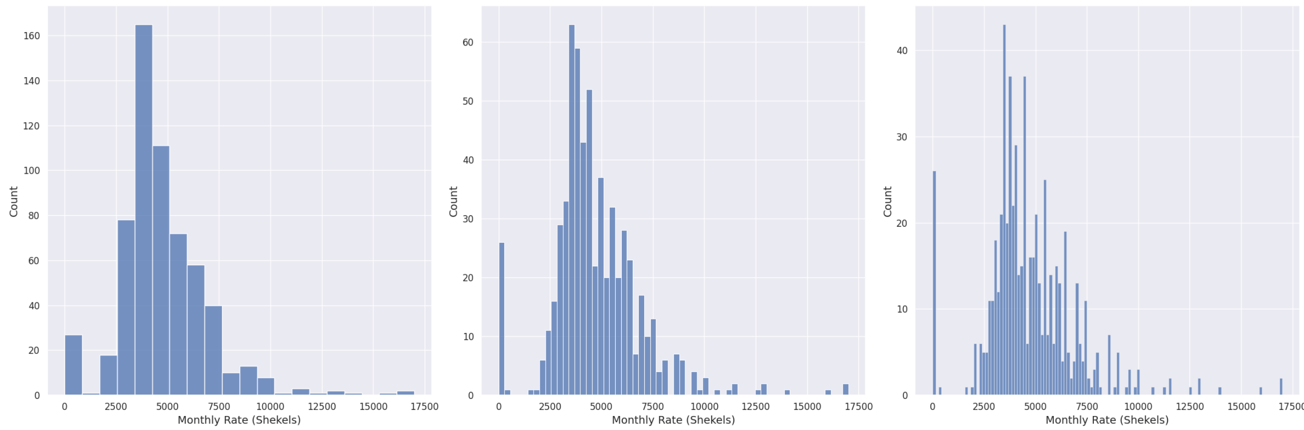
Let's go back to the distribution of monthly rental prices in the dataset. Are there interesting trends in the distribution that we missed in the visualizations before?

Use only `part1_df` for the coding questions in this part

Question 1

Plot 3 different histograms of the monthly prices with 20, 60 and 120 bins respectively, each in a different axis/figure.

In [23]:
```
# Part 1 - Question 1
fig, axes = plt.subplots(1,3, figsize=(24,8))
veci= [20,60,120]
for i,bins in enumerate(veci):
  sns.histplot(part1_df['monthlyRate'], bins= bins,ax=axes[i])
  axes[i].set_xlabel("Monthly Rate (Shekels)")
  plt.tight_layout()
```



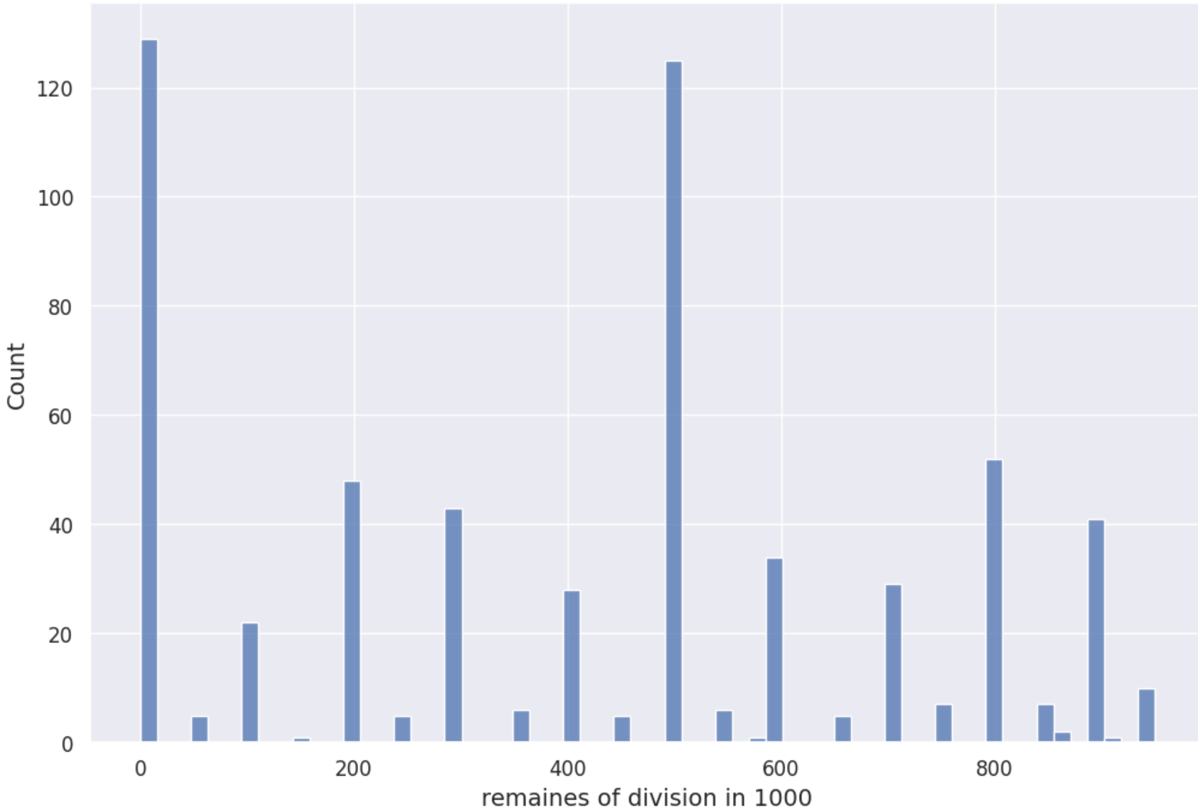
Question 2

For 60 and 120 bins, you can see a repeating pattern of "peaks" and "vallies" in the distribution (mostly in the range between 500 and 7000). Is this pattern due to people rounding the rental prices? Please create a visualization that answers this question. Describe in words how the graph shows what the answer is (Hint: you can use the '%' operator to compute the remainder of dividing values in a pandas Series by a scalar number).

In [24]:
```
# @title **extra hint**: please open this cell only after discussing with the course staff the best solution you could come up with

#
# Plot the distribution of values of the 'monthlyRate' column modulu (%) 1000
#
```

In [25]:
```
# Part 1 - Question 2
leftovers= part1_df['monthlyRate']% 1000
fig, axes = plt.subplots( figsize=(12,8))
sns.histplot(leftovers, bins= 60)
plt.xlabel("remaines of division in 1000")
```

Out[25]: `Text(0.5, 0, 'remaines of division in 1000')`



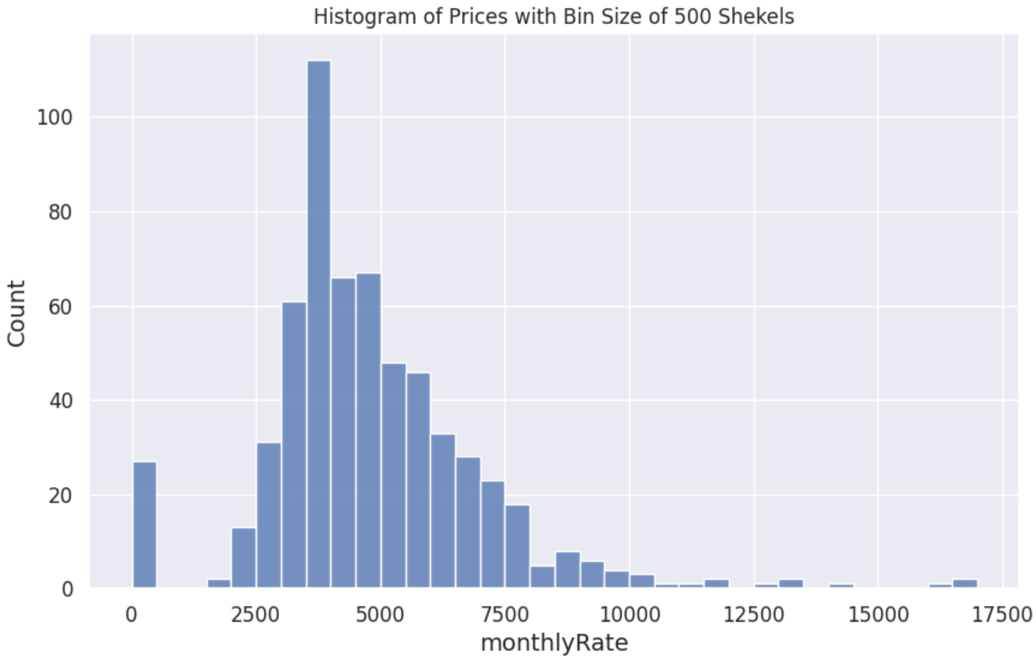
Part 1 Question 2 - textual Answer:

Yes, this pattern is due to that people tend to round the rental prices. The graph shows that the remainder of rental prices when divided by 1000. It can be seen that there are two modes: 0 and 500. This suggests that people tend to round rental prices to the nearest thousand or five hundred. Therefore, the most common remainders when dividing most observations in the sample by 1000 is either 500 or 0.

Question 3

We expect to see a "drop" in prices frequency near the 5000 Shekels mark due to tax considerations (See here for an explanation). Create a histogram visualization of the data with the smallest possible bins such that every bin will include exactly one multiplication of 500 (Hint: read the `bins` parameter documentation and what types it accepts). Explain why does this choice of bin size ensures that we will not see rounding effects. Do you see a "drop" around 5000 Shekels? Are there other "drops"?

In [26]:
```
# Part 1 - Question 3
bin_edges = np.arange(0, part1_df['monthlyRate'].max() + 500, 500)
plt.figure(figsize=(10, 6))
sns.histplot(part1_df['monthlyRate'], bins=bin_edges)
plt.xlabel('monthlyRate')
plt.title('Histogram of Prices with Bin Size of 500 Shekels')
plt.show()
```



Part 1 Question 3 - textual Answer:

Using bins of 500 Shekels ensures that each bin captures only one rounding effect (either to the nearest 500 or 1000), thus isolating the rounding effects and providing a more accurate distribution of rental prices. This method prevents overlapping and skewing caused by rounding, allowing us to see the true distribution patterns. There's a "drop" around 5000 Shekels, but there are also drops around there 7500 Shekels, and one before 2500.

Part 2: Size or number of rooms?

In [27]:
```
# @title Part 2 - Create a DataFrame for Part 2

# Create the dataframe and remove the outliers we found in the intro part:
part2_df = rent_df_backup_for_exercise.copy()
part2_df = part2_df[part2_df['monthlyRate'] > 0].reset_index(drop=True);
part2_df = part2_df[part2_df['area'] < 800].reset_index(drop=True)
part2_df = part2_df[part2_df['area'] > 10].reset_index(drop=True)
```

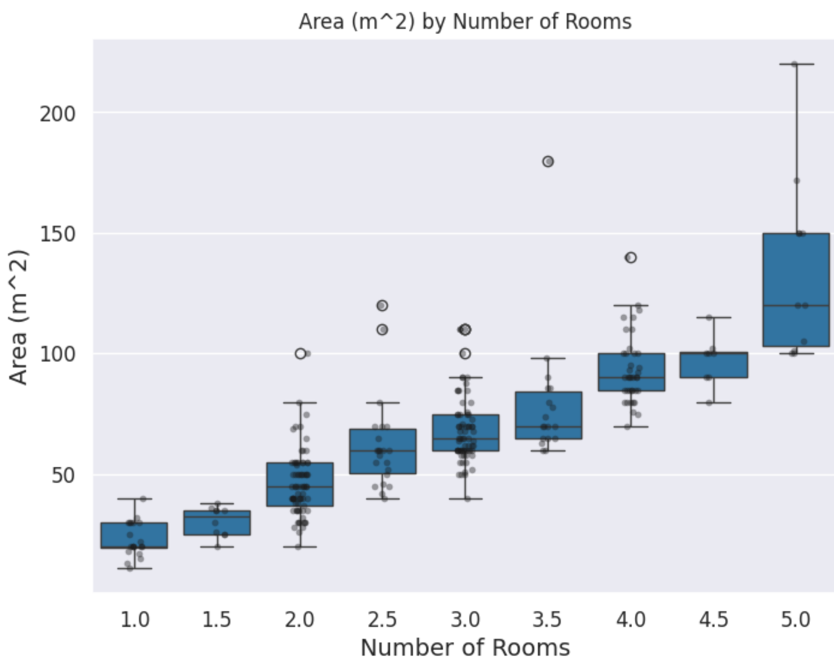
We saw that both the number of rooms and the area of an apartment are strongly associated with the monthly rate. We now want to check if those are just two perspectives of the same relation (how big is the apartment) or is there something more to it. We will use the cleaned dataframe for this exercise.

Use only `part2_df` for the coding questions in this part

Question 1

Generate a visualization to show that there is a strong association between the number of rooms and the area of the apartment. Explain your choice of plot type and your conclusion from the graph.

In [28]:
```
# Part 2 - Question 1

if part2_df is None:
  print("Can't run until 'part2_df' is created!")
else:
  plt.figure(figsize=(8,6))
  sns.boxplot(x='rooms', y='area', data=part2_df, color='tab:blue')
  sns.stripplot(x='rooms', y='area', alpha=0.4 ,size=4,color='k',data=part2_df)
  plt.xlabel("Number of Rooms")
  plt.ylabel("Area (m^2)")
  plt.title("Area (m^2) by Number of Rooms")
  plt.xlim(left=None, right=8.5)  # x-axis limit
  plt.show()
```



Part 2 Question 1 - textual Answer:

We have chosen a boxplot and strip plot, where the number of rooms is the x-axis and the area in sq-m is the y-axis.

These are good here since those plots can show well the different percentiles and distribution, as well as variation of apartments' areas, according to different number of rooms in each apartment.

We can see that there is a strong positive correlation between the two variables, showing that large in size apartment tend to have more rooms.

Question 2

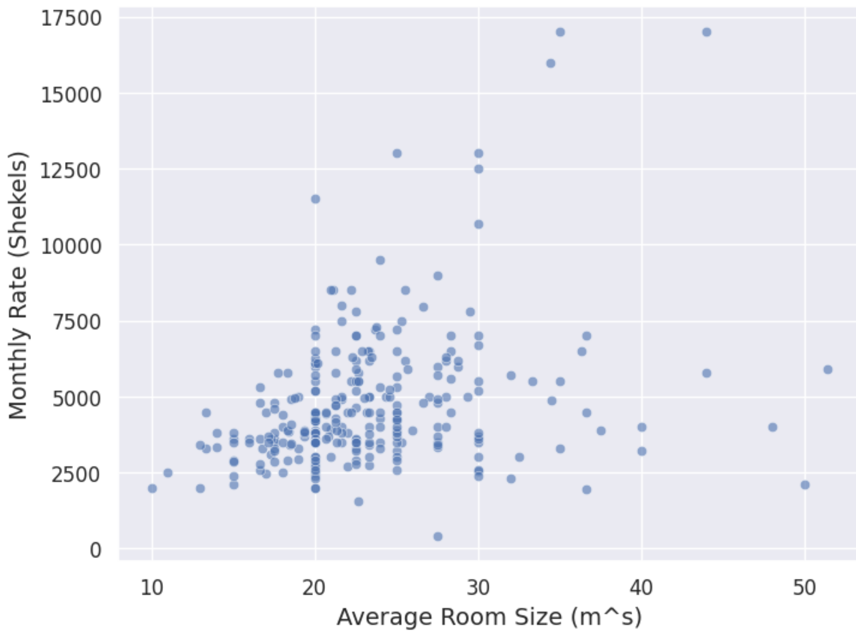
Add a new column to the dataframe named `"averageRoomSize"` with the average room size in the given listing.

In [29]:
```
# Part 2 - Question 2

part2_df['averageRoomSize'] = part2_df['area'] / part2_df['rooms']
#part2_df.tail()
```

Question 3

Create a plot of the relation between the average room size and the monthly rate.

In [30]:
```
# Part 2 - Question 3

if part2_df is None:
  print("Can't run until 'part2_df' is created!")
else:
  plt.figure(figsize=(8,6))
  sns.scatterplot(x='averageRoomSize', y='monthlyRate', data=part2_df, alpha=0.6)
  plt.xlabel("Average Room Size (m^s)")
  plt.ylabel("Monthly Rate (Shekels)");
  plt.show()
```



We can see that overall there is a positive correlation between the average room size and monthly rate, meaning thet rise together. However, this relationship is shown as the average room size <= 30, and above that, we can see that some apartments have a very high monthly rate (supporting the positive correlation), yet some apartments have larger room sizes with rental prices that are similar to prices of smaller rooms.

This variation may be resulted from larger variation of rental prices across neighborhoods, as a room's average size can be more expensive in one neighborhood that another neighborhood.

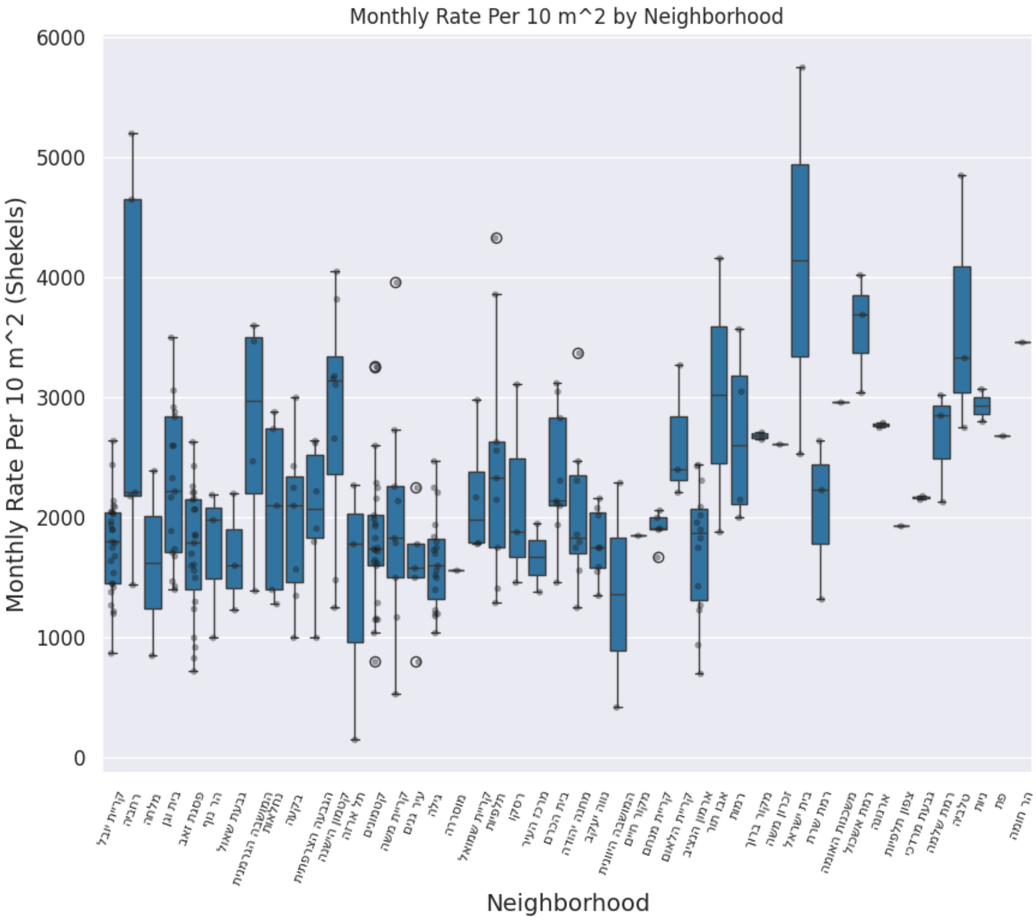
Question 4 - **bonus**

We can see that the variance of the monthly rate increases with the average room size.

Suggest what might be the reason for the increase in the variance and create a visualization to support or refute your suggestion.

In [31]:
```
# Part 2 - Question 4

# neighborhood's number
part2_df['neighborhood'].unique()
print("Number of Neighborhoods: ", len(part2_df['neighborhood'].unique()))  # 46 neighborhoods

# making the neighborhood names readable
def reverse_string(a):
  return a[::-1]
part2_df["neighborhood_flipped"] = part2_df["neighborhood"].apply(reverse_string)

# create varible Monthly Rate Per 10 m^2
part2_df['monthlyRatePer10m2'] = part2_df['monthlyRate'] / part2_df['averageRoomSize'] * 10
part2_df.head()

if part2_df is None:
  print("Can't run until 'part2_df' is created!")
else:
  plt.figure(figsize=(10,8))
  sns.boxplot(x='neighborhood_flipped', y='monthlyRatePer10m2', data=part2_df, color='tab:blue')
  sns.stripplot(x='neighborhood_flipped', y='monthlyRatePer10m2', alpha=0.4 ,size=4,color='k',data=part2_df)
  plt.xlabel("Neighborhood")
  plt.ylabel("Monthly Rate Per 10 m^2 (Shekels)")
  plt.title("Monthly Rate Per 10 m^2 by Neighborhood")
  plt.xticks(rotation=70, fontsize=8)  # Rotate x-axis labels
  plt.show()
```

```
Number of Neighborhoods:  46
```



Part 2 Question 4 - textual Answer:

We think that the neighborhood could influence in variation of the increase in monthly rate with room size.

Therefore a boxplot of the average room size and the monthly rate per neighborhood can show that the neighborhood is one of the causes of the higher variation in monthly rate over different average room sizes.

Thus maybe if we normalize the monthly rent for 10m^2 in each neighborhood we will see that neighborgoods can influence the variation in rental prices and average room size.

Rehavia for example is a more expensive neighborhood per 10m^2 and is skewed to right and has a large variation, whereas Kiryat Menachem or Ir Ganim are less expenstive so that even as a room in average is larger, its price isn't necessarily more expensive.

Part 3: Neighborhoods

In [32]:
```
# @title Part 3 - Function Definitions and DataFrame Creation
def reverse_string(a):
  return a[::-1]


socialrank_df = load_df(SOCIORANK_ID)
neighborhood_ranks = {k: v for k,v in zip(socialrank_df['neighborhood'], socialrank_df['socioEconomicRank'])}

def get_neighborhood_rank(neighborhood):
  if neighborhood in neighborhood_ranks:
    return neighborhood_ranks[neighborhood]
  else:
    return None

# Create the dataframe and remove the outliers we found in the intro part:
part3_df = rent_df_backup_for_exercise.copy()
part3_df = part3_df[part3_df['monthlyRate'] > 0].reset_index(drop=True);
part3_df = part3_df[part3_df['area'] < 800].reset_index(drop=True)
part3_df = part3_df[part3_df['area'] > 10].reset_index(drop=True)
part3_df["neighborhood_flipped"] = part3_df["neighborhood"].apply(reverse_string) # making the neighborhood names readable
```

We now want to focus on the differences between different neighborhoods in Jerusalem.

Use only `part3_df` for the coding questions in this part

*Use the `"neighborhood_flipped"` column for visualizations as seaborn will flip the order of letters in hebrew.

Question 1

Print the number of unique neighborhoods that appear in the dataset.

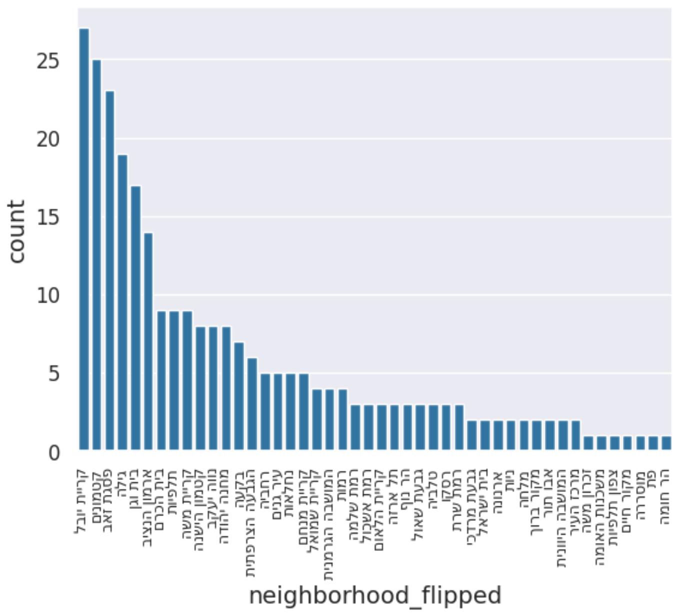
In [33]:
```
# Part 3 - Question 1
print(len(np.unique(part3_df["neighborhood"])))
```

```
46
```

Question 2

Visualize the number of listings per neighborhood in a way that will allow you to easily identify those with the highest count.

In [34]:
```
# Part 3 - Question 2
sns.countplot(x='neighborhood_flipped', data=part3_df, color='tab:blue',
              order=part3_df['neighborhood_flipped'].value_counts().index)
plt.xticks(rotation=90, fontsize=9)
plt.show()
```



Question 3 - Heavy-tailed distributions

Print the number of neighborhoods with less than 5 listings and the fraction of their total number of listings out of the total number of listings. Also print the fraction of listings from the 8 most frequent neighborhoods out of the total number of listings.

In [35]:
```
# Part 3 - Question 3
neighborhood_listing = pd.DataFrame(part3_df["neighborhood"].value_counts())
neighborhood_listing['fraction'] = part3_df["neighborhood"].value_counts(normalize=True)
print('Number of neighborhoods with less than 5 listings:', np.sum(neighborhood_listing['count']<5), '\n',
       'The fraction of their total number of listings out of the total number of listings:',
      np.sum(neighborhood_listing.loc[neighborhood_listing['count']<5, 'fraction']).round(3))
print('The fraction of listings from the 8 most frequent neighborhoods out of the total number of listings:',
      np.sum(neighborhood_listing.head(8)['fraction']).round(5))
```

```
Number of neighborhoods with less than 5 listings: 28
 The fraction of their total number of listings out of the total number of listings: 0.234
The fraction of listings from the 8 most frequent neighborhoods out of the total number of listings: 0.52381
```

Those types of distributions where there are many categories that appear only a few times but together take a large portion of the distribution are called heavy-tailed (or long-tailed) distributions. This is a real issue in many data science applications, since even if we have a large dataset there are still some sub-populations or sub-categories that are not well represented.

Question 4

Create a new filtered dataframe with listings from only the 8 most frequent neighborhoods.

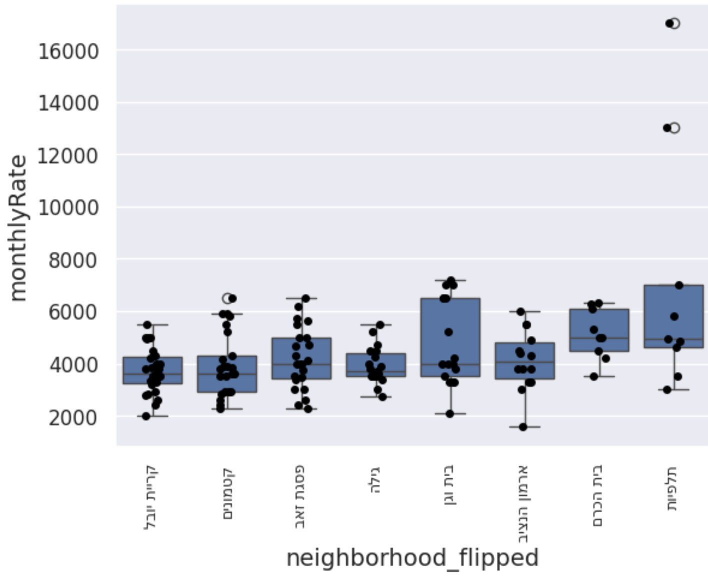
In [36]:
```
# Part 3 - Question 4
top8 = neighborhood_listing.head(8).index
part3_filtered = part3_df[part3_df['neighborhood'].isin(top8)]
```

Question 5

Plot a graph to check whether there are different distributions of monthly rates in the eight neighborhoods. Explain your choice for the visualization and your conclusions.
Note: Make sure that the neighborhoods are ordered in the plot based on their tendency for higher or lower monthly rates.

Hint: Which is a better descriptor of the central tendency of monthly rates when the distributions are skewed?

In [37]:
```
# Part 3 - Question 5
top8_flipped = []
for x in top8:
  top8_flipped.append(reverse_string(x))
sns.boxplot(x='neighborhood_flipped',y='monthlyRate',data=part3_filtered,
            order=top8_flipped)
sns.stripplot(x='neighborhood_flipped', y='monthlyRate', data=part3_filtered, color='black')
plt.xticks(rotation=90, fontsize=9)
plt.show()
```



Part 3 Question 5 - textual Answer:

We chose to present the distribution of th data with boxplot and a stripplot.The boxplot presents the median and the quantiles of the monthly rate for each neighborhood, values which are not effected by extreme values.

The comparisson between the median and the quantile allow us to examine whether the distribution is skewed (as we can see for "תלפיות" for example). The stripplot itself allow us to examine the way the data is distributed too.

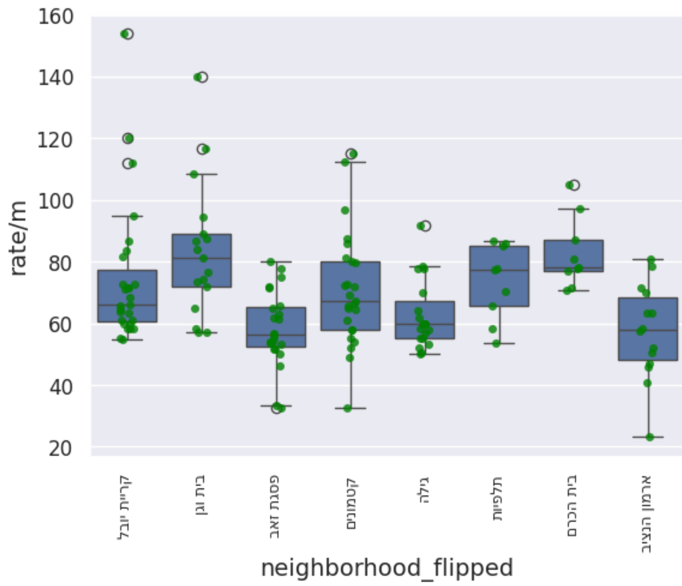
Question 6

Now that we compared the different distributions of monthly rates betwen neighborhoods, we can check whether we can explain some of the differences using our common-sense and the data we already have. For example, perhaps different neighborhoods have different distributions of apartment sizes?

Think of a new variable that will allow you to check the relationship between neighborhoods and prices fairly, factoring different apartment sizes out of the equation. Save this measure into the dataframe and create a new visualization to answer the question.

In [38]:
```
# Part 3 - Question 6
part3_filtered["rate/m"] = part3_filtered['monthlyRate']/part3_filtered['area']
sns.boxplot(x='neighborhood_flipped',y='rate/m',data=part3_filtered)
sns.stripplot(x='neighborhood_flipped', y='rate/m', data=part3_filtered, color='green', alpha=0.8)
plt.xticks(rotation=90, fontsize=9)
plt.show()
```

```
<ipython-input-38-295030b44c09>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  part3_filtered["rate/m"] = part3_filtered['monthlyRate']/part3_filtered['area']
```



Part 3 Question 6 - textual Answer:

We chose to calculate the monthly rate per squered meter. This parameter factors the apartment monthly rate by it's size. As in question 5, we chose to present it in a boxplot and a stripplot for the same reasons. As we can see there is still variance among neighborhoods, but it is smaller for this parameter.

Given the conclusions from the previous steps, we may think that the apartment's neighborhood gives us additional information about the expected monthly rate. But the sample size for most neighborhoods is rather small. So let's examine another way to utilize the location information. Luckily, we also have data about the socio-economic rank of most neighborhoods (between 1 and 10).

Question 7 - **bonus**

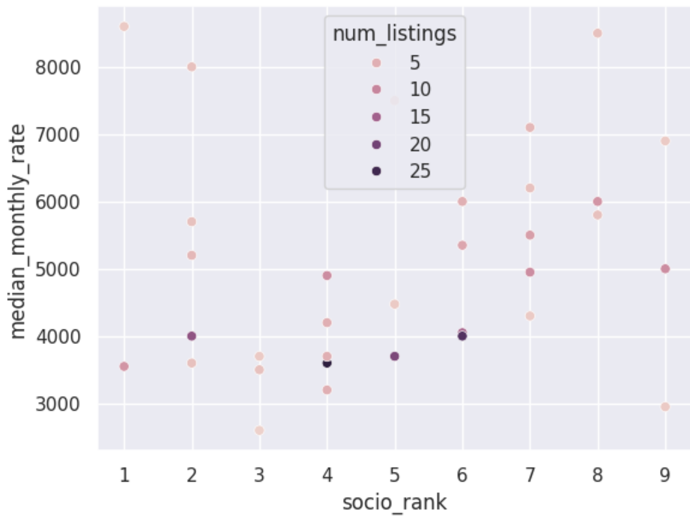
Use again the full dataset (without filtering by neighborhood).

Create an aggregated dataframe where every record represents a neighborhood, with columns for:

1. neighborhood name
2. flipped neighborhood name
3. The number of listings in a neighborhood
4. The median monthly rate for listings in this neighborhood.

Add a column with the neighborhood socio-economic rank to the dataframe (you can use the provided `get_neighborhood_rank` function that takes as an input a neighborhood name and returns its socio-economic rank.) Use this dataframe to visualize the association between socio-economic rank and pricing for all neighborhoods with at least 5 listings. What is you conclusion?

In [39]:
```
# Part 3 - Question 7
sns.reset_defaults()
sns.set_theme()
grouped = part3_df.groupby('neighborhood')
agged = grouped.agg(flipped_neighborhood_name=('neighborhood_flipped', 'first'),
                    num_listings=('neighborhood', 'size'),
                    median_monthly_rate=('monthlyRate', 'median')).reset_index()
agged['socio_rank'] = agged['neighborhood'].apply(get_neighborhood_rank)
sns.scatterplot(x='socio_rank', y='median_monthly_rate', data=agged, hue='num_listings')
plt.show()
```



Part 3 Question 7 - textual Answer:

Scatterplot will be the best way to describe the connection between a quasi continues variable and a continues variable. It allows us to see trends in the data, and to recognize patterns in it.

As we can see, monthly rate could be positively correlated with socio economic rank, but the variance in the data seems too high to conclude it just from this scatterplot.

Part 4: Are private houses more expensive than apartments?

In [40]:
```
# @title Part 4 - Create a DataFrame and remove outliers for Part 4
part4_df = rent_df_backup_for_exercise.copy()
part4_df = part4_df[part4_df['monthlyRate'] > 0].reset_index(drop=True);
part4_df = part4_df[part4_df['area'] < 800].reset_index(drop=True)
part4_df = part4_df[part4_df['area'] > 10].reset_index(drop=True)
```

Finally, we want to check if listings in private houses tend to be more expensive than apartments in a building.

Use only `part4_df` for the coding questions in this part

Question 1

The current dataset doesn't include a variable that describes whether a listing is in a building or a private house but this can be inferred from the existing variables. Create a new column named "is_a_house" with value of `True` if a listing is in the first (or zero) floor in a building with only one floor. Print the number of private houses and print the descriptions of three random listings with 'is_a_house' equal to `True`.

In [41]:
```
# Part 4 - Question 1
part4_df["is_a_house"] = part4_df['numFloors'] <= 1
num_privates = part4_df["is_a_house"].sum()
print("Number of private house listings:", num_privates)
np.random.seed(6)
sample = part4_df[part4_df["is_a_house"] == True]["description"].reset_index(drop=True).sample(3).tolist()
print("\n".join(sample))
```

```
Number of private house listings: 17
להשכרה, דירה, קומה ראשונה, בירושלים
דירת 2 חדרים חמודה בשכונת מלחה הישנה.  מרוהטת קומפלט (ארון, ספה, טלוויזיה, מקרר, מכונת כביסה, שולחן אוכל, מיטה). יש חנייה בשפע.  מיקום מעולה-
מרחק הליכה 5 דקות מקניון מלחה, תחבורה ציבורית מתחת לבית לכל מקום, יציאה לבגין. ללא אפשרות לבעלי חיים.  ללא תיווך. לא מתאים לזוג עם ילדים
מתאים לצעירים / סטודנטים
בלב נחלאות, דירה מתוקה להשכרה עם כניסה פרטית. סלון עם מטבחון, חדר שינה וחדר אמבטיה. לכניסה מיידית
```

Question 2

Create a visualization that compares the **average** monthly rates in houses vs. apartments. Which are more expensive on average?

In [42]:
```
# Part 4 - Question 2
sns.barplot(x='is_a_house', y='monthlyRate', data=part4_df)
plt.show()
```

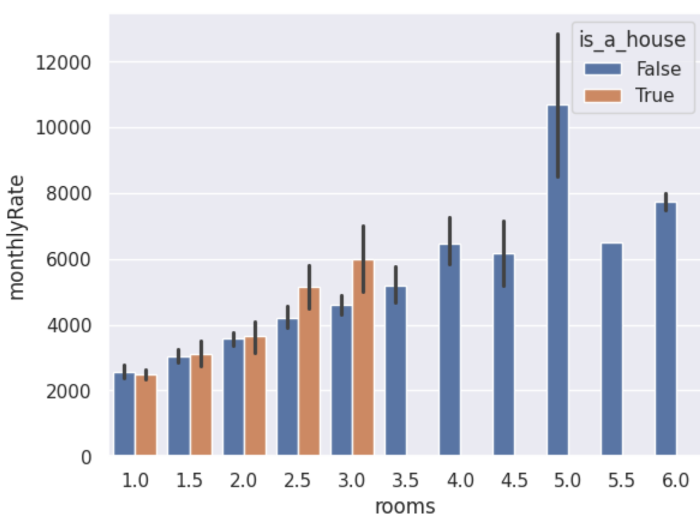
Part 4 Question 2 - textual Answer:

Apartments are more expensive on average.

Question 3

Now, let's look at the data in a higher resolution. Create a visualization that compares the average monthly rates of houses vs. apartments separetly for any number of rooms. Do the results align with the results from the previous question?

In [43]:
```
# Part 4 - Question 3
sns.barplot(x="rooms", y='monthlyRate', hue = "is_a_house", data=part4_df)
plt.show()
```



Part 4 Question 3 - textual Answer:

No. Now we can see that on average, houses are more expensive than apartments (except for 1-room places).

However, we could have assumed this because there are no houses with 3.5 rooms or more. Therefore, the cost of apartments increases while there is no information available for houses in this category.

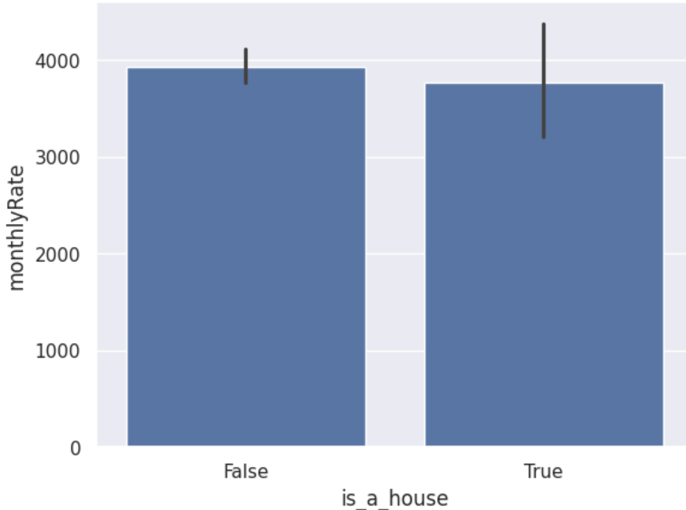
Question 4

Dan saw those visualizations and suggested that the trend in **question 2** is due to the fact that apartments in this dataset have larger maximal number of rooms than houses.

Create a new visualization similar to **question 2**, but consider only apartment listings with a number of rooms less or equal to the maximal number of rooms for a private house listing. Does the result now align with the trend in **question 3**? If not, is the discrepancy smaller than before?

In [44]:
```
# Part 4 - Question 4
q4_df = part4_df[part4_df['rooms'] < 3.5].reset_index(drop=True)
```

```
sns.barplot(x='is_a_house', y='monthlyRate', data=q4_df)
plt.show()
```



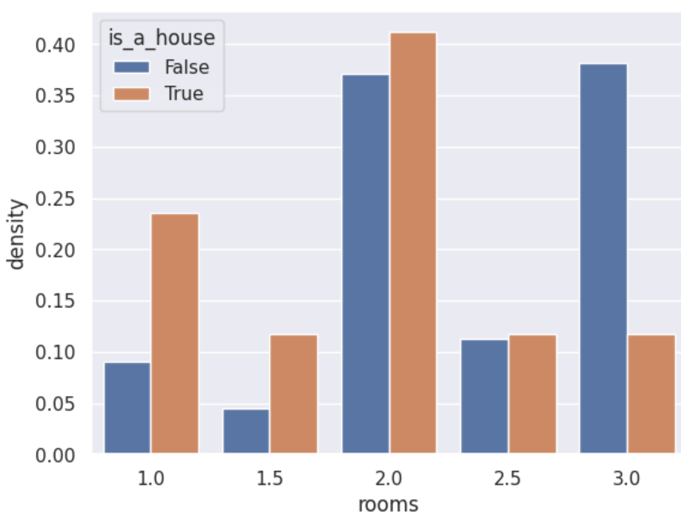
Part 4 Question 4 - textual Answer:

The result do not align with the trend in question 3, however the discrepancy is smaller.

Question 5

Create a visualization that compares the proportion of listings with every value of "number of rooms" in each of the two groups (is_a_house == True and is_a_house == False). How can the results here explain the discrepancy between the results of **question 2** and **question 3**? (Hint: recall the UC Berkeley admission rates example from the first lecture)

In [45]:
```
# Part 4 - Question 5
density_df = q4_df.groupby(['is_a_house', 'rooms']).size().reset_index(name='count')
total_counts = density_df.groupby('is_a_house')['count'].transform('sum')
density_df['density'] = density_df['count'] / total_counts
sns.barplot(x="rooms", y="density", hue="is_a_house", data=density_df)
plt.show()
```



Part 4 Question 5 - textual Answer:

The discrepancy is explained by the fact that most of the houses in the data are smaller and have lower average rent, therefore they have less impact on the overall average rent.