In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import scipy as stats
import seaborn as sns
from statsmodels.sandbox.stats.runs import runstest_1samp
import statistics as s
from sklearn.preprocessing import MinMaxScaler, normalize
from scipy.stats import chi2_contingency
from pandasql import sqldf
from collections import OrderedDict
import os
```

```
F:\Anaconda\lib\site-packages\pandas\core\computation\expressions.py:20: UserWarni
ng: Pandas requires version '2.7.3' or newer of 'numexpr' (version '2.7.1' current
ly installed).
  from pandas.core.computation.check import NUMEXPR_INSTALLED
```

In [2]:

```
dir = 'D:/Computational Thinking and DS/HW1 8.22-8.26/data_airbnb'
os.chdir(dir)
```

In [3]:

```
listing = pd.read_csv('Listings.csv', encoding = 'latin1')
review = pd.read_csv('Reviews.csv', encoding = 'latin1')

raw_listing = listing.copy()
raw_review = review.copy()
```

```
<ipython-input-3-98ff1cfd470c>:1: DtypeWarning: Columns (5,13) have mixed types. S
pecify dtype option on import or set low_memory=False.
  listing = pd.read_csv('Listings.csv', encoding = 'latin1')
```

In [4]:

```
raw_listing.sort_values('listing_id').head()
```

Out[4]:

	listing_id	name	host_id	host_since	host_location	host_response_time	host_re
85045	2577	Loft for 4 by Canal Saint Martin	2827	2008-09-09	Casablanca, Grand Casablanca, Morocco	a few days or more	
37163	2595	Skylit Midtown Castle	2845	2008-09-09	New York, New York, United States	within a few hours	
105556	2737	Elif's room in cozy, clean flat.	3047	2008-09-18	Rome, Lazio, Italy	within a day	
159807	2903	Stay a night in Calisto6 B&B Rome	3280	2008-09-28	Rome, Lazio, Italy	within a few hours	
227261	3079	Cozy apartment (2-4)with Colisseum view	3504	2008-10-08	Rome, Lazio, Italy	NaN	

5 rows × 33 columns

Formalize the dataset, giving readable columns readable and capitalized names.

In [5]:

```
'''
def formalize(df):
    new_col = []
    for i in df.columns:
        new_col.append(i.title())

    for i in new_col:
        for j in range(len(i)):
            if i[j] == '_':
                upper(i[j + 1])
                i.pop(j)
    return new_col
formalize(raw_review)'''
```

Out[5]:

```
"\ndef formalize(df):\n    new_col = []\n    for i in df.columns:\n        new_co
l.append(i.title())\n    \n    for i in new_col:\n        for j in range(len
(i)):\n            if i[j] == '_':\n                upper(i[j + 1])\n
i.pop(j)\n    return new_col\nformalize(raw_review)"
```

Preprocessing the Datasets

To check the overall conditions and null values, wrap functions up to summarize.

In [6]:

```
def overall_cond(df):
    # 1 Summary
    df.info()

    # 2 Empty Values
    n_null = df.isnull().sum().values

    with_null = n_null[n_null > 0]

    # 3 Histogram for empty values
    if sum(with_null) > 0:
        labels = list(df.columns[n_null > 0])
        plt.figure(figsize = (20, 10))
        plt.bar(labels, with_null, linewidth = 10)
        plt.xticks(rotation = 40)
        plt.title('Null Values')
    else: print('There is no empty values in the table.')
    return
```

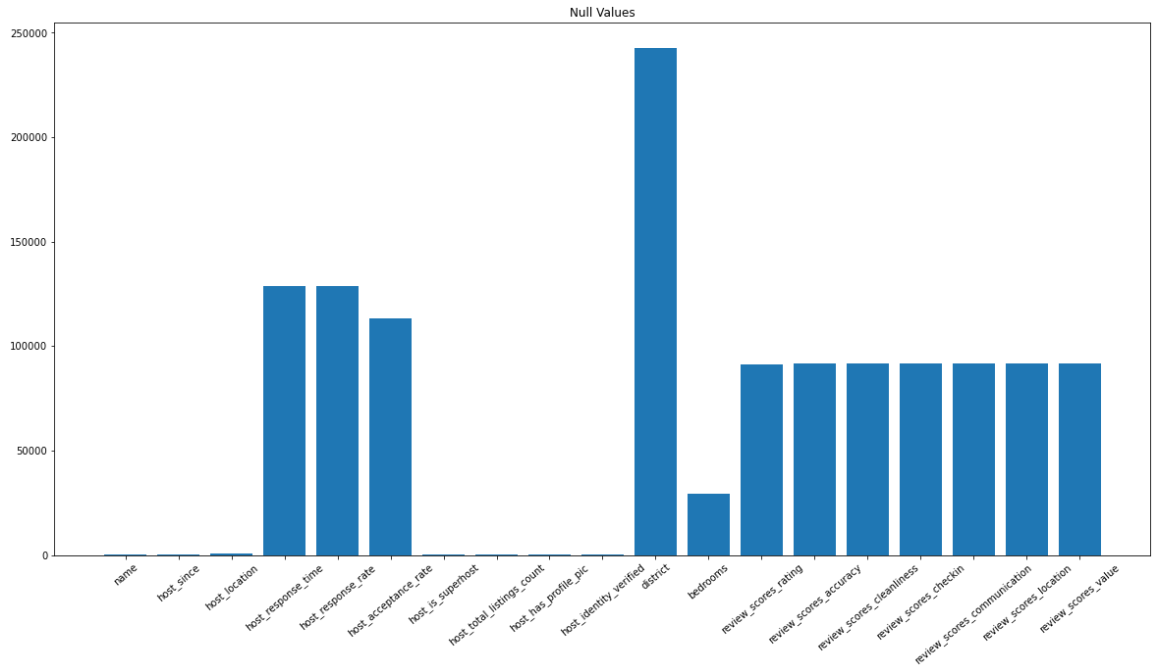
Checking Data

Listing Data

In [7]:

```
overall_cond(raw_listing)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 279712 entries, 0 to 279711
Data columns (total 33 columns):
 #   Column                        Non-Null Count   Dtype
---  ------                        --------------   -----
 0   listing_id                    279712 non-null  int64
 1   name                          279539 non-null  object
 2   host_id                       279712 non-null  int64
 3   host_since                    279547 non-null  object
 4   host_location                 278872 non-null  object
 5   host_response_time            150930 non-null  object
 6   host_response_rate            150930 non-null  float64
 7   host_acceptance_rate          166625 non-null  float64
 8   host_is_superhost             279547 non-null  object
 9   host_total_listings_count     279547 non-null  float64
 10  host_has_profile_pic          279547 non-null  object
 11  host_identity_verified        279547 non-null  object
 12  neighbourhood                 279712 non-null  object
 13  district                      37012 non-null   object
 14  city                          279712 non-null  object
 15  latitude                      279712 non-null  float64
 16  longitude                     279712 non-null  float64
 17  property_type                 279712 non-null  object
 18  room_type                     279712 non-null  object
 19  accommodates                  279712 non-null  int64
 20  bedrooms                      250277 non-null  float64
 21  amenities                     279712 non-null  object
 22  price                         279712 non-null  int64
 23  minimum_nights                279712 non-null  int64
 24  maximum_nights                279712 non-null  int64
 25  review_scores_rating          188307 non-null  float64
 26  review_scores_accuracy        187999 non-null  float64
 27  review_scores_cleanliness     188047 non-null  float64
 28  review_scores_checkin         187941 non-null  float64
 29  review_scores_communication   188025 non-null  float64
 30  review_scores_location        187937 non-null  float64
 31  review_scores_value           187927 non-null  float64
 32  instant_bookable              279712 non-null  object
dtypes: float64(13), int64(6), object(14)
memory usage: 70.4+ MB
```



Rating Times Data

In [8]:

```
overall_cond(raw_review)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5373143 entries, 0 to 5373142
Data columns (total 4 columns):
 #   Column       Dtype
---  ------       -----
 0   listing_id   int64
 1   review_id    int64
 2   date         object
 3   reviewer_id  int64
dtypes: int64(3), object(1)
memory usage: 164.0+ MB
There is no empty values in the table.
```

There is no empty values in the rating times data.

Data Cleaning

First, join the two tables using the listing ID column.

In [9]:

```
'''
raw_review.sort_values('listing_id'); raw_listing.sort_values('listing_id')
raw_df = raw_listing.merge(raw_review, how = 'right')
raw_df.head()
raw_df.columns'''
```

Out[9]:

```
"\nraw_review.sort_values('listing_id'); raw_listing.sort_values('listing_id')\nra
w_df = raw_listing.merge(raw_review, how = 'right')\nraw_df.head()\nraw_df.column
s"
```

Note that a listing may have more than one review, thus I used left join.

Correlation

Note that missing values concentrate in rating terms (which might be due to simply skipping these scorings when writing feedbacks), I decide to estimate these missing values with the current available ones.

I first try to find the correlations between features require filling and other features that might be decisive to them. For instance, the most important feature, overall ratings, might be mostly correlated to the cleanness,then accuracy, ..., so I rank the correlations between these deciding features and overall ratings using their currently available values.

Then according to the rank, I fill the overall ratings with these features values in descending correlation order: **values of more important deciding features will be priorly used to fll the overall ratings first**.

First, I fill the overall rating ('review_scores_value' in the columns) as it is the most notable thing in the reviews and we concern the most.

I choose 'price', 'host_acceptance_rate', 'host_is_superhost', 'host_total_listings_count', 'host_has_profile_pic' and 'host_identity_verified' to do the correlation design. There are non-digital features among these so I find them out and transfer them. Use 0 to stand for 'f' and 1 for 't'.

We want to find those features correlated to overall rating the most.

In [10]:

```
rating_features = ['host_is_superhost', 'host_total_listings_count', 'host_has_profile_pic', 'ho
st_identity_verified','review_scores_accuracy', 'review_scores_cleanliness', 'review_scores_comm
unication', 'review_scores_location']

def transtf(col):
    if col == 'f': col = 0
    elif col == 't': col = 1
    return col

tf_code = {'t': 1, 'f': 0, 'T': 1, 'F': 0}
for f in rating_features:
    raw_listing[f] = raw_listing[f].replace(tf_code)

raw_listing[rating_features].dtypes
```

Out[10]:

```
host_is_superhost             float64
host_total_listings_count     float64
host_has_profile_pic          float64
host_identity_verified        float64
review_scores_accuracy        float64
review_scores_cleanliness     float64
review_scores_communication   float64
review_scores_location        float64
dtype: object
```

In [11]:

```
rating_coefs = []

for i in rating_features:
    extr = raw_listing[~(raw_listing[i].isnull()) & ~(raw_listing['review_scores_value'].isnull
())].copy()
    rating_coefs.append(extr[[i, 'review_scores_value']].corr().iloc[0][1])

dict_coef = {rating_features[i]: rating_coefs[i] for i in range(len(rating_features))}
sorted_fnc =  sorted(dict_coef.items(), key = lambda x: x[1], reverse = True)
sorted_fnc
```

Out[11]:

```
[('review_scores_accuracy', 0.7174472944584721),
 ('review_scores_cleanliness', 0.6541490370282881),
 ('review_scores_communication', 0.6348343386411659),
 ('review_scores_location', 0.5326444904575227),
 ('host_is_superhost', 0.1861488743425945),
 ('host_identity_verified', 0.03663924051165198),
 ('host_has_profile_pic', 0.007309295152885904),
 ('host_total_listings_count', -0.04902706628447202)]
```

The results above indeed show factors we attach importance to when we book housings. After checking in, customers use 'review_scores_accuracy', the most correlated feature, to rate the accuracy of houses' description on the Airbnb according to what they see. This highly indicates the descrepancy between the customers' expectation and what they actually get, thus rating the truthfulness of the business. Cleanliness, the runner up, is another important feature customer look at. Also, quality communication has a similar importance.

I will add more features to help fill the null value of overall ratings.

The function below summarizes the methods above: coding boolean features, excluding nulls, calculating correlations and sorting features by correlation coefficients in descending order. I will prioritize features with a higher correlation coefficient with the overall rating to, using its value to fill the empty overall rating of a sample if this feature is not null; otherwise, I will use the second correlated feature value, ..., until the overall rating is filled.

In [12]:

```
def choose_features(rating_features, target_feature, df):
    # For binary features
    def transtf(col):
        if col == 'f': col = 0
        elif col == 't': col = 1
        return col

    # For other features ---------------------------------------------------------
    def transobj(dfcolumn):
        dict_val = {}
        nonull_col = dfcolumn[dfcolumn.notnull()].copy()  # Do not encode Nulls
        for i in nonull_col.index:
            if dfcolumn.iloc[i] not in dict_val.keys():
                dict_val[dfcolumn.iloc[i]] = []
            dict_val[dfcolumn.iloc[i]].append(i)
        #dict_val = OrderedDict(sorted(dict_val.items()))# Sort the keys (unique column values)
alphabetically
        return dict_val

    # Encode features, from string type to numerical type.
    non_incld = []
    for i in range(len(rating_features)):
        if df[df[rating_features[i]].notnull()][rating_features[i]].iloc[0] == 't' or 'f':
            df[rating_features[i]] = df[rating_features[i]].map(transtf)
        elif [df[df[rating_features[i]].notnull()][rating_features[i]].dtypes][0] == 'str' :
            dic = transobj(df[rating_features[i]])
            for j in range(len(dic.keys())):
                df.loc[dic[rating_features[i]], [rating_features[i]]] = float(j)
        else:
            non_incld.append(rating_features[i])   # If a selected feature does not belong to bo
th boolean and categorical type.

    #-------------------------------------------------------------------------------



    rating_coefs = []

    for i in rating_features:
        extr = df[~(df[i].isnull()) & ~(df[target_feature].isnull())]
        rating_coefs.append(extr[[i, target_feature]].corr().iloc[0][1])

    dict_coef = {rating_features[i]: rating_coefs[i] for i in range(len(rating_features))}
    sorted_fnc =  sorted(dict_coef.items(), key = lambda x: x[1], reverse = True)


    return df, sorted_fnc, non_incld
```

In [13]:

```
rating_features = ['host_response_rate', 'review_scores_checkin', 'host_is_superhost', 'host_tot
al_listings_count', 'host_has_profile_pic', 'host_identity_verified','review_scores_accuracy',
'review_scores_cleanliness', 'review_scores_communication', 'review_scores_location']
trans_df, cor_chart, not_included = choose_features(rating_features, 'review_scores_value', raw_
listing)
```

In [14]:

```
cor_chart
```

Out[14]:

```
[('review_scores_accuracy', 0.7174472944584721),
 ('review_scores_cleanliness', 0.6541490370282881),
 ('review_scores_communication', 0.6348343386411659),
 ('review_scores_checkin', 0.5951674090869673),
 ('review_scores_location', 0.5326444904575227),
 ('host_is_superhost', 0.1861488743425945),
 ('host_response_rate', 0.0992337279246503),
 ('host_identity_verified', 0.03663924051165198),
 ('host_has_profile_pic', 0.007309295152885904),
 ('host_total_listings_count', -0.04902706628447202)]
```

1.2.2 Filling Empty Values

In [15]:

```
data_wiz_null = trans_df.copy()
data_wiz_null
```

Out[15]:

	listing_id	name	host_id	host_since	host_location	host_response_time	hos
0	281420	Beautiful Flat in le Village Montmartre, Paris	1466919	2011-12-03	Paris, Ile-de-France, France	NaN	
1	3705183	39 mÃ Â² Paris (Sacre CÃ â ur)	10328771	2013-11-29	Paris, Ile-de-France, France	NaN	
2	4082273	Lovely apartment with Terrace, 60m2	19252768	2014-07-31	Paris, Ile-de-France, France	NaN	
3	4797344	Cosy studio (close to Eiffel tower)	10668311	2013-12-17	Paris, Ile-de-France, France	NaN	
4	4823489	Close to Eiffel Tower - Beautiful flat : 2 rooms	24837558	2014-12-14	Paris, Ile-de-France, France	NaN	
...	...	...	...	...	...	...	
279707	38338635	Appartement T2 neuf prÃ Â¨s du tram T3a Porte ...	31161181	2015-04-13	Paris, Ile-de-France, France	NaN	
279708	38538692	Cozy Studio in Montmartre	10294858	2013-11-27	Paris, Ile-de-France, France	NaN	
279709	38683356	Nice and cosy mini-appartement in Paris	2238502	2012-04-27	Paris, Ile-de-France, France	NaN	
279710	39659000	Charming apartment near Rue Saint Maur / Oberk...	38633695	2015-07-16	Paris, Ile-de-France, France	NaN	
279711	40219504	Cosy apartment with view on Canal St Martin	6955618	2013-06-17	Paris, Ile-de-France, France	NaN	

279712 rows × 33 columns

In this way, I can fill the feature 'review_scores_value' according to values of features in this order: 'review_scores_accuracy', 'review_scores_cleanliness', 'review_scores_communication'. I will choose those features with a correlation coefficient higher than 0.5.

In [16]:

```
good_features = {}
for i in cor_chart:
    if i[1] >= 0.5:
        good_features[i[0]] = i[1]
good_features
```

Out[16]:

```
{'review_scores_accuracy': 0.7174472944584721,
 'review_scores_cleanliness': 0.6541490370282881,
 'review_scores_communication': 0.6348343386411659,
 'review_scores_checkin': 0.5951674090869673,
 'review_scores_location': 0.5326444904575227}
```

In [17]:

```
df_null_rating = data_wiz_null[data_wiz_null['review_scores_rating'].isnull()]
idx_null_rating = df_null_rating.index
```

In [18]:

```
if data_wiz_null['review_scores_value'].iloc[idx_null_rating[0]] == np.nan:
    print(data_wiz_null['review_scores_value'].iloc[idx_null_rating[0]])
```

I was confused about the insignificant correlation between superhost title and the ratings ('review_scores_value'), as normally, superhosts are those constantly recieve high ratings. Maybe it is the correlation coefficient that ignores their internal relationship.

So, I also want to use hypothesis tests to see the difference in distributions of overall ratings, between housings with different boolean feature values. Features 'host_is_superhost' and 'host_total_listings_count' are the two I want to use different ways to test their correlation to the overall ratings.

For 'host_is_superhost', a boolean feature, I first draw histogram of the rating values binarily partitioned into two classes by the 'host_is_superhost' values: whether the host is a superhost. This helps me estimate the possible distribution of the ratings from the two classes.

In [19]:

```
raw_listing[['host_total_listings_count', 'host_is_superhost']].describe()
```

Out[19]:

	host_total_listings_count	host_is_superhost
count	279547.000000	279547.000000
mean	24.581612	0.179766
std	284.041143	0.383993
min	0.000000	0.000000
25%	1.000000	0.000000
50%	1.000000	0.000000
75%	4.000000	0.000000
max	7235.000000	1.000000

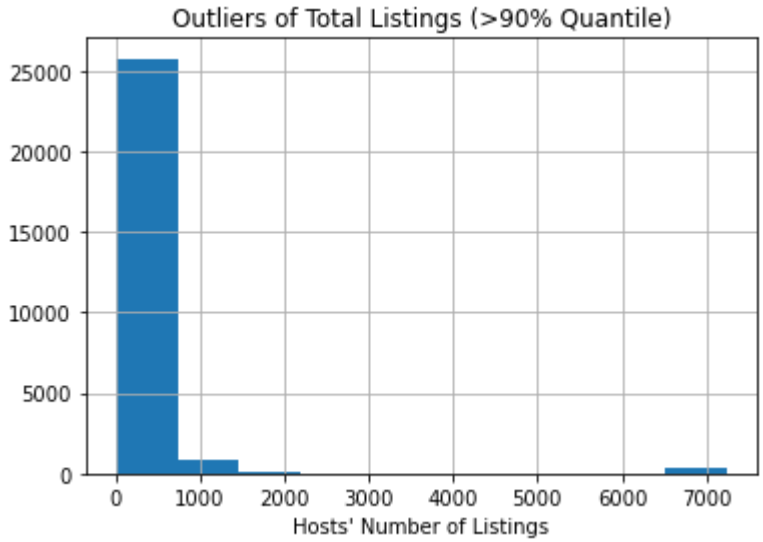
It is quite likely that the listing count has outliers. Due to the distance between outliers and the majority which makes histogram unintelligible, I calculate 90% quantile to check the place of these outliers. Also, I want to see their distribution.

In [20]:

```
non_null_nlisting = raw_listing[(raw_listing['host_total_listings_count'].notnull()) & (raw_list
ing['host_total_listings_count'].notnull())]
q_nlisting = np.quantile(non_null_nlisting['host_total_listings_count'], .90)
non_null_nlisting[non_null_nlisting['host_total_listings_count'] > q_nlisting]['host_total_listi
ngs_count'].hist()
plt.title('Outliers of Total Listings (>90% Quantile)')
plt.xlabel('Hosts\' Number of Listings')
```

Out[20]:

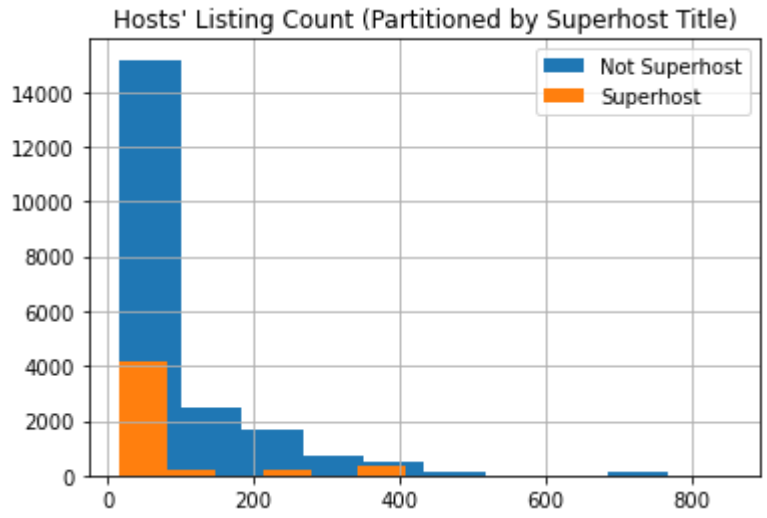
```
Text(0.5, 0, "Hosts' Number of Listings")
```



We exclude those listings whoes hosts have had more than 1000 deals; also, we classify the pillars into whether hosts are superhost .

In [21]:

```
non_null_nlisting[(non_null_nlisting['host_total_listings_count'] > q_nlisting) & (non_null_nlis
ting['host_total_listings_count'] < 1000)\
                  & (non_null_nlisting['host_is_superhost'] == 0)]\
['host_total_listings_count'].hist()
non_null_nlisting[(non_null_nlisting['host_total_listings_count'] > q_nlisting) & (non_null_nlis
ting['host_total_listings_count'] < 1000)\
                  & (non_null_nlisting['host_is_superhost'] == 1)]\
['host_total_listings_count'].hist()
plt.legend(['Not Superhost', 'Superhost'])
plt.title('Hosts\' Listing Count (Partitioned by Superhost Title)')
plt.show()
```



According to this figure, I wonder if the percentage of popular hosts (have more listings) is higher in the superhost population than that in the non-superhosts, i.e. superhosts tend to have more of their houses rent.

I decide to firt use Chi-square Test: partition the counts of listings that hosts made into two parts: if it is higher than 50, then suppose the host to be a popular host. This tests whether the superhost is a influencing factor.

In [22]:

```
pop_ns_hosts = non_null_nlisting[(non_null_nlisting['host_total_listings_count'] > 50) & (non_nu
ll_nlisting['host_is_superhost'] == 0)]\
['host_total_listings_count']
pop_s_hosts = non_null_nlisting[(non_null_nlisting['host_total_listings_count'] > 50) & (non_nul
l_nlisting['host_is_superhost'] == 1)]\
['host_total_listings_count']

norm_ns_hosts = non_null_nlisting[(non_null_nlisting['host_total_listings_count'] <= 50) & (non_
null_nlisting['host_is_superhost'] == 0)]\
['host_total_listings_count']
norm_s_hosts = non_null_nlisting[(non_null_nlisting['host_total_listings_count'] <= 50) & (non_n
ull_nlisting['host_is_superhost'] == 1)]\
['host_total_listings_count']

infom = np.array([[len(pop_ns_hosts), len(norm_ns_hosts)], [len(pop_s_hosts), len(norm_s_host
s)]])
res = chi2_contingency(infom)
res
```

Out[22]:

```
(475.20583123446914,
 2.360233090147678e-105,
 1,
 array([[ 10129.07169814,  219164.92830186],
        [  2219.92830186,   48033.07169814]]))
```

The p value is quite small, close to 0, so that it is confident enough to say superhost is an influencing factor. The percentage of popular hosts in the superhosts are significantly higher than that of the normal hosts.

So a superhost title makes more listings.

In [23]:

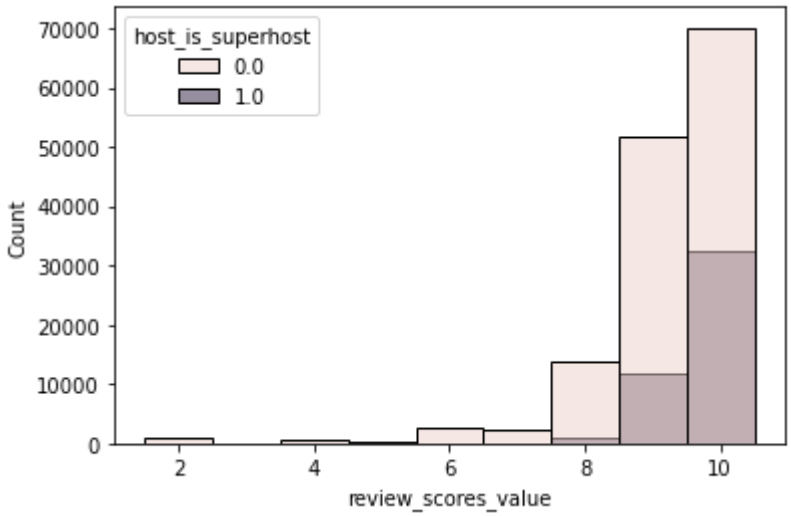
```
from scipy.stats import chi2_contingency
```

In [24]:

```
sns.histplot(raw_listing, x='review_scores_value', hue='host_is_superhost', discrete = True)
```

Out[24]:

<matplotlib.axes._subplots.AxesSubplot at 0x25a45e35340>



From the figure above, the distributions of overall ratings of the two classes seem to be the same. Most listings in both kinds of hosts tend to be scored high. The superhost title does not necessarily make customers more satisfied.

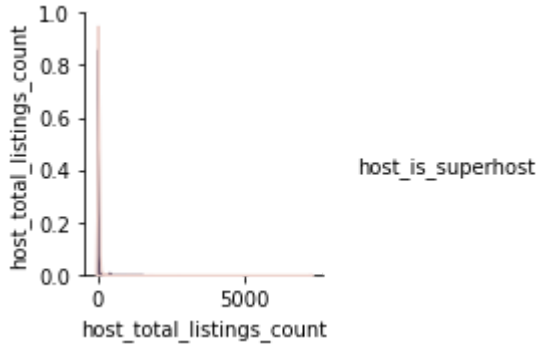
Then will best sellers tend to be scored higher?

In [25]:

```
sns.pairplot(raw_listing[['host_is_superhost', 'host_total_listings_count']], hue='host_is_superhost')
```

Out[25]:

<seaborn.axisgrid.PairGrid at 0x25a45b6d0d0>



Correlation Design

Amenity vs. Price

In [26]:

```
df = raw_listing.copy()
df['amenities'][0]
```

Out[26]:

```
'["Heating", "Kitchen", "Washer", "Wifi", "Long term stays allowed"]'
```

First, for each value in the amenities column, convert the string with square brackets and quotation marks into a string with seperate words.

In [27]:

```
def remove_b_q(df_col): # Input a column whose instances are strings.
    to_blank = ['"', '[', ']', '/', '\\', '?', '!']
    for i in to_blank:
        df_col = df_col.replace(i, '')

    df_col = df_col.replace(' ,', ','); df_col = df_col.replace(', ', ',')
    df_col = df_col.lower() # For convenience, convert all words into lower cases.
    df_col = df_col.split(',')
    return df_col
```

In [28]:

```
df['amenities'] = df['amenities'].map(remove_b_q)
```

We try to explore whether there is a correlation between number of amenities of each house and price. This let us know **whether more amenities means a higher price**. Tally the number of amenities for each house; the number of amenities and price are both continuous variable thus we first try **Pearson Correlation**.

In [29]:

```
df['n_amenities'] = df['amenities'].map(len)
df[['amenities', 'n_amenities', 'price']]
```

Out[29]:

	amenities	n_amenities	price
0	[heating, kitchen, washer, wifi, long term sta...	5	53
1	[shampoo, heating, kitchen, essentials, washer...	8	120
2	[heating, tv, kitchen, washer, wifi, long term...	6	89
3	[heating, tv, kitchen, wifi, long term stays a...	5	58
4	[heating, tv, kitchen, essentials, hair dryer,...	12	60
...	...	...	...
279707	[iron, heating, washer, dedicated workspace, e...	12	120
279708	[shampoo, iron, heating, washer, hair dryer, e...	12	60
279709	[paid parking off premises, shampoo, first aid...	15	50
279710	[tv, iron, kitchen, hangers, smoke alarm, cabl...	15	105
279711	[shower gel, shampoo, iron, heating, washer, d...	17	70

279712 rows × 3 columns

In [30]:

```
df[['n_amenities', 'price']].corr()
```

Out[30]:

	n_amenities	price
n_amenities	1.000000	0.028429
price	0.028429	1.000000

It seems that there is no significant correlation between the number of amenities and price.

To further explore something about amenities, I create a dictionary to store each distinctive amenity (keys) and the index of houses that own it (values).

In [31]:

```
def distinct_words(col_):
    words = {};
    for i in range(len(col_)):
        for j in col_[i]:
            if j not in words.keys():
                words[j] = []
            words[j].append(i)
    return words
```

In [32]:

```
all_amenities = distinct_words(df['amenities'])
```

In [33]:

```
sorted(all_amenities.keys())
# Remove the ''
all_amenities.pop('')
sorted(all_amenities.keys())[0]
```

Out[33]:

```
' amenities realgemu2019s -talentos do brasil feita a base de mel'
```

In [34]:

```
''' # One-hot coding for each amenity.
idx_amn = list(range(0, len(df), 1))
N_amenity = pd.DataFrame(index = idx_amn, columns = all_amenities.keys())
for i in N_amenitiy.col():
    N_amenity[all_amenities[i]] = 1
    N_amenity.all_amenities.fillna(value = 0)
'''
```

Out[34]:

```
' # One-hot coding for each amenity.\nidx_amn = list(range(0, len(df), 1))\nN_amen
ity = pd.DataFrame(index = idx_amn, columns = all_amenities.keys())\nfor i in N_am
enitiy.col():\n    N_amenity[all_amenities[i]] = 1\n    N_amenity.all_amenities.fi
llna(value = 0)\n'
```

Therefore, I want to know the distribution of housing price.

When customer choose houses, they tend to set a range for housing prices choose from. Instead of regarding prices as continuous, **I use quartiles to partition the housing according to their prices into four classes: economical, comfortable, premium and luxury**. Let's assume that we working classes never consider houses of more than $1500 per night, which also makes the boxplot more intelligible.

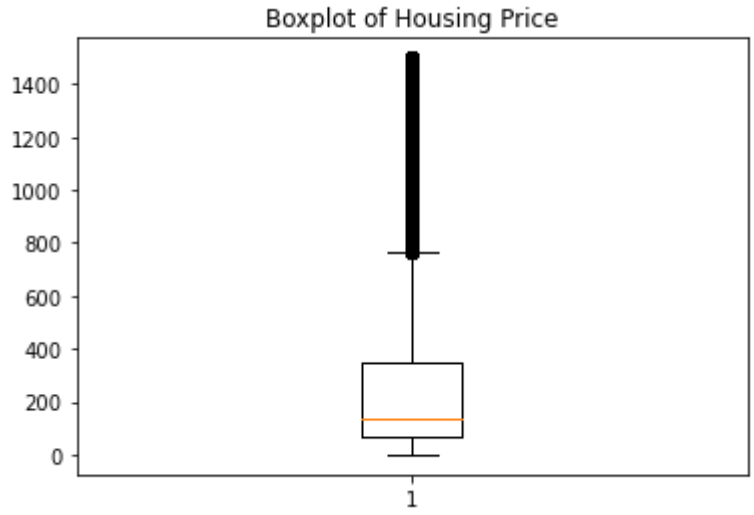
First, check the boxplot of the housing prices and find the quartiles.

In [35]:

```
houses_cnsd = df[df['price'] <= 1500].copy()

plt.boxplot(np.array(houses_cnsd['price']).reshape(-1, 1))
plt.title('Boxplot of Housing Price')
```

Out[35]:

```
Text(0.5, 1.0, 'Boxplot of Housing Price')
```



Prices lower than the first quartile are in economical class, between the 25% quantile (q_1) and the 75% quantile (q_3) are comfortable, between the 75% quantile and *theoretical maximum* ($q_3 + 1.5(q_3 - q_1)$) are permium, and the houses with prices higher than the theoretical maximum are luxury. In this way, we assign labels to them.

In [36]:

```
q_ = s.quantiles(houses_cnsd['price'], n = 4)
q1 = q_[0]; q2 = q_[1]; q3 = q_[2]
```

In [37]:

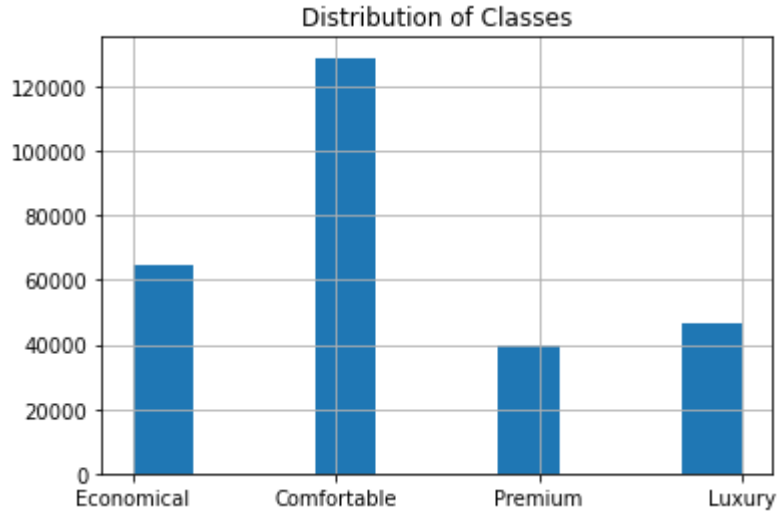
```
df['Label'] = np.nan
temp_p = df['price'].values
temp_lab = []
for i in range(len(temp_p)):
    if temp_p[i] < q1:
        temp_lab.append('Economical')
    elif q1 <= temp_p[i] < q3:
        temp_lab.append('Comfortable')
    elif q3 <= temp_p[i] < q3 + 1.5 * (q3 - q1):
        temp_lab.append('Premium')
    else:  temp_lab.append('Luxury')

df['Label'] = temp_lab
```

In [38]:

```
df['Label'].hist()
plt.title('Distribution of Classes')
```

Out[38]:

```
Text(0.5, 1.0, 'Distribution of Classes')
```



Also I would like to know the distribution of the amenities, checking thoes mostly pervasively owned.

In [39]:

```
n_amn = []
for i in sorted(all_amenities.keys()):
    n_amn.append(len(all_amenities))
Amenities = pd.DataFrame(columns = ['Amenity Names', 'Count'])
```

In [40]:

```
Amenities['Amenity Names'] = sorted(all_amenities.keys())
for i in range(len(Amenities)):
    Amenities['Count'][i] = len(all_amenities[Amenities['Amenity Names'][i]])
```

In [41]:

```
Amenities.sort_values(['Count'], ascending = False)
```

Out[41]:

	Amenity Names	Count
2835	wifi	260090
1036	essentials	253532
1610	long term stays allowed	241054
1503	kitchen	240923
2697	tv	213037
...	...	...
1677	mellerware stainless steel electric stove	1
1676	mellerware induction stove	1
659	cambridge soundworks sound system with aux	1
1674	meditation room	1
2952	zeytuni (olive) shampoo	1

2953 rows × 2 columns

Time Series Pattern Mining: Cycle of Order Volume and Housing Prices

By merging the listing with reviews, I can get a time series table, which time stamps are the dates housings in listings were rated. I thus plan to see the locations of housings and times listings were made. I will first select a city and then in a time range spanning several years, I set month as the granularity, calculate the monthly mean price of listings and the volume of orders. Then I will use autocorrelation function to check if each series is autocorrelated thus has seasonality; if it has seasonality, I will try to describe the pattern of it. If both of them are periodic, then I try to find the correlation between them and build a quantitative model.

To ensure that every listing and price has a time stamp, I review left join listing data. Making sure there is no empth values.

In [42]:

```
rv = raw_listing[['listing_id', 'city', 'price']].copy();
ts = raw_review[['listing_id', 'date']].copy();
price_time = pd.merge(ts, rv, how = 'left')
```

In [43]:

```
price_time.isnull().sum()
```

Out[43]:

```
listing_id    0
date          0
city          0
price         0
dtype: int64
```

In [44]:

```
spa = raw_listing[['listing_id', 'latitude', 'longitude', 'property_type', 'room_type', 'city',
'price']][raw_listing['city'] == 'New York'].copy();
temp = raw_review[['listing_id', 'date']].copy();
st_data = pd.merge(spa, temp, how = 'left')
st_data.to_csv('spatio_temporal_abnb.csv')
```

Next, find a city.

In [45]:

```
price_time['city'].unique()
```

Out[45]:

```
array(['Paris', 'New York', 'Bangkok', 'Hong Kong', 'Mexico City',
       'Cape Town', 'Rio de Janeiro', 'Sydney', 'Istanbul', 'Rome'],
      dtype=object)
```

In [46]:

```
def price_a_city(df, city):

    def get_month_year(date):
        return date[: -3]

    # Constructing the Month-Year table for a city.
    city_price = df[df['city'] == city][['city', 'date', 'price']].copy()
    city_price['Month_Year'] = city_price['date'].map(get_month_year)

    # The table of monthly average price and order volume.
    avgpn_city = pd.DataFrame(columns = ['Month_Year', 'Avg_Price', 'n_Order'])
    avgp_ = []
    avgn_ = []
    for i in city_price['Month_Year'].unique():
        avgp_.append(city_price[city_price['Month_Year'] == i]['price'].mean())
        avgn_.append(sum(city_price[city_price['Month_Year'] == i]['price']))

    avgpn_city['Month_Year'] = city_price['Month_Year'].unique();
    avgpn_city['Avg_Price'] = avgp_
    avgpn_city['n_Order'] = avgn_
    avgpn_city = avgpn_city.sort_values('Month_Year').reset_index()

    return city_price, avgpn_city # Return the two tables.

def vis_p_n(city, avgpn_city):
    t_ = np.arange(0, len(avgpn_city), 1)

    sns.set(rc={"figure.figsize":(16, 8)})

    ax1 = sns.lineplot(t_, avgpn_city['Avg_Price'], color='blue')
    ax1.set_ylabel('Monthly Average Prices')
    ax1.set_ylim(avgpn_city['Avg_Price'].min(), max(avgpn_city['Avg_Price']))
    ax1.legend(['Monthly Average Prices, {}'.format(city)], loc="upper left")

    ax2 = ax1.twinx()

    ax2 = sns.lineplot(t_, avgpn_city['n_Order'], color='orange')
    ax2.set_ylabel('Monthly Order Volume')
    ax2.set_ylim(min(avgpn_city['n_Order']), max(avgpn_city['n_Order']))
    ax2.set_xlabel('Time/Days')
    ax2.legend(['Monthly Order Volume, {}'.format(city)], loc="upper right")
```

First I will try New York housing prices. I built a new column 'Year_Month' facilitating calculation.

In [47]:

```
NY_price = price_time[price_time['city'] == 'New York'][['city', 'date', 'price']]
```

In [48]:

```
def get_month_year(date):
    return date[: -3]

NY_price['Month_Year'] = NY_price['date'].map(get_month_year)
NY_price
```

Out[48]:

	city	date	price	Month_Year
1049370	New York	2019-12-01	74	2019-12
1049371	New York	2019-12-01	89	2019-12
1049372	New York	2019-12-01	85	2019-12
1049373	New York	2019-12-01	135	2019-12
1049374	New York	2019-12-01	250	2019-12
...	...	...	...	...
2065521	New York	2021-02-05	110	2021-02
2065522	New York	2021-01-30	46	2021-01
2065523	New York	2021-02-04	65	2021-02
2065524	New York	2021-01-31	30	2021-01
2065525	New York	2021-02-02	111	2021-02

847727 rows × 4 columns

Then I simply calculate the monthly mean of prices and corresponding counts of orders.

In [49]:

```
avgp_NY = pd.DataFrame(columns = ['Month_Year', 'Avg_Price'])
avgp_ny = []
avgn_ny = []
for i in NY_price['Month_Year'].unique():
    avgp_ny.append(NY_price[NY_price['Month_Year'] == i]['price'].mean())
    avgn_ny.append(sum(NY_price[NY_price['Month_Year'] == i]['price']))

avgp_NY['Month_Year'] = NY_price['Month_Year'].unique();
avgp_NY['Avg_Price'] = avgp_ny
avgp_NY['n_Order'] = avgn_ny
avgp_NY = avgp_NY.sort_values('Month_Year').reset_index()
avgp_NY
```

Out[49]:

	index	Month_Year	Avg_Price	n_Order
0	141	2009-04	83.000000	83
1	84	2009-05	86.500000	519
2	108	2009-06	95.000000	380
3	85	2009-07	92.625000	741
4	109	2009-08	183.428571	1284
...	...	...	...	...
138	15	2020-10	116.701857	1212649
139	25	2020-11	115.747641	1177385
140	27	2020-12	113.548595	1054980
141	24	2021-01	113.215798	1096495
142	142	2021-02	109.232941	46424

143 rows × 4 columns

To check the overall tendency of monthly average prices in NY and refer to the volume of orders at the same time, I use the dual axis plot.

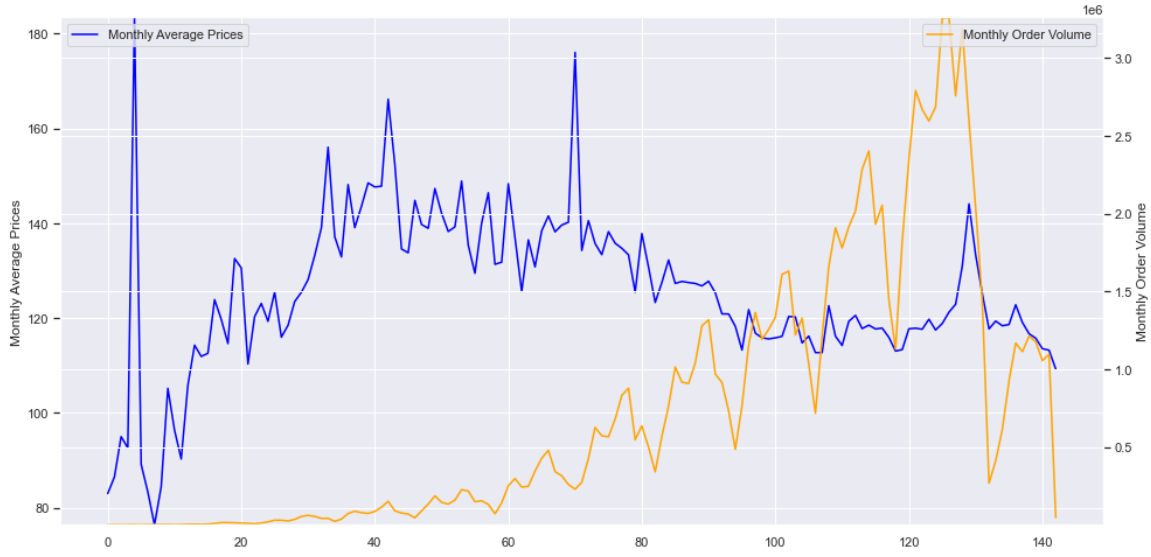
In [50]:

```
t_NY = np.arange(0, len(avgp_NY), 1)

sns.set(rc={"figure.figsize":(16, 8)})

ax1 = sns.lineplot(t_NY, avgp_NY['Avg_Price'], color='blue')
ax1.set_ylabel('Monthly Average Prices')
ax1.set_ylim(avgp_NY['Avg_Price'].min(), max(avgp_NY['Avg_Price']))
ax1.legend(['Monthly Average Prices'], loc="upper left")

ax2 = ax1.twinx()

ax2 = sns.lineplot(t_NY, avgp_NY['n_Order'], color='orange')
ax2.set_ylabel('Monthly Order Volume')
ax2.set_ylim(min(avgp_NY['n_Order']), max(avgp_NY['n_Order']))
ax2.set_xlabel('Time/Days')
ax2.legend(['Monthly Order Volume'], loc="upper right")
```

```
F:\Anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the f
ollowing variables as keyword args: x, y. From version 0.12, the only valid positi
onal argument will be `data`, and passing other arguments without an explicit keyw
ord will result in an error or misinterpretation.
  warnings.warn(
F:\Anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the f
ollowing variables as keyword args: x, y. From version 0.12, the only valid positi
onal argument will be `data`, and passing other arguments without an explicit keyw
ord will result in an error or misinterpretation.
  warnings.warn(
```

Out[50]:

```
<matplotlib.legend.Legend at 0x25a9e754fa0>
```



It is clear that, the monthly order volume has a significant seasonality and a increasing tendency; the sharp decrese of order volume in the back is likely due to the epidemic in 2020. But the series of the monthly order volue has a stable one-year's cycle.

Then plot the autocorrelation function of monthly prices after normalization to see if there is seasonality.

In [51]:

```
pd.plotting.autocorrelation_plot(normalize(avgp_NY[['Avg_Price']], axis = 0))
```

Out[51]:

<matplotlib.axes._subplots.AxesSubplot at 0x25a9e79da00>

As it shows, the monthly mean price series is not stationary as it does not truncate fast.
But the ACF cannot interpret its specific fluctuations, like the main and subordinate cycles in potential seasonal fluctuation.So I decide to use wavelet transformation to ① denoise the monthly mean price series and ② use the denoised series to find the largest cycle and the finest.
Furthermore, I will try to detect their causality and build a quantitative model to show this. Hopefully, the monthly order volume could be a predictor of the prices.

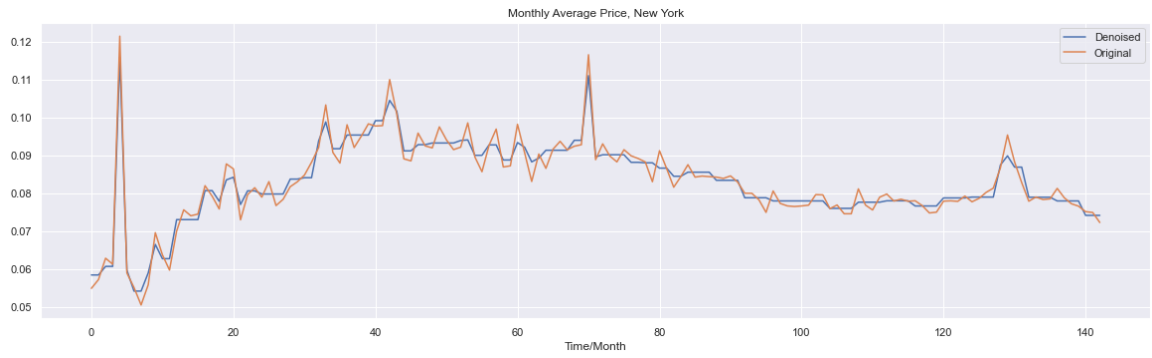
In [52]:

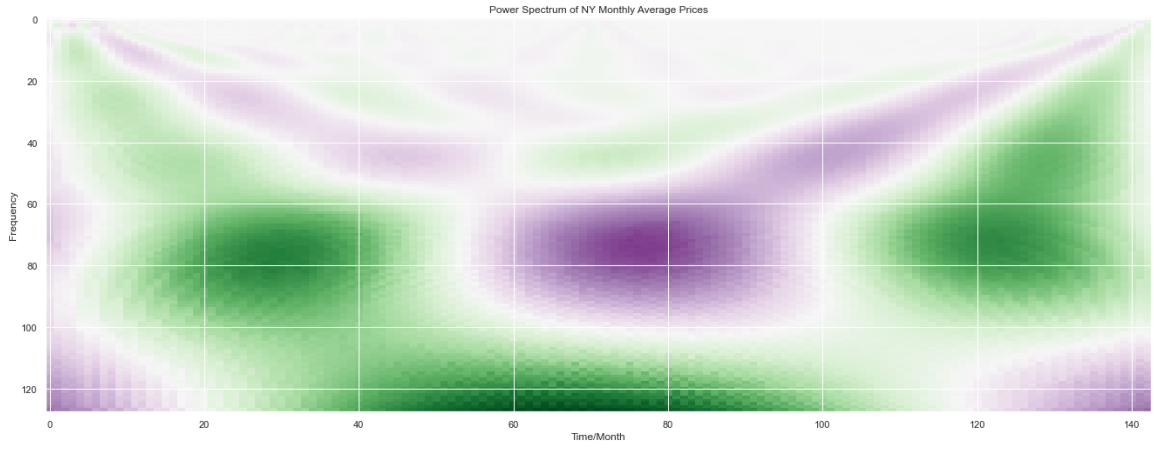
```
import pywt
```

First, normalize the monthly average price data (min-max) and try denoising it at **signal level (one level)** with db wavelets. When denoising, remove the low frequency part to eliminate the temporal trend of the series.

In [53]:

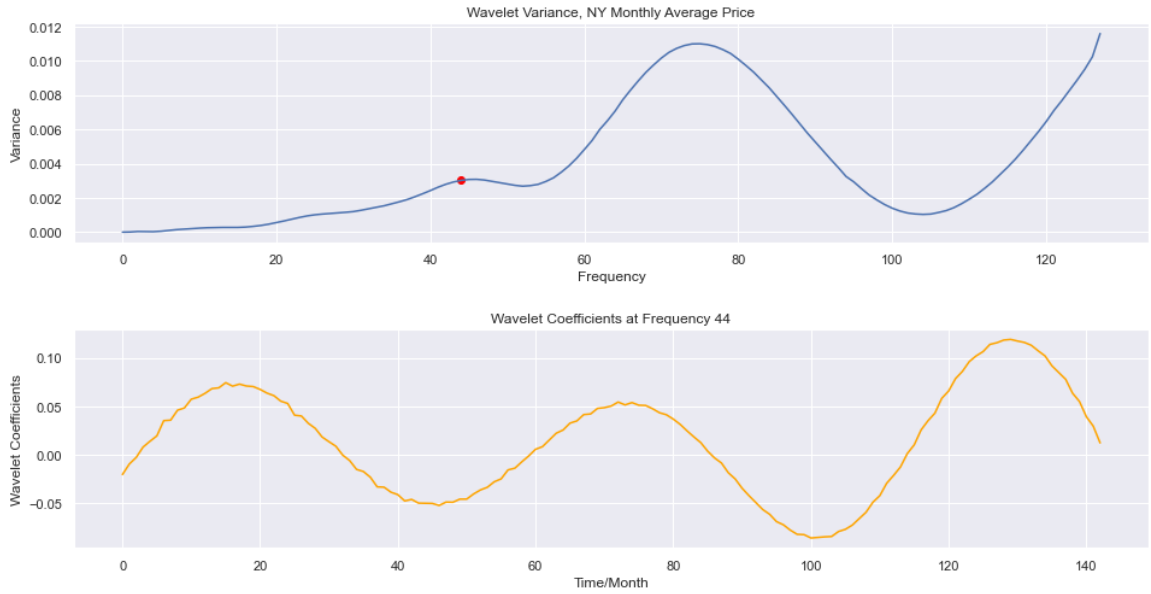
```
'''With Temporal Trend'''
plt.figure(figsize = (20, 12))
# Denoising
avgp_ny_ = normalize(np.array(avgp_NY['Avg_Price']).reshape(1, -1))[0]
coef = pywt.wavedec(avgp_ny_, 'db1', level = 3)
for i in range(1, len(coef)):
    coef[i] = pywt.threshold(coef[i], .1 * max(coef[i]))
dno_avgp_ny_wizt = pywt.waverec(coef[:], 'db1')
dno_avgp_ny_wizt = dno_avgp_ny_wizt[: -1]
plt.subplot(211)
plt.plot(np.arange(0, len(dno_avgp_ny_wizt)), dno_avgp_ny_wizt)
plt.plot(np.arange(0, len(avgp_ny_)), avgp_ny_)
plt.title('Monthly Average Price, New York')
plt.xlabel('Time/Month');
plt.legend(['Denoised', 'Original'])
plt.show()

# Continuous Wavelet Decomposition
coefs_ctn_wizt, f = pywt.cwt(dno_avgp_ny_wizt, np.arange(1, 129, 1), 'morl')
plt.figure(figsize = (50, 20))
plt.subplot(221)
plt.imshow(coefs_ctn_wizt, cmap = 'PRGn', aspect = 'auto',
           vmax = abs(coefs_ctn_wizt).max(), vmin = -abs(coefs_ctn_wizt).max())
plt.ylabel('Frequency');
plt.xlabel('Time/Month');
plt.title('Power Spectrum of NY Monthly Average Prices')

plt.subplots_adjust(hspace = 0.4)
```





In [54]:

```
plt.subplot(211)
plt.plot(np.arange(0, len(coefs_ctn_wizt), 1), np.var(coefs_ctn_wizt, axis = 1))
freq = 44
plt.xlabel('Frequency'); plt.ylabel('Variance')
plt.scatter(freq, np.var(coefs_ctn_wizt[int(freq)]), c = 'red')
plt.title('Wavelet Variance, NY Monthly Average Price')

plt.subplot(212)
plt.plot(np.arange(0, len(dno_avgp_ny_wizt), 1), coefs_ctn_wizt[int(freq)], c = 'orange')
plt.title('Wavelet Coefficients at Frequency {}'.format(freq))
plt.xlabel('Time/Month'); plt.ylabel('Wavelet Coefficients')

plt.subplots_adjust(hspace = 0.4)
```



With the variance plot, we can see the market cycle of roughly 40 months (44).

In [55]:

```
'''Without Temporal Tendency'''
avgp_ny_ = normalize(np.array(avgp_NY['Avg_Price']).reshape(1, -1))[0]
coef = pywt.wavedec(avgp_ny_, 'db1', level = 3)
for i in range(1, len(coef)):
    coef[i] = pywt.threshold(coef[i], .1 * max(coef[i]))
coef[0] = coef[0] - coef[0] # Eliminating the Temporal Tendency
dno_avgp_ny = pywt.waverec(coef[:], 'db1')
dno_avgp_ny = dno_avgp_ny[: -1]
plt.plot(np.arange(0, len(dno_avgp_ny)), dno_avgp_ny)
plt.plot(np.arange(0, len(avgp_ny_)), avgp_ny_)
plt.title('Monthly Average Price (Without Temporal Trend), New York')
plt.legend(['No Temporal Tendency', 'Original'])
```

Out[55]:

<matplotlib.legend.Legend at 0x25a9f0060a0>

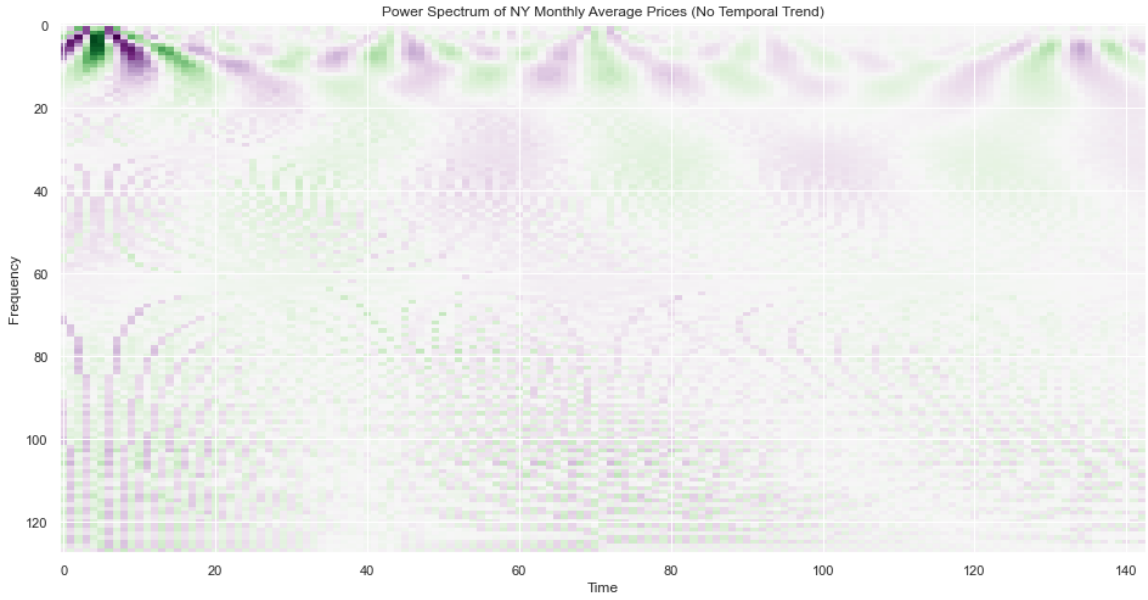
We assume the sampling period is 1 (a special unit here is trivial), then choose Morlet wavelet for continuous decomposition. To visualize the result, plot the global power spectrum.

In [56]:

```
coefs_ctn, f = pywt.cwt(dno_avgp_ny, np.arange(1, 129, 1), 'morl')
plt.imshow(coefs_ctn, cmap = 'PRGn', aspect = 'auto',
           vmax = abs(coefs_ctn).max(), vmin = -abs(coefs_ctn).max())
plt.ylabel('Frequency');
plt.xlabel('Time');
plt.title('Power Spectrum of NY Monthly Average Prices (No Temporal Trend)')
```

Out[56]:

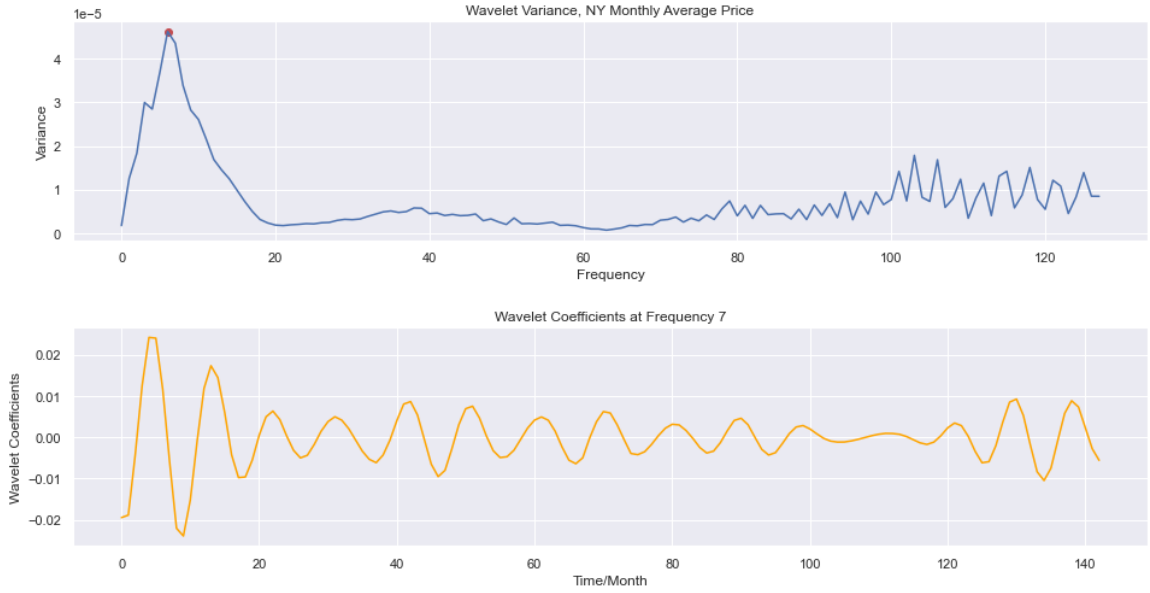
```
Text(0.5, 1.0, 'Power Spectrum of NY Monthly Average Prices (No Temporal Trend)')
```



If we search for a main and a finest cycle on purpose, we may see a roughly 4 years' when frequency is 50 Hertz and a 6 month's cycle when frequency is 10 Hertz. The latter is mych less significant (lighter color) as it does not have a significant fluctuation globally as the main cycles do, however this does not mean such cycle does not exist. As long as at this frequency, it has a more significant fluctuation than the ambient frequencies do, we can say there is a locally significant cycle.
To show this clearer, I remove the temporal tendency and use variance of continuous wavelet coefficients to see the local maximum of fluctuation in the frequency region.

In [57]:

```
plt.subplot(211)
plt.plot(np.arange(0, len(coefs_ctn), 1), np.var(coefs_ctn, axis = 1))
plt.xlabel('Frequency'); plt.ylabel('Variance')
plt.title('Wavelet Variance, NY Monthly Average Price')
freq = None
for i in range(len(np.var(coefs_ctn, axis = 1))):
    if np.var(coefs_ctn, axis = 1)[i] == max(np.var(coefs_ctn, axis = 1)):
        freq = i
plt.scatter(freq, np.var(coefs_ctn[int(freq)]), c = 'r')

plt.subplot(212)
plt.plot(np.arange(0, len(dno_avgp_ny), 1), coefs_ctn[int(freq)], c = 'orange')
plt.title('Wavelet Coefficients at Frequency {}'.format(freq + 1))
plt.xlabel('Time/Month'); plt.ylabel('Wavelet Coefficients')

plt.subplots_adjust(hspace = 0.4)
```



After eliminating temporal tendency, it is noticeable that the former frequencies where the cycles of the series were global significant are now no longer significant, while it was insignificant before but now significant after when frequency equals 10 or so: we see there is a local maximum of coefficient variance when frequency equals 7, so we can say there is a seven-months' cycle int the price fluctuation. In fact, we can regard it as a half year's cycle.

Then I want to use Granger Causality Test to see if there is causality between monthly average price and order volume. The null hypothesis is 'Granger non causality'. Before testing, I make sure the series stationary by Augmented Dickey-fuller Test.

In [58]:

```
from statsmodels.tsa.stattools import adfuller
print('\033[1mAugmented Dickey-fuller Test for Denoised NYC Monthly Order Volume\033[0m')
dftest = adfuller(dno_avgp_ny, autolag='AIC')
dfoutput=pd.Series(dftest[0:4],index=['Test Statistic','p-value','#lags used','number of observations used'])
for key,value in dftest[4].items():
    dfoutput['critical value (%s)'%key]= value
print(dfoutput)
```

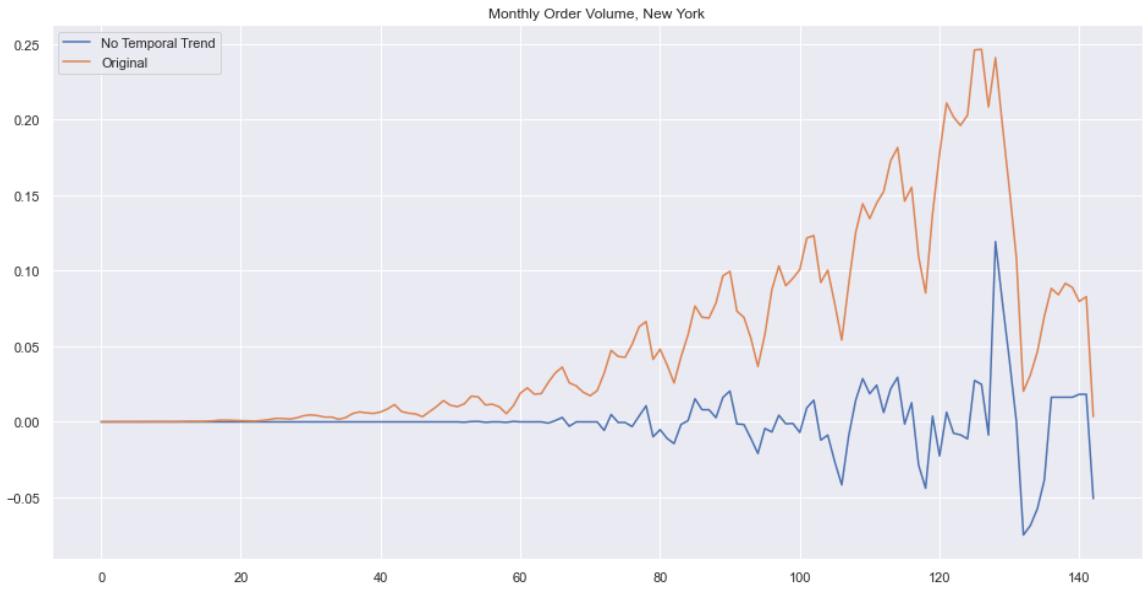
```
Augmented Dickey-fuller Test for Denoised NYC Monthly Order Volume
Test Statistic                -7.965792e+00
p-value                        2.867456e-12
#lags used                     5.000000e+00
number of observations used    1.370000e+02
critical value (1%)           -3.479007e+00
critical value (5%)           -2.882878e+00
critical value (10%)          -2.578149e+00
dtype: float64

F:\Anaconda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:7: FutureWarning:
pandas.Int64Index is deprecated and will be removed from pandas in a future versio
n. Use pandas.Index with the appropriate dtype instead.
  from pandas import (to_datetime, Int64Index, DatetimeIndex, Period,
F:\Anaconda\lib\site-packages\statsmodels\tsa\base\tsa_model.py:7: FutureWarning:
pandas.Float64Index is deprecated and will be removed from pandas in a future vers
ion. Use pandas.Index with the appropriate dtype instead.
  from pandas import (to_datetime, Int64Index, DatetimeIndex, Period,
```

In [59]:

```
avgn_ny_ = normalize(np.array(avgp_NY['n_Order']).reshape(1, -1))[0]
coef_n = pywt.wavedec(avgn_ny_, 'db1', level = 3)
for i in range(1, len(coef_n)):
    coef_n[i] = pywt.threshold(coef_n[i], .1 * max(coef_n[i]))
coef_n[0] = coef_n[0] - coef_n[0]
dno_avgn_ny = pywt.waverec(coef_n[:], 'db1') # To eliminate the temporal temdency, remove the lo
w frequency part when filter the signal
dno_avgn_ny = dno_avgn_ny[: -1]
plt.plot(np.arange(0, len(dno_avgn_ny)), dno_avgn_ny)
plt.plot(np.arange(0, len(avgn_ny_)), avgn_ny_)
plt.title('Monthly Order Volume, New York')
plt.legend(['No Temporal Trend', 'Original'])
```

Out[59]:

<matplotlib.legend.Legend at 0x25aa0dc9430>



In [60]:

```
print('\033[1mAugmented Dickey-fuller Test for Denoised NYC Monthly Housing Price\033[0m')
dftest = adfuller(dno_avgn_ny, autolag='AIC')
dfoutput=pd.Series(dftest[0:4],index=['Test Statistic','p-value','#lags used','number of observa
tions used'])
for key,value in dftest[4].items():
    dfoutput['critical value (%s)'%key]= value
print(dfoutput)
```

```
Augmented Dickey-fuller Test for Denoised NYC Monthly Housing Price
Test Statistic                  -3.359499
p-value                          0.012420
#lags used                      14.000000
number of observations used    128.000000
critical value (1%)             -3.482501
critical value (5%)             -2.884398
critical value (10%)            -2.578960
dtype: float64
```

With a 0.05 significance level, the denoised series are stationary, then I use Granger Causality Test, seting the maximum lag order as 3 months.

In [61]:

```
from statsmodels.tsa.stattools import grangercausalitytests
```

In [62]:

```
price_volume_ny = pd.DataFrame([dno_avgp_ny, dno_avgn_ny]).transpose()
grangercausalitytests(price_volume_ny, 3)
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=3.4424  , p=0.0657  , df_denom=139, df_num=1
ssr based chi2 test:   chi2=3.5167  , p=0.0608  , df=1
likelihood ratio test: chi2=3.4738  , p=0.0623  , df=1
parameter F test:         F=3.4424  , p=0.0657  , df_denom=139, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=2.0307  , p=0.1352  , df_denom=136, df_num=2
ssr based chi2 test:   chi2=4.2107  , p=0.1218  , df=2
likelihood ratio test: chi2=4.1491  , p=0.1256  , df=2
parameter F test:         F=2.0307  , p=0.1352  , df_denom=136, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=1.5514  , p=0.2042  , df_denom=133, df_num=3
ssr based chi2 test:   chi2=4.8993  , p=0.1793  , df=3
likelihood ratio test: chi2=4.8155  , p=0.1858  , df=3
parameter F test:         F=1.5514  , p=0.2042  , df_denom=133, df_num=3
```

Out[62]:

```
{1: ({'ssr_ftest': (3.4423645499460744, 0.06566279380028915, 139.0, 1),
   'ssr_chi2test': (3.516660187714695, 0.060754759240606776, 1),
   'lrtest': (3.473820615840623, 0.06234715108292425, 1),
   'params_ftest': (3.4423645499460798, 0.06566279380028879, 139.0, 1.0)},
  [<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x25ab6751a30
>,
   <statsmodels.regression.linear_model.RegressionResultsWrapper at 0x25ab6751eb0
>,
   array([[0., 1., 0.]])]),
 2: ({'ssr_ftest': (2.0306991039952433, 0.13520434792444572, 136.0, 2),
   'ssr_chi2test': (4.210714318578373, 0.12180216372522797, 2),
   'lrtest': (4.149065910186891, 0.12561508167914628, 2),
   'params_ftest': (2.0306991039952504, 0.13520434792444572, 136.0, 2.0)},
  [<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x25a9f37cc40
>,
   <statsmodels.regression.linear_model.RegressionResultsWrapper at 0x25a9f37c4f0
>,
   array([[0., 0., 1., 0., 0.],
          [0., 0., 0., 1., 0.]])]),
 3: ({'ssr_ftest': (1.5514330456989105, 0.20424597866622986, 133.0, 3),
   'ssr_chi2test': (4.899262249575506, 0.17932403261797086, 3),
   'lrtest': (4.8154869362697355, 0.18581753142098428, 3),
   'params_ftest': (1.5514330456989154, 0.20424597866229477, 133.0, 3.0)},
  [<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x25ab6756f10
>,
   <statsmodels.regression.linear_model.RegressionResultsWrapper at 0x25a9f37c5b0
>,
   array([[0., 0., 0., 1., 0., 0., 0.],
          [0., 0., 0., 0., 1., 0., 0.],
          [0., 0., 0., 0., 0., 1., 0.]])])}
```

In [63]:

```
price_volume_ny = pd.DataFrame([dno_avgn_ny, dno_avgp_ny]).transpose()
grangercausalitytests(price_volume_ny, 3)
```

```
Granger Causality
number of lags (no zero) 1
ssr based F test:         F=0.0220  , p=0.8823  , df_denom=139, df_num=1
ssr based chi2 test:   chi2=0.0225  , p=0.8808  , df=1
likelihood ratio test: chi2=0.0225  , p=0.8808  , df=1
parameter F test:         F=0.0220  , p=0.8823  , df_denom=139, df_num=1

Granger Causality
number of lags (no zero) 2
ssr based F test:         F=0.0836  , p=0.9199  , df_denom=136, df_num=2
ssr based chi2 test:   chi2=0.1733  , p=0.9170  , df=2
likelihood ratio test: chi2=0.1732  , p=0.9170  , df=2
parameter F test:         F=0.0836  , p=0.9199  , df_denom=136, df_num=2

Granger Causality
number of lags (no zero) 3
ssr based F test:         F=0.0639  , p=0.9788  , df_denom=133, df_num=3
ssr based chi2 test:   chi2=0.2018  , p=0.9773  , df=3
likelihood ratio test: chi2=0.2017  , p=0.9773  , df=3
parameter F test:         F=0.0639  , p=0.9788  , df_denom=133, df_num=3
```

Out[63]:

```
{1: ({'ssr_ftest': (0.02200772822377891, 0.8822815371297588, 139.0, 1),
   'ssr_chi2test': (0.02248271516386047, 0.8808100809267863, 1),
   'lrtest': (0.022480935519070044, 0.8808147630813092, 1),
   'params_ftest': (0.02200772822376299, 0.8822815371297588, 139.0, 1.0)},
  [<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x25ab6760b20
>,
   <statsmodels.regression.linear_model.RegressionResultsWrapper at 0x25ab6760a00
>,
   array([[0., 1., 0.]])]),
 2: ({'ssr_ftest': (0.08359123794628696, 0.9198543824858934, 136.0, 2),
   'ssr_chi2test': (0.17332889044744798, 0.9169847426242168, 2),
   'lrtest': (0.17322244255342412, 0.9170335494704039, 2),
   'params_ftest': (0.08359123794626684, 0.9198543824859142, 136.0, 2.0)},
  [<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x25aa0db6370
>,
   <statsmodels.regression.linear_model.RegressionResultsWrapper at 0x25a9f136c70
>,
   array([[0., 0., 1., 0., 0.],
          [0., 0., 0., 1., 0.]])]),
 3: ({'ssr_ftest': (0.06391107204404602, 0.9788205831170533, 133.0, 3),
   'ssr_chi2test': (0.20182443803382952, 0.9772942350587493, 3),
   'lrtest': (0.2016791023238511, 0.9773177791122447, 3),
   'params_ftest': (0.06391107204404543, 0.9788205831170533, 133.0, 3.0)},
  [<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x25ab6751d00
>,
   <statsmodels.regression.linear_model.RegressionResultsWrapper at 0x25ab6a013d0
>,
   array([[0., 0., 0., 1., 0., 0., 0.],
          [0., 0., 0., 0., 1., 0., 0.],
          [0., 0., 0., 0., 0., 1., 0.]])])}
```

With significance level 0.1, we can say without the temporal tendency, **the first-order lag series of monthly order volume is a Granger Cause of monthly average price in NYC**; the series of monthly average price is not a Cause of order volume at any lag order.

I also want to check the temporal pattern of monthly average price in other cities.

In [64]:

```
price_time['city'].unique()
```

Out[64]:

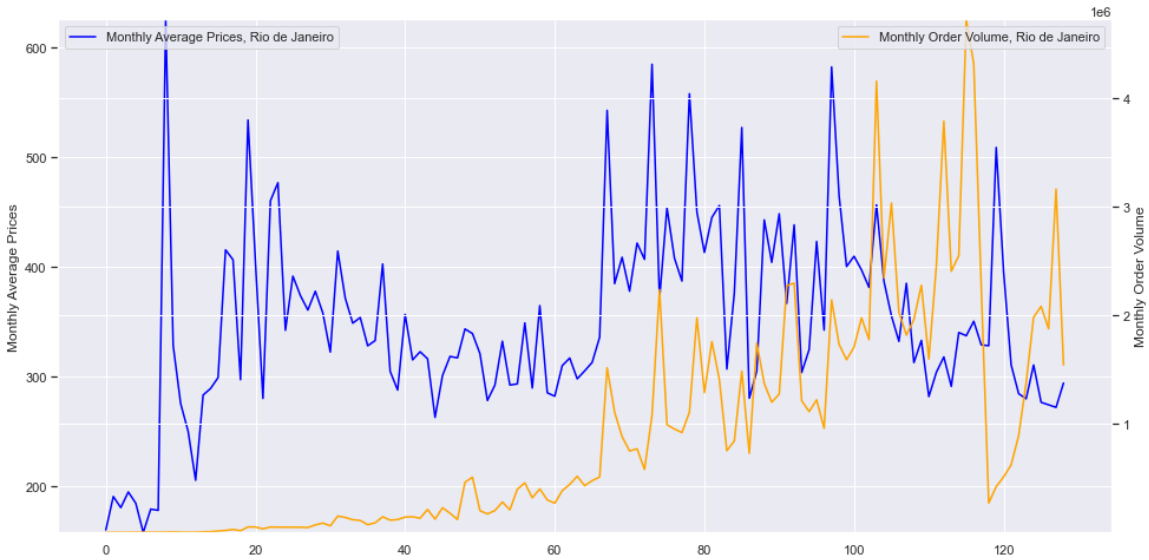
```
array(['Paris', 'New York', 'Bangkok', 'Hong Kong', 'Mexico City',
       'Cape Town', 'Rio de Janeiro', 'Sydney', 'Istanbul', 'Rome'],
      dtype=object)
```

The listings covers cities almost in every continent, so I want to apply the same methods above to visualize the monthly average housing price and order volume of these cities. Assembling the procedures above as functions.

In [65]:

```
Price_Rio, p_n_Rio = price_a_city(price_time, 'Rio de Janeiro')
vis_p_n('Rio de Janeiro', p_n_Rio)
```

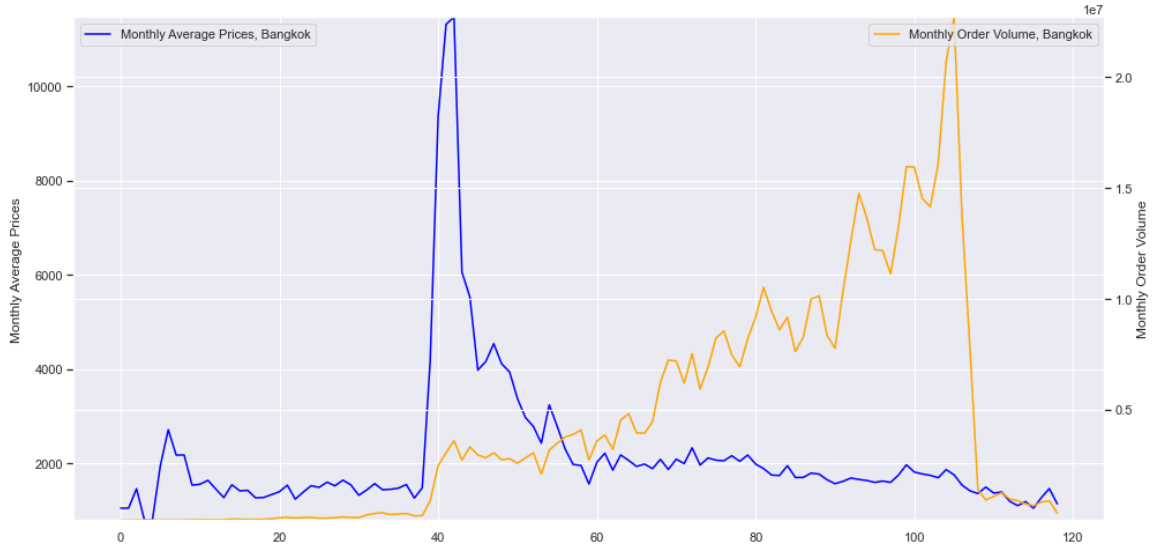
```
F:\Anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the f
ollowing variables as keyword args: x, y. From version 0.12, the only valid positi
onal argument will be `data`, and passing other arguments without an explicit keyw
ord will result in an error or misinterpretation.
  warnings.warn(
F:\Anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the f
ollowing variables as keyword args: x, y. From version 0.12, the only valid positi
onal argument will be `data`, and passing other arguments without an explicit keyw
ord will result in an error or misinterpretation.
  warnings.warn(
```



In [66]:

```
Price_Bangkok, p_n_Bangkok = price_a_city(price_time, 'Bangkok')
vis_p_n('Bangkok', p_n_Bangkok)
```

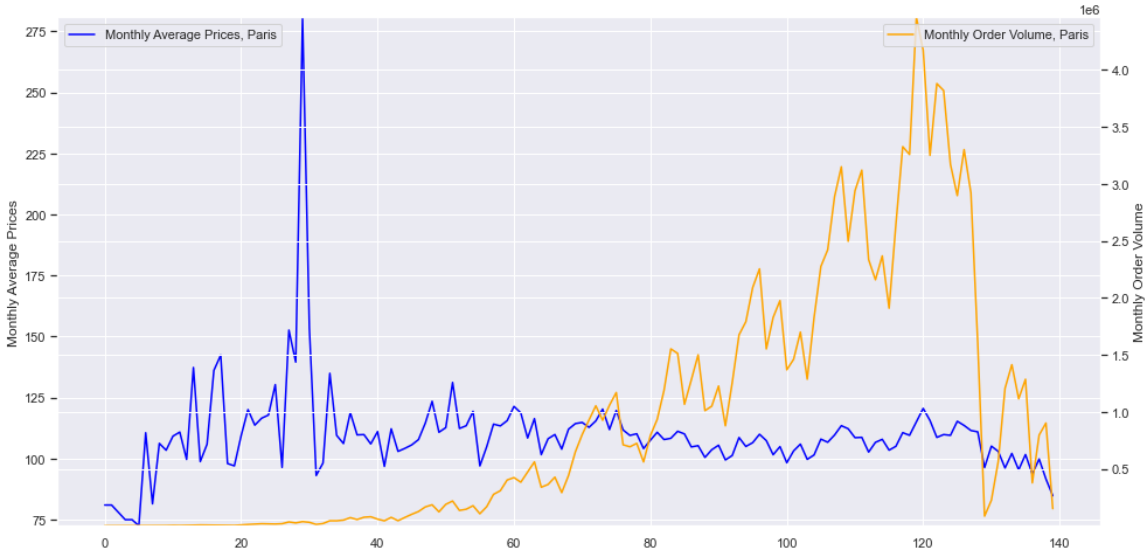
```
F:\Anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the f
ollowing variables as keyword args: x, y. From version 0.12, the only valid positi
onal argument will be `data`, and passing other arguments without an explicit keyw
ord will result in an error or misinterpretation.
  warnings.warn(
F:\Anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the f
ollowing variables as keyword args: x, y. From version 0.12, the only valid positi
onal argument will be `data`, and passing other arguments without an explicit keyw
ord will result in an error or misinterpretation.
  warnings.warn(
```



In [67]:

```
Price_Paris, p_n_Paris = price_a_city(price_time, 'Paris')
vis_p_n('Paris', p_n_Paris)
```

```
F:\Anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the f
ollowing variables as keyword args: x, y. From version 0.12, the only valid positi
onal argument will be `data`, and passing other arguments without an explicit keyw
ord will result in an error or misinterpretation.
  warnings.warn(
F:\Anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the f
ollowing variables as keyword args: x, y. From version 0.12, the only valid positi
onal argument will be `data`, and passing other arguments without an explicit keyw
ord will result in an error or misinterpretation.
  warnings.warn(
```



There are seasonalies on different extent in the three chosen cities, Rio, Paris and Bangkok. But note that there are significant spiking average prices in Paris and Bangkok, while **the order volume in Bangkok significantly rises but stays normal in Paris**. I want to find possible causation for the sudden rising prices in Paris and Bankok. I locate the year-month of the two extremes then search if there are big events that may pertain to.

In [68]:

```
ext_date_Bangkok = p_n_Bangkok['Month_Year'].iloc[p_n_Bangkok[['Avg_Price']].idxmax(axis = 0)]
ext_date_Paris = p_n_Paris['Month_Year'].iloc[p_n_Paris[['Avg_Price']].idxmax(axis = 0)]
```

In [69]:

```
print('Abnormal Average Price in Bangkok, {}; in Paris, {}'.format(ext_date_Bangkok.values, ext
_date_Paris.values))
```

```
Abnormal Average Price in Bangkok, ['2014-10']; in Paris, ['2011-12']
```

For Paris, I found its Residential Property Index (RPI) (https://www.compassft.com/indice/parissqm/ (https://www.compassft.com/indice/parissqm/)) and plot it. In 2011 and 2012, the RPI rises unprecedentedly, which corresponds to the monthly average prices during that time. So the rising price of residential property might be a cause.

In [70]:

```
RPI_Paris = pd.read_csv('D:\DS\parissqm_20221216_230025.csv')
RPI_Paris
```

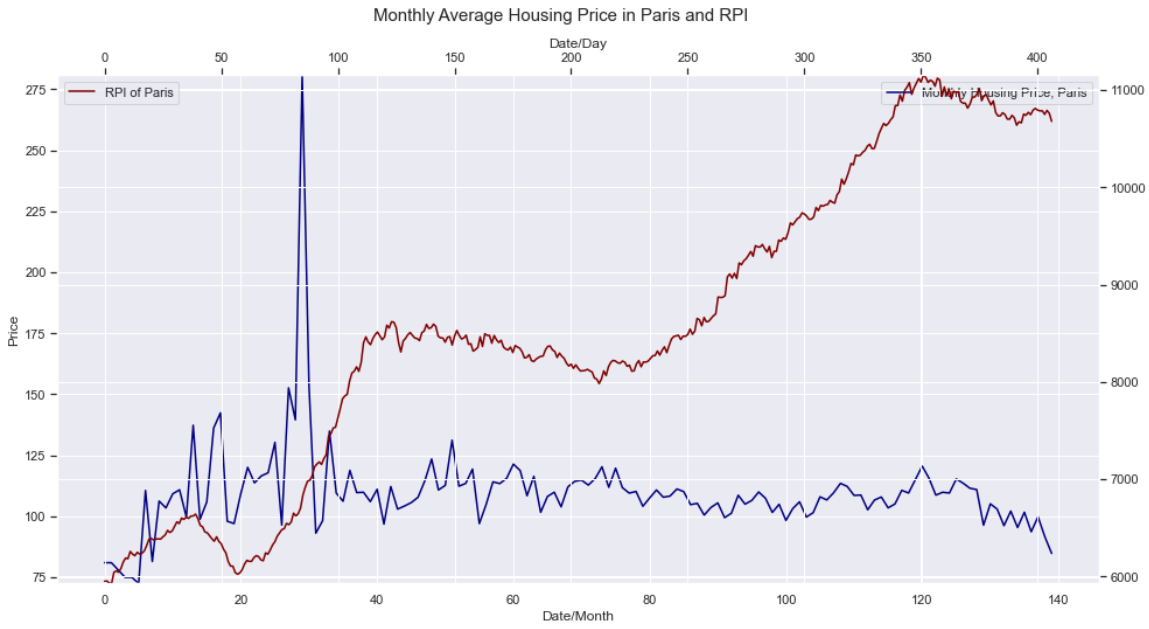
Out[70]:

	Date	PARISSQM
0	2022-12-16T00:00:00	10676
1	2022-12-02T00:00:00	10759
2	2022-11-18T00:00:00	10789
3	2022-11-04T00:00:00	10748
4	2022-10-21T00:00:00	10785
...	...	...
402	2007-07-20T00:00:00	6044
403	2007-07-06T00:00:00	5929
404	2007-06-22T00:00:00	5932
405	2007-06-08T00:00:00	5954
406	2007-05-25T00:00:00	5952

407 rows × 2 columns

In [71]:

```
t1 = np.arange(0, len(p_n_Paris)); y1 = p_n_Paris['Avg_Price']
fig, axes = plt.subplots()
axes.plot(t1, y1, c = 'navy')
axes.set_xlabel('Date/Month', fontsize=12)
axes.set_ylabel('Price', fontsize=12)
axes.set_ylim(min(y1), max(y1))
axes.legend(['Monthly Housing Price, Paris'])

twin_axes = axes.twinx().twiny()

t2 = np.arange(0, len(RPI_Paris))
y2 = RPI_Paris['PARISSQM'][:: -1]
twin_axes.plot(t2, y2, c = 'maroon')
twin_axes.set_ylim(min(y2), max(y2))
twin_axes.set_xlabel('Date/Day',fontsize=12)
twin_axes.set_ylabel('Residential Property Index, Paris', fontsize=12)

twin_axes.legend(['RPI of Paris'])

fig.suptitle('Monthly Average Housing Price in Paris and RPI', fontsize=15)
#fig.set_size_inches(10, 8)
plt.show()
```



In [ ]:

```
```