Project: Investigation on Brazallian Appointments Dataset (Finding the reasons for non showing of the patients)

Table of Contents

Introduction

This dataset collects information from 100k medical appointments in Brazil and is focused on the question of whether or not patients show up for their appointment. A number of characteristics about the patient are included in each row.

Questions Asked in This Analysis:

- Does Age Affect the no-show percentage?
- Does Gender affect the appointments?
- Does Diseases affect the appointments?
- Does SMS affect the appointments?
- Does Neighbourhood affect the appointments?
- Does Difference between schedule day and appointments day have an effect ?

In [36]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
plt.style.use('seaborn')
%matplotlib inline
```

Data Wrangling

General Properties

In [37]:
```
#load data
df = pd.read_csv('no-show-original.csv').copy()
#View dataset
df
```

Out[37]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourho
0	2.987250e+13	5642903	F	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	62	JARDIM PEN
1	5.589978e+14	5642503	M	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	56	JARDIM PEN

Loading [MathJax]/extensions/Safe.js

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourho
2	4.262962e+12	5642549	F	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	62	MATA DA PRA
3	8.679512e+11	5642828	F	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	8	PONTAL CAMBU
4	8.841186e+12	5642494	F	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	56	JARDIM PEN
...	...	...	...	...	...	...	
110522	2.572134e+12	5651768	F	2016-05-03T09:15:35Z	2016-06-07T00:00:00Z	56	MARIA OR
110523	3.596266e+12	5650093	F	2016-05-03T07:27:33Z	2016-06-07T00:00:00Z	51	MARIA OR
110524	1.557663e+13	5630692	F	2016-04-27T16:03:52Z	2016-06-07T00:00:00Z	21	MARIA OR
110525	9.213493e+13	5630323	F	2016-04-27T15:09:23Z	2016-06-07T00:00:00Z	38	MARIA OR
110526	3.775115e+14	5629448	F	2016-04-27T13:30:56Z	2016-06-07T00:00:00Z	54	MARIA OR

110527 rows × 14 columns

In [38]:

```
#General information about the data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 14 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   PatientId       110527 non-null  float64
 1   AppointmentID   110527 non-null  int64
 2   Gender          110527 non-null  object
 3   ScheduledDay    110527 non-null  object
 4   AppointmentDay  110527 non-null  object
 5   Age             110527 non-null  int64
 6   Neighbourhood   110527 non-null  object
 7   Scholarship     110527 non-null  int64
 8   Hipertension    110527 non-null  int64
 9   Diabetes        110527 non-null  int64
 10  Alcoholism      110527 non-null  int64
 11  Handcap         110527 non-null  int64
 12  SMS_received    110527 non-null  int64
 13  No-show         110527 non-null  object
dtypes: float64(1), int64(8), object(5)
memory usage: 11.8+ MB
```

In [39]:

```
#creating new list for the columns names that will be changed
new_names=['patient_id','appointment_id','gender','scheduled_date','appointment_date','ag
#Apply the new column names
df.columns=new_names
#view dataframe after renaming the columns
df
```

Out[39]:

	patient_id	appointment_id	gender	scheduled_date	appointment_date	age	neighbour
0	2.987250e+13	5642903	F	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	62	JARDI P
1	5.589978e+14	5642503	M	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	56	JARDI P

Loading [MathJax]/extensions/Safe.js

	patient_id	appointment_id	gender	scheduled_date	appointment_date	age	neighbour
2	4.262962e+12	5642549	F	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	62	MATA DA I
3	8.679512e+11	5642828	F	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	8	PONT/ CAM
4	8.841186e+12	5642494	F	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	56	JARDI P
...	...	...	...	...	...	...	
110522	2.572134e+12	5651768	F	2016-05-03T09:15:35Z	2016-06-07T00:00:00Z	56	MARIA (
110523	3.596266e+12	5650093	F	2016-05-03T07:27:33Z	2016-06-07T00:00:00Z	51	MARIA (
110524	1.557663e+13	5630692	F	2016-04-27T16:03:52Z	2016-06-07T00:00:00Z	21	MARIA (
110525	9.213493e+13	5630323	F	2016-04-27T15:09:23Z	2016-06-07T00:00:00Z	38	MARIA (
110526	3.775115e+14	5629448	F	2016-04-27T13:30:56Z	2016-06-07T00:00:00Z	54	MARIA (

110527 rows × 14 columns

In [40]:

```
#Changing the scheduled_date and appointment_date to appropriate date and time format to
df['scheduled_date'] = pd.to_datetime(df['scheduled_date'])
df['appointment_date'] = pd.to_datetime(df['appointment_date'])
# Extracting appointment day from the apoointment date
df['appointment_day']=df['appointment_date'].dt.strftime('%A')

# Finding the days differnece between scheduled day and appointment day
df['days_difference']=df['appointment_date'].dt.date - df['scheduled_date'].dt.date
# Changing the date to days format
df['days_difference']=df['days_difference'].dt.days

# Creating new order for the dataframe to make sure that relevant data re next to each ot
order=['patient_id','appointment_id','gender','scheduled_date','appointment_date','appoint
# Applying the new ordering
df=df[order]

df
```

Out[40]:

	patient_id	appointment_id	gender	scheduled_date	appointment_date	appointment_da
0	2.987250e+13	5642903	F	2016-04-29 18:38:08+00:00	2016-04-29 00:00:00+00:00	Frida
1	5.589978e+14	5642503	M	2016-04-29 16:08:27+00:00	2016-04-29 00:00:00+00:00	Frida
2	4.262962e+12	5642549	F	2016-04-29 16:19:04+00:00	2016-04-29 00:00:00+00:00	Frida
3	8.679512e+11	5642828	F	2016-04-29 17:29:31+00:00	2016-04-29 00:00:00+00:00	Frida
4	8.841186e+12	5642494	F	2016-04-29 16:07:23+00:00	2016-04-29 00:00:00+00:00	Frida
...	...	...	...	...	...	.
110522	2.572134e+12	5651768	F	2016-05-03 09:15:35+00:00	2016-06-07 00:00:00+00:00	Tuesda
110523	3.596266e+12	5650093	F	2016-05-03 07:27:33+00:00	2016-06-07 00:00:00+00:00	Tuesda

Loading [MathJax]/extensions/Safe.js

	patient_id	appointment_id	gender	scheduled_date	appointment_date	appointment_da
110524	1.557663e+13	5630692	F	2016-04-27 16:03:52+00:00	2016-06-07 00:00:00+00:00	Tuesda
110525	9.213493e+13	5630323	F	2016-04-27 15:09:23+00:00	2016-06-07 00:00:00+00:00	Tuesda
110526	3.775115e+14	5629448	F	2016-04-27 13:30:56+00:00	2016-06-07 00:00:00+00:00	Tuesda

110527 rows × 16 columns

Data Cleaning ()

In [41]:

```
#  Summery describtion for the data
df.describe()
```

Out[41]:

	patient_id	appointment_id	days_difference	age	scholarship	hipertension
count	1.105270e+05	1.105270e+05	110527.000000	110527.000000	110527.000000	110527.000000
mean	1.474963e+14	5.675305e+06	10.183702	37.088874	0.098266	0.197246
std	2.560949e+14	7.129575e+04	15.254996	23.110205	0.297675	0.397921
min	3.921784e+04	5.030230e+06	-6.000000	-1.000000	0.000000	0.000000
25%	4.172614e+12	5.640286e+06	0.000000	18.000000	0.000000	0.000000
50%	3.173184e+13	5.680573e+06	4.000000	37.000000	0.000000	0.000000
75%	9.439172e+13	5.725524e+06	15.000000	55.000000	0.000000	0.000000
max	9.999816e+14	5.790484e+06	179.000000	115.000000	1.000000	1.000000

What is needed to be cleaned

- There is wrong value of -1 in age column
- the handcap has wrong value of 4 in multiplie columns which need to be changed to 0 or 1
- days_differnce has negative values which is not correct
- no_show column has values of 1 not no or yes which need to be changed

In [42]:

```
# Checking for null rows
df.isnull().sum()
```

Out[42]:

```
patient_id          0
appointment_id      0
gender              0
scheduled_date      0
appointment_date    0
appointment_day     0
days_difference     0
age                 0
neighbourhood       0
scholarship         0
hipertension        0
diabetes            0
alcoholism          0
handcap             0
sms_received        0
no_show             0
dtype: int64
```

In [43]:

```
# Finding Duplicated rows
df.duplicated().sum()
```

Out[43]: 0

In [44]:
```python
# Checking for duplicated appointments ID
df['appointment_id'].duplicated().sum()
```

Out[44]: 0

In [45]:
```python
#Checking for duplicated patients with same appointment date
duplicated_patients = df[['patient_id','appointment_date']].duplicated()
# Dropping the duplicated patients
df=df[~(duplicated_patients)]
df
```

Out[45]:

	patient_id	appointment_id	gender	scheduled_date	appointment_date	appointment_da
0	2.987250e+13	5642903	F	2016-04-29 18:38:08+00:00	2016-04-29 00:00:00+00:00	Frida
1	5.589978e+14	5642503	M	2016-04-29 16:08:27+00:00	2016-04-29 00:00:00+00:00	Frida
2	4.262962e+12	5642549	F	2016-04-29 16:19:04+00:00	2016-04-29 00:00:00+00:00	Frida
3	8.679512e+11	5642828	F	2016-04-29 17:29:31+00:00	2016-04-29 00:00:00+00:00	Frida
4	8.841186e+12	5642494	F	2016-04-29 16:07:23+00:00	2016-04-29 00:00:00+00:00	Frida
...	...	...	...	...	...	.
110522	2.572134e+12	5651768	F	2016-05-03 09:15:35+00:00	2016-06-07 00:00:00+00:00	Tuesda
110523	3.596266e+12	5650093	F	2016-05-03 07:27:33+00:00	2016-06-07 00:00:00+00:00	Tuesda
110524	1.557663e+13	5630692	F	2016-04-27 16:03:52+00:00	2016-06-07 00:00:00+00:00	Tuesda
110525	9.213493e+13	5630323	F	2016-04-27 15:09:23+00:00	2016-06-07 00:00:00+00:00	Tuesda
110526	3.775115e+14	5629448	F	2016-04-27 13:30:56+00:00	2016-06-07 00:00:00+00:00	Tuesda

101808 rows × 16 columns

In [46]:
```python
# Getting the rows which ages is negative value
passed_date=df.query('days_difference < 0').index
# Dropping these rows
df= df.drop(passed_date)
```

In [47]:
```python
# Dropping rows which has negative value age
df=df.drop(df.query('age < 0').index)
```

In [48]:
```python
# Changing handcap value which is not 1 or 2 to 1
df.loc[df['handcap'] > 1] = 1
df
```

Out[48]:

	patient_id	appointment_id	gender	scheduled_date	appointment_date	appointment_da
0	2.987250e+13	5642903	F	2016-04-29 18:38:08+00:00	2016-04-29 00:00:00+00:00	Frida
1	5.589978e+14	5642503	M	2016-04-29 16:08:27+00:00	2016-04-29 00:00:00+00:00	Frida

	patient_id	appointment_id	gender	scheduled_date	appointment_date	appointment_da
2	4.262962e+12	5642549	F	2016-04-29 16:19:04+00:00	2016-04-29 00:00:00+00:00	Frida
3	8.679512e+11	5642828	F	2016-04-29 17:29:31+00:00	2016-04-29 00:00:00+00:00	Frida
4	8.841186e+12	5642494	F	2016-04-29 16:07:23+00:00	2016-04-29 00:00:00+00:00	Frida
...	...	...	...	...	...	.
110522	2.572134e+12	5651768	F	2016-05-03 09:15:35+00:00	2016-06-07 00:00:00+00:00	Tuesda
110523	3.596266e+12	5650093	F	2016-05-03 07:27:33+00:00	2016-06-07 00:00:00+00:00	Tuesda
110524	1.557663e+13	5630692	F	2016-04-27 16:03:52+00:00	2016-06-07 00:00:00+00:00	Tuesda
110525	9.213493e+13	5630323	F	2016-04-27 15:09:23+00:00	2016-06-07 00:00:00+00:00	Tuesda
110526	3.775115e+14	5629448	F	2016-04-27 13:30:56+00:00	2016-06-07 00:00:00+00:00	Tuesda

101803 rows × 16 columns

In [49]:
```
# Describtion of data after cleaning
df.describe()
```

Out[49]:

	patient_id	appointment_id	days_difference	age	scholarship	hipertension
count	1.018030e+05	1.018030e+05	101803.000000	101803.000000	101803.000000	101803.000000
mean	1.462776e+14	5.664867e+06	10.272762	36.980816	0.099241	0.199356
std	2.547061e+14	2.482472e+05	15.300436	23.232044	0.298986	0.399518
min	1.000000e+00	1.000000e+00	0.000000	0.000000	0.000000	0.000000
25%	4.111959e+12	5.639644e+06	0.000000	17.000000	0.000000	0.000000
50%	3.135918e+13	5.680044e+06	4.000000	37.000000	0.000000	0.000000
75%	9.419408e+13	5.725038e+06	15.000000	55.000000	0.000000	0.000000
max	9.999816e+14	5.790484e+06	179.000000	115.000000	1.000000	1.000000

In [50]:
```
# Changing no_show rows which has value of 1 to Yes
no_show_wrong = df.query('no_show == 1')

no_show_wrong['no_show'].replace({1:"Yes"})
```

Out[50]:
```
946       Yes
1665      Yes
2091      Yes
2213      Yes
2214      Yes
         ...
108376    Yes
109484    Yes
109733    Yes
109975    Yes
110107    Yes
Name: no_show, Length: 179, dtype: object
```

In [51]:
```
# Total number of cases
[0]
```

Loading [MathJax]/extensions/Safe.js

```
# Number of abscent cases
number_no_show = len(df.query('no_show == "Yes"'))

# Ratio Between total number of cases and number of abscecnt cases
ratio = number_no_show/total
print('Total Number of Cases = {} \n Number of No show Cases ={} \n Ratio = {}\n'.format(
```

```
Total Number of Cases = 101803
 Number of No show Cases =20383
 Ratio = 0.2002200328084634
```

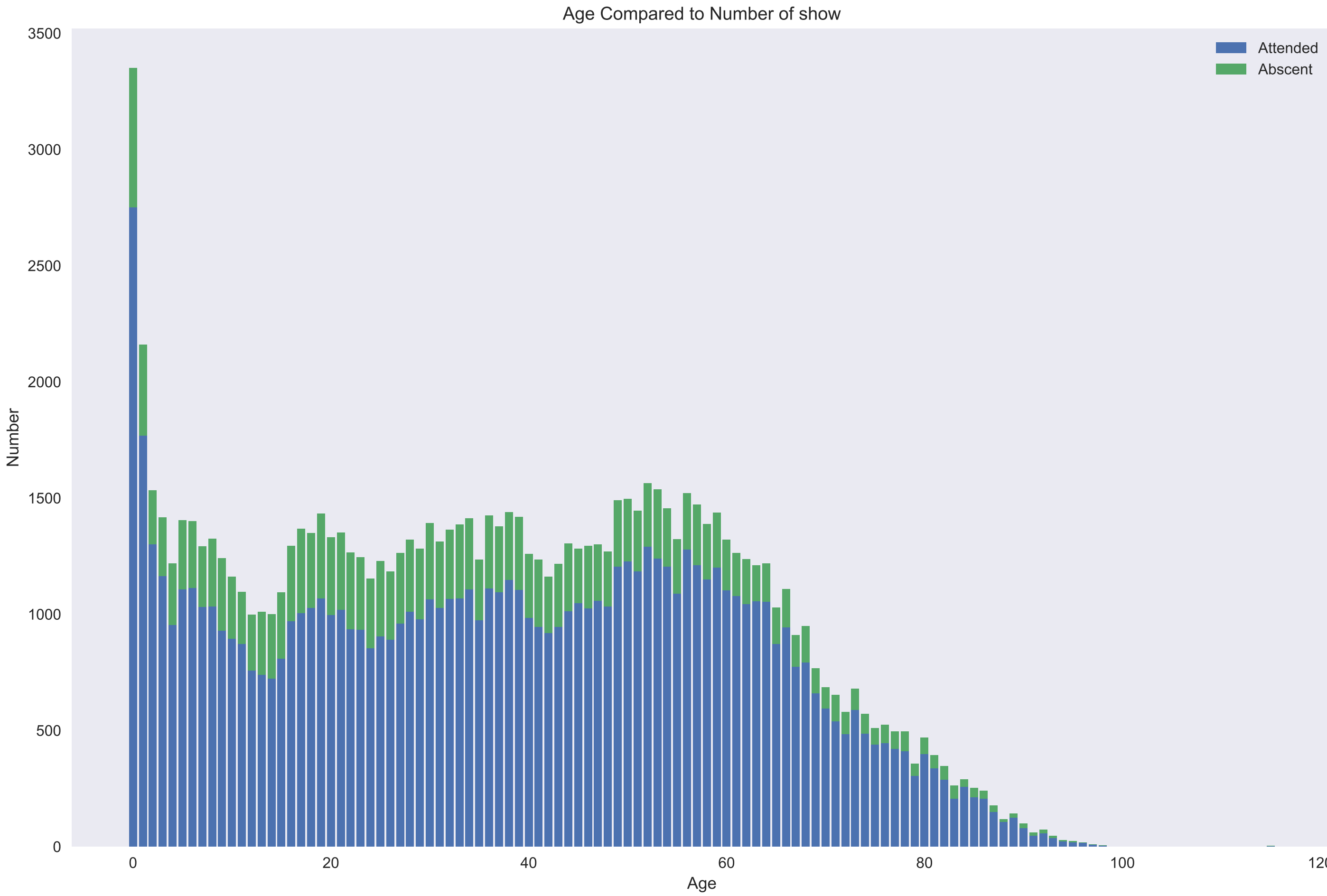
Exploratory Data Analysis

Research Question 1 (Does Age Affect the no-show percentage)

> This question is important as the age has a huge factor on whether the patient will attend or become abscent. by performing abscent to attend ratio comparing to the age, we can see if the age really affect the attend or no show of the patient

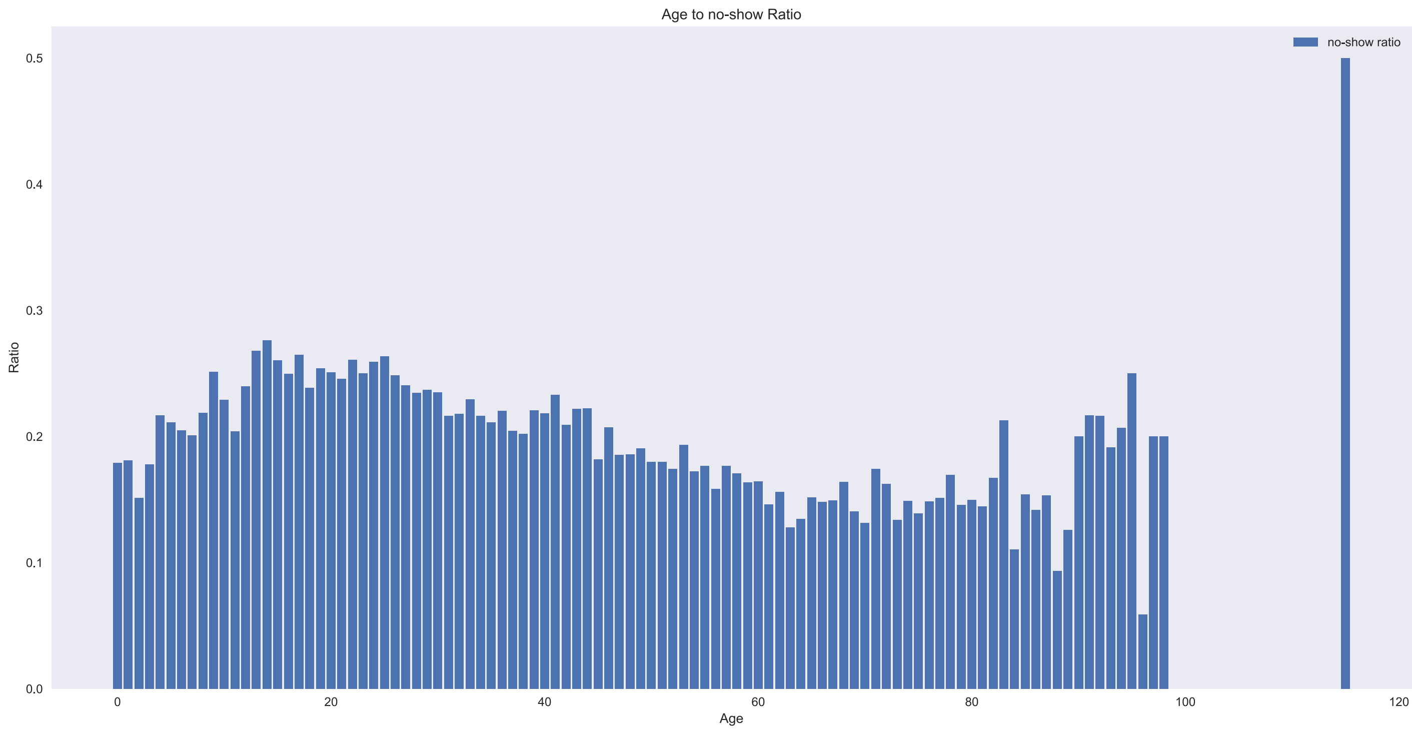
In [52]:

```
no_show = df[df['no_show'] == 'Yes']

df_age_no_show = df[df['no_show'] == 'Yes'][['age','patient_id']].groupby('age').count()
df_age_show = df[df['no_show'] == 'No'][['age','patient_id']].groupby('age').count()

df_age_merge = pd.merge(df_age_show,df_age_no_show,how='right',on='age',suffixes=['_attend

figure,ax = plt.subplots()
ax.bar(df_age_merge.index,df_age_merge['patient_id_attend'],label='Attended')
ax.bar(df_age_merge.index,df_age_merge['patient_id_abscent'],label='Abscent',bottom=df_age
ax.set_title("Age Compared to Number of show")
ax.set_ylabel('Number')
ax.set_xlabel('Age')
ax.legend()
ax.grid()
figure.set_figheight(10)
figure.set_figwidth(15)
```



As we can see, the patient with age 0 which may be a newborn babies has a high attend rate which is naturally as the new born need a greater attention than the adult one

In [53]:
```
df_age_merge['ratio']=df_age_merge['patient_id_abscent']/(df_age_merge['patient_id_attend

figure,ax = plt.subplots()
ax.bar(df_age_merge.index,df_age_merge['ratio'],label='no-show ratio')
ax.set_title("Age to no-show Ratio")
ax.set_ylabel('Ratio')
ax.set_xlabel('Age')
ax.legend()
ax.grid()
figure.set_figheight(10)
figure.set_figwidth(20)
```



- There is outlier here of age 115
- There is no significence difference between age ratios. thus, age has no effect on abscence

Research Question 2 (Does Gender affect the appointments?)

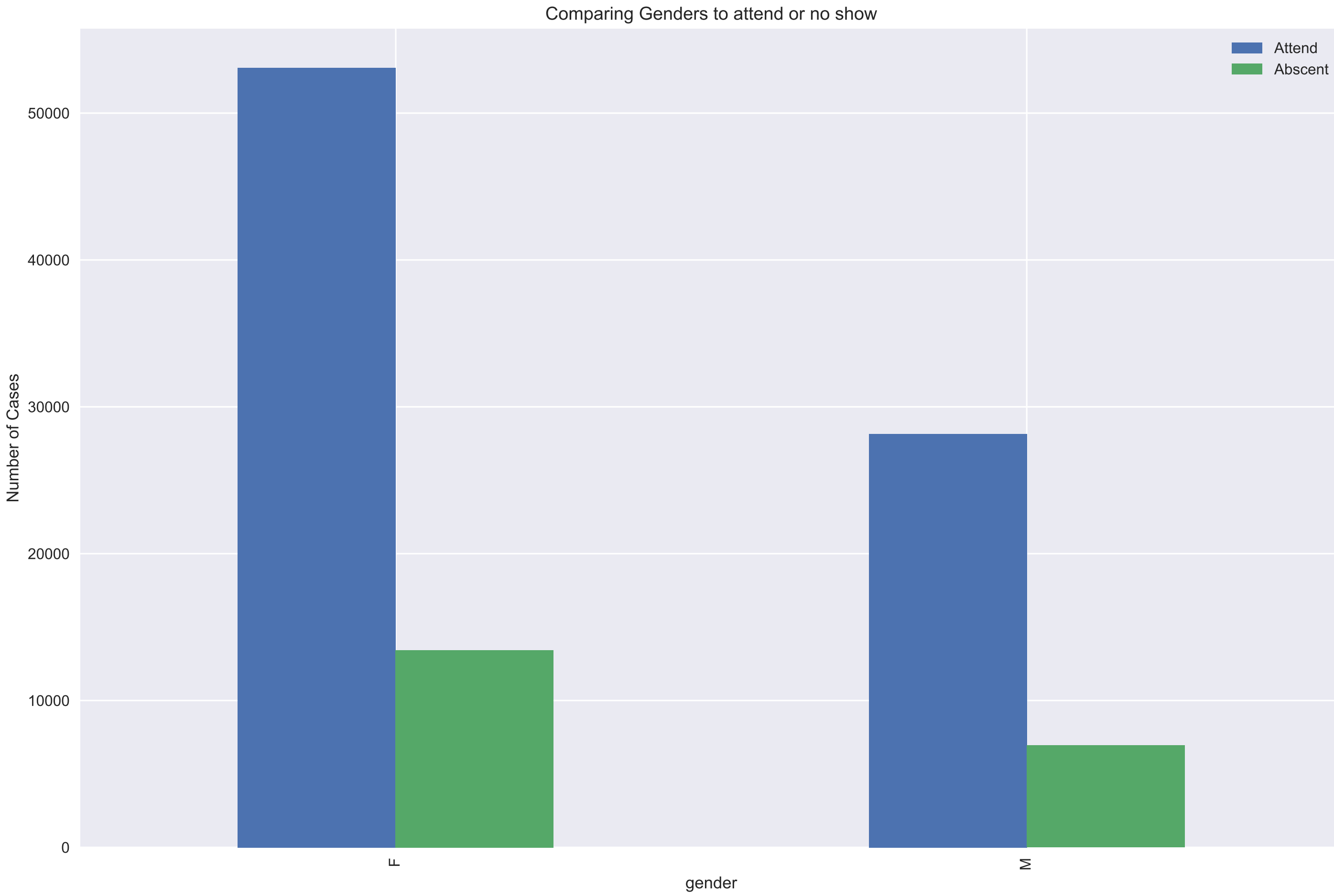
> This question shows if the gender has really effect on attending the appointment or not. it is useful sometimes as may there is a problem that prevent a specific gender from attending the appointment

In [72]:

```
df_gender_show = df.query('no_show == "No"')[['gender','patient_id']].groupby('gender').c

df_gender_no_show = df[df['no_show'] == 'Yes'][['gender','patient_id']].groupby('gender')

df_gender_merge = pd.merge(df_gender_show,df_gender_no_show,how='left',on='gender',suffix
df_gender_merge.columns=['Attend','Abscent']
df_gender_merge


df_gender_merge.plot.bar(title='Comparing Genders to attend or no show',ylabel='Number of
```

Out[72]:

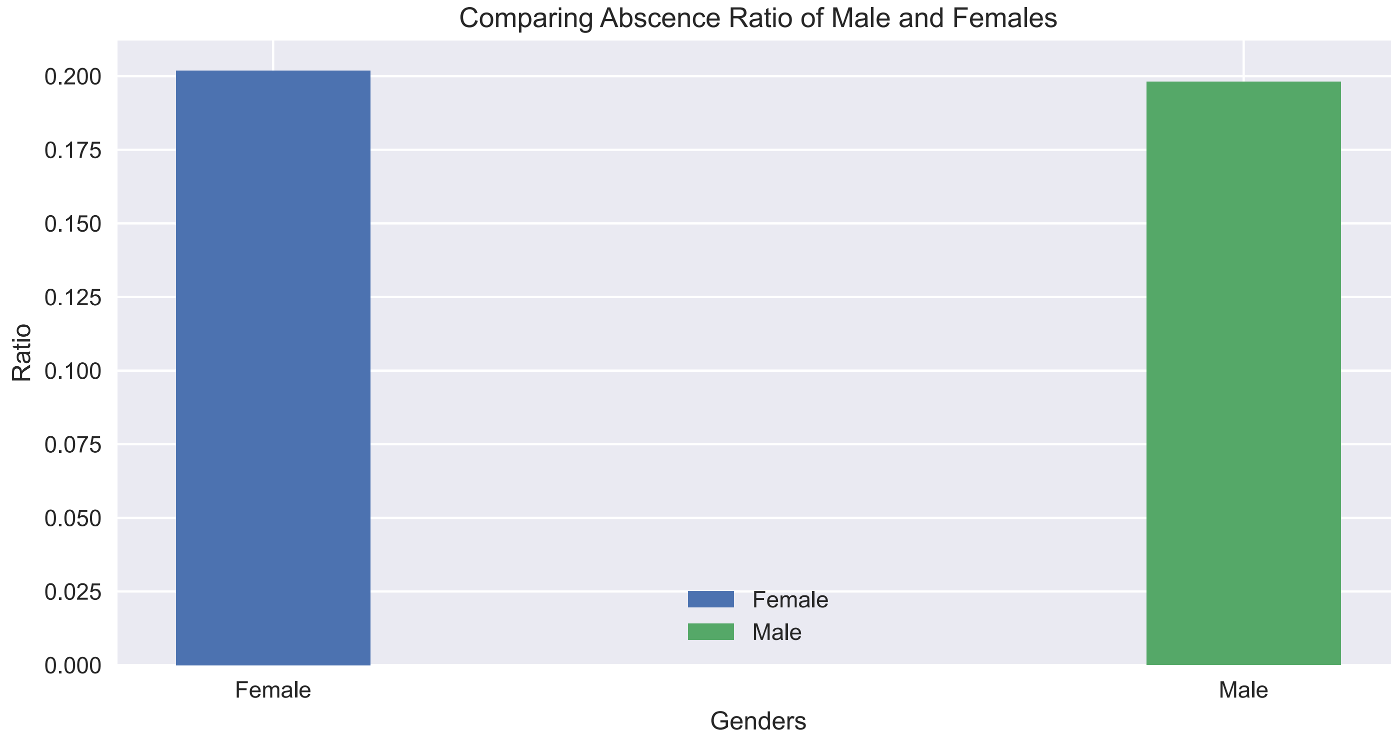
```
<AxesSubplot:title={'center':'Comparing Genders to attend or no show'}, xlabel='gender', y
label='Number of Cases'>
```



- wow, the females has much higher attending number than males. when linking the number of females with number of new born babies, we can see that there is a high pregnency rate and females maybe has higher sick rate

In [74]:
```
male_ratio= df_gender_merge['Abscent']['M']/(df_gender_merge['Abscent']['M']+df_gender_me
female_ratio =  df_gender_merge['Abscent']['F']/(df_gender_merge['Abscent']['F']+df_gende

x=[0,1]
plt.rcParams["figure.figsize"] = (10,5)
plt.bar(0,female_ratio,width=0.2,label='Female')
plt.bar(1,male_ratio,width=0.2,label='Male')
plt.legend()
plt.xticks(ticks=[0,1],labels=['Female','Male'])
plt.title('Comparing Abscence Ratio of Male and Females')
plt.ylabel('Ratio')
plt.xlabel('Genders')

print('Male Ratio: {} \nFemale Ratio:{}'.format(male_ratio,female_ratio))
```

```
Male Ratio: 0.19809708295350958
Female Ratio:0.20187913409500902
```



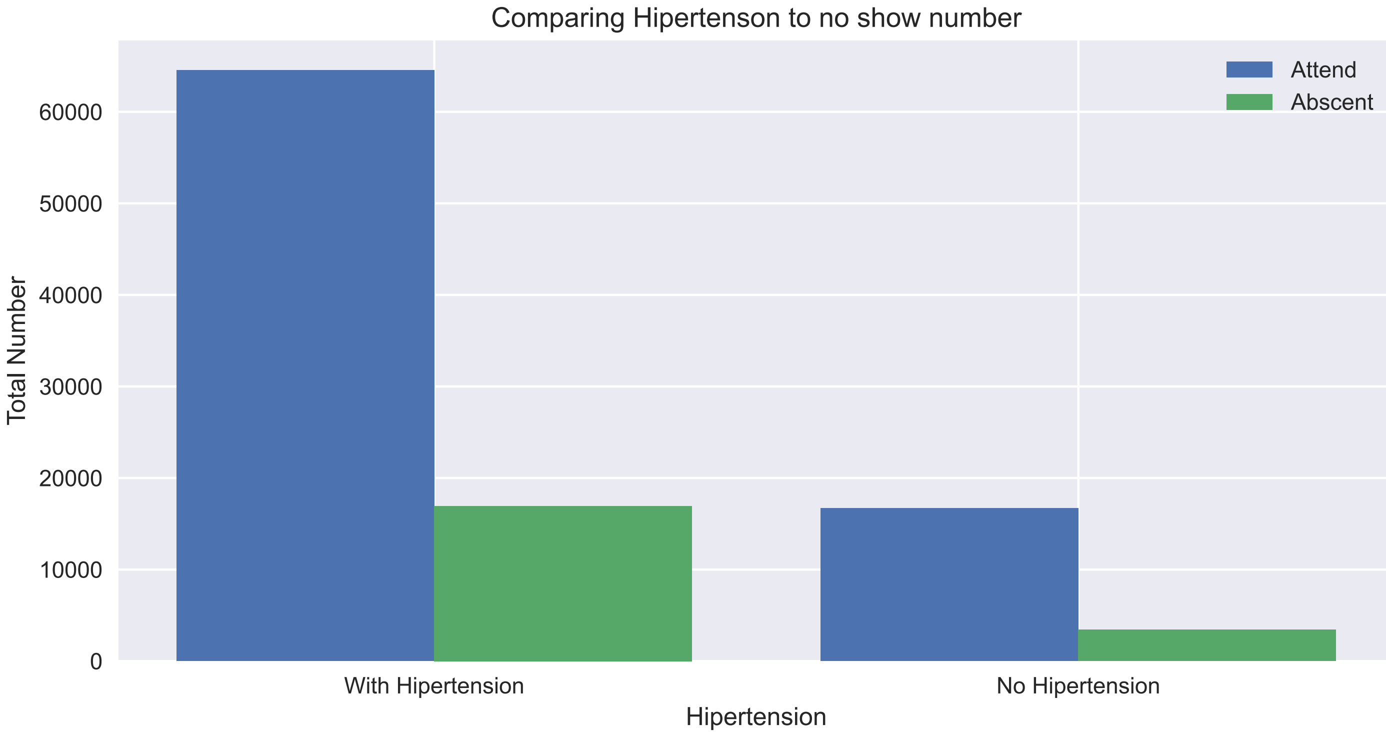
- The difference between two ratios are small. thus, the gender has no effect on whether the patient will attend or not

Research Question 3 (Does Diseases affect the appointments?)

> Maybe a certain disease cause an increased attendence of the appointments. we will discuss and graph each disease individualy(hipertension, diabetes, alcholism and handcap)

In [75]:
```
df_hiper_show = df.query('no_show == "No"')[['hipertension','patient_id']].groupby('hiper

df_hiper_no_show = df.query('no_show == "Yes"')[['hipertension','patient_id']].groupby('h

df_hiper_merge = pd.merge(df_hiper_show,df_hiper_no_show,how='right',on='hipertension',su

df_hiper_merge.columns =['Attend','Abscent']
df_hiper_merge

bar = np.arange(len(df_hiper_merge))
width=0.4

plt.bar(x=bar,height=df_hiper_merge['Attend'],width=width,label='Attend')
plt.bar(x=bar+0.4,height=df_hiper_merge['Abscent'],width=width,label='Abscent')
plt.xticks(bar+0.2,labels=['With Hipertension','No Hipertension'])
plt.legend()
plt.ylabel('Total Number')
plt.xlabel('Hipertension')
plt.title('Comparing Hipertenson to no show number')
```

Out[75]:
```
Text(0.5, 1.0, 'Comparing Hipertenson to no show number')
```

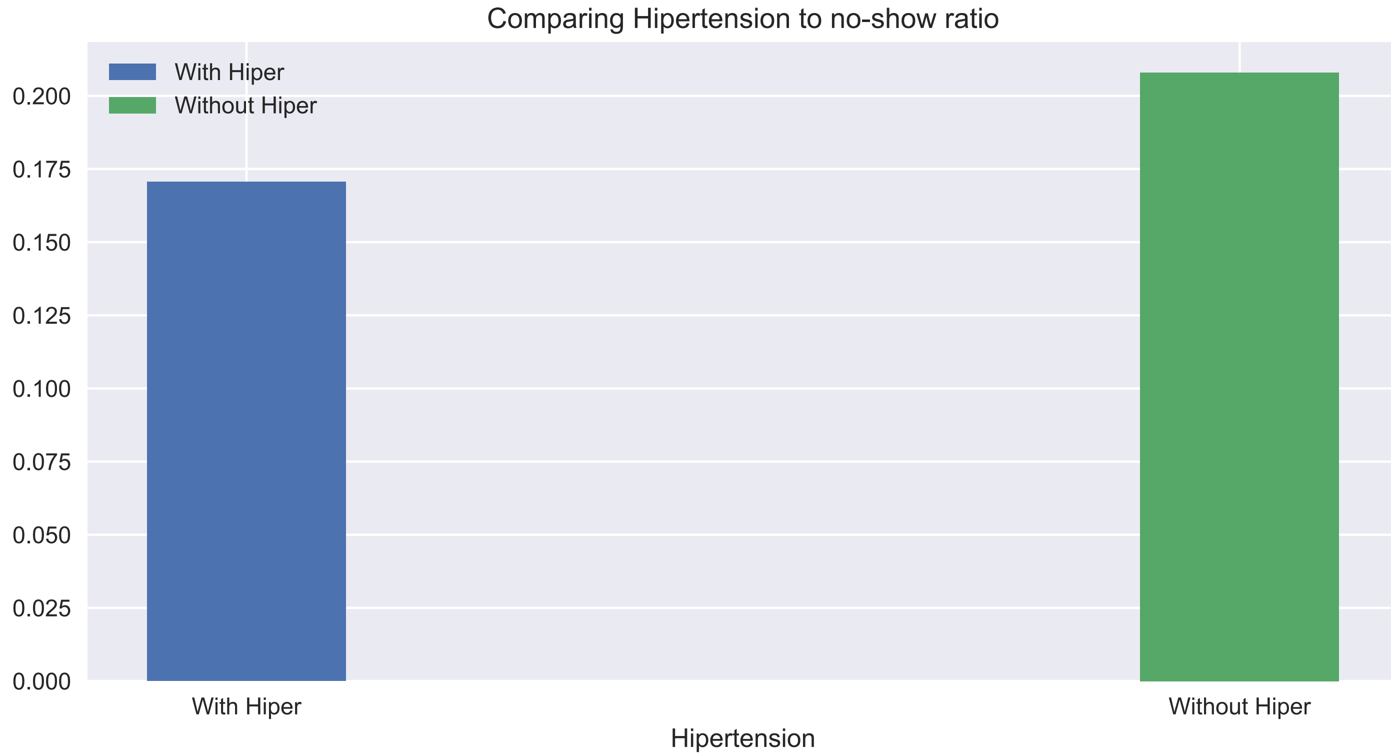


- higher attend cases is accompined by existing of hipertension

In [76]:
```
with_hiper_ratio= df_hiper_merge['Abscent'][1]/(df_hiper_merge['Abscent'][1]+df_hiper_merg
without_hiper_ratio =  df_hiper_merge['Abscent'][0]/(df_hiper_merge['Abscent'][0]+df_hipe

x=[0,1]
plt.bar(0,with_hiper_ratio,width=0.2,label='With Hiper')
plt.bar(1,without_hiper_ratio,width=0.2,label='Without Hiper')
plt.legend()
plt.xticks(ticks=[0,1],labels=['With Hiper','Without Hiper'])
plt.xlabel('Hipertension')
plt.title('Comparing Hipertension to no-show ratio')


print('With Hipertension Ratio: {} \nWithout Hipertension Ratio:{}'.format(with_hiper_rat
```

```
With Hipertension Ratio: 0.1705607476635514
Without Hipertension Ratio:0.20797958482602935
```

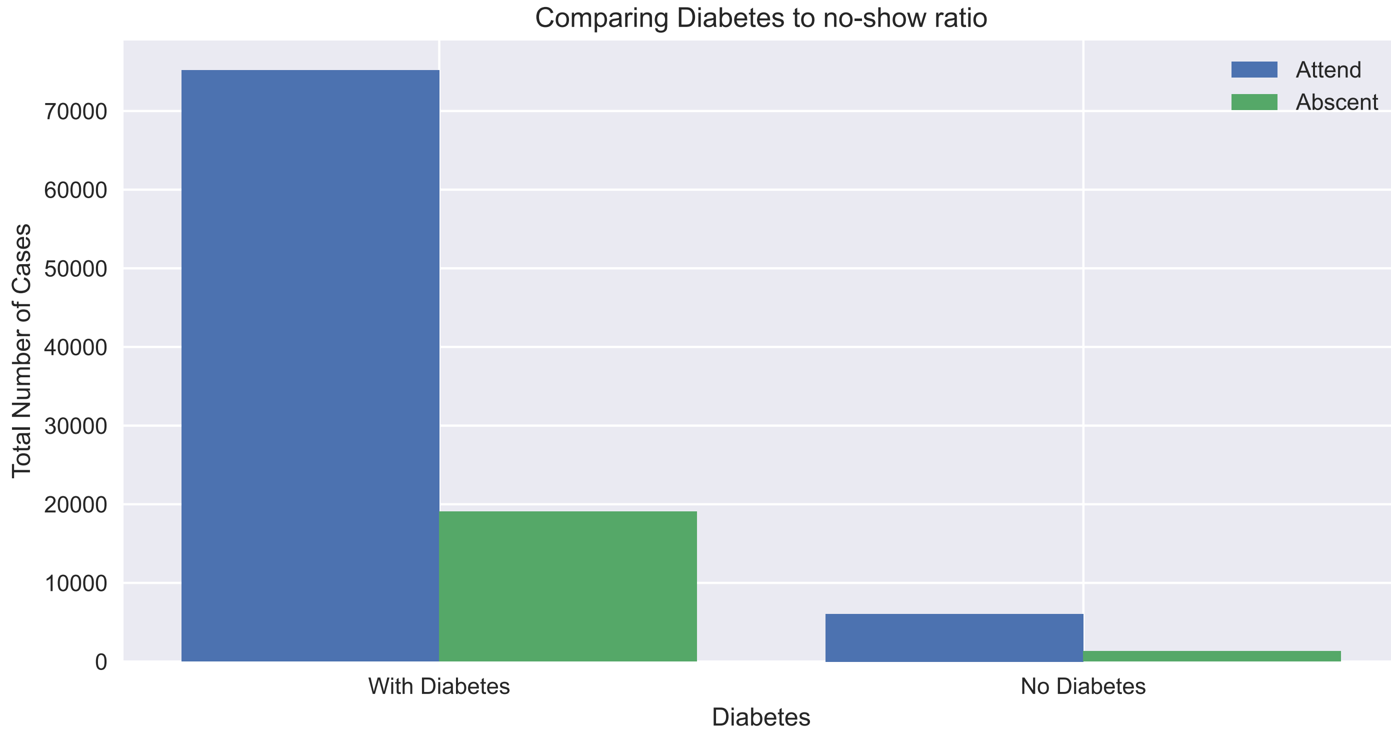
Loading [MathJax]/extensions/Safe.js



- There is a very small difference between the hipertension no-show ratios, concluding that hieprtension has no effect on attending the appointments or not

In [77]:
```
df_diabetes_show = df.query('no_show == "No"')[['diabetes','patient_id']].groupby('diabet

df_diabetes_no_show = df.query('no_show == "Yes"')[['diabetes','patient_id']].groupby('di

df_diabetes_merge = pd.merge(df_diabetes_show,df_diabetes_no_show,how='left',on='diabetes

df_diabetes_merge.columns =['Attend','Abscent']
df_diabetes_merge

bar = np.arange(len(df_diabetes_merge))
width=0.4

plt.bar(x=bar,height=df_diabetes_merge['Attend'],width=width,label='Attend')
plt.bar(x=bar+0.4,height=df_diabetes_merge['Abscent'],width=width,label='Abscent')
plt.xticks(bar+0.2,labels=['With Diabetes','No Diabetes'])
plt.legend()
plt.ylabel('Total Number of Cases')
plt.xlabel('Diabetes')
plt.title('Comparing Diabetes to attendence and abscence')
```

Out[77]:
```
Text(0.5, 1.0, 'Comparing Diabetes to no-show ratio')
```

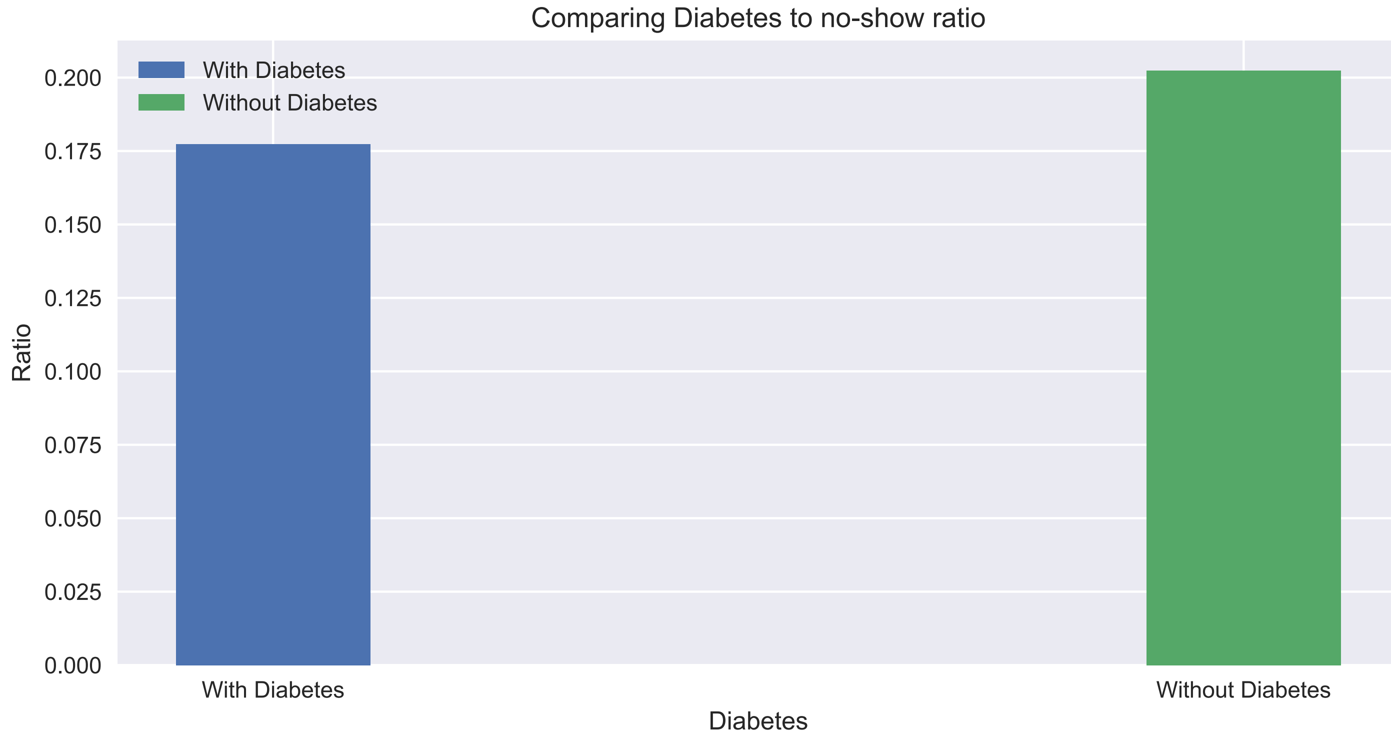


- people with diabetes has high higher attend rate than people with no diabetes

In [82]:

```
with_diabetes_ratio= df_diabetes_merge['Abscent'][1]/(df_diabetes_merge['Abscent'][1]+df_
without_diabetes_ratio =  df_diabetes_merge['Abscent'][0]/(df_diabetes_merge['Abscent'][0

x=[0,1]
plt.bar(0,with_diabetes_ratio,width=0.2,label='With Diabetes')
plt.bar(1,without_diabetes_ratio,width=0.2,label='Without Diabetes')
plt.legend()
plt.xticks(ticks=[0,1],labels=['With Diabetes','Without Diabetes'])
plt.xlabel('Diabetes')
plt.ylabel('Ratio')
plt.title('Comparing Diabetes to no-show ratio')


print('With Diabetes Ratio: {} \nWithout Diabetes Ratio:{}'.format(with_diabetes_ratio,wi
```

```
With Diabetes Ratio: 0.17739083117943136
Without Diabetes Ratio:0.20238032098267797
```

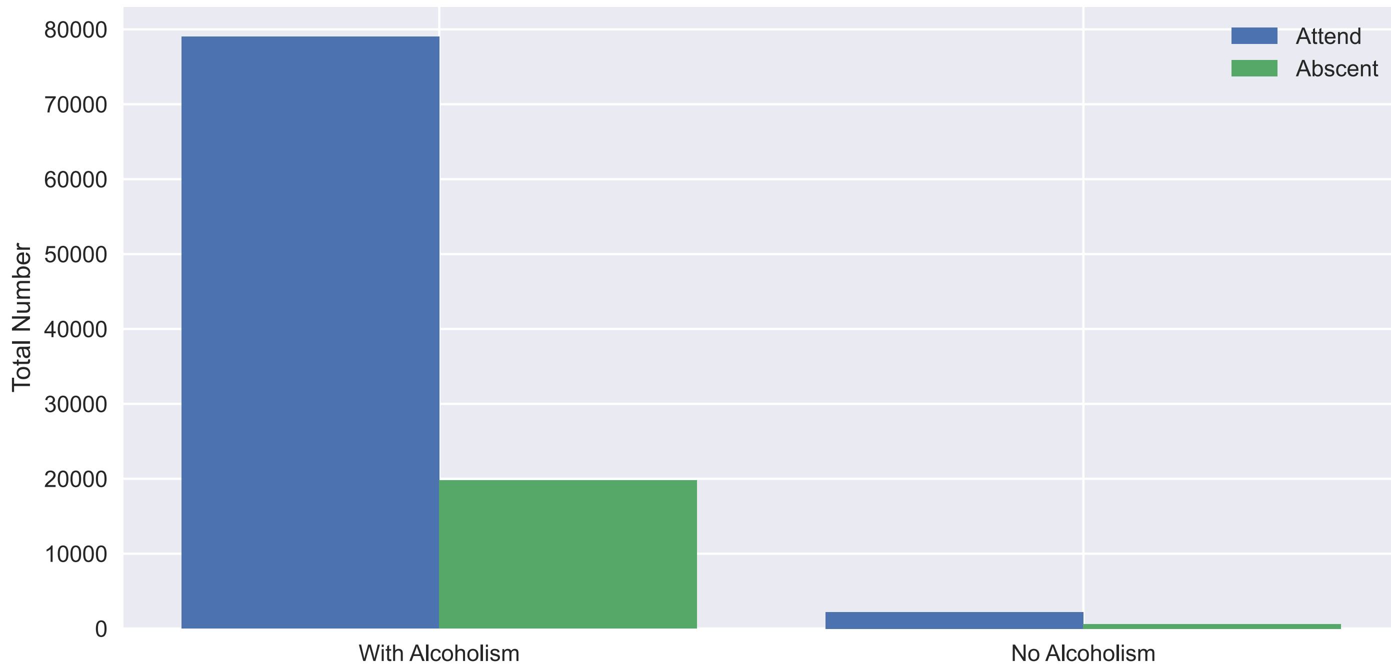


- the difference of ratios isn't big which indicate that diabetes has no effect on abscence

In [60]:
```
df_alcoholism_show = df.query('no_show == "No"')[['alcoholism','patient_id']].groupby('al

df_alcoholism_no_show = df.query('no_show == "Yes"')[['alcoholism','patient_id']].groupby

df_alcoholism_merge = pd.merge(df_alcoholism_show,df_alcoholism_no_show,how='left',on='al

df_alcoholism_merge.columns =['Attend','Abscent']
df_alcoholism_merge

bar = np.arange(len(df_alcoholism_merge))
width=0.4

plt.bar(x=bar,height=df_alcoholism_merge['Attend'],width=width,label='Attend')
plt.bar(x=bar+0.4,height=df_alcoholism_merge['Abscent'],width=width,label='Abscent')
plt.xticks(bar+0.2,labels=['With Alcoholism','No Alcoholism'])
plt.legend()
plt.xlabel('Alcholism')
plt.title('Comparing existance of Alcholism to no-show ')
plt.ylabel('Total Number of Cases')
```

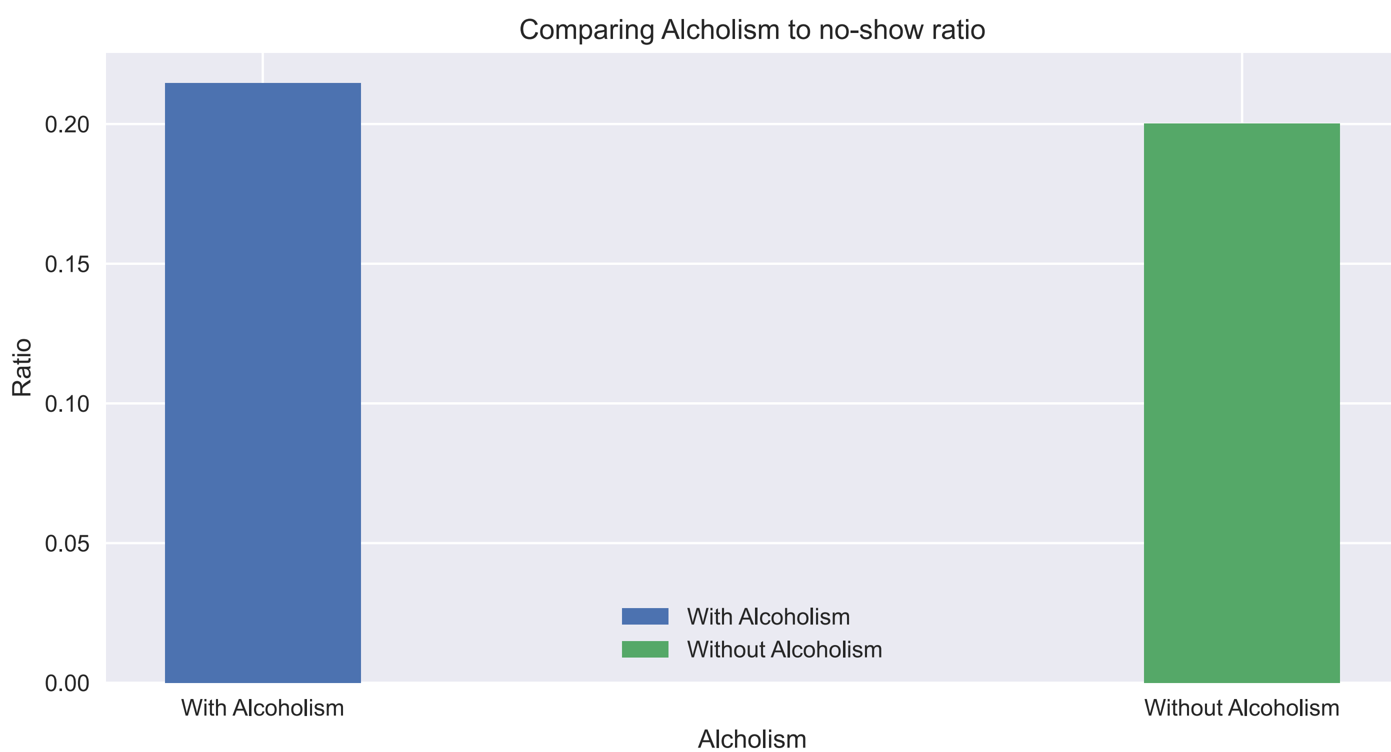
Out[60]:
```
Text(0, 0.5, 'Total Number')
```

Loading [MathJax]/extensions/Safe.js



In [81]:
```
with_alcoholism_ratio= df_alcoholism_merge['Abscent'][1]/(df_alcoholism_merge['Abscent'][
without_alcoholism_ratio =  df_alcoholism_merge['Abscent'][0]/(df_alcoholism_merge['Absce

x=[0,1]
plt.bar(0,with_alcoholism_ratio,width=0.2,label='With Alcoholism')
plt.bar(1,without_alcoholism_ratio,width=0.2,label='Without Alcoholism')
plt.legend()
plt.xticks(ticks=[0,1],labels=['With Alcoholism','Without Alcoholism'])
plt.xlabel('Alcholism')
plt.ylabel('Ratio')
plt.title('Comparing Alcholism to no-show ratio')



print('With Alcoholism Ratio: {} \nWithout Alcoholism Ratio:{}'.format(with_alcoholism_ra
```

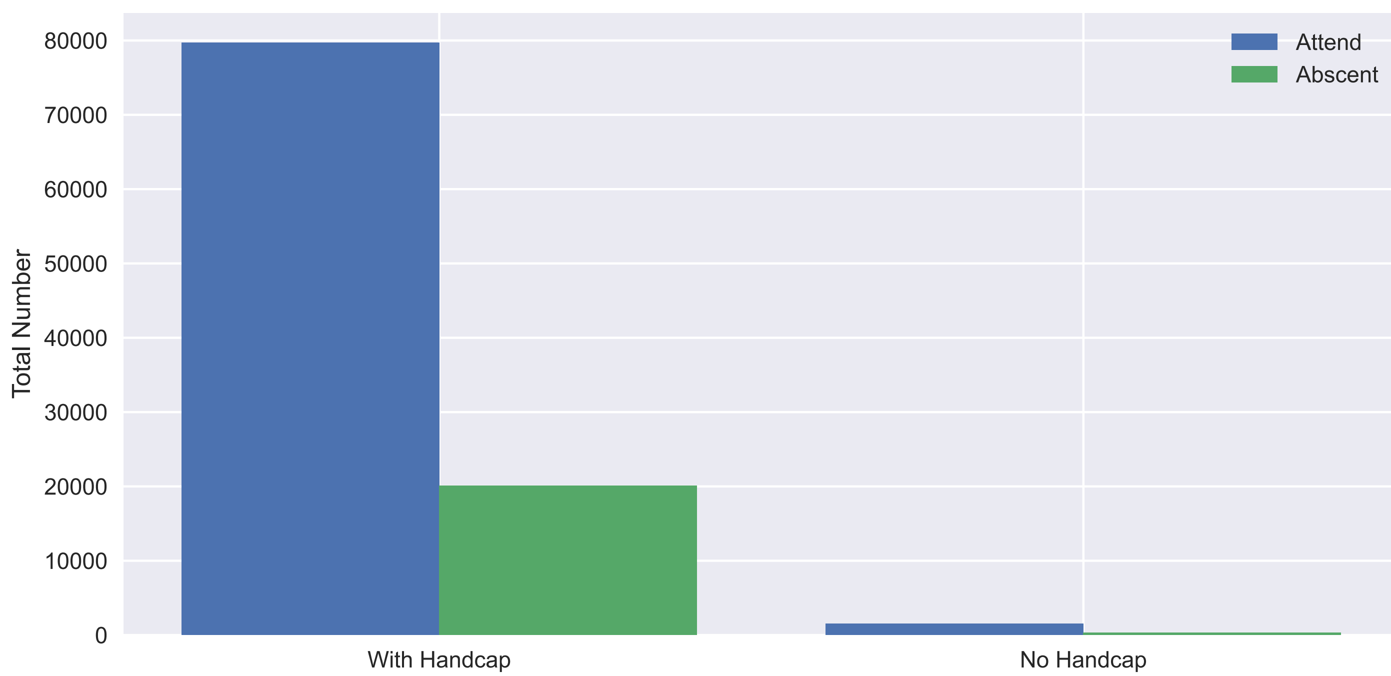
```
With Alcoholism Ratio: 0.21474358974358973
Without Alcoholism Ratio:0.20017001295336787
```



- as the chart prevail, the alcholism has no effect on attending the appointments

In [62]:
```
df_handcap_show = df.query('no_show == "No"')[['handcap','patient_id']].groupby('handcap'

df_handcap_no_show = df.query('no_show == "Yes"')[['handcap','patient_id']].groupby('hand

df_handcap_merge = pd.merge(df_handcap_show,df_handcap_no_show,how='left',on='handcap',su

df_handcap_merge.columns =['Attend','Abscent']
df_handcap_merge

bar = np.arange(len(df_handcap_merge))
width=0.4

plt.bar(x=bar,height=df_handcap_merge['Attend'],width=width,label='Attend')
plt.bar(x=bar+0.4,height=df_handcap_merge['Abscent'],width=width,label='Abscent')
plt.xticks(bar+0.2,labels=['With Handcap','No Handcap'])
plt.legend()
plt.ylabel('Total Number of Cases')
plt.xlabel('Handcap')
plt.title('Comparing Handcap with no-show')
```

Out[62]:
```
Text(0, 0.5, 'Total Number')
```



In [ ]:

In [63]:
```
with_handcap_ratio= df_handcap_merge['Abscent'][1]/(df_handcap_merge['Abscent'][1]+df_hand
without_handcap_ratio =  df_handcap_merge['Abscent'][0]/(df_handcap_merge['Abscent'][0]+d

x=[0,1]
plt.bar(0,with_handcap_ratio,width=0.2,label='With Handcap')
plt.bar(1,without_handcap_ratio,width=0.2,label='Without Handcap')
plt.legend()
plt.xticks(ticks=[0,1],labels=['With Handcap','Without Handcap'])
plt.xlabel('Handcap')
plt.ylabel('Ratio')
plt.title('Comparing Handcap to no-show ratio')


print('With Handcap Ratio: {} \nWithout Handcap Ratio:{}'.format(with_handcap_ratio,witho
```

```
With Handcap Ratio: 0.16848418756815703
Ratio:0.20116244112636536
```

- The ratio is small enough that means that handcap has no effect on abscence

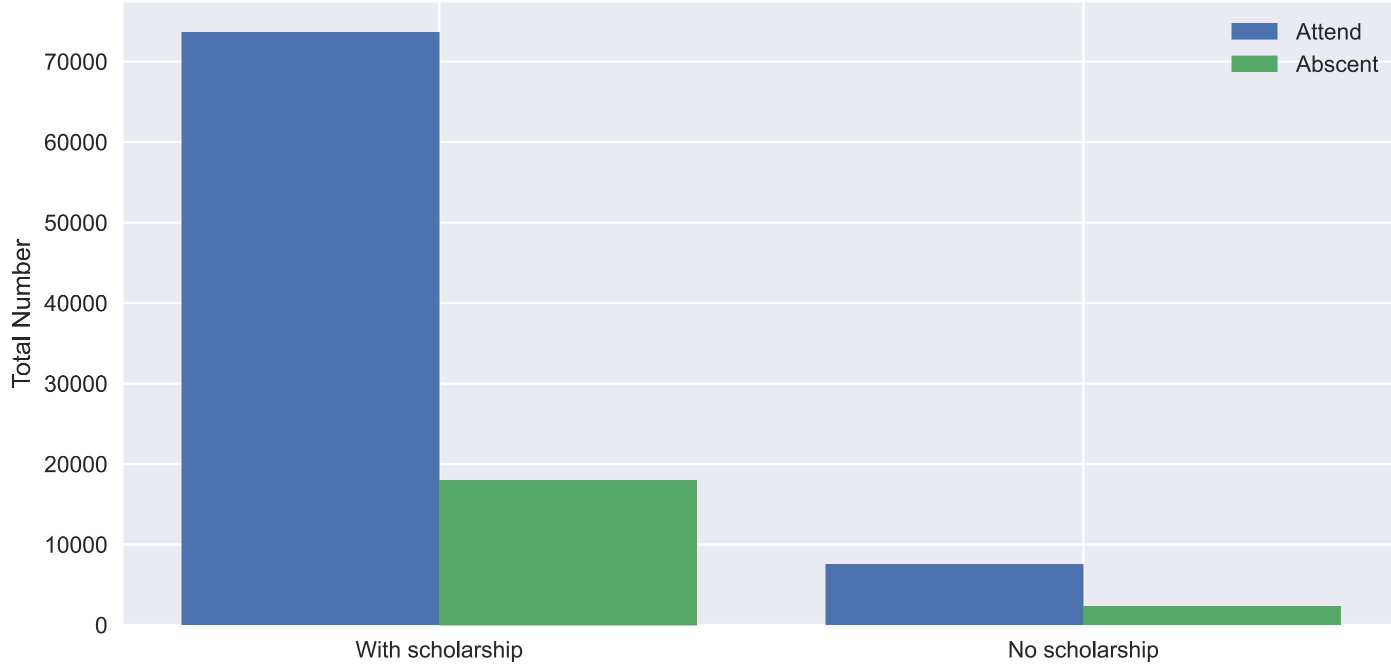
Research Question 4 (Does Scholarship affect the appointments?)

> maybe the people with scholarship or medical insurance has highe attendence rate as they don't pay as much as people with no insurance

In [64]:

```
df_scholarship_show = df.query('no_show == "No"')[['scholarship','patient_id']].groupby('

df_scholarship_no_show = df.query('no_show == "Yes"')[['scholarship','patient_id']].group

df_scholarship_merge = pd.merge(df_scholarship_show,df_scholarship_no_show,how='left',on=

df_scholarship_merge.columns =['Attend','Abscent']
df_scholarship_merge

bar = np.arange(len(df_scholarship_merge))
width=0.4

plt.bar(x=bar,height=df_scholarship_merge['Attend'],width=width,label='Attend')
plt.bar(x=bar+0.4,height=df_scholarship_merge['Abscent'],width=width,label='Abscent')
plt.xticks(bar+0.2,labels=['With scholarship','No scholarship'])
plt.legend()
plt.ylabel('Total Number of Cases')
plt.xlabel('Schoalrship')
plt.title('Comparing Schoalrship to no-show ')
```

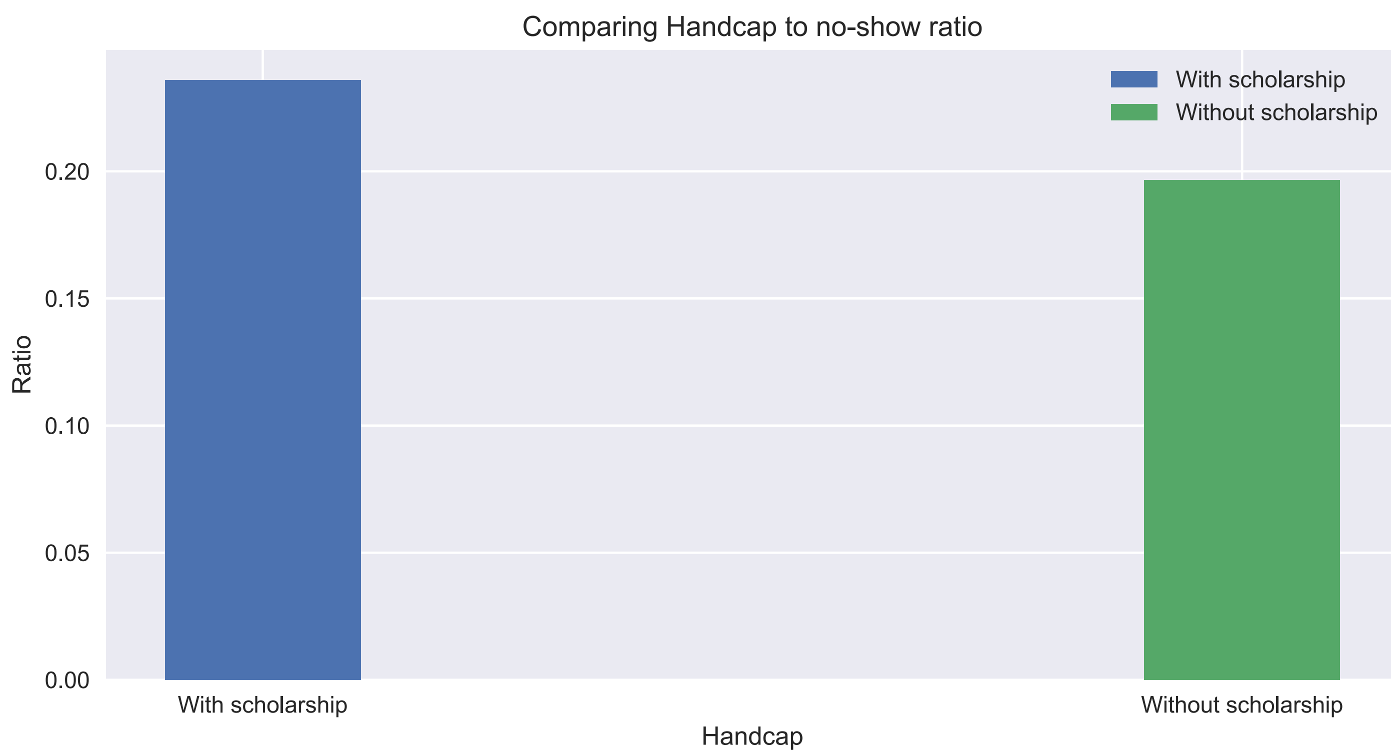
Out[64]: `Text(0, 0.5, 'Total Number')`



In [83]:

```
with_scholarship_ratio= df_scholarship_merge['Abscent'][1]/(df_scholarship_merge['Abscent
without_scholarship_ratio =  df_scholarship_merge['Abscent'][0]/(df_scholarship_merge['Ab

x=[0,1]
plt.bar(0,with_scholarship_ratio,width=0.2,label='With scholarship')
plt.bar(1,without_scholarship_ratio,width=0.2,label='Without scholarship')
plt.legend()
plt.xticks(ticks=[0,1],labels=['With scholarship','Without scholarship'])
plt.xlabel('Handcap')
plt.ylabel('Ratio')
plt.title('Comparing Handcap to no-show ratio')


print('With scholarship Ratio: {} \nWithout scholarship Ratio:{}'.format(with_scholarship_
```

```
With scholarship Ratio: 0.23599355098750505
Without scholarship Ratio:0.19673936750272628
```



Loading [MathJax]/extensions/Safe.js

- as it clear tho. scholarship is not the main problem for absence of the patients

Research Question 5 (Does SMS affect the appointments?)

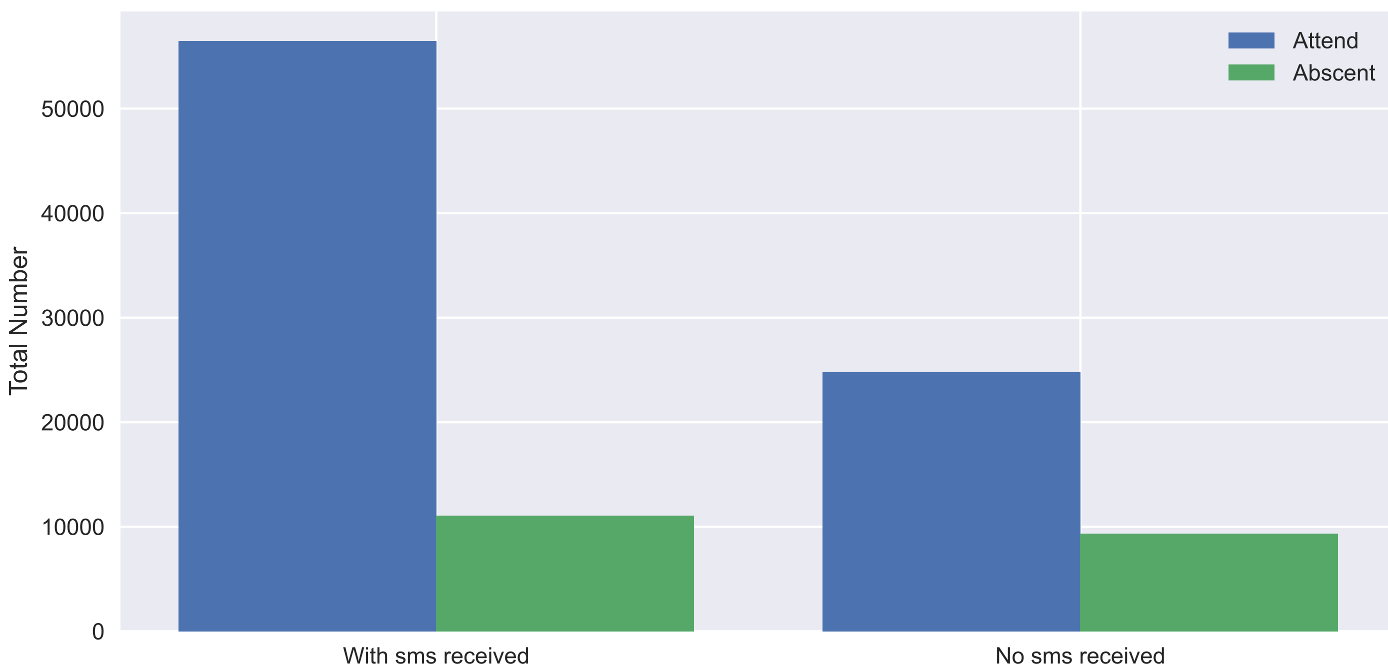
> maybe people forget that they have an appointments later on and the message has in impact on attendence

In [66]:

```
df_sms_received_show = df.query('no_show == "No"')[['sms_received','patient_id']].groupby

df_sms_received_no_show = df.query('no_show == "Yes"')[['sms_received','patient_id']].grou

df_sms_received_merge = pd.merge(df_sms_received_show,df_sms_received_no_show,how='left',

df_sms_received_merge.columns =['Attend','Abscent']
df_sms_received_merge

bar = np.arange(len(df_sms_received_merge))
width=0.4

plt.bar(x=bar,height=df_sms_received_merge['Attend'],width=width,label='Attend')
plt.bar(x=bar+0.4,height=df_sms_received_merge['Abscent'],width=width,label='Abscent')
plt.xticks(bar+0.2,labels=['With sms received','No sms received'])
plt.legend()
plt.ylabel('Total Number of Cases')
plt.xlabel('Diabetes')
plt.title('Comparing SMS Recived to number of attendece')
```

Out[66]:

```
Text(0, 0.5, 'Total Number')
```



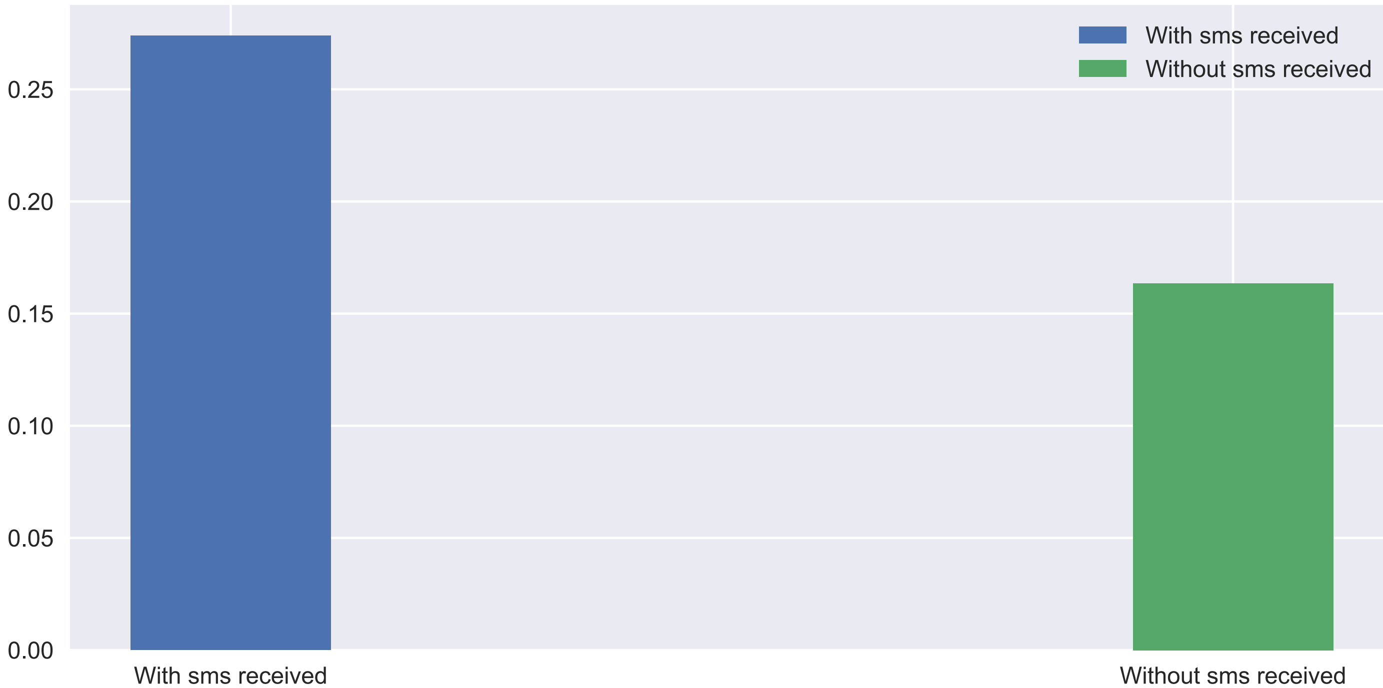
In [67]:

```
with_sms_received_ratio= df_sms_received_merge['Abscent'][1]/(df_sms_received_merge['Absc
without_sms_received_ratio =  df_sms_received_merge['Abscent'][0]/(df_sms_received_merge[

x=[0,1]
plt.bar(0,with_sms_received_ratio,width=0.2,label='With sms received')
plt.bar(1,without_sms_received_ratio,width=0.2,label='Without sms received')
plt.legend()
plt.xticks(ticks=[0,1],labels=['With sms received','Without sms received'])
plt.xlabel('SMS Received')
plt.ylabel('Ratio')
plt.title('Comparing SMS Received to no-show ratio')
```

Loading [MathJax]/extensions/Safe.js

```
print('With sms received Ratio: {} \nWithout sms received Ratio:{}'.format(with_sms_recei
```

```
With sms received Ratio: 0.2738653688284273
Without sms received Ratio:0.1635464186266959
```



- wow, peope who received sms has higher abscence rate than peopl who didn't receive a sms

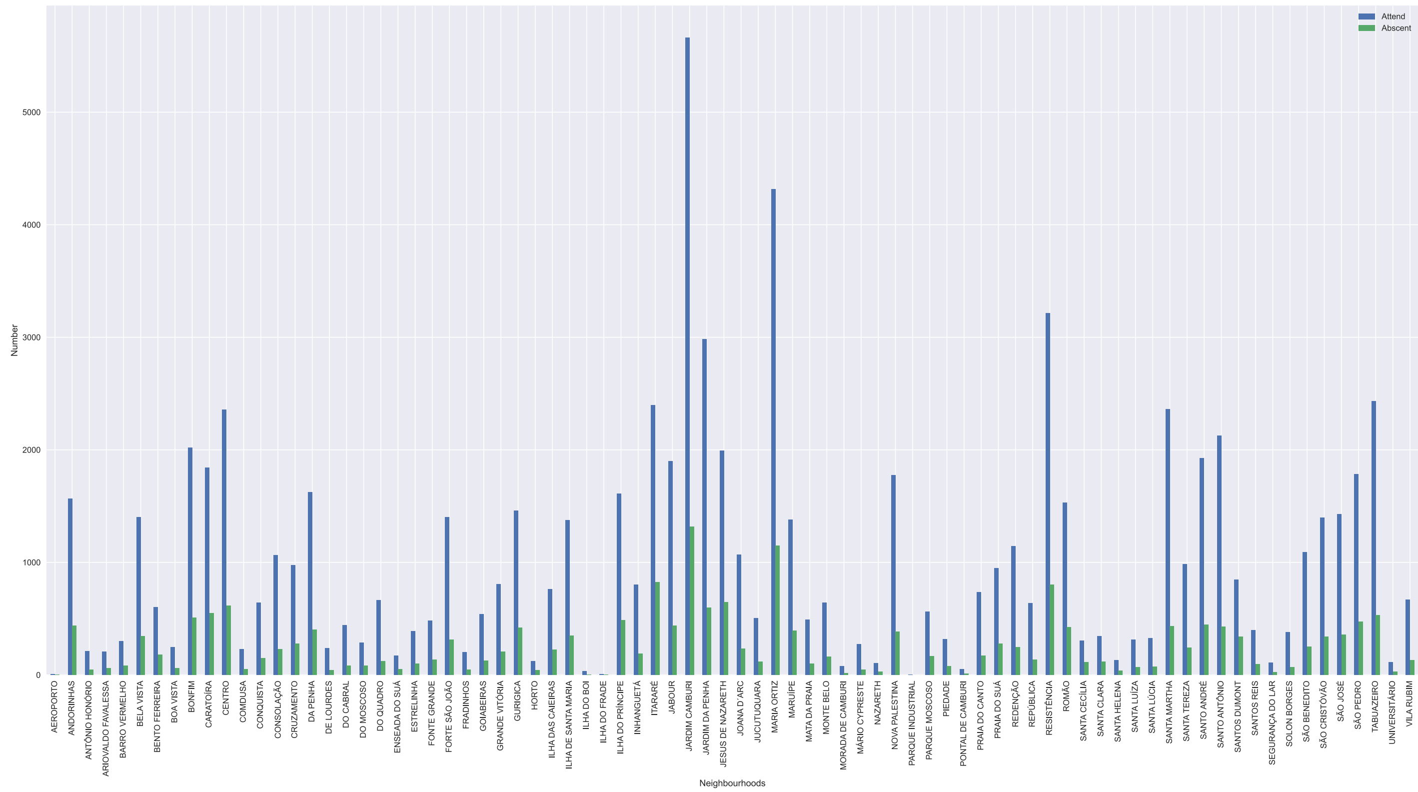
Research Question 6 (Does Neighbourhood affect the appointments?)

> maybe Neighbourhood has a problem or the hospital itself got something wrong that affect the attendence of the appointments

In [68]:

```
df_neighbourhood_show = df.query('no_show == "No"')[['neighbourhood','patient_id']].group
df_neighbourhood_no_show = df.query('no_show == "Yes"')[['neighbourhood','patient_id']].g
df_neighbourhood_merge = pd.merge(df_neighbourhood_show,df_neighbourhood_no_show,how='lef


df_neighbourhood_merge.columns =['Attend','Abscent']

#Filling Abscent  NaN Neighbourhood
df_neighbourhood_merge = df_neighbourhood_merge.fillna(0)

df_neighbourhood_merge['Attend']=df_neighbourhood_merge['Attend'].astype(int)
df_neighbourhood_merge['Abscent']=df_neighbourhood_merge['Abscent'].astype(int)


df_neighbourhood_merge.plot.bar(xlabel='Neighbourhoods',ylabel='Number',figsize=(30,15))
```

Out[68]: <AxesSubplot:xlabel='Neighbourhoods', ylabel='Number'>

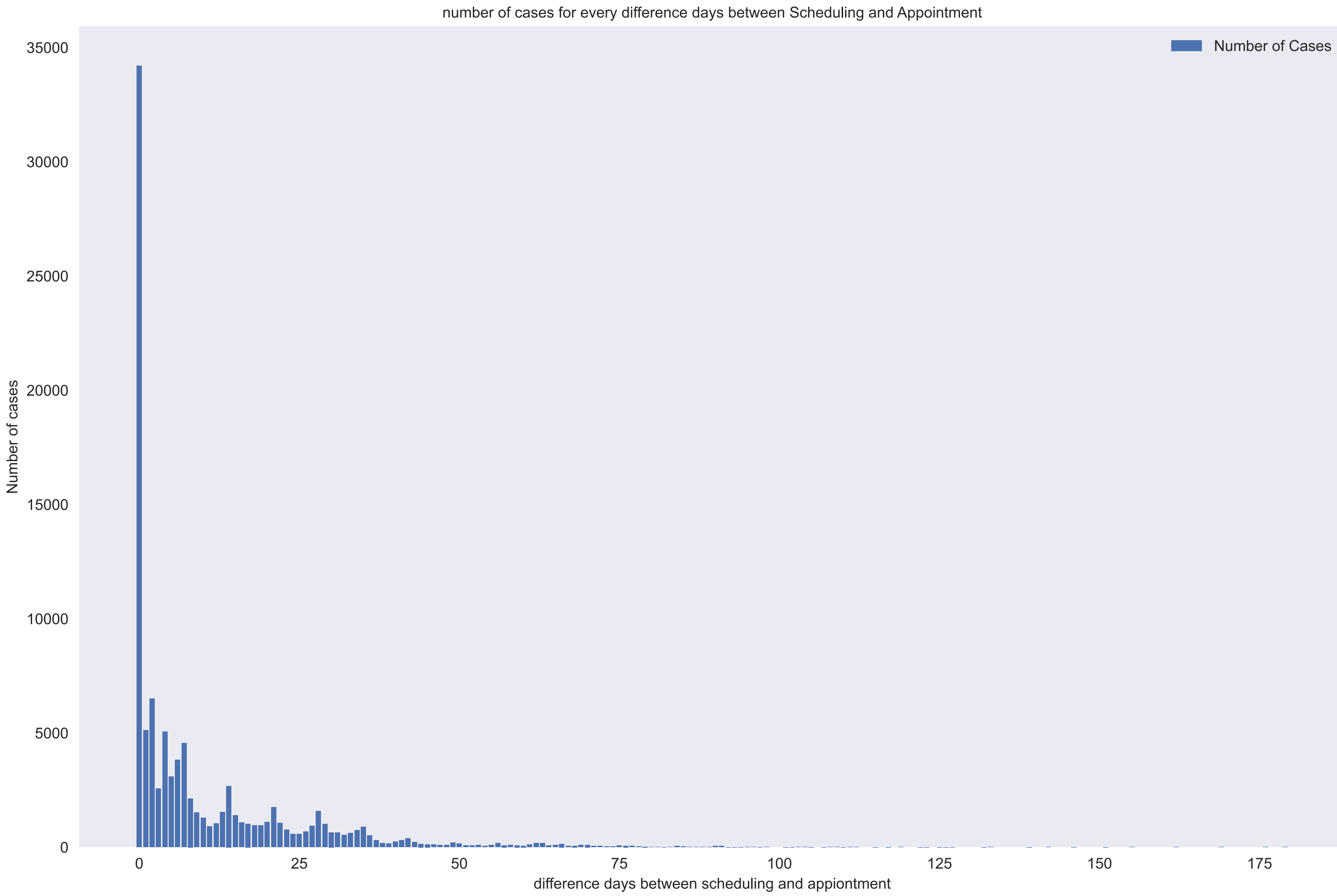


- it is clear that neighbourhoods has higher attendence than abscence which means that there is no problem regarding neighbourhoods

Research Question 7 (Does Difference between schedule day and appointments day have an effect ?)

>

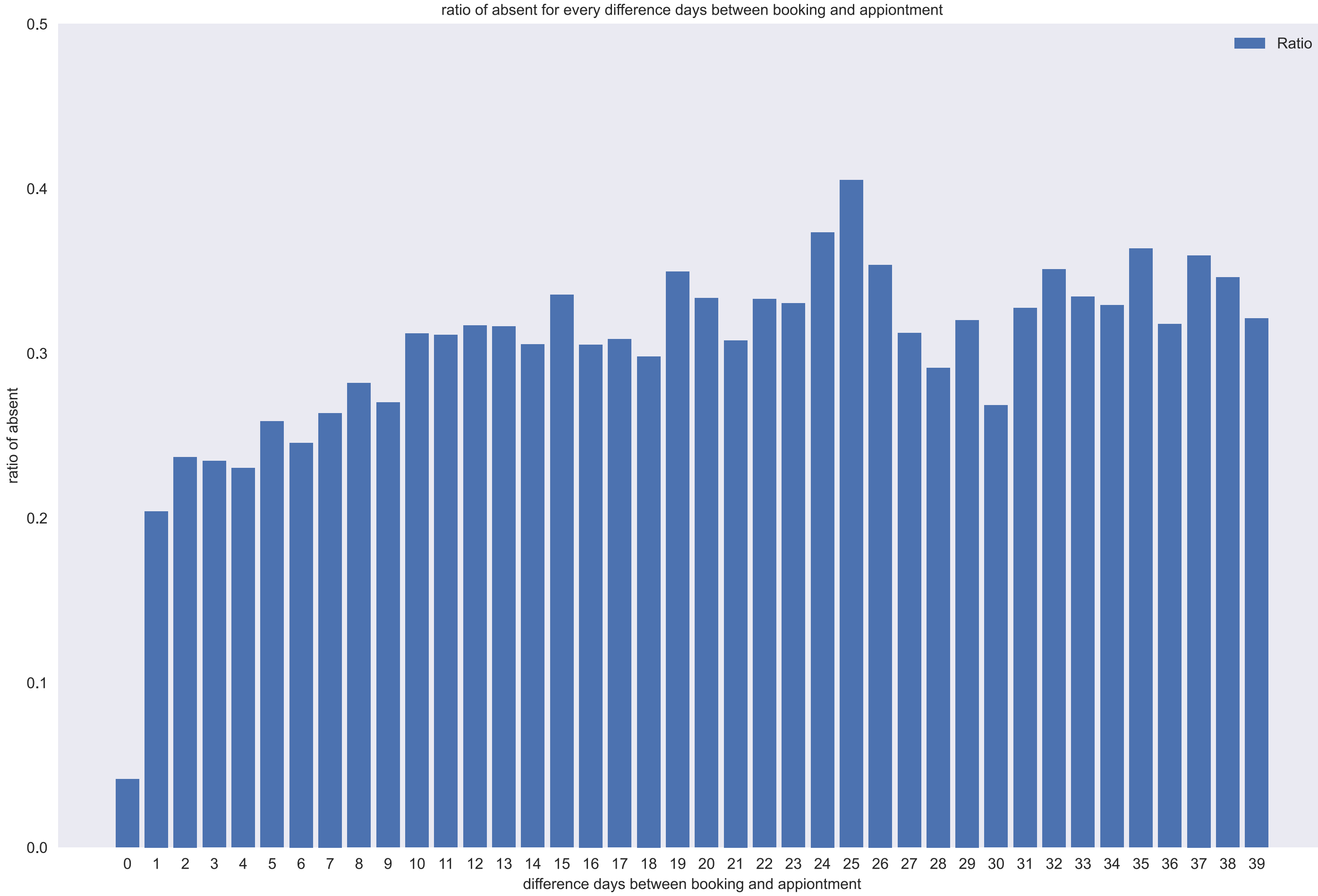
In [69]:
```
df_days_abscent = df.query('no_show == "Yes" ').groupby('days_difference').count().patien

df_total_days = df.groupby('days_difference').count().patient_id

days_difference_ratio = df_days_abscent/df_total_days


fig , ax = plt.subplots()
ax.bar(df_total_days.index,df_total_days.values,label="Number of Cases")
ax.grid()
ax.set_ylabel('Number of cases',size=10)
ax.set_title('number of cases for every difference days between Scheduling and Appointmen
ax.set_xlabel('difference days between scheduling and appiontment',size=10)
ax.legend()
fig.set_figheight(10)
fig.set_figwidth(15)
```



- people tend to schedule and attend at the same day rather than waiting a few days later

In [70]:

```
fig_ratio ,ax_ratio = plt.subplots()

ax_ratio.bar(days_difference_ratio.index[0:40],days_difference_ratio.values[0:40],label="
ax_ratio.set_xticks(days_difference_ratio.index[0:40])
ax_ratio.set_xticklabels(days_difference_ratio.index[0:40])
ax_ratio.set_ylim(0,0.5)
ax_ratio.set_ylabel('ratio of absent',size=10)
ax_ratio.set_title('ratio of absent for every difference days between booking and appiont
ax_ratio.set_xlabel('difference days between booking and appiontment',size=10)
ax_ratio.legend()
ax_ratio.grid()
fig_ratio.set_figheight(10)
fig_ratio.set_figwidth(15)
```



- hmmm strange, the longer the days, an increase of no show ratio occurs

In [71]:
```
for index in days_difference_ratio.index:
    print('{} Days Difference Ratio: {} & Number of Cases Were: {}\n'.format(index,days_d
    if index == 50:
        break
```

```
0 Days Difference Ratio: 0.04139503610372146 & Number of Cases Were: 34207

1 Days Difference Ratio: 0.20413335932930396 & Number of Cases Were: 5129

2 Days Difference Ratio: 0.23709280885064535 & Number of Cases Were: 6508

3 Days Difference Ratio: 0.23453908984830804 & Number of Cases Were: 2571

4 Days Difference Ratio: 0.23028266455821308 & Number of Cases Were: 5059

5 Days Difference Ratio: 0.25872093023255816 & Number of Cases Were: 3096

6 Days Difference Ratio: 0.24567836563645887 & Number of Cases Were: 3818

7 Days Difference Ratio: 0.26373626373626374 & Number of Cases Were: 4550

8 Days Difference Ratio: 0.2818352059925094 & Number of Cases Were: 2136

9 Days Difference Ratio: 0.2701639344262295 & Number of Cases Were: 1525

10 Days Difference Ratio: 0.3120184899845917 & Number of Cases Were: 1298

11 Days Difference Ratio: 0.3111353711790393 & Number of Cases Were: 916

12 Days Difference Ratio: 0.3168604651162791 & Number of Cases Were: 1032

13 Days Difference Ratio: 0.31633311814073595 & Number of Cases Were: 1549
```

Loading [MathJax]/extensions/Safe.js

14 Days Difference Ratio: 0.30548302872062666 & Number of Cases Were: 2681

15 Days Difference Ratio: 0.33548387096774196 & Number of Cases Were: 1395

16 Days Difference Ratio: 0.30527289546716 & Number of Cases Were: 1081

17 Days Difference Ratio: 0.308666017526777 & Number of Cases Were: 1027

18 Days Difference Ratio: 0.29809725158562367 & Number of Cases Were: 946

19 Days Difference Ratio: 0.3496868475991649 & Number of Cases Were: 958

20 Days Difference Ratio: 0.3336380255941499 & Number of Cases Were: 1094

21 Days Difference Ratio: 0.3079128440366973 & Number of Cases Were: 1744

22 Days Difference Ratio: 0.3330197554092192 & Number of Cases Were: 1063

23 Days Difference Ratio: 0.3302872062663185 & Number of Cases Were: 766

24 Days Difference Ratio: 0.37349397590361444 & Number of Cases Were: 581

25 Days Difference Ratio: 0.40512820512820513 & Number of Cases Were: 585

26 Days Difference Ratio: 0.3537117903930131 & Number of Cases Were: 687

27 Days Difference Ratio: 0.31223175965665234 & Number of Cases Were: 932

28 Days Difference Ratio: 0.2912192040429564 & Number of Cases Were: 1583

29 Days Difference Ratio: 0.32019704433497537 & Number of Cases Were: 1015

30 Days Difference Ratio: 0.2684049079754601 & Number of Cases Were: 652

31 Days Difference Ratio: 0.3275316455696203 & Number of Cases Were: 632

32 Days Difference Ratio: 0.35110294117647056 & Number of Cases Were: 544

33 Days Difference Ratio: 0.3343949044585987 & Number of Cases Were: 628

34 Days Difference Ratio: 0.3293172690763052 & Number of Cases Were: 747

35 Days Difference Ratio: 0.3635346756152125 & Number of Cases Were: 894

36 Days Difference Ratio: 0.3178294573643411 & Number of Cases Were: 516

37 Days Difference Ratio: 0.35947712418300654 & Number of Cases Were: 306

38 Days Difference Ratio: 0.34615384615384615 & Number of Cases Were: 182

39 Days Difference Ratio: 0.3212121212121212 & Number of Cases Were: 165

40 Days Difference Ratio: 0.4085106382978723 & Number of Cases Were: 235

41 Days Difference Ratio: 0.33876221498371334 & Number of Cases Were: 307

42 Days Difference Ratio: 0.36523929471032746 & Number of Cases Were: 397

43 Days Difference Ratio: 0.29515418502202645 & Number of Cases Were: 227

44 Days Difference Ratio: 0.30405405405405406 & Number of Cases Were: 148

45 Days Difference Ratio: 0.3700787401574803 & Number of Cases Were: 127

46 Days Difference Ratio: 0.358974358974359 & Number of Cases Were: 117

47 Days Difference Ratio: 0.2871287128712871 & Number of Cases Were: 101

48 Days Difference Ratio: 0.2871287128712871 & Number of Cases Were: 101

```
49 Days Difference Ratio: 0.3350253807106599 & Number of Cases Were: 197

50 Days Difference Ratio: 0.25308641975308643 & Number of Cases Were: 162
```

As we can see from the difference in days ratio and graph, this is the most satisfying reason for why there is no show in appointments.

Conclusions

This analysis containt 101803 sample with 20383 no show case with a ratio of 20%. which is considered a high ratio. after analysing alot of factors, the most satysfying reason was the difference between scheduling days and the actual appointment day. the ratio of 0 days difference was 0.04 for 34027 patient which is big number. the ratio keeps increasing when the differnce between days goes forward.

- diseases has no effect on no-show ratio. the ratio of the diseases are less than 20% of thw whole population
- a bigger sample would be enough to making a point around the problem itself

There are Limitation in this analysis conducted as follows:

- Are patient with age 0 a new born or not? if yes it indicates that there is high pregnency rate and the sick ratio of new born is high and need an attention to avoid death and symptoms duplication.
- There were no rating available for the hospital which could help in going deeper in analysis and finding if the hospital in a certain neighbourhood has a problem or not
- scholarships should have more details to find if the schoalrship itself ha a certain problem or not.
- need more data to analyse the relation between no-show and days differnce and where the problem arise from