Exploratory Data Analysis

Import packages

In [1]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import seaborn
import pandas as pd
import numpy as np
%matplotlib inline
import datetime



from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedKFold
```

In [2]:
```
# Set plot style
import seaborn as sns
sns.set(color_codes=True)
plt.style.use('fivethirtyeight')
```

In [3]:
```
# remove warning
import warnings
warnings.filterwarnings('ignore')
```

Loading data with Pandas

We need to load `client_data.csv` and `price_data.csv` into individual dataframes so that we can work with them in Python.

In [4]:
```
client_df = pd.read_csv('./client_data.csv')
price_df = pd.read_csv('./price_data.csv')
churn_df = pd.read_csv('./churn_data.csv')
```

You can view the first 3 rows of a dataframe using the `head` method. Similarly, if you wanted to see the last 3, you can use `tail(3)`

In [5]:
```
client_df.head(5)
```

Out[5]:

	id	channel_sales	cons_12m	cons_
0	24011ae4ebbe3035111d65fa7c15bc57	foosdfpfkusacimwkcsosbicdxkicaua	0	
1	d29c2c54acc38ff3c0614d0a653813dd	MISSING	4660	
2	764c75f661154dac3a6c254cd082ea7d	foosdfpfkusacimwkcsosbicdxkicaua	544	
3	bba03439a292a1e166f80264c16191cb	lmkebamcaaclubfxadlmueccxoimlema	1584	
4	149d57cf92fc41cf94415803a877cb4b	MISSING	4425	

5 rows × 26 columns

In [6]:
```
client_df.describe()
```

Out[6]:

	cons_12m	cons_gas_12m	cons_last_month	forecast_cons_12m	forecast_cons_yea
count	1.460600e+04	1.460600e+04	14606.000000	14606.000000	14606.000000
mean	1.592203e+05	2.809238e+04	16090.269752	1868.614880	1399.762906
std	5.734653e+05	1.629731e+05	64364.196422	2387.571531	3247.786255
min	0.000000e+00	0.000000e+00	0.000000	0.000000	0.000000
25%	5.674750e+03	0.000000e+00	0.000000	494.995000	0.000000
50%	1.411550e+04	0.000000e+00	792.500000	1112.875000	314.000000
75%	4.076375e+04	0.000000e+00	3383.000000	2401.790000	1745.750000
max	6.207104e+06	4.154590e+06	771203.000000	82902.830000	175375.000000

In [7]:
```
price_df.head(5)
```

Out[7]:

	id	price_date	price_off_peak_var	price_peak_var	price_
0	038af19179925da21a25619c5a24b745	1/1/2015	0.151367	0.0	
1	038af19179925da21a25619c5a24b745	2/1/2015	0.151367	0.0	
2	038af19179925da21a25619c5a24b745	3/1/2015	0.151367	0.0	
3	038af19179925da21a25619c5a24b745	4/1/2015	0.149626	0.0	
4	038af19179925da21a25619c5a24b745	5/1/2015	0.149626	0.0	

In [8]:
```
price_df.describe()
```

Out[8]:

	price_off_peak_var	price_peak_var	price_mid_peak_var	price_off_peak_fix	price_peak
count	193002.000000	193002.000000	193002.000000	193002.000000	193002.000
mean	0.141027	0.054630	0.030496	43.334477	10.622
std	0.025032	0.049924	0.036298	5.410297	12.841
min	0.000000	0.000000	0.000000	0.000000	0.000
25%	0.125976	0.000000	0.000000	40.728885	0.000
50%	0.146033	0.085483	0.000000	44.266930	0.000
75%	0.151635	0.101673	0.072558	44.444710	24.339
max	0.280700	0.229788	0.114102	59.444710	36.490

Descriptive statistics of data

Data types

To get an overview of the data types within a data frame, use the `info()` method.

In [9]:
```
client_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14606 entries, 0 to 14605
Data columns (total 26 columns):
 #   Column                            Non-Null Count  Dtype  
---  ------                            --------------  -----  
 0   id                                14606 non-null  object 
 1   channel_sales                     14606 non-null  object 
 2   cons_12m                          14606 non-null  int64  
 3   cons_gas_12m                      14606 non-null  int64  
 4   cons_last_month                   14606 non-null  int64  
 5   date_activ                        14606 non-null  object 
 6   date_end                          14606 non-null  object 
 7   date_modif_prod                   14606 non-null  object 
 8   date_renewal                      14606 non-null  object 
 9   forecast_cons_12m                 14606 non-null  float64
 10  forecast_cons_year                14606 non-null  int64  
 11  forecast_discount_energy          14606 non-null  int64  
 12  forecast_meter_rent_12m           14606 non-null  float64
 13  forecast_price_energy_off_peak    14606 non-null  float64
 14  forecast_price_energy_peak        14606 non-null  float64
 15  forecast_price_pow_off_peak       14606 non-null  float64
 16  has_gas                           14606 non-null  object 
 17  imp_cons                          14606 non-null  float64
 18  margin_gross_pow_ele              14606 non-null  float64
 19  margin_net_pow_ele                14606 non-null  float64
 20  nb_prod_act                       14606 non-null  int64  
 21  net_margin                        14606 non-null  float64
 22  num_years_antig                   14606 non-null  int64  
 23  origin_up                         14606 non-null  object 
 24  pow_max                           14606 non-null  float64
 25  churn                             14606 non-null  int64  
dtypes: float64(10), int64(8), object(8)
memory usage: 2.9+ MB
```

In [10]:
```
price_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 193002 entries, 0 to 193001
Data columns (total 8 columns):
 #   Column              Non-Null Count   Dtype  
---  ------              --------------   -----  
 0   id                  193002 non-null  object 
 1   price_date          193002 non-null  object 
 2   price_off_peak_var  193002 non-null  float64
 3   price_peak_var      193002 non-null  float64
 4   price_mid_peak_var  193002 non-null  float64
 5   price_off_peak_fix  193002 non-null  float64
 6   price_peak_fix      193002 non-null  float64
 7   price_mid_peak_fix  193002 non-null  float64
dtypes: float64(6), object(2)
memory usage: 11.8+ MB
```

In [11]:
```
print('Total records in client dataset :{}'.format(client_df.shape[0]))
print('Total records in price dataset :{}'.format(price_df.shape[0]))
```

```
Total records in client dataset :14606
Total records in price dataset :193002
```

In [12]:
```
## Merge these two dataset

churn_data = pd.merge(client_df,price_df,left_on='id', right_on='id', how='inner')
print('Total records in churn Dataset :{}'.format(churn_data.shape[0]))
```

```
Total records in churn Dataset :175149
```

In [13]:
```
churn_data.head()
```

Out[13]:

	id	channel_sales	cons_12m	cons_gas
0	24011ae4ebbe3035111d65fa7c15bc57	foosdfpfkusacimwkcsosbicdxkicaua	0	
1	24011ae4ebbe3035111d65fa7c15bc57	foosdfpfkusacimwkcsosbicdxkicaua	0	
2	24011ae4ebbe3035111d65fa7c15bc57	foosdfpfkusacimwkcsosbicdxkicaua	0	
3	24011ae4ebbe3035111d65fa7c15bc57	foosdfpfkusacimwkcsosbicdxkicaua	0	
4	24011ae4ebbe3035111d65fa7c15bc57	foosdfpfkusacimwkcsosbicdxkicaua	0	

5 rows × 33 columns

Statistics

Now let's look at some statistics about the datasets. We can do this by using the `describe()` method.

In [14]:
```
churn_data.describe()
```

Out[14]:

	cons_12m	cons_gas_12m	cons_last_month	forecast_cons_12m	forecast_cons_yea
count	1.751490e+05	1.751490e+05	175149.000000	175149.000000	175149.00000(
mean	1.592606e+05	2.808072e+04	16095.518404	1868.343884	1399.78238(
std	5.735413e+05	1.629400e+05	64376.741908	2387.560169	3248.33127(
min	0.000000e+00	0.000000e+00	0.000000	0.000000	0.00000(
25%	5.674000e+03	0.000000e+00	0.000000	494.980000	0.00000(
50%	1.411500e+04	0.000000e+00	792.000000	1112.610000	314.00000(
75%	4.076300e+04	0.000000e+00	3383.000000	2400.350000	1745.00000(
max	6.207104e+06	4.154590e+06	771203.000000	82902.830000	175375.00000(

8 rows × 24 columns

Find Missing Data and Clean

In [15]:
```
null_columns = churn_data.columns[churn_data.isnull().any()]
```

```
null_columns
```

Out[15]:
```
Index([], dtype='object')
```

In [16]:
```
churn_data = churn_data.dropna()
churn_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 175149 entries, 0 to 175148
Data columns (total 33 columns):
 #   Column                          Non-Null Count   Dtype  
---  ------                          --------------   -----  
 0   id                              175149 non-null  object 
 1   channel_sales                   175149 non-null  object 
 2   cons_12m                        175149 non-null  int64  
 3   cons_gas_12m                    175149 non-null  int64  
 4   cons_last_month                 175149 non-null  int64  
 5   date_activ                      175149 non-null  object 
 6   date_end                        175149 non-null  object 
 7   date_modif_prod                 175149 non-null  object 
 8   date_renewal                    175149 non-null  object 
 9   forecast_cons_12m               175149 non-null  float64
 10  forecast_cons_year              175149 non-null  int64  
 11  forecast_discount_energy        175149 non-null  int64  
 12  forecast_meter_rent_12m         175149 non-null  float64
 13  forecast_price_energy_off_peak  175149 non-null  float64
 14  forecast_price_energy_peak      175149 non-null  float64
 15  forecast_price_pow_off_peak     175149 non-null  float64
 16  has_gas                         175149 non-null  object 
 17  imp_cons                        175149 non-null  float64
 18  margin_gross_pow_ele            175149 non-null  float64
 19  margin_net_pow_ele              175149 non-null  float64
 20  nb_prod_act                     175149 non-null  int64  
 21  net_margin                      175149 non-null  float64
 22  num_years_antig                 175149 non-null  int64  
 23  origin_up                       175149 non-null  object 
 24  pow_max                         175149 non-null  float64
 25  churn                           175149 non-null  int64  
 26  price_date                      175149 non-null  object 
 27  price_off_peak_var              175149 non-null  float64
 28  price_peak_var                  175149 non-null  float64
 29  price_mid_peak_var              175149 non-null  float64
 30  price_off_peak_fix              175149 non-null  float64
 31  price_peak_fix                  175149 non-null  float64
 32  price_mid_peak_fix              175149 non-null  float64
dtypes: float64(16), int64(8), object(9)
memory usage: 45.4+ MB
```

Check For Missing Values

In [17]:
```
#Check how much of our data is missing
pd.DataFrame({"Missing value (%)": client_df.isnull().sum()/len(client_df.index)*10
```

Out[17]:

	Missing value (%)
id	0.0
channel_sales	0.0
cons_12m	0.0
cons_gas_12m	0.0
cons_last_month	0.0
date_activ	0.0
date_end	0.0
date_modif_prod	0.0
date_renewal	0.0
forecast_cons_12m	0.0
forecast_cons_year	0.0
forecast_discount_energy	0.0
forecast_meter_rent_12m	0.0
forecast_price_energy_off_peak	0.0
forecast_price_energy_peak	0.0
forecast_price_pow_off_peak	0.0
has_gas	0.0
imp_cons	0.0
margin_gross_pow_ele	0.0
margin_net_pow_ele	0.0
nb_prod_act	0.0
net_margin	0.0
num_years_antig	0.0
origin_up	0.0
pow_max	0.0
churn	0.0

In [18]:
```
pd.DataFrame({"Missing value (%)": price_df.isnull().sum()/len(price_df.index)*100}
```

Out[18]:

	Missing value (%)
id	0.0
price_date	0.0
price_off_peak_var	0.0
price_peak_var	0.0
price_mid_peak_var	0.0
price_off_peak_fix	0.0
price_peak_fix	0.0
price_mid_peak_fix	0.0

Good There are no missing values Foound

The above churn data is completly clean and has no null values,its looking Fine after merging

Churn

In [19]:
```
churn_data = client_df[['id', 'churn']]
churn_data.rename(columns={'id':'Companies'}, inplace=True)
churn_count = churn_data.groupby(['churn']).count().reset_index()
churn_count.rename(columns={'Companies' : 'Num'},inplace=True)
churn_count['Num'] = round((churn_count['Num']/churn_count['Num'].sum())*100,1)
churn_count.rename(columns={'Num' : 'Companies'},inplace=True)
```

In [20]:
```
churn_count
```

Out[20]:

	churn	Companies
0	0	90.3
1	1	9.7

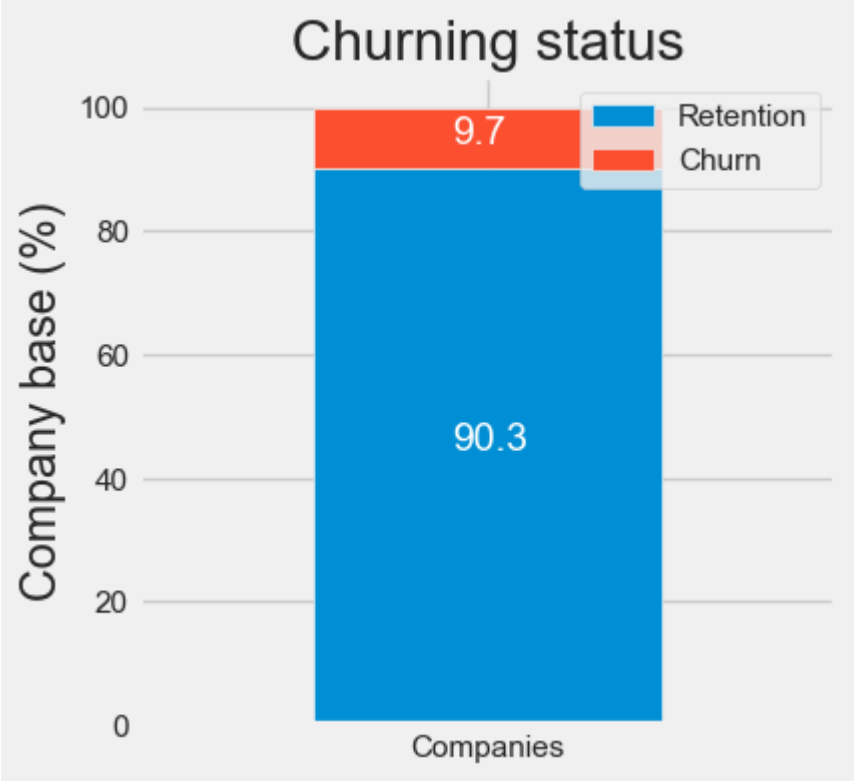
The first function `plot_stacked_bars` is used to plot a stacked bar chart. An example of how you could use this is shown below:The second function `annotate_bars` is used by the first function, but the third function `plot_distribution` helps you to plot the distribution of a numeric column. An example of how it can be used is given below:

In [21]:
```
def plot_stacked_bars(dataframe, title_, size_=(18, 10), rot_=0, legend_="upper rig
    """
    Plot stacked bars with annotations
    """
    ax = dataframe.plot(
        kind="bar",
        stacked=True,
        figsize=size_,
        rot=rot_,
        title=title_
    )
```

```
    # Annotate bars
    annotate_stacked_bars(ax, textsize=14)
    # Rename legend
    plt.legend(["Retention", "Churn"], loc=legend_)
    # Labels
    plt.ylabel("Company base (%)")
    plt.show()

def annotate_stacked_bars(ax, pad=0.99, colour="white", textsize=13):
    """
    Add value annotations to the bars
    """

    # Iterate over the plotted rectanges/bars
    for p in ax.patches:

        # Calculate annotation
        value = str(round(p.get_height(),1))
        # If value is 0 do not annotate
        if value == '0.0':
            continue
        ax.annotate(
            value,
            ((p.get_x()+ p.get_width()/2)*pad-0.05, (p.get_y()+p.get_height()/2)*pa
            color=colour,
            size=textsize
        )

def plot_distribution(dataframe, column, ax, bins_=50):
    """
    Plot variable distirbution in a stacked histogram of churned or retained compan
    """
    # Create a temporal dataframe with the data to be plot
    temp = pd.DataFrame({"Retention": dataframe[dataframe["churn"]==0][column],
    "Churn":dataframe[dataframe["churn"]==1][column]})
    # Plot the histogram
    temp[["Retention","Churn"]].plot(kind='hist', bins=bins_, ax=ax, stacked=True)
    # X-axis label
    ax.set_xlabel(column)
    # Change the x-axis to plain style
    ax.ticklabel_format(style='plain', axis='x')
```

In [22]:

```
churn = client_df[['id', 'churn']]
churn.columns = ['Companies', 'churn']
churn_total = churn.groupby(churn['churn']).count()
churn_percentage = churn_total / churn_total.sum() * 100
plot_stacked_bars(churn_percentage.transpose(), "Churning status", (4, 4), legend_=
```



So by this Graph we can understand around 9.7% customers are churn customers and stopped using PoweCo Services

SME Activity

In [23]:
```
sme_activity = client_df[['id','channel_sales','churn']]
sme_activity.head()
```

Out[23]:

	id	channel_sales	churn
0	24011ae4ebbe3035111d65fa7c15bc57	foosdfpfkusacimwkcsosbicdxkicaua	1
1	d29c2c54acc38ff3c0614d0a653813dd	MISSING	0
2	764c75f661154dac3a6c254cd082ea7d	foosdfpfkusacimwkcsosbicdxkicaua	0
3	bba03439a292a1e166f80264c16191cb	lmkebamcaaclubfxadlmueccxoimlema	0
4	149d57cf92fc41cf94415803a877cb4b	MISSING	0

In [24]:
```
# Number of companies under SME Activity

num_comp_per_sme_activity = sme_activity.groupby(['channel_sales', 'churn'])['id'].
num_comp_per_sme_activity
```

Out[24]:

churn	0	1
channel_sales		
MISSING	3442.0	283.0
epumfxlbckeskwekxbiuasklxalciiuu	3.0	NaN
ewpakwlliwisiwduibdlfmalxowmwpci	818.0	75.0
fixdbufsefwooaasfcxdxadsiekoceaa	2.0	NaN
foosdfpfkusacimwkcsosbicdxkicaua	5934.0	820.0
lmkebamcaaclubfxadlmueccxoimlema	1740.0	103.0
sddiedcslfslkckwlfkdpoeeailfpeds	11.0	NaN
usilxuppasemubllopkaafesmlibmsdf	1237.0	138.0

In [25]:
```
num_comp_per_sme_activity.plot(kind='bar', figsize=(20,10), width=0.5, stacked=True

plt.ylabel('Number of Companies')
plt.xlabel('SME Activity')

plt.legend(['Retention', 'Churn'])
plt.xticks([])
plt.show()
```

In [26]:
```
#Percentage wise

sme_activity_total = num_comp_per_sme_activity.fillna(0)[0]+num_comp_per_sme_activi
sme_activity_total_percentage =  num_comp_per_sme_activity.fillna(0)[1]/(sme_activi
pd.DataFrame({'Churn Percentage': sme_activity_total_percentage, 'Number of Compani
by='Churn Percentage', ascending=False).head(20)
```

Out[26]:

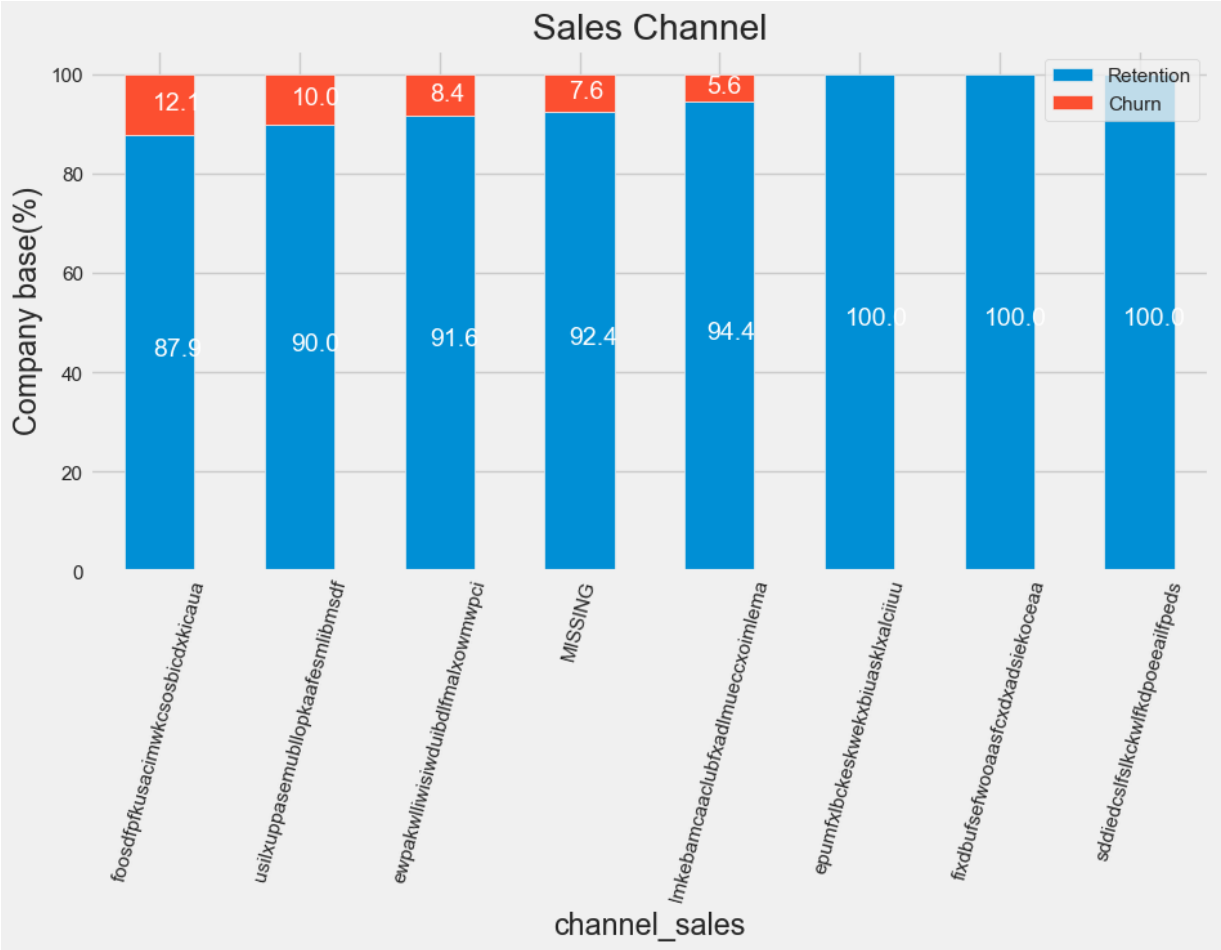
channel_sales	Churn Percentage	Number of Companies
foosdfpfkusacimwkcsosbicdxkicaua	12.140954	6754.0
usilxuppasemubllopkaafesmlibmsdf	10.036364	1375.0
ewpakwlliwisiwduibdlfmalxowmwpci	8.398656	893.0
MISSING	7.597315	3725.0
lmkebamcaaclubfxadlmueccxoimlema	5.588714	1843.0
epumfxlbckeskwekxbiuasklxalciiuu	0.000000	3.0
fixdbufsefwooaasfcxdxadsiekoceaa	0.000000	2.0
sddiedcslfslkckwlfkdpoeeailfpeds	0.000000	11.0

In [27]:
```
channel=client_df[['id', 'channel_sales', 'churn']]
channel = channel.groupby([channel['channel_sales'], channel['churn']])['id'].count
```

In [28]:
```
channel_churn=(channel.div(channel.sum(axis=1),axis=0)*100).sort_values(by=[1],asce
```

In [29]:
```
ax=channel_churn.plot(kind='bar',stacked=True,figsize=(10,5),rot=75)
annotate_stacked_bars(ax, textsize=14)
plt.title('Sales Channel')
plt.legend(['Retention','Churn'],loc='upper right')
plt.ylabel('Company base(%)')
```

Out[29]:
```
Text(0, 0.5, 'Company base(%)')
```



Consumption

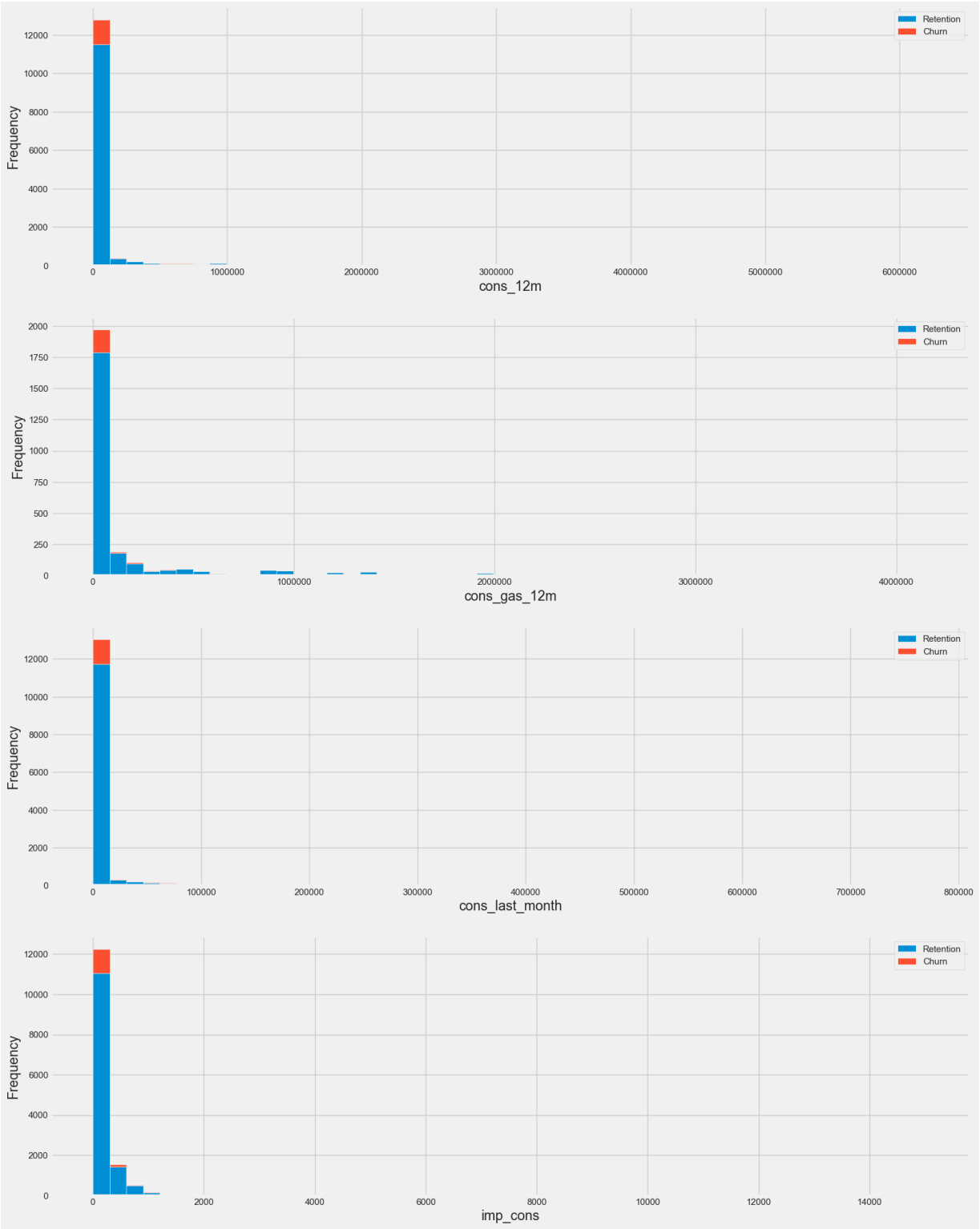
consumption of customer during the last month, 12 months against the churn

Now, we will see the consumption of customers during the last month and 12 months againt the churn. Because this is a numeric - categorical comparison therefore we can use histogram distribution or box plot visualization.We Will Create a plot_distribution function to see the spread and skewness of the churn data

In [30]:
```
consumption = client_df[["cons_12m", "cons_gas_12m", "cons_last_month", "imp_cons",
```

In [31]:
```
def plot_distribution(dataframe, column, ax, bins_=50):
    """
    Plot variable distirbution in a stacked histogram of churned or retained compan
    """
    # Create a temporal dataframe with the data to be plot
    temp = pd.DataFrame({"Retention": dataframe[dataframe["churn"]==0][column],
    "Churn":dataframe[dataframe["churn"]==1][column]})
    # Plot the histogram
    temp[["Retention","Churn"]].plot(kind='hist', bins=bins_, ax=ax, stacked=True)
    # X-axis label
    ax.set_xlabel(column)
    # Change the x-axis to plain style
    ax.ticklabel_format(style='plain', axis='x')
```

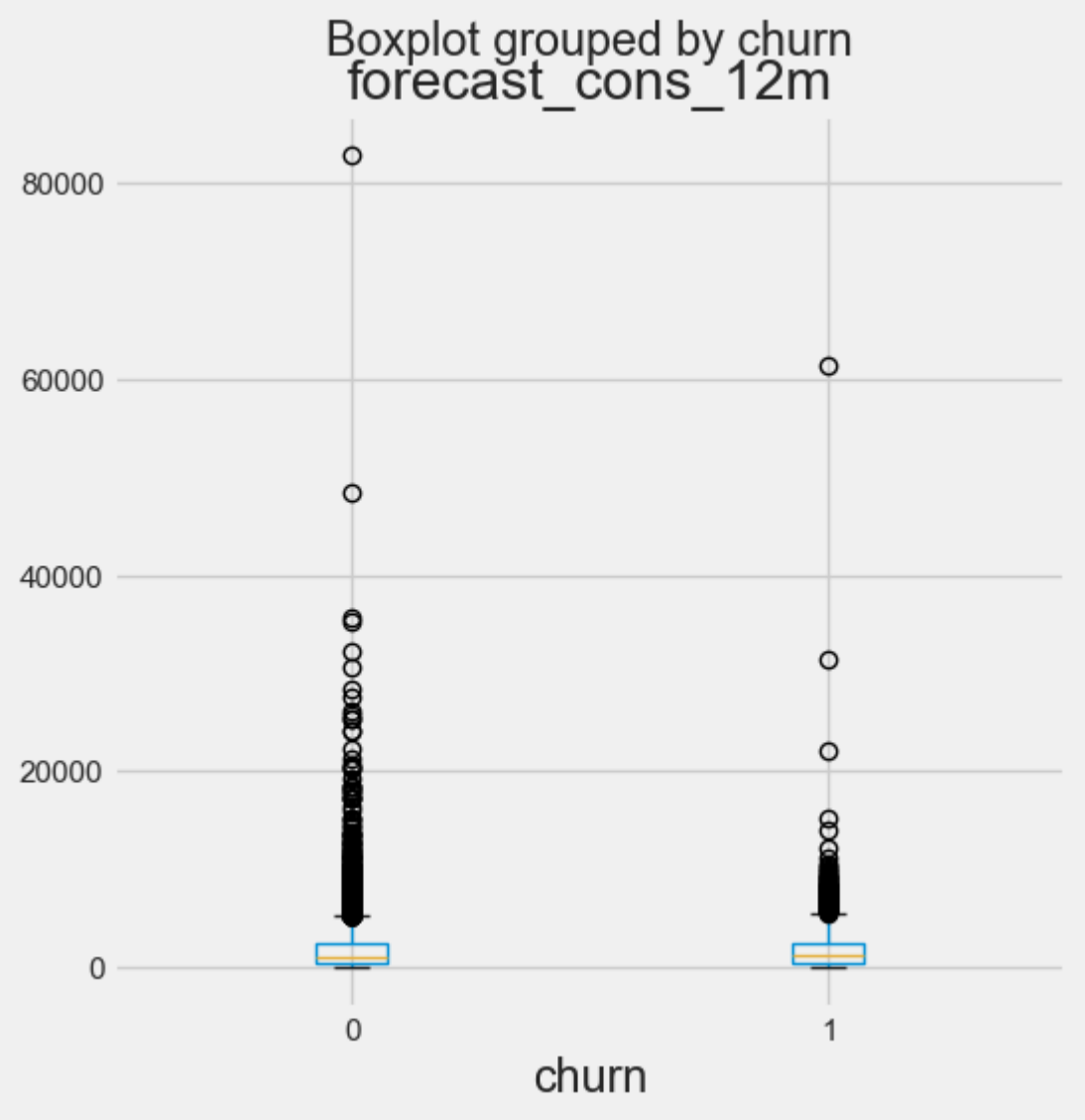
In [32]:
```
fig, axs = plt.subplots(nrows=4, figsize=(18, 25))

plot_distribution(consumption, 'cons_12m', axs[0])
plot_distribution(consumption[consumption['has_gas'] == 't'], 'cons_gas_12m', axs[1
plot_distribution(consumption, 'cons_last_month', axs[2])
plot_distribution(consumption, 'imp_cons', axs[3])
```

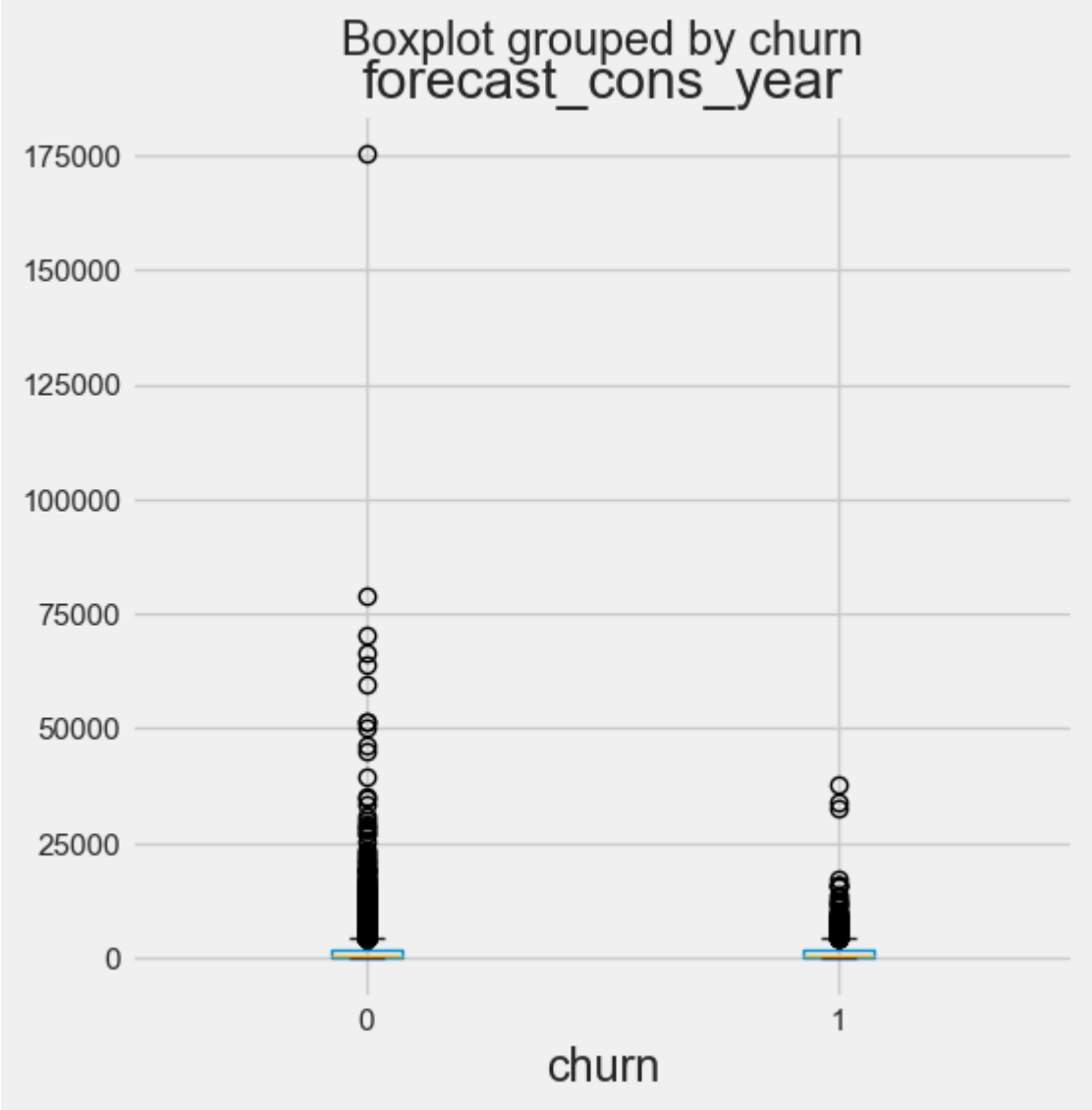


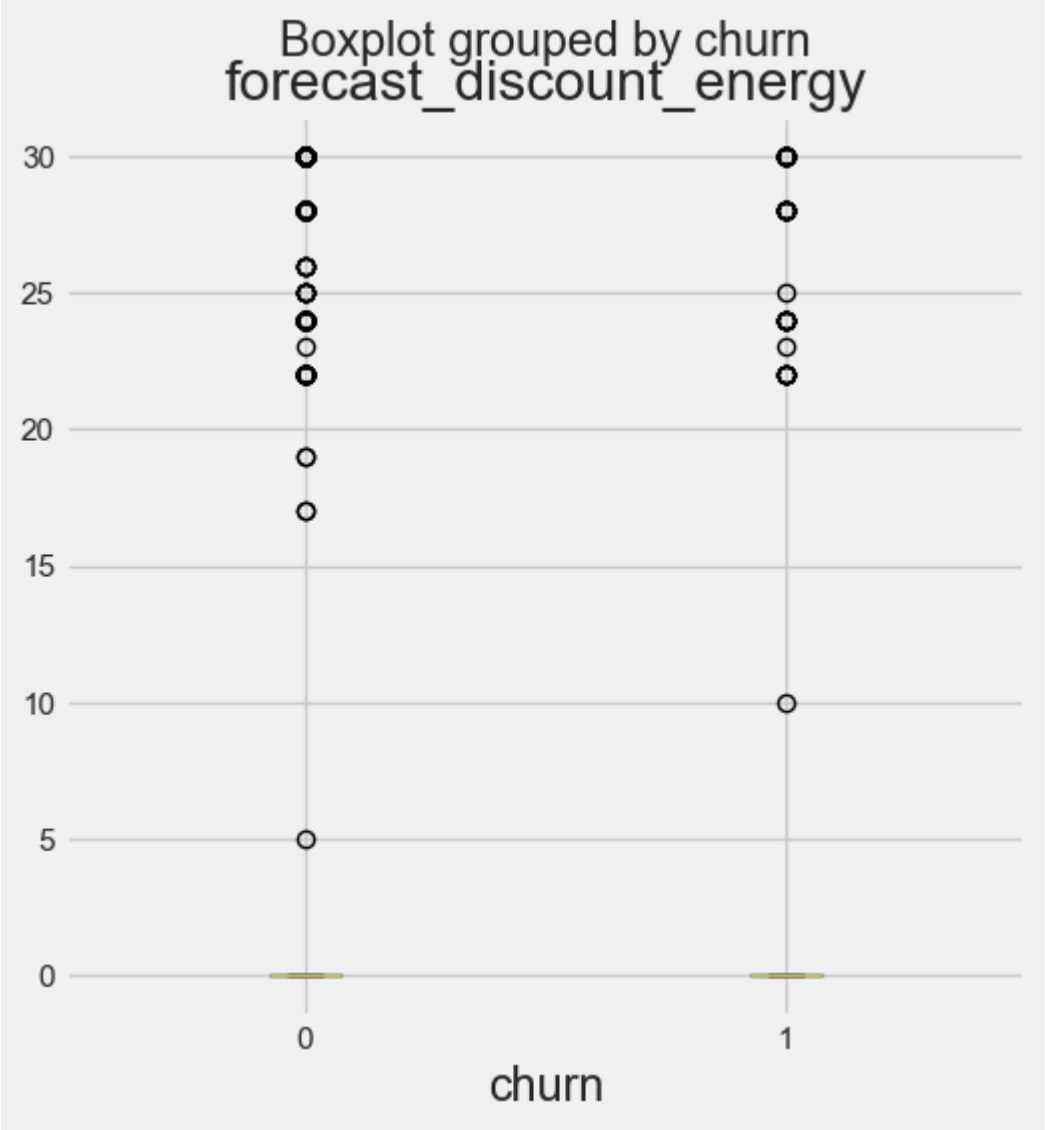
Forecast

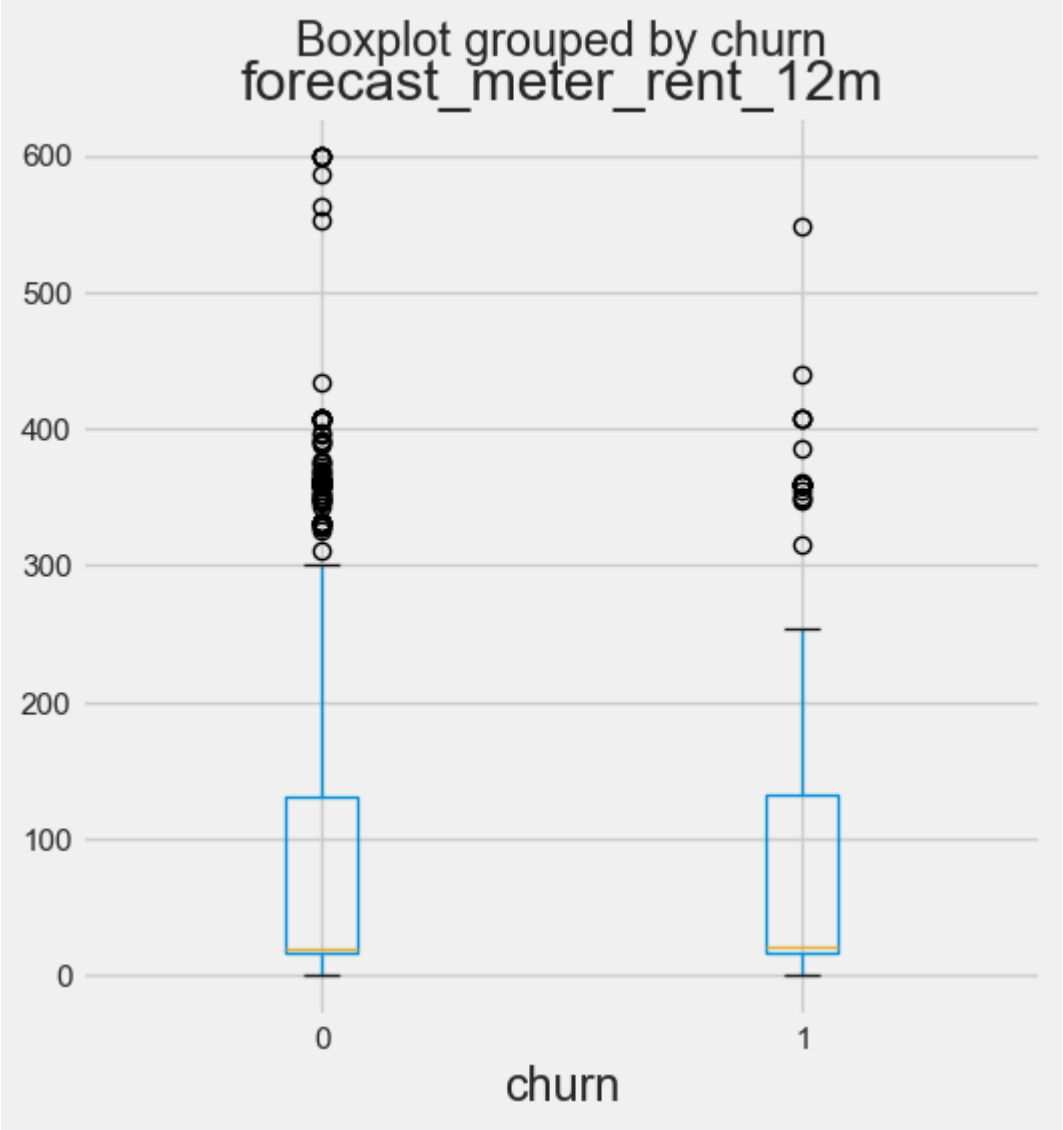
In [33]:
```
forecast = client_df[["forecast_cons_12m", "forecast_cons_year","forecast_discount_
    "forecast_price_energy_off_peak","forecast_price_energy_peak", "forecast_price_
```

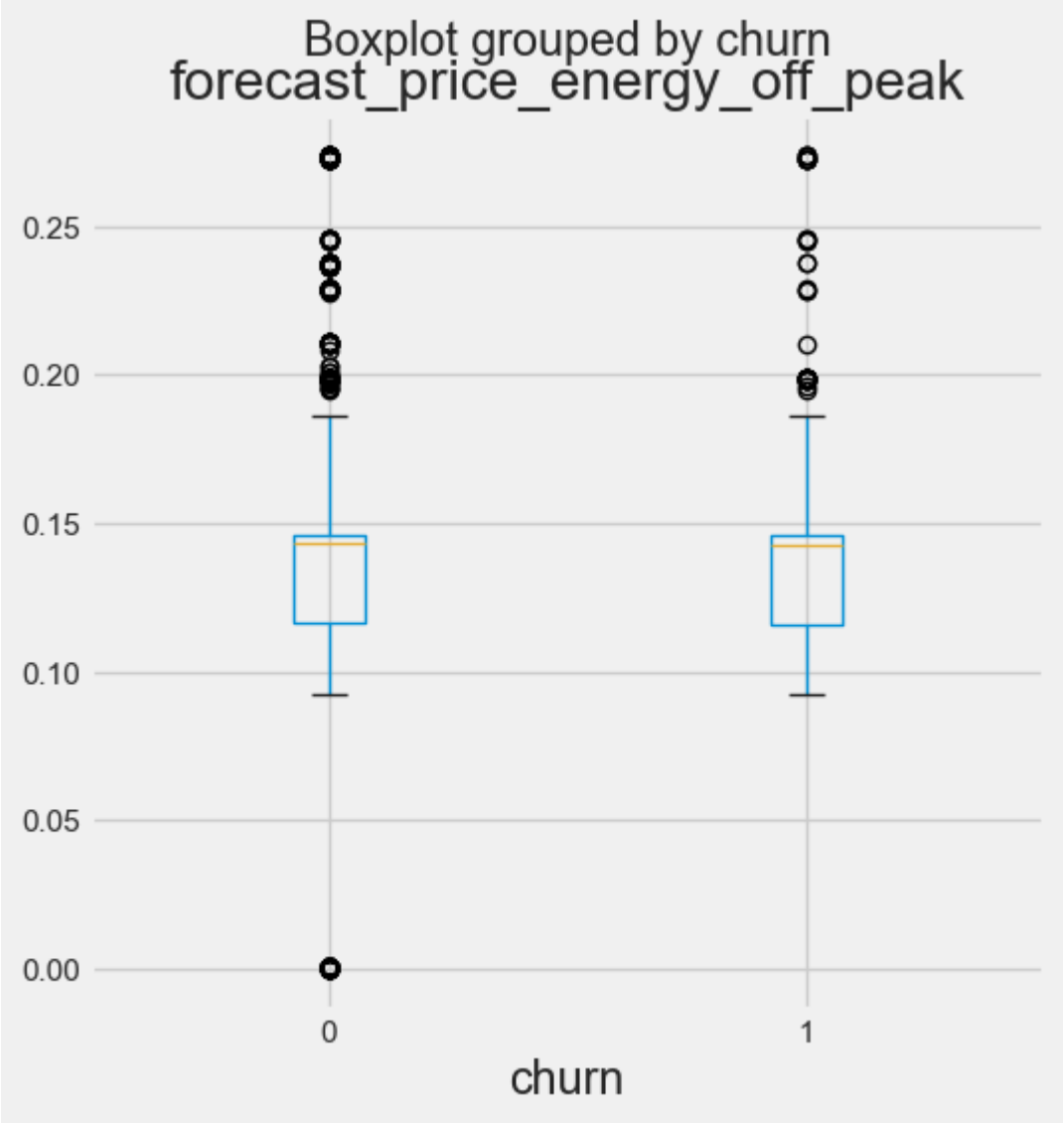
In [34]:
```
for col in forecast:
    client_df.boxplot(column=col, by='churn', figsize=(6,6))
    plt.title(col)
plt.show()
```

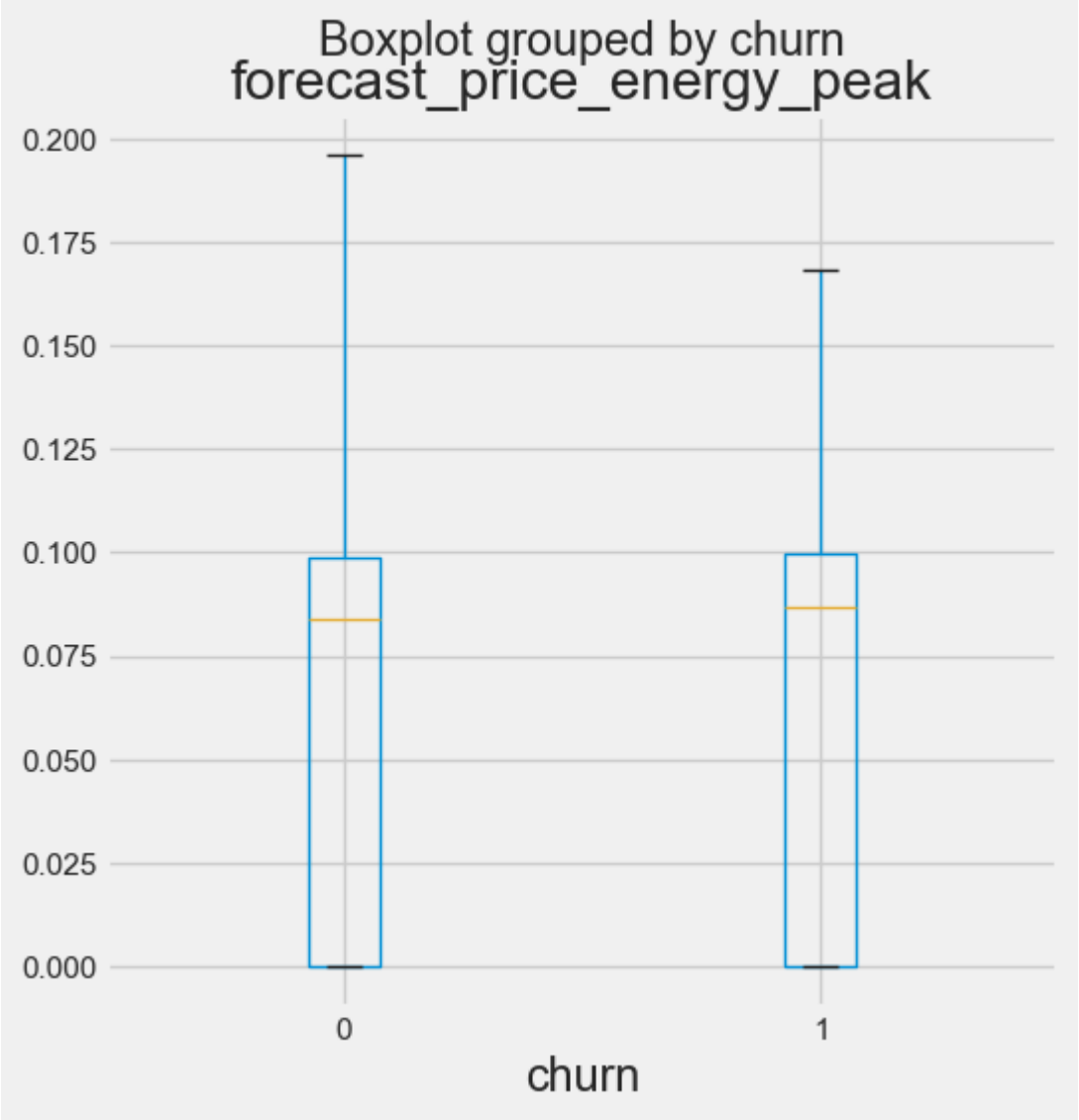


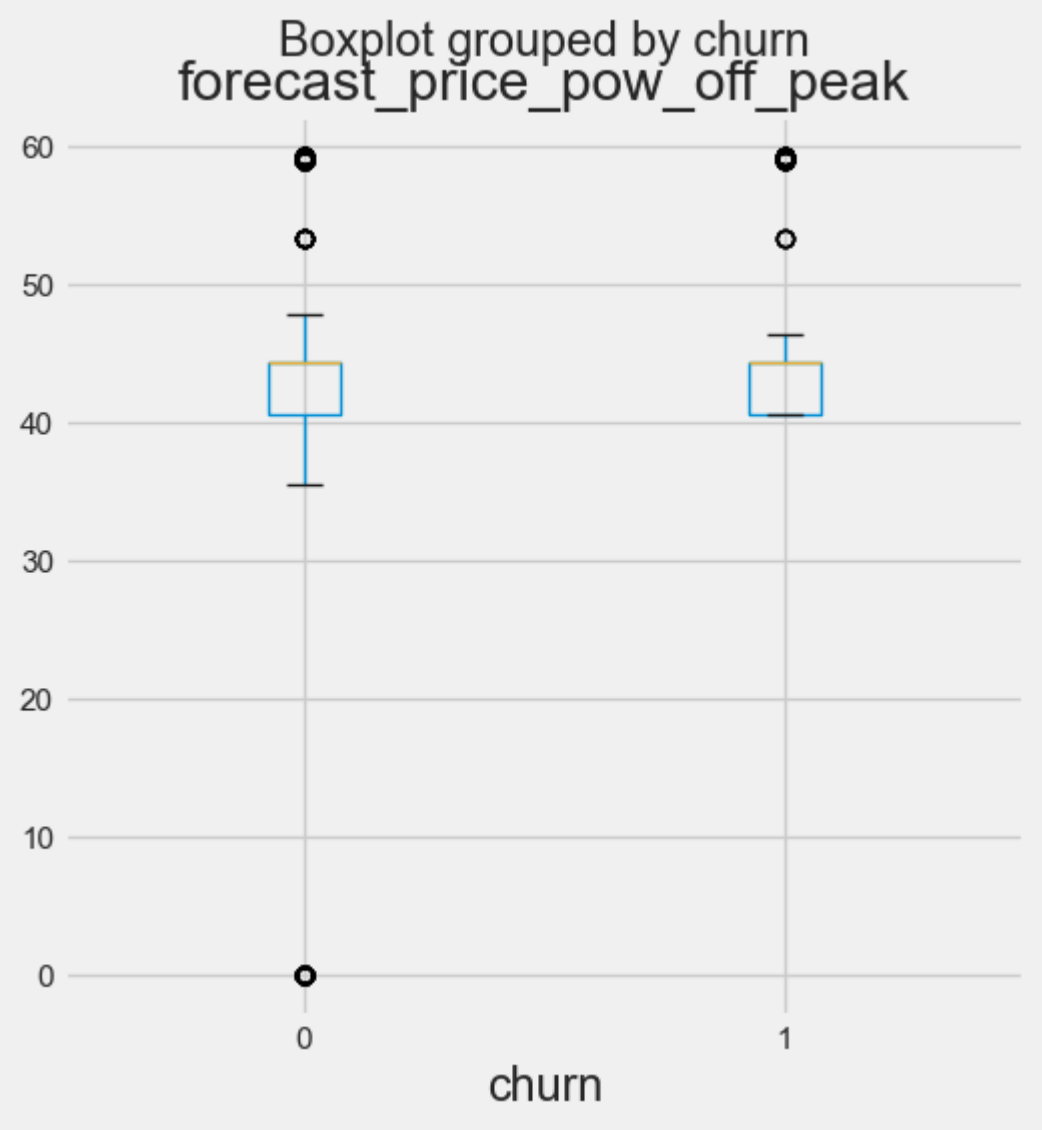

Boxplot grouped by churn
forecast_cons_year
175000
150000
125000
100000
75000
50000
25000
0
0
1
churn


Boxplot grouped by churn
forecast_discount_energy
30
25
20
15
10
5
0
0
1
churn


Boxplot grouped by churn
forecast_meter_rent_12m
600
500
400
300
200
100
0
0
1
churn

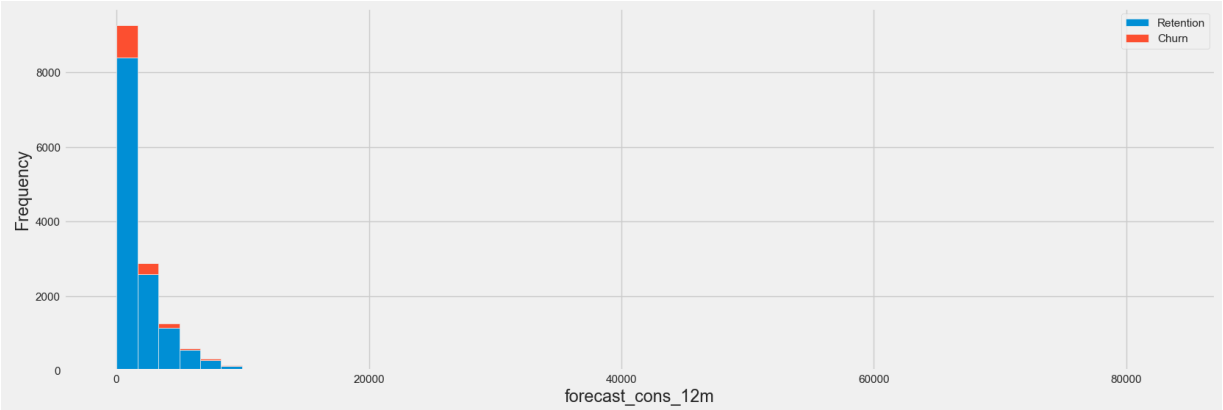

Boxplot grouped by churn
forecast_price_energy_off_peak
0.25
0.20
0.15
0.10
0.05
0.00
0
1
churn

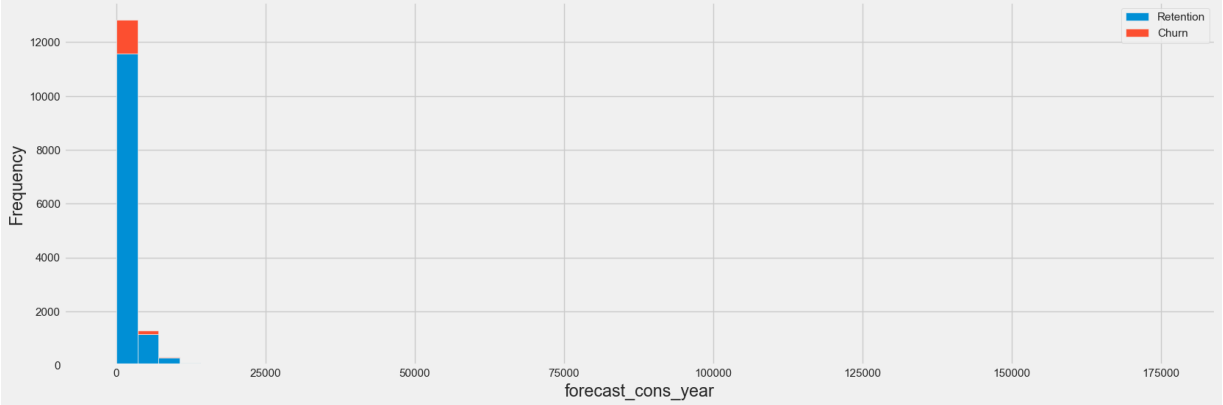

Boxplot grouped by churn
forecast_price_energy_peak
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
0
1
churn

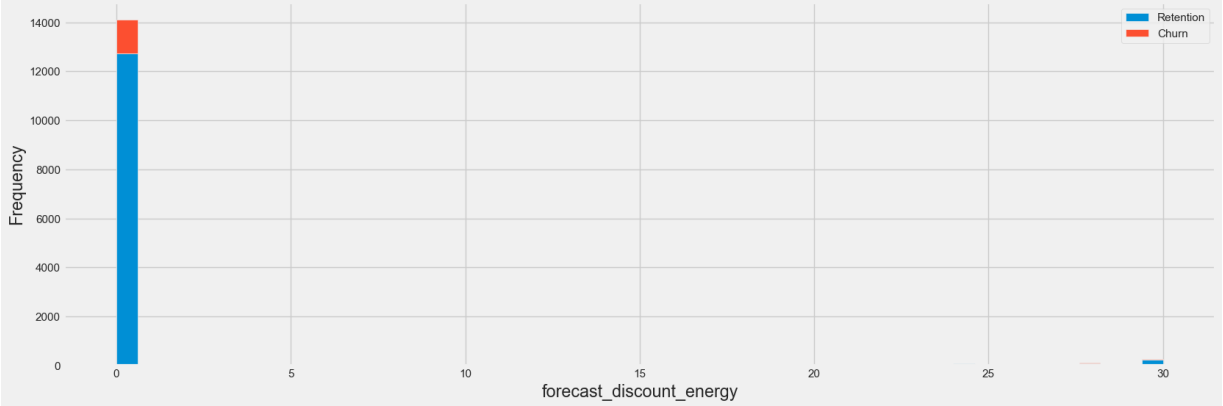


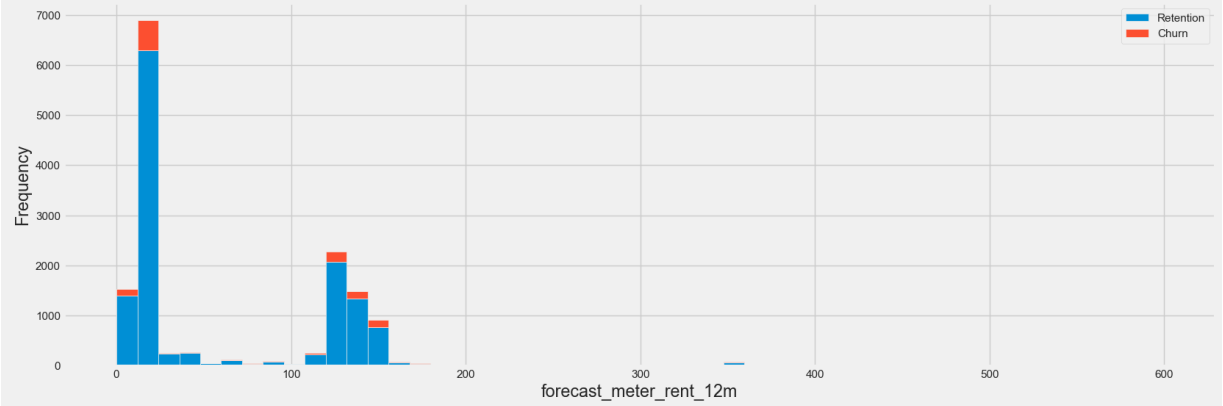
AS you can see even forecast data is skewed like consumption

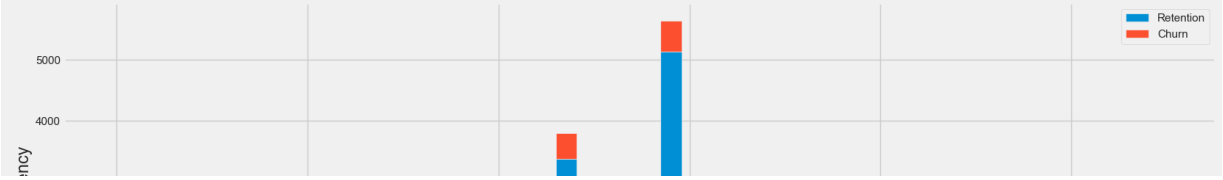
In [35]:
```
fig, axs = plt.subplots(nrows=7, figsize=(18,50))

# Plot histogram
plot_distribution(client_df, "forecast_cons_12m", axs[0])
plot_distribution(client_df, "forecast_cons_year", axs[1])
plot_distribution(client_df, "forecast_discount_energy", axs[2])
plot_distribution(client_df, "forecast_meter_rent_12m", axs[3])
plot_distribution(client_df, "forecast_price_energy_off_peak", axs[4])
plot_distribution(client_df, "forecast_price_energy_peak", axs[5])
plot_distribution(client_df, "forecast_price_pow_off_peak", axs[6])
```

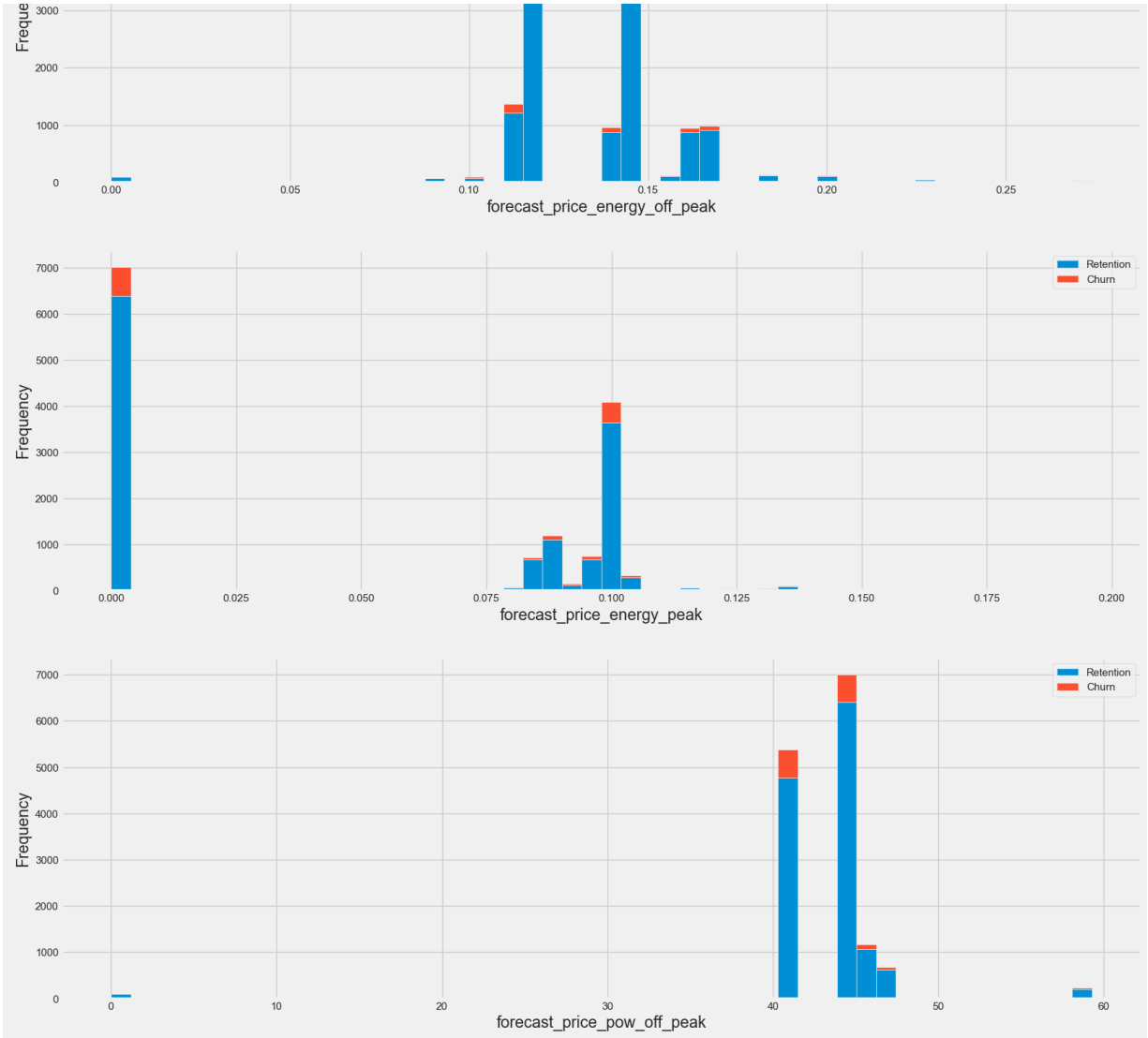

Retention
Churn
Frequency
0
2000
4000
6000
8000
0
20000
40000
60000
80000
forecast_cons_12m


Retention
Churn
Frequency
0
2000
4000
6000
8000
10000
12000
0
25000
50000
75000
100000
125000
150000
175000
forecast_cons_year


Retention
Churn
Frequency
0
2000
4000
6000
8000
10000
12000
14000
0
5
10
15
20
25
30
forecast_discount_energy

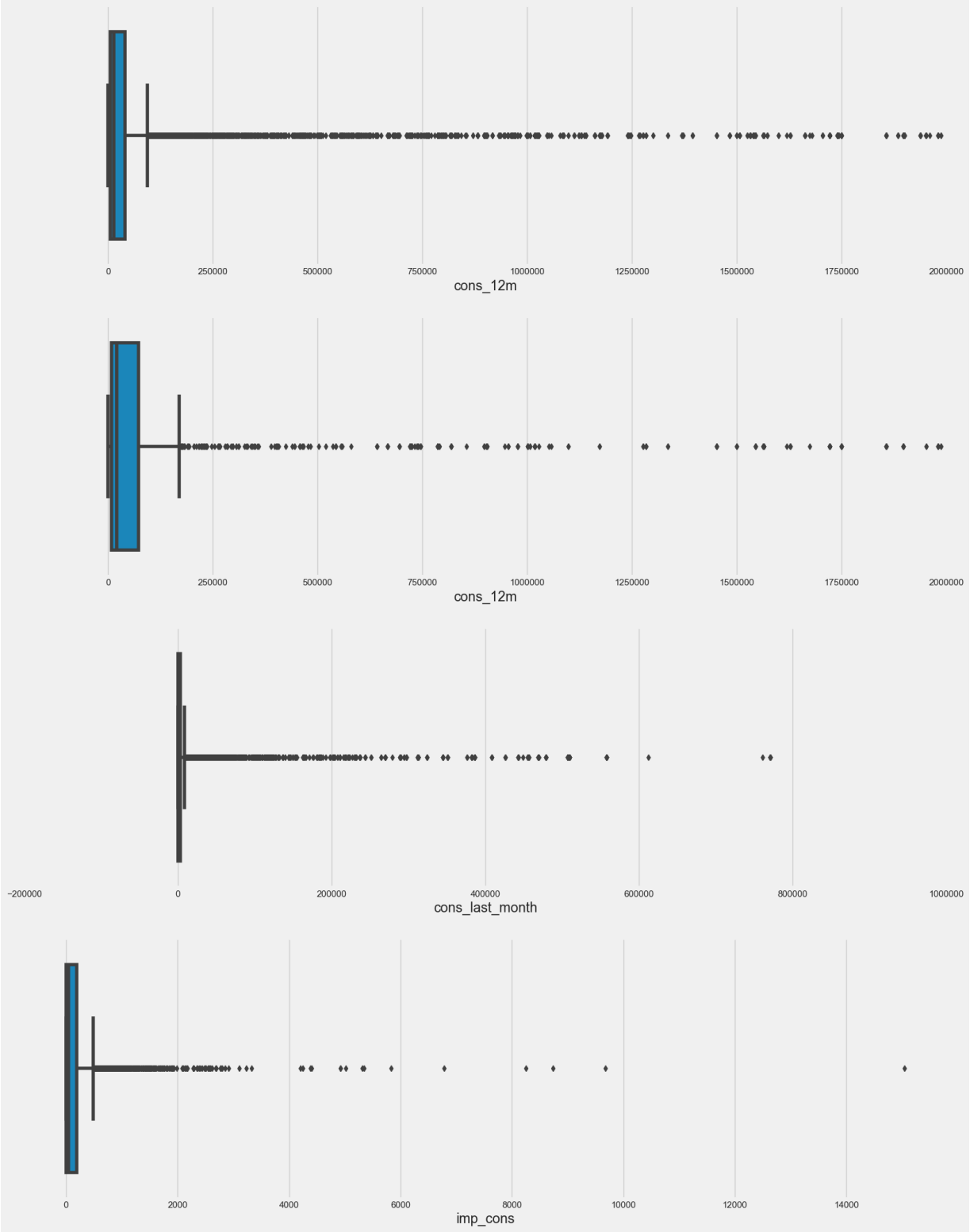

Retention
Churn
Frequency
0
1000
2000
3000
4000
5000
6000
7000
0
100
200
300
400
500
600
forecast_meter_rent_12m


Retention
Churn
5000
4000



The consumption data exhibits a strong right-skewness, characterized by an elongated right-tail, which is predominantly composed of higher values in the distribution. Values at the extreme ends of the distribution, both on the higher and lower sides, are likely to be considered outliers. To visualize these outliers more effectively, we can utilize a standard plot, such as a boxplot. A boxplot provides a standardized representation of the data distribution through a five-number summary: "minimum," first quartile (Q1), median, third quartile (Q3), and "maximum." By employing a boxplot, we can easily identify the outliers and discern their respective values. Additionally, the plot can offer insights into the symmetry of the data, the level of data clustering, and the presence and extent of skewness in the data.

In [36]:
```
fig, axs = plt.subplots(nrows=4, figsize=(18,25))
sns.boxplot(consumption['cons_12m'], ax=axs[0])
sns.boxplot(consumption[consumption['has_gas']=='t']['cons_12m'], ax=axs[1])
sns.boxplot(consumption['cons_last_month'], ax=axs[2])
sns.boxplot(consumption['imp_cons'], ax=axs[3])

for ax in axs :
    ax.ticklabel_format(style='plain', axis='x')

axs[0].set_xlim(-200000,2000000)
axs[1].set_xlim(-200000,2000000)
axs[2].set_xlim(-200000,1000000)
plt.show()
```



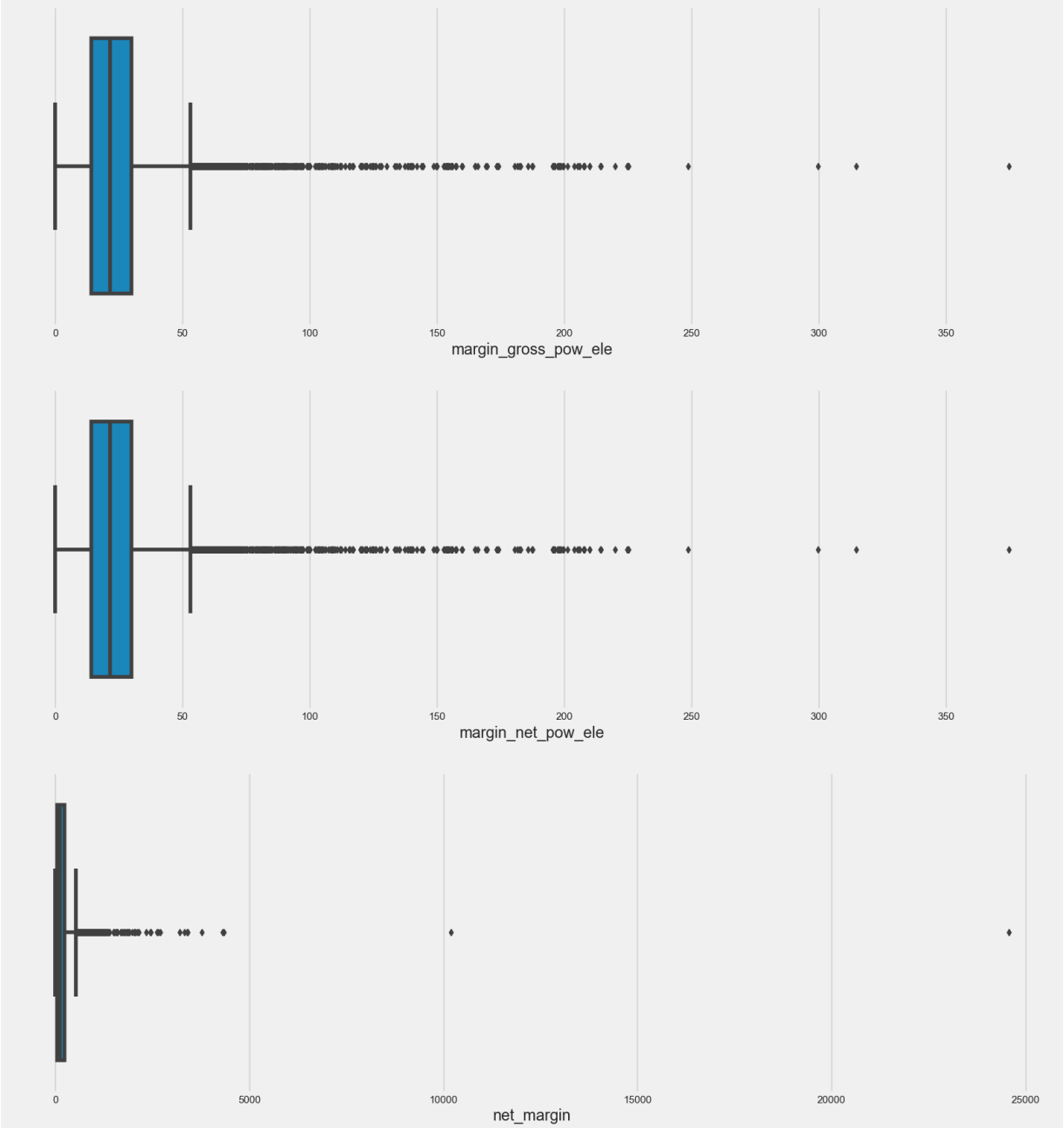
Here We can see highly skewed distribution and several outliers

Margins

In [37]:
```
margin_churn = client_df[['id', 'margin_gross_pow_ele', 'margin_net_pow_ele', 'net_
```

In [38]:
```
fig, axs = plt.subplots(nrows=3, figsize=(18,20))
sns.boxplot(margin_churn['margin_gross_pow_ele'] , ax=axs[0])
sns.boxplot(margin_churn['margin_net_pow_ele'] , ax=axs[1])
```

```
sns.boxplot(margin_churn['net_margin'] , ax=axs[2])

plt.show()
```

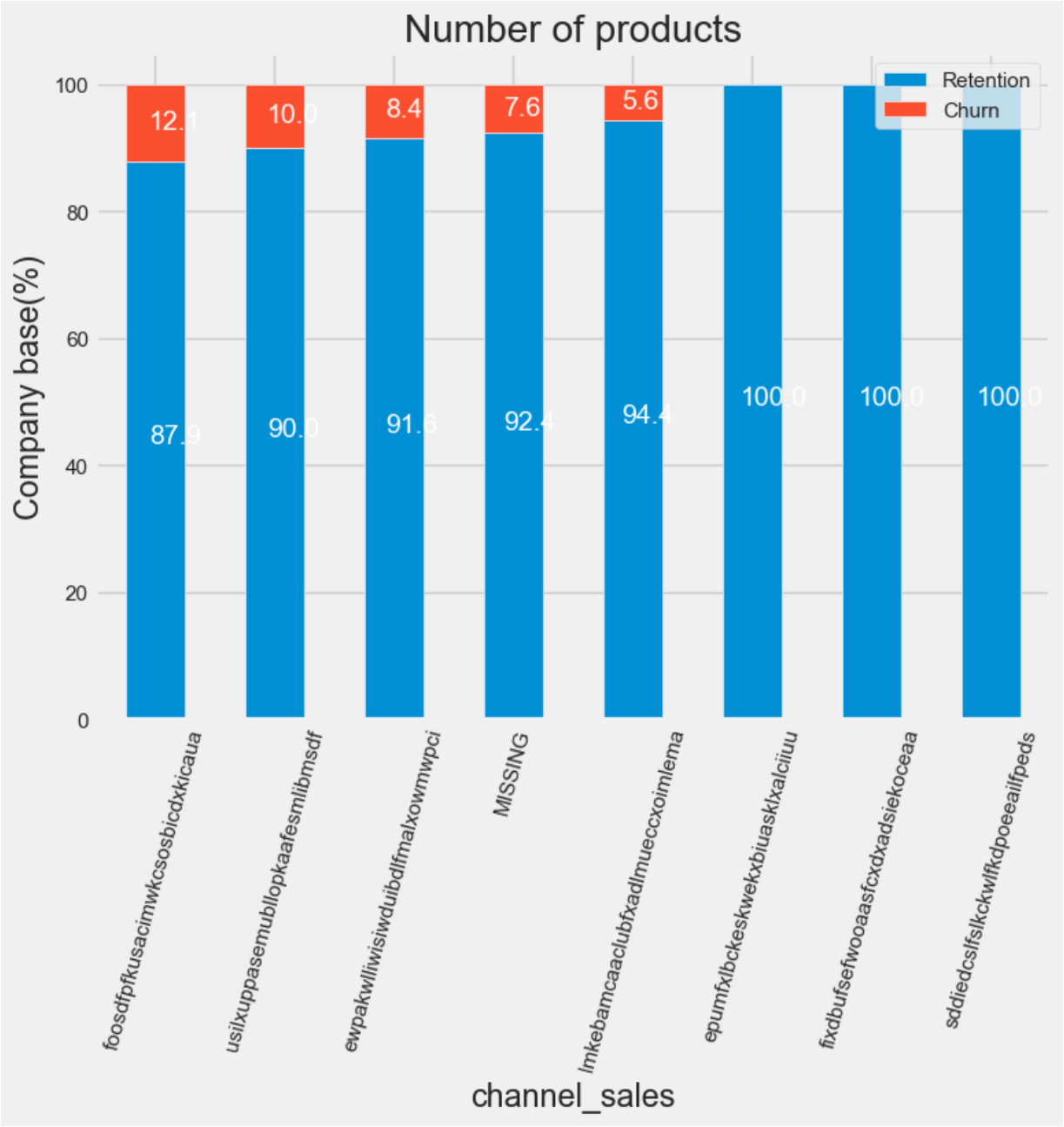


Other Columns

In [39]:
```
other_cols = client_df[['id', 'nb_prod_act', 'num_years_antig', 'origin_up', 'churn
products = other_cols.groupby([other_cols["nb_prod_act"], other_cols["churn"]])["id
products_percentage = (products.div(products.sum(axis=1), axis=0)*100).sort_values(
```

In [40]:
```
ax=channel_churn.plot(kind='bar',stacked=True,figsize=(8,6),rot=75)
annotate_stacked_bars(ax, textsize=14)
plt.title('Number of products')
plt.legend(['Retention','Churn'],loc='upper right')
plt.ylabel('Company base(%)')
```

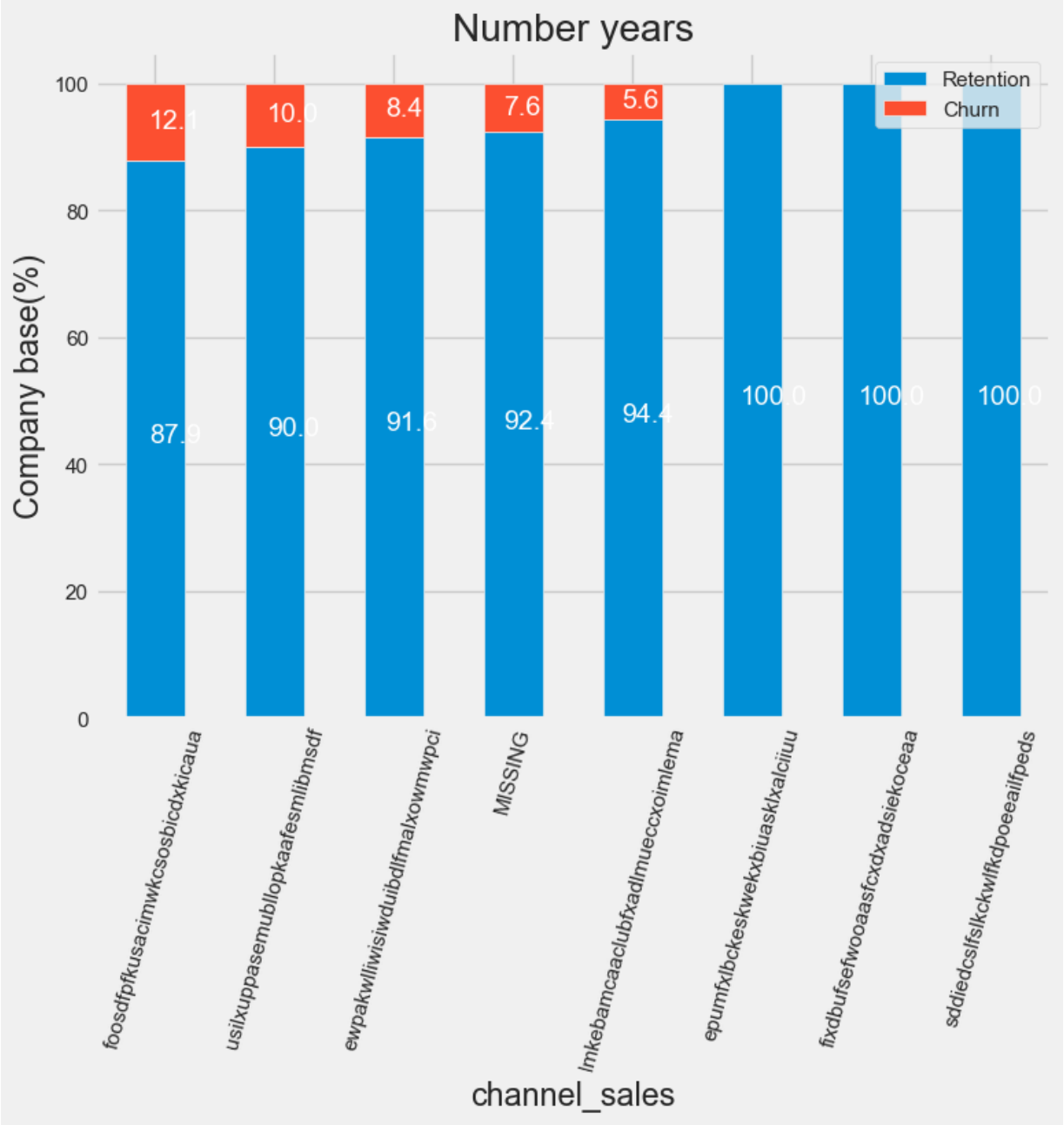
Out[40]: Text(0, 0.5, 'Company base(%)')



In [41]:
```
years_antig = other_cols.groupby([other_cols["num_years_antig"], other_cols["churn"]
years_antig_percentage = (years_antig.div(years_antig.sum(axis=1), axis=0)*100)
```

In [42]:
```
ax=channel_churn.plot(kind='bar',stacked=True,figsize=(8,6),rot=75)
annotate_stacked_bars(ax, textsize=14)
plt.title('Number years')
plt.legend(['Retention','Churn'],loc='upper right')
plt.ylabel('Company base(%)')
```

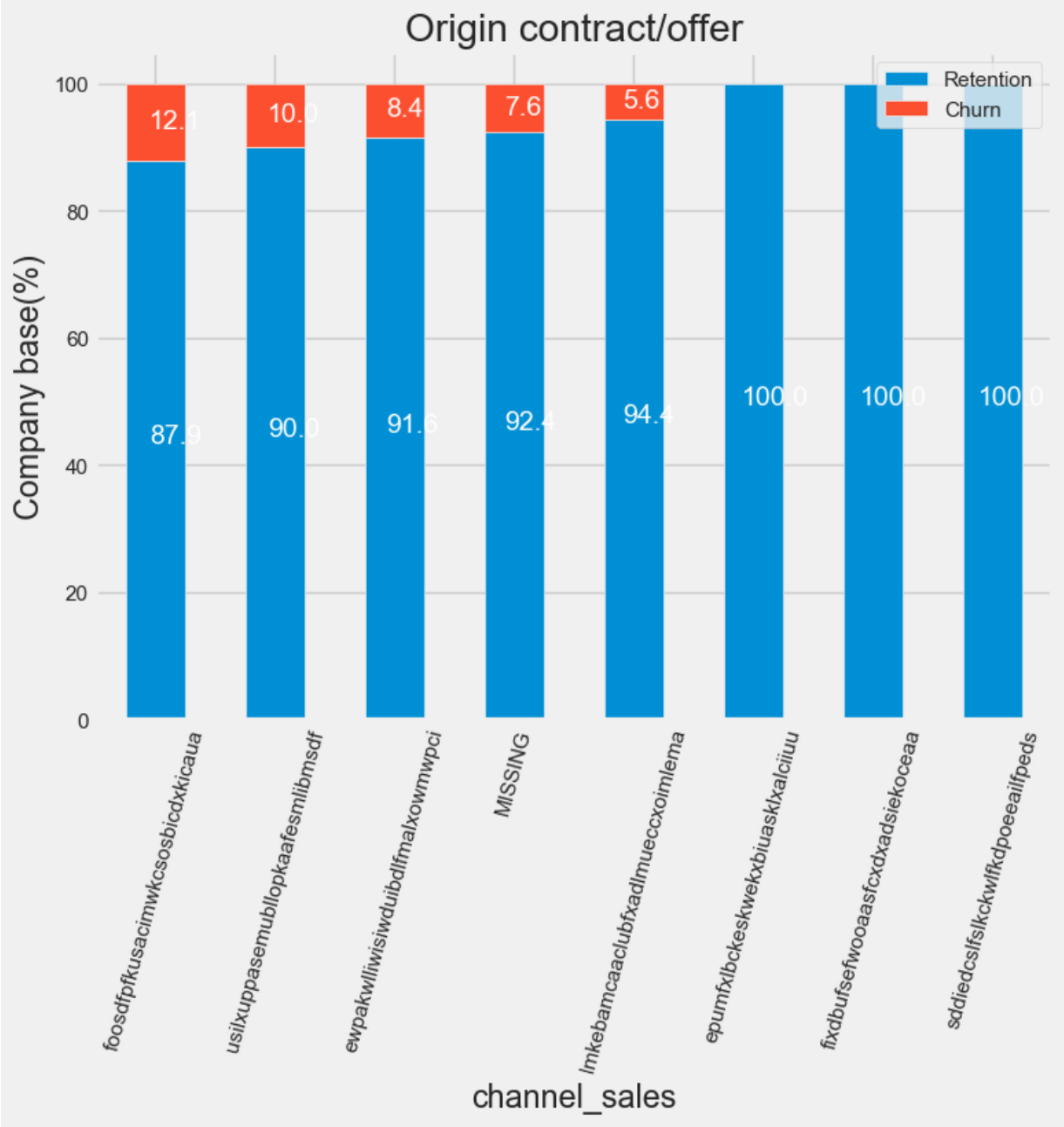
Out[42]: Text(0, 0.5, 'Company base(%)')



In [43]:
```
origin = other_cols.groupby([other_cols["origin_up"], other_cols["churn"]])["id"].c
origin_percentage = (origin.div(origin.sum(axis=1), axis=0)*100)
```

In [44]:
```
ax=channel_churn.plot(kind='bar',stacked=True,figsize=(8,6),rot=75)
annotate_stacked_bars(ax, textsize=14)
plt.title('Origin contract/offer')
plt.legend(['Retention','Churn'],loc='upper right')
plt.ylabel('Company base(%)')
```

Out[44]:
```
Text(0, 0.5, 'Company base(%)')
```



Dates

In [45]:
```
from datetime import datetime
```

In [46]:
```
client_df.head(10)
```

Out[46]:

	id	channel_sales	cons_12m	cons_
0	24011ae4ebbe3035111d65fa7c15bc57	foosdfpfkusacimwkcsosbicdxkicaua	0	
1	d29c2c54acc38ff3c0614d0a653813dd	MISSING	4660	
2	764c75f661154dac3a6c254cd082ea7d	foosdfpfkusacimwkcsosbicdxkicaua	544	
3	bba03439a292a1e166f80264c16191cb	lmkebamcaaclubfxadlmueccxoimlema	1584	
4	149d57cf92fc41cf94415803a877cb4b	MISSING	4425	
5	1aa498825382410b098937d65c4ec26d	usilxuppasemubllopkaafesmlibmsdf	8302	
6	7ab4bf4878d8f7661dfc20e9b8e18011	foosdfpfkusacimwkcsosbicdxkicaua	45097	
7	01495c955be7ec5e7f3203406785aae0	foosdfpfkusacimwkcsosbicdxkicaua	29552	
8	f53a254b1115634330c12c7fdbf7958a	usilxuppasemubllopkaafesmlibmsdf	2962	
9	10c1b2f97a2d2a6f10299dc213d1a370	lmkebamcaaclubfxadlmueccxoimlema	26064	

10 rows × 26 columns

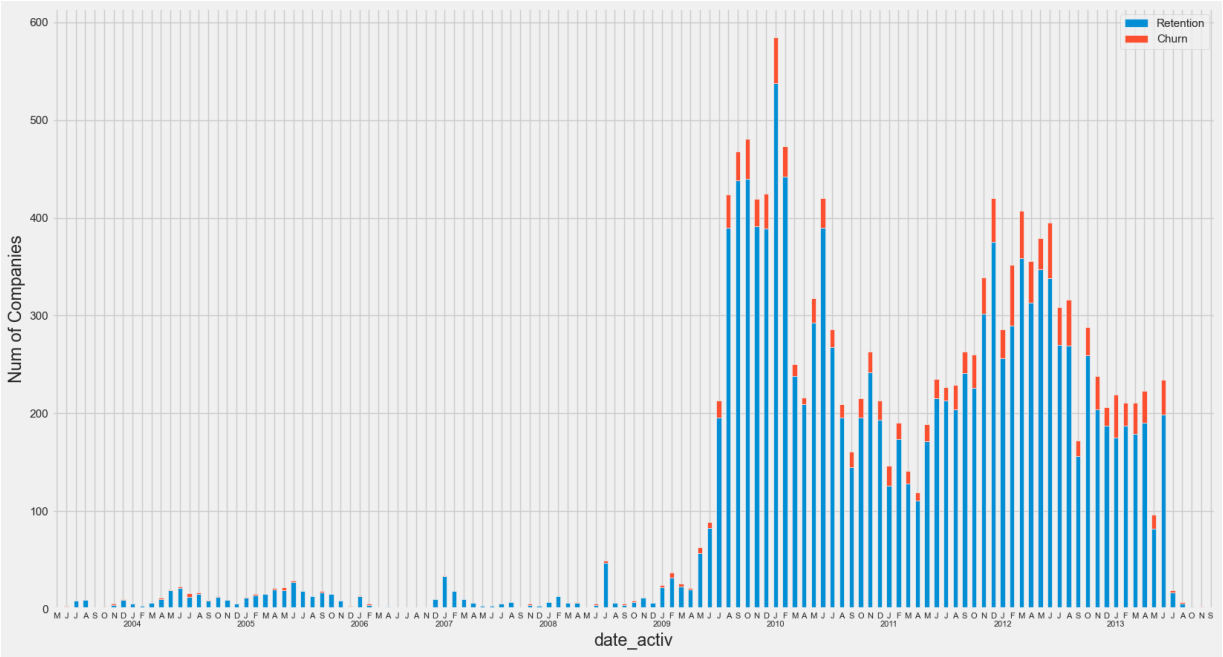
In [47]:
```
date = client_df[['id', 'date_activ', 'date_end', 'date_modif_prod', 'date_renewal'
```

In [48]:
```
date['date_activ'] = pd.to_datetime(date['date_activ'] , format='%m/%d/%Y')
date['date_end'] = pd.to_datetime(date['date_end'] ,  format='%m/%d/%Y')
date['date_modif_prod'] = pd.to_datetime(date['date_modif_prod'] ,  format='%m/%d/%
date['date_renewal'] = pd.to_datetime(date['date_renewal'] ,  format='%m/%d/%Y')
```

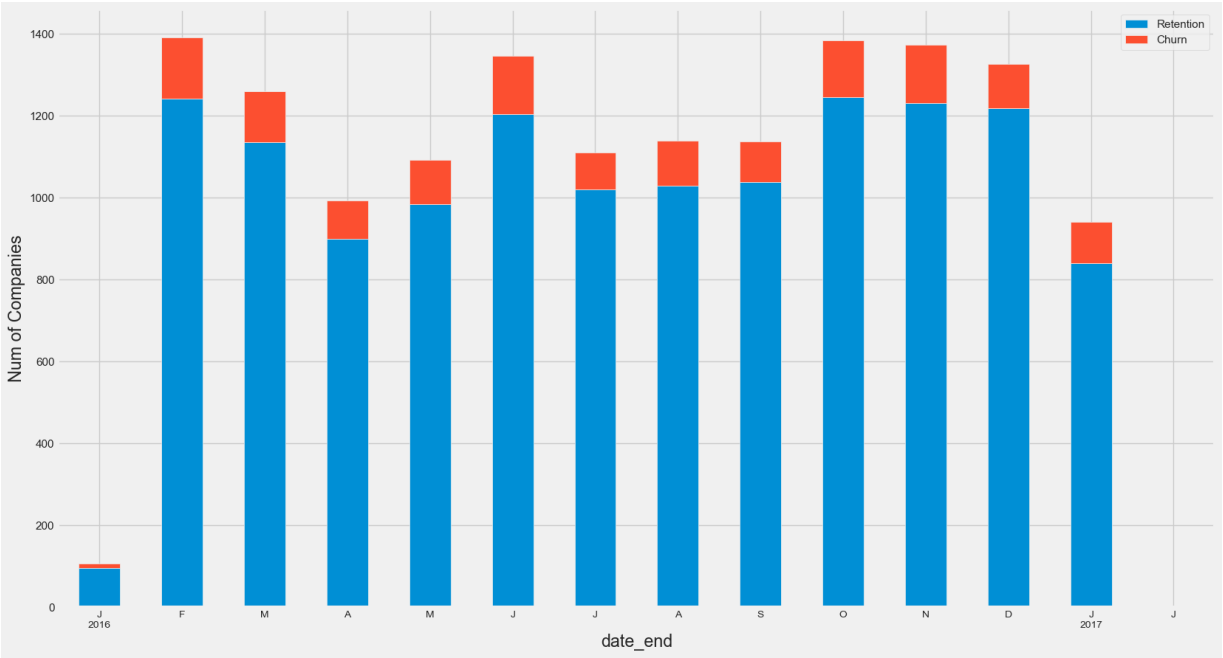
In [49]:
```
# Function to plot monthly churn and retention distribution

def plot_dates(df, col , fontsize_=12) :

    date_df = df[[col, 'churn', 'id']].set_index(col).groupby([pd.Grouper(freq='M')

    ax = date_df.plot(kind='bar', stacked=True, figsize=(18,10), rot=0)
    ax.set_xticklabels(map(lambda x: line_format(x), date_df.index))
    plt.xticks(fontsize = fontsize_)
    plt.ylabel('Num of Companies')
    plt.legend(['Retention', 'Churn'], loc='upper right')
    plt.show()
```

In [50]:
```
# Function to convert time label to the format of pandas line plot

def line_format(label):

    month = label.month_name()[:1]
    if label.month_name()=='January':
        month+=f'\n{label.year}'
    return month
```

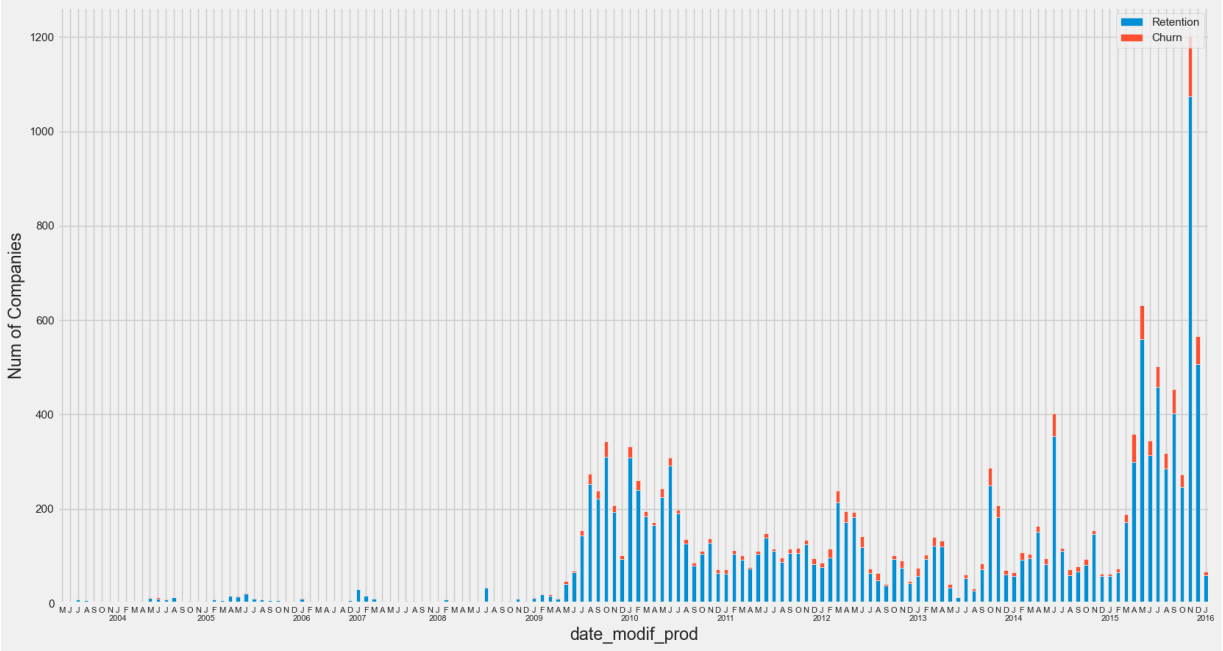
In [51]:
```
plot_dates(date, 'date_activ', fontsize_=8)
```



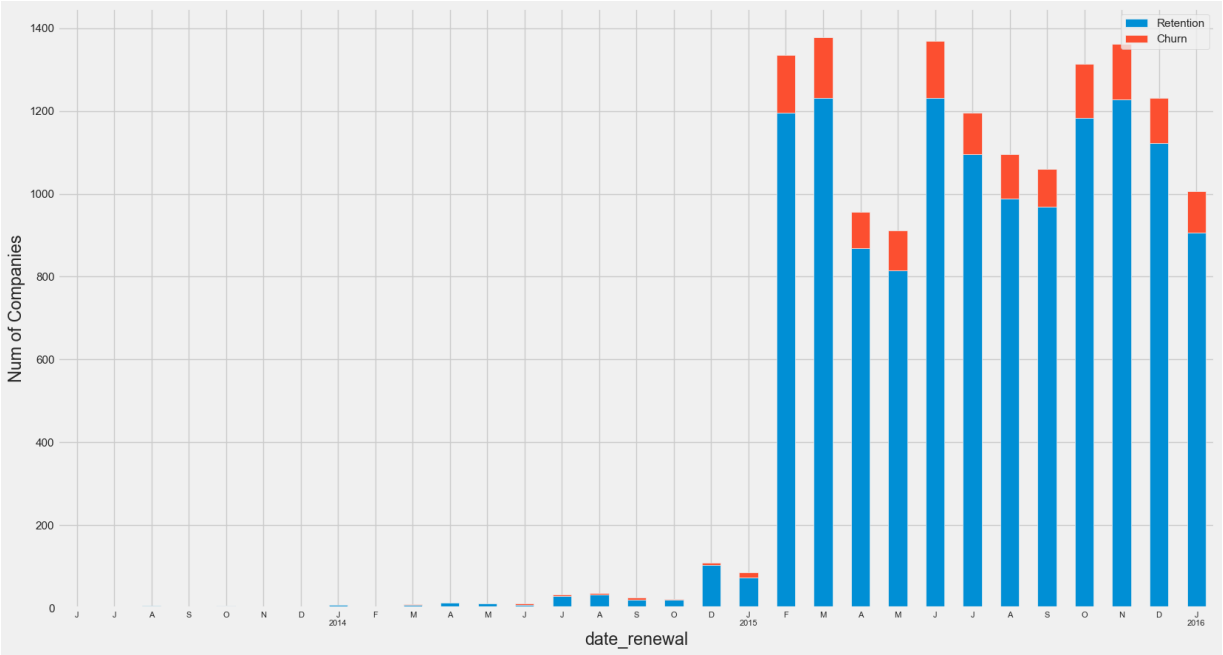
In [52]:
```
plot_dates(date, 'date_end', fontsize_=10)
```



In [53]:
```
plot_dates(date, 'date_modif_prod', fontsize_=8)
```



In [54]:
```
plot_dates(date, 'date_renewal', fontsize_=8)
```



we will enhance our analysis by creating a new feature based on the raw date information. This feature will offer valuable insights into the distribution of churned companies, moving beyond a simple date-based visualization.

Contract type (electricity, gas)

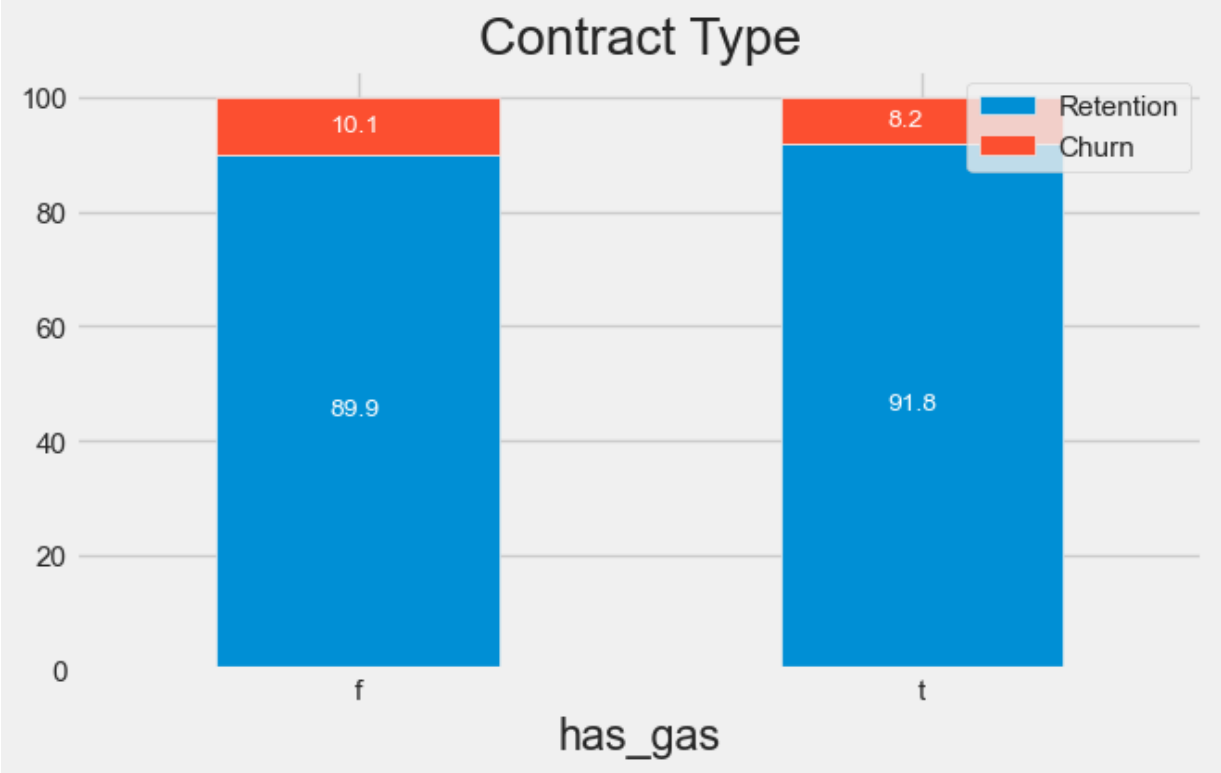
In [55]:
```
contract_type = client_df[["id","has_gas","churn"]]
contract = contract_type.groupby([contract_type["churn"], contract_type["has_gas"]]
contract_percentage = (contract.div(contract.sum(axis=1), axis=0) * 100).sort_value
contract_percentage
```

Out[55]:

churn	0	1
has_gas		
f	89.945629	10.054371
t	91.814410	8.185590

In [56]:
```
ax=contract_percentage.plot(kind='bar',stacked=True,figsize=(7,4),rot=0)
annotate_stacked_bars(ax, textsize=10)
plt.legend(['Retention','Churn'],loc="upper right")
plt.title("Contract Type")
```

Out[56]:
```
Text(0.5, 1.0, 'Contract Type')
```



The churn rate for customer without contract is a little bit higher than customers with contract.

Hypothesis Investigation

Next, we'll assess customer price sensitivity. If a price hike prompts customer departures, it indicates price sensitivity as increased prices drive churn. If prices remain stable or decrease and customers still leave, attributing it to price sensitivity becomes challenging.

In [57]:
```
# Create mean average data
mean_year = price_df.groupby(['id']).mean().reset_index()
mean_6m = price_df[price_df['price_date'] > '2015-06-01'].groupby(['id']).mean().re
mean_3m = price_df[price_df['price_date'] > '2015-10-01'].groupby(['id']).mean().re
```

In [58]:
```
mean_year.head()
```

Out[58]:

	id	price_off_peak_var	price_peak_var	price_mid_peak_v
0	0002203ffbb812588b632b9e628cc38d	0.124338	0.103794	0.0731
1	0004351ebdd665e6ee664792efc4fd13	0.146426	0.000000	0.0000
2	0010bcc39e42b3c2131ed2ce55246e3c	0.181558	0.000000	0.0000
3	0010ee3855fdea87602a5b7aba8e42de	0.118757	0.098292	0.0690
4	00114d74e963e47177db89bc70108537	0.147926	0.000000	0.0000

In [59]:
```
#rename the columns of mean year
mean_year = mean_year.rename(

    columns={
        "price_off_peak_var": "mean_year_price_off_peak_var",
        "price_peak_var": "mean_year_price_peak_var",
        "price_mid_peak_var": "mean_year_price_mid_peak_var",
        "price_off_peak_fix": "mean_year_price_off_peak_fix",
        "price_peak_fix": "mean_year_price_peak_fix",
        "price_mid_peak_fix": "mean_year_price_mid_peak_fix"
    }
)
```

In [60]:
```
mean_year["mean_year_price_off_peak"] = mean_year["mean_year_price_off_peak_var"] +
mean_year["mean_year_price_peak"] = mean_year["mean_year_price_peak_var"] + mean_ye
mean_year["mean_year_price_med_peak"] = mean_year["mean_year_price_mid_peak_var"] +
```

In [61]:
```
#rename the columns of mean 6 month
mean_6m = mean_6m.rename(

    columns={
        "price_off_peak_var": "mean_6m_price_off_peak_var",
        "price_peak_var": "mean_6m_price_peak_var",
        "price_mid_peak_var": "mean_6m_price_mid_peak_var",
        "price_off_peak_fix": "mean_6m_price_off_peak_fix",
        "price_peak_fix": "mean_6m_price_peak_fix",
        "price_mid_peak_fix": "mean_6m_price_mid_peak_fix"
    }
)

mean_6m["mean_6m_price_off_peak"] = mean_6m["mean_6m_price_off_peak_var"] + mean_6m
mean_6m["mean_6m_price_peak"] = mean_6m["mean_6m_price_peak_var"] + mean_6m["mean_6
mean_6m["mean_6m_price_med_peak"] = mean_6m["mean_6m_price_mid_peak_var"] + mean_6m
```

In [62]:
```
#rename the columns of mean 3 month
mean_3m = mean_3m.rename(

    columns={
        "price_off_peak_var": "mean_year_price_off_peak_var",
        "price_peak_var": "mean_year_price_peak_var",
        "price_mid_peak_var": "mean_year_price_mid_peak_var",
        "price_off_peak_fix": "mean_year_price_off_peak_fix",
        "price_peak_fix": "mean_year_price_peak_fix",
```

```
        "price_mid_peak_fix": "mean_year_price_mid_peak_fix"
    }
)

mean_3m["mean_year_price_off_peak"] = mean_3m["mean_year_price_off_peak_var"] + mea
mean_3m["mean_year_price_peak"] = mean_3m["mean_year_price_peak_var"] + mean_3m["me
mean_3m["mean_year_price_med_peak"] = mean_3m["mean_year_price_mid_peak_var"] + mea
```

In [63]:
```
# Merge into 1 dataframe
price_features = pd.merge(mean_year, mean_6m, on='id')
price_features = pd.merge(price_features, mean_3m, on='id')
```

In [64]:
```
price_features.head()
```

Out[64]:

	id	mean_year_price_off_peak_var_x	mean_year_price_pea
0	0002203ffbb812588b632b9e628cc38d	0.124338	0
1	0004351ebdd665e6ee664792efc4fd13	0.146426	0
2	0010bcc39e42b3c2131ed2ce55246e3c	0.181558	0
3	0010ee3855fdea87602a5b7aba8e42de	0.118757	0
4	00114d74e963e47177db89bc70108537	0.147926	0

5 rows × 28 columns

Now we need to merge the priice df with churn variable to check whether price sensitivity of customers has any relation with churn.

In [65]:
```
price_churn = pd.merge(price_features, client_df[['id', 'churn']], on='id')
price_churn.head()
```

Out[65]:

	id	mean_year_price_off_peak_var_x	mean_year_price_pea
0	0002203ffbb812588b632b9e628cc38d	0.124338	0
1	0004351ebdd665e6ee664792efc4fd13	0.146426	0
2	0010bcc39e42b3c2131ed2ce55246e3c	0.181558	0
3	00114d74e963e47177db89bc70108537	0.147926	0
4	0013f326a839a2f6ad87a1859952d227	0.126076	0

5 rows × 29 columns

In [66]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Calculate the correlation
corr = price_churn.corr()
```

```
# Set the figure size
plt.figure(figsize=(20, 18))

# Create a heatmap of the correlation matrix
sns.heatmap(corr, cmap='Blues', annot=True, annot_kws={'size': 10})

# Adjust the font size of axis ticks
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)

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

The preceding plot illustrates the correlations among price variables and their relationship with churn. Notably, the correlation between churn and price variables is quite low, indicating that customer churn is not significantly influenced by price changes.

In the next step, we will combine client data with the price-churn dataset for modeling purposes.

In [67]:
```
churn_data = pd.merge(client_df.drop(columns=['churn']), price_churn, on='id')


churn_data.head()
```

Out[67]:

	id	channel_sales	cons_12m	cons_
0	24011ae4ebbe3035111d65fa7c15bc57	foosdfpfkusacimwkcsosbicdxkicaua	0	
1	d29c2c54acc38ff3c0614d0a653813dd	MISSING	4660	
2	764c75f661154dac3a6c254cd082ea7d	foosdfpfkusacimwkcsosbicdxkicaua	544	
3	bba03439a292a1e166f80264c16191cb	lmkebamcaaclubfxadlmueccxoimlema	1584	
4	149d57cf92fc41cf94415803a877cb4b	MISSING	4425	

5 rows × 53 columns

In [68]:
```
churn_data.to_csv('churn_data_modeling.csv')
```

Formatting Data

Missing dates

There could be several ways in which we could deal with the missing dates. One way, we could "engineer" the dates from known values. For example, the date_renewal is usually the same date as the date_modif_prod but one year ahead. The simplest way, we will replace the missing values with the median (the most frequent date). For numerical values, the built-in function .median() can be used, but this will not work for dates or strings, so we will use a workaround using .valuecounts()

In [69]:
```
churn_data.loc[churn_data['date_modif_prod'].isnull(), 'date_modif_prod'] = churn_d
churn_data.loc[churn_data['date_end'].isnull(), 'date_end'] = churn_data['date_end'
churn_data.loc[churn_data['date_renewal'].isnull(), 'date_renewal'] = churn_data['d
```

We might have some prices missing for some companies and months

In [70]:
```
(price_df.isnull().mean()*100)
```

Out[70]:
```
id                  0.0
price_date          0.0
price_off_peak_var  0.0
price_peak_var      0.0
price_mid_peak_var  0.0
price_off_peak_fix  0.0
price_peak_fix      0.0
price_mid_peak_fix  0.0
dtype: float64
```

In [71]:
```
price_df.columns
```

Out[71]:
```
Index(['id', 'price_date', 'price_off_peak_var', 'price_peak_var',
       'price_mid_peak_var', 'price_off_peak_fix', 'price_peak_fix',
       'price_mid_peak_fix'],
      dtype='object')
```

In [72]:
```
price_df.loc[price_df['price_off_peak_var'].isnull(), 'price_off_peak_var']=price_d
price_df.loc[price_df['price_peak_var'].isnull(), 'price_peak_var']=price_df['price
price_df.loc[price_df['price_mid_peak_var'].isnull(), 'price_mid_peak_var']=price_d
price_df.loc[price_df['price_off_peak_fix'].isnull(), 'price_off_peak_fix']=price_d
price_df.loc[price_df['price_peak_fix'].isnull(), 'price_peak_fix']=price_df['price
price_df.loc[price_df['price_mid_peak_fix'].isnull(), 'price_mid_peak_fix']=price_d
```

In order to use the dates in our churn prediction model we are going to change the representation of these dates. Instead of using the date itself, wewill be transforming it in number of months. In order to make this transformation we need to change the dates to datetime and create a reference date which will be January 2016

Formatting dates - customer churn data and price history data

In [73]:
```
churn_data['date_activ'] = pd.to_datetime(churn_data['date_activ'] , format='%m/%d/
churn_data['date_end'] = pd.to_datetime(churn_data['date_end'] , format='%m/%d/%Y')
churn_data['date_modif_prod'] = pd.to_datetime(churn_data['date_modif_prod'] ,forma
churn_data['date_renewal'] = pd.to_datetime(churn_data['date_renewal'] , format='%m
```

In [74]:
```
price_df['price_date'] = pd.to_datetime(price_df['price_date'], format='%m/%d/%Y')
```

In [75]:
```
price_df.describe()
```

Out[75]:

	price_off_peak_var	price_peak_var	price_mid_peak_var	price_off_peak_fix	price_peak
count	193002.000000	193002.000000	193002.000000	193002.000000	193002.000
mean	0.141027	0.054630	0.030496	43.334477	10.622
std	0.025032	0.049924	0.036298	5.410297	12.841
min	0.000000	0.000000	0.000000	0.000000	0.000
25%	0.125976	0.000000	0.000000	40.728885	0.000
50%	0.146033	0.085483	0.000000	44.266930	0.000
75%	0.151635	0.101673	0.072558	44.444710	24.339
max	0.280700	0.229788	0.114102	59.444710	36.490

We can see that there are negative values for price_p1_fix , price_p2_fix and price_p3_fix . Further exploring on those we can see there are only about 10 entries which are negative. This is more likely to be due to corrupted data rather thana "price discount". We will replace the negative values with the median (most frequent value)

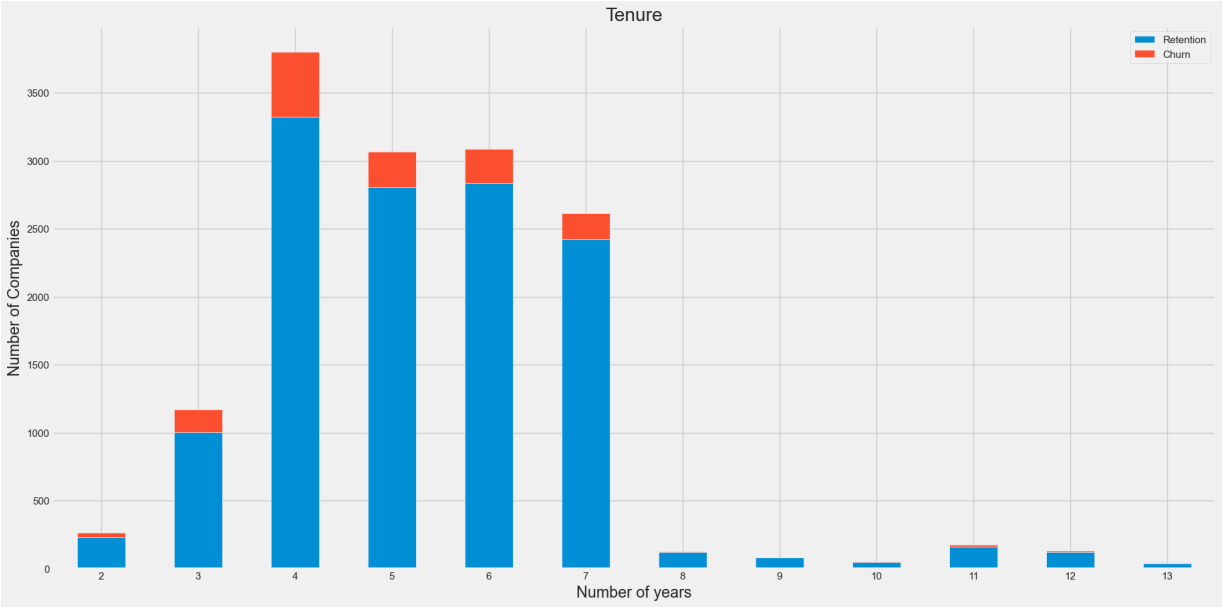
Feature Engineering

We create a new feature, tenure = date_end - date_activ

In [76]:
```
churn_data['tenure'] = ((churn_data['date_end'] - churn_data['date_activ'])/np.time
```

In [77]:
```
tenure = churn_data[['tenure', 'churn' , 'id']].groupby(['tenure', 'churn'])['id'].
tenure_percentage = (tenure.div(tenure.sum(axis=1) , axis=0)*100)
```

In [78]:
```
tenure.plot(kind = 'bar' , figsize=(20,10) , stacked=True, rot=0, title='Tenure')

plt.legend(['Retention', 'Churn'], loc='upper right')
plt.ylabel('Number of Companies')
plt.xlabel('Number of years')
plt.show()
```



The churn is very low for companies which joined recently or that have made the contract a long time ago. With the higher number of churners within the 3-7 years of tenure.

Need to transform the date columns to gain more insights. months_activ : Number of months active until reference date (Jan 2016) months_to_end : Number of months of the contract left at reference date (Jan 2016) months_modif_prod : Number of months since last modification at reference date (Jan 2016) months_renewal : Number of months since last renewal at reference date (Jan 2016)

In [79]:
```
def get_months(ref_date, df , col):

    time_diff = ref_date-df[col]
    months = (time_diff / np.timedelta64(1, "M")).astype(int)

    return months
```

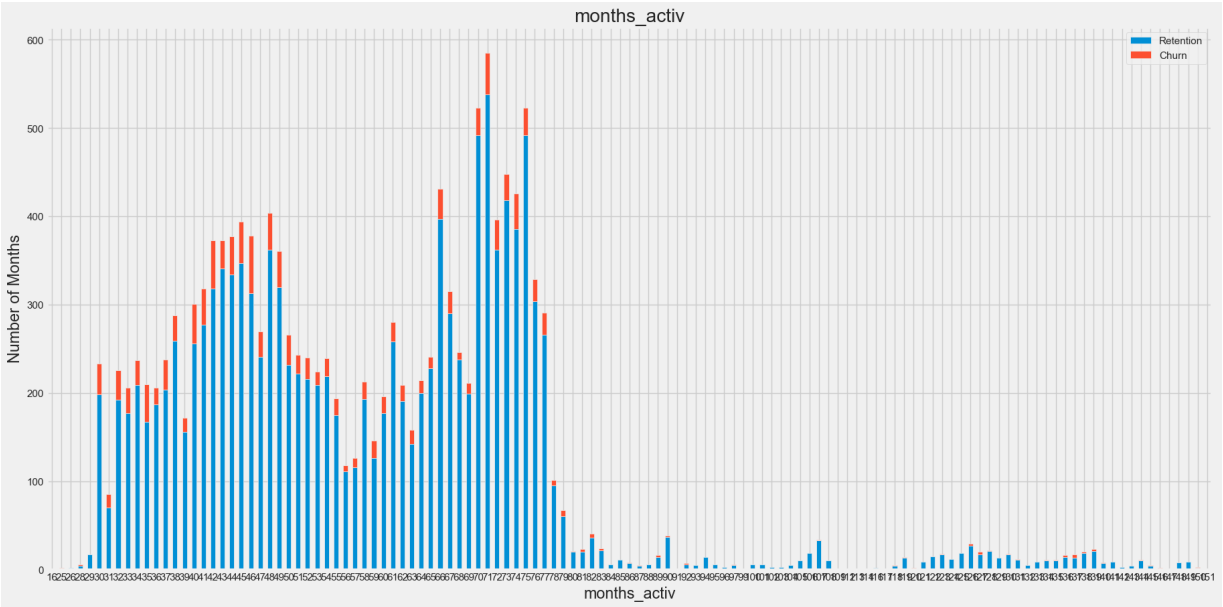
In [80]:
```
from datetime import datetime  # Import the 'datetime' class from the 'datetime' mo
```

```
ref_date = datetime(2016, 1, 1)  # Create a datetime object
```

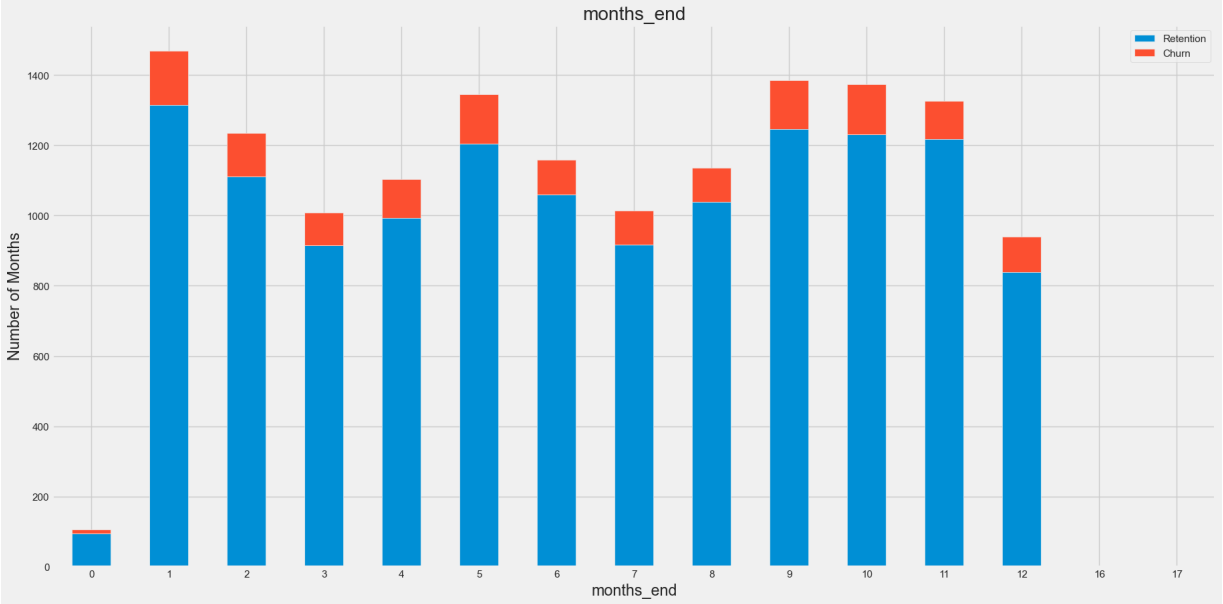
In [81]:
```
churn_data['months_activ'] = get_months(ref_date, churn_data , 'date_activ')
churn_data['months_end'] = -get_months(ref_date, churn_data , 'date_end')
churn_data['months_modif_prod'] = get_months(ref_date, churn_data , 'date_modif_pro
churn_data['months_renewal'] = get_months(ref_date, churn_data , 'date_renewal')
```

In [82]:
```
def plot_monthly_churn(df, col):

    churn_per_month = df[[col, 'churn', 'id']].groupby([col, 'churn'])['id'].count(
    churn_per_month.plot(kind = 'bar', figsize=(20,10) , stacked=True, rot=0, title
    plt.legend(['Retention', 'Churn'], loc='upper right')
    plt.ylabel('Number of companies')
    plt.ylabel('Number of Months')
    plt.show()
```

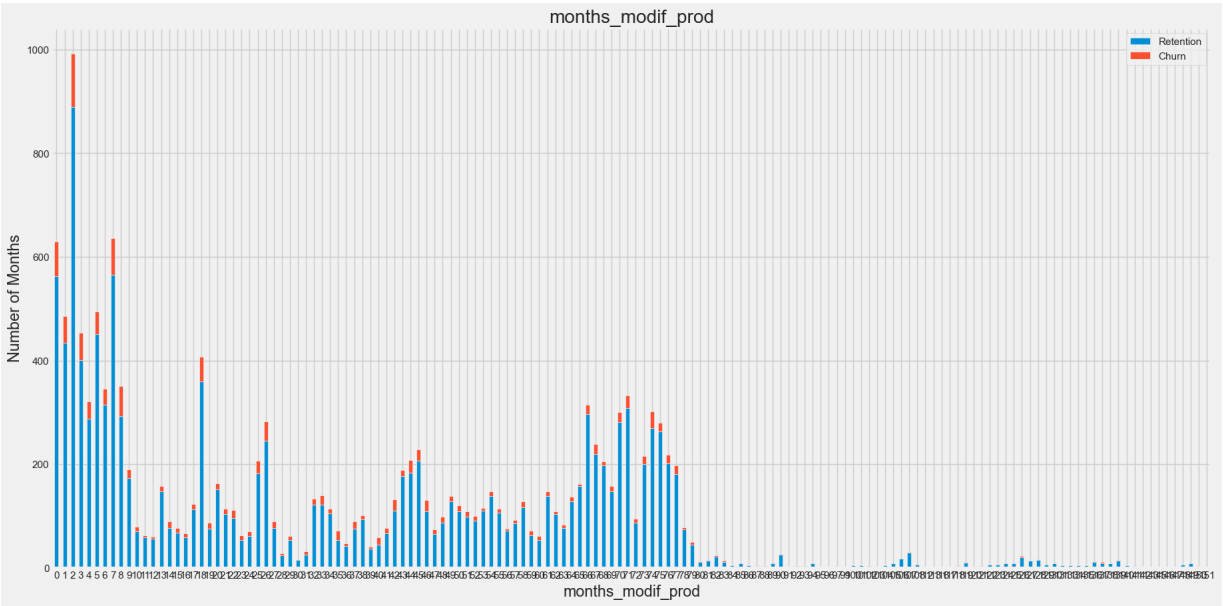
In [83]:
```
plot_monthly_churn(churn_data, 'months_activ')
```



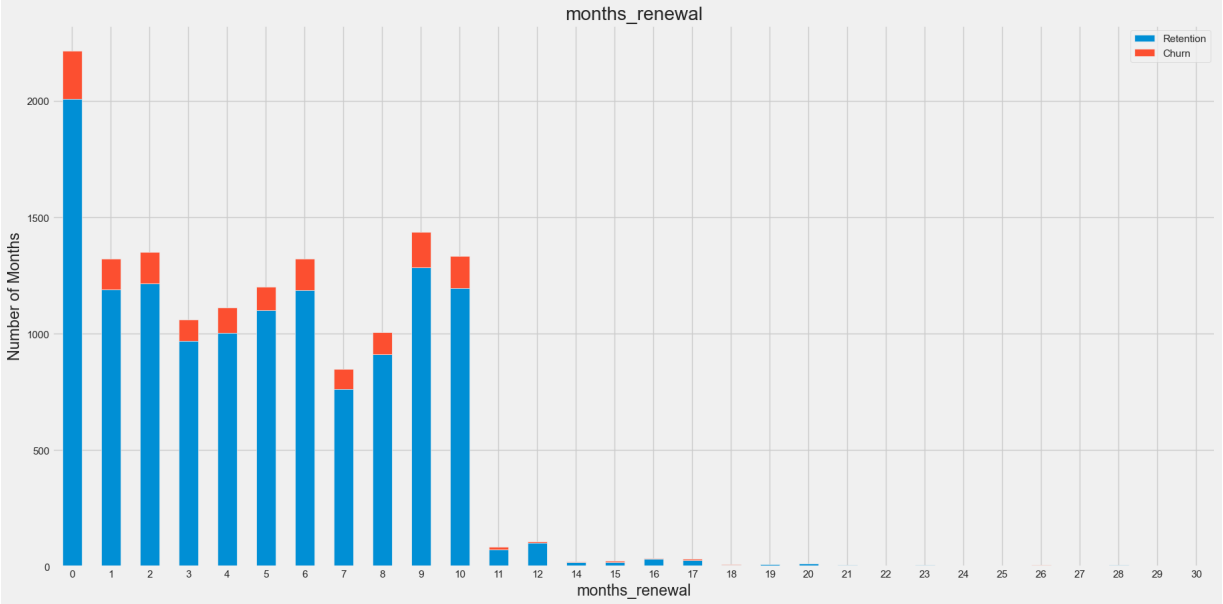
In [84]:
```
plot_monthly_churn(churn_data, 'months_end')
```



In [85]:
```
plot_monthly_churn(churn_data, 'months_modif_prod')
```



In [86]:
```
plot_monthly_churn(churn_data, 'months_renewal')
```



In [87]:
```
#Removing date columns

churn_data.drop(columns=['date_activ', 'date_end', 'date_modif_prod', 'date_renewal
```

In [88]:
```
#Boolean Data Transformation
#For the column has_gas, we will replace t for True or 1 and f for False or 0 (oneh

churn_data['has_gas'] = churn_data['has_gas'].replace(['t', 'f'], [1,0])
```

Categorical data and dummy variables

Categorical data channel_sales

Categorical data channel_sales What we are doing here relatively simple, we want to convert each category into a new dummy variable which will have 0 s and 1 s depending whether than entry belongs to that particular category or not First of all let's replace the Nan values with a string called null_values_channel

In [89]:
```
churn_data['channel_sales'] = churn_data['channel_sales'].fillna('null_channels')
```

Now transform the channel_sales column into categorical data type

In [90]:
```
churn_data['channel_sales'] = churn_data['channel_sales'].astype('category')
churn_data['channel_sales'].value_counts().reset_index()
```

Out[90]:

	index	channel_sales
0	foosdfpfkusacimwkcsosbicdxkicaua	6754
1	MISSING	3725
2	lmkebamcaaclubfxadlmueccxoimlema	1843
3	usilxuppasemubllopkaafesmlibmsdf	1375
4	ewpakwlliwisiwduibdlfmalxowmwpci	893
5	sddiedcslfslkckwlfkdpoeeailfpeds	11
6	epumfxlbckeskwekxbiuasklxalciiuu	3
7	fixdbufsefwooaasfcxdxadsiekoceaa	2

So that means we will create 8 different dummy variables . Each variable will become a different column.

In [91]:
```
# Dummy Variables
channels_category = pd.get_dummies(churn_data['channel_sales'] , prefix='channel')
channels_category.columns = [col[:11] for col in channels_category.columns]
channels_category.head(10)
```

Out[91]:

	channel_MIS	channel_epu	channel_ewp	channel_fix	channel_foo	channel_lmk	channe
0	0	0	0	0	1	0	
1	1	0	0	0	0	0	
2	0	0	0	0	1	0	
3	0	0	0	0	0	1	
4	1	0	0	0	0	0	
5	0	0	0	0	0	0	
6	0	0	0	0	1	0	
7	0	0	0	0	1	0	
8	0	0	0	0	0	0	
9	0	0	0	0	0	1	

In [92]:
```
#Categorical data origin_up

churn_data['origin_up'] = churn_data['origin_up'].fillna('null_origin')
churn_data['origin_up'] = churn_data['origin_up'].astype('category')


churn_data['origin_up'].value_counts().reset_index()
```

Out[92]:

	index	origin_up
0	lxidpiddsbxsbosboudacockeimpuepw	7097
1	kamkkxfxxuwbdslkwifmmcsiusiuosws	4294
2	ldkssxwpmemidmecebumciepifcamkci	3148
3	MISSING	64
4	usapbepcfoloekilkwsdiboslwaxobdp	2
5	ewxeelcelemmiwuafmddpobolfuxioce	1

In [93]:
```
origin_categories = pd.get_dummies(churn_data['origin_up'] , prefix='origin')
origin_categories.columns = [col[:11] for col in origin_categories.columns]

origin_categories.head(10)
```

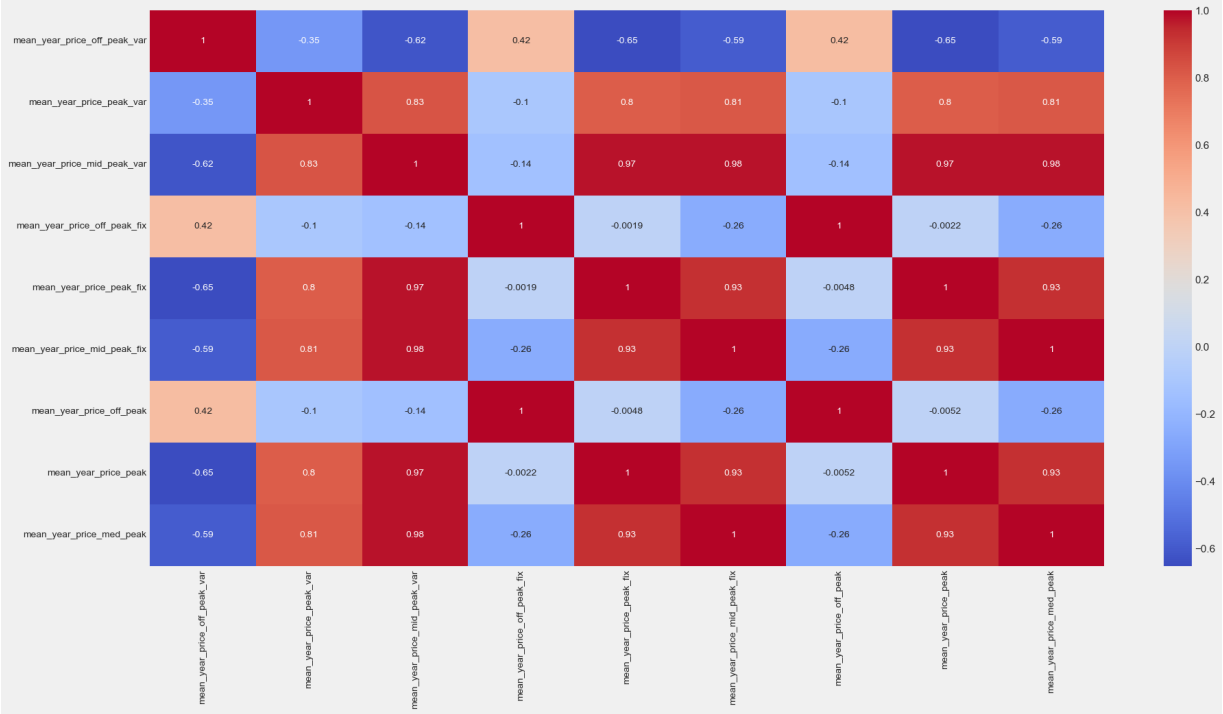
Out[93]:

	origin_MISS	origin_ewxe	origin_kamk	origin_ldks	origin_lxid	origin_usap
0	0	0	0	0	1	0
1	0	0	1	0	0	0
2	0	0	1	0	0	0
3	0	0	1	0	0	0
4	0	0	1	0	0	0
5	0	0	0	0	1	0
6	0	0	0	0	1	0
7	0	0	0	0	1	0
8	0	0	1	0	0	0
9	0	0	0	0	1	0

High Correlation Features

In [94]:
```
features = mean_year

correlation = features.corr()
```

In [95]:
```
plt.figure(figsize=(20,10))

sns.heatmap(correlation, cmap ='coolwarm',  xticklabels=correlation.columns.values,
            annot_kws={'size' : 10})

plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.show();
```



In [96]:
```
#We can remove highly correlated variables.

correlation = churn_data.corr()
correlation
```

Out[96]:

	cons_12m	cons_gas_12m	cons_last_month	forecast_cons_1
cons_12m	1.000000	0.488474	0.968212	0.193
cons_gas_12m	0.488474	1.000000	0.507007	0.084
cons_last_month	0.968212	0.507007	1.000000	0.177
forecast_cons_12m	0.193947	0.084359	0.177773	1.000
forecast_cons_year	0.167093	0.080934	0.193574	0.647
forecast_discount_energy	-0.043282	-0.012595	-0.040874	0.058
forecast_meter_rent_12m	0.065268	0.041393	0.057476	0.305
forecast_price_energy_off_peak	-0.007748	-0.017684	-0.005187	-0.135
forecast_price_energy_peak	0.145908	0.074002	0.136802	0.254
forecast_price_pow_off_peak	-0.026566	-0.020558	-0.023017	-0.018
has_gas	0.212973	0.359679	0.210662	0.097
imp_cons	0.159711	0.077846	0.187034	0.634
margin_gross_pow_ele	-0.011926	0.006868	-0.011498	-0.023
margin_net_pow_ele	-0.011905	0.006852	-0.011477	-0.023
nb_prod_act	0.154251	0.239387	0.169099	0.055
net_margin	0.133614	0.070867	0.121835	0.768
num_years_antig	-0.003565	-0.013815	-0.003677	0.021
pow_max	0.082889	0.054317	0.074529	0.393
mean_year_price_off_peak_var_x	0.000694	-0.013211	0.002429	-0.126
mean_year_price_peak_var_x	0.142933	0.073693	0.134537	0.251
mean_year_price_mid_peak_var_x	0.050555	0.044746	0.046373	0.244
mean_year_price_off_peak_fix_x	-0.013744	-0.015544	-0.012171	0.012
mean_year_price_peak_fix_x	0.051751	0.042796	0.047585	0.258
mean_year_price_mid_peak_fix_x	0.055081	0.046995	0.050166	0.235
mean_year_price_off_peak_x	-0.013695	-0.015558	-0.012119	0.012
mean_year_price_peak_x	0.052168	0.042957	0.047980	0.258
mean_year_price_med_peak_x	0.055062	0.046986	0.050151	0.235
mean_6m_price_off_peak_var	0.002004	-0.011619	0.003538	-0.122
mean_6m_price_peak_var	0.142712	0.073745	0.134420	0.250
mean_6m_price_mid_peak_var	0.050451	0.044532	0.046402	0.242

	cons_12m	cons_gas_12m	cons_last_month	forecast_cons_1
mean_6m_price_off_peak_fix	-0.011277	-0.013708	-0.009805	0.014
mean_6m_price_peak_fix	0.051602	0.042478	0.047581	0.256
mean_6m_price_mid_peak_fix	0.055014	0.046724	0.050241	0.234
mean_6m_price_off_peak	-0.011230	-0.013720	-0.009756	0.013
mean_6m_price_peak	0.052020	0.042641	0.047978	0.256
mean_6m_price_med_peak	0.054996	0.046716	0.050226	0.234
mean_year_price_off_peak_var_y	0.002004	-0.011619	0.003538	-0.122
mean_year_price_peak_var_y	0.142712	0.073745	0.134420	0.250
mean_year_price_mid_peak_var_y	0.050451	0.044532	0.046402	0.242
mean_year_price_off_peak_fix_y	-0.011277	-0.013708	-0.009805	0.014
mean_year_price_peak_fix_y	0.051602	0.042478	0.047581	0.256
mean_year_price_mid_peak_fix_y	0.055014	0.046724	0.050241	0.234
mean_year_price_off_peak_y	-0.011230	-0.013720	-0.009756	0.013
mean_year_price_peak_y	0.052020	0.042641	0.047978	0.256
mean_year_price_med_peak_y	0.054996	0.046716	0.050226	0.234
churn	-0.045968	-0.037957	-0.045284	0.012
tenure	-0.028522	-0.014543	-0.023946	-0.001
months_activ	-0.016249	-0.015803	-0.015746	0.016
months_end	-0.051148	0.009261	-0.040025	-0.063
months_modif_prod	0.117373	0.049467	0.113164	0.011
months_renewal	0.032982	-0.011506	0.023450	0.072

51 rows × 51 columns

Log Transformation

There are several methods in which we can reduce skewness such as square root , cube root , and log . In this case, we will use a log transformation which is usually recommended for right skewed data.

In [97]:
```
churn_data.describe()
```

Out[97]:

	cons_12m	cons_gas_12m	cons_last_month	forecast_cons_12m	forecast_cons_yea
count	1.460600e+04	1.460600e+04	14606.000000	14606.000000	14606.000000
mean	1.592203e+05	2.809238e+04	16090.269752	1868.614880	1399.762906
std	5.734653e+05	1.629731e+05	64364.196422	2387.571531	3247.786255
min	0.000000e+00	0.000000e+00	0.000000	0.000000	0.000000
25%	5.674750e+03	0.000000e+00	0.000000	494.995000	0.000000
50%	1.411550e+04	0.000000e+00	792.500000	1112.875000	314.000000
75%	4.076375e+04	0.000000e+00	3383.000000	2401.790000	1745.750000
max	6.207104e+06	4.154590e+06	771203.000000	82902.830000	175375.000000

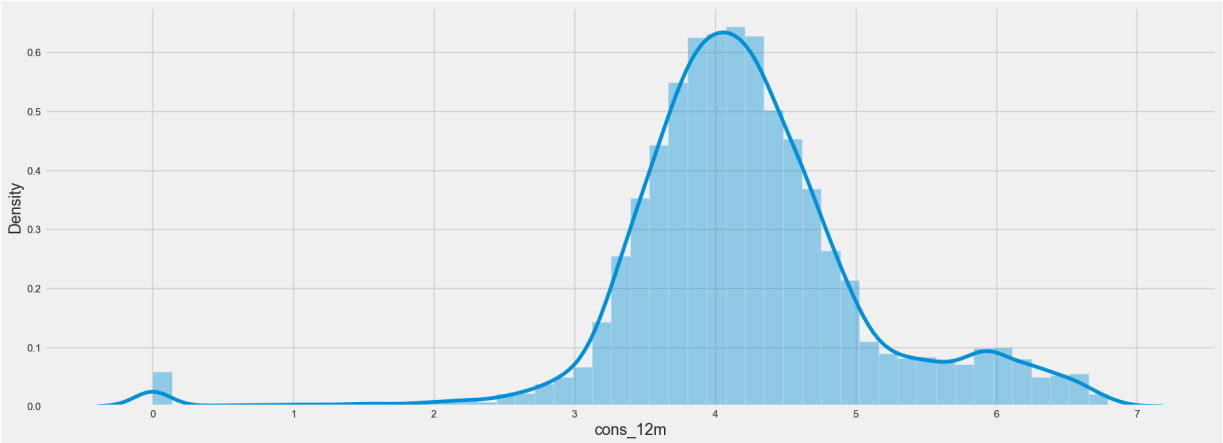
8 rows × 51 columns

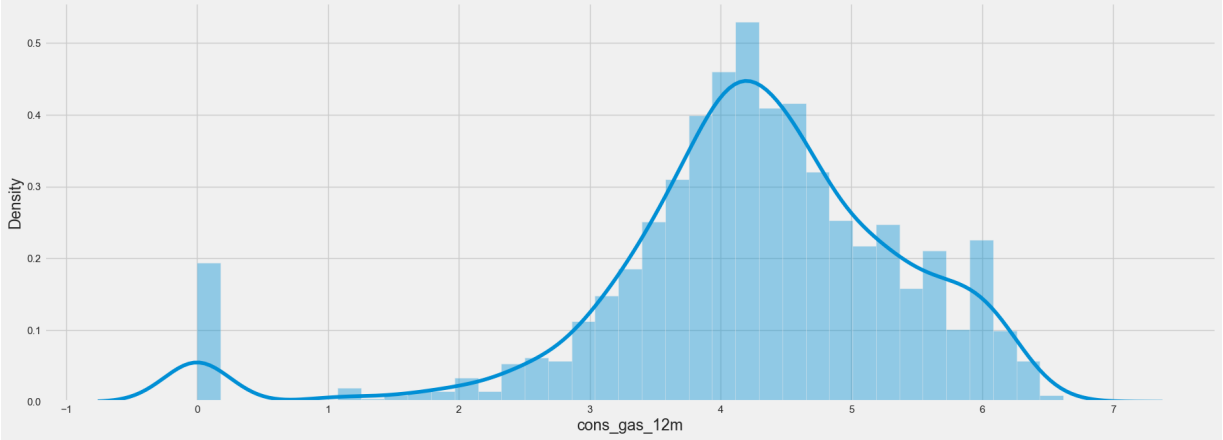
Columns having large standard deviation std need log trnsformation for skewness. Log transformation doesnot work with negative data, in such case we will convert the values to Nan. Also for 0 data we will add 1 then apply Log transformation.

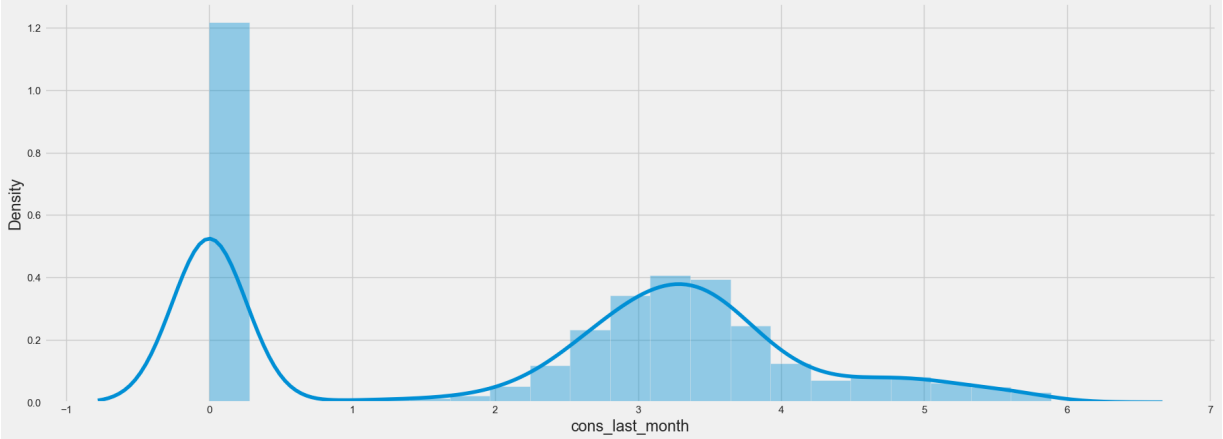
In [98]:
```
# Removing negative data

churn_data.loc[churn_data['cons_12m'] < 0 , 'cons_12m'] = np.nan
churn_data.loc[churn_data['cons_gas_12m'] < 0 , 'cons_gas_12m'] = np.nan
churn_data.loc[churn_data['cons_last_month'] < 0 , 'cons_last_month'] = np.nan
churn_data.loc[churn_data['forecast_cons_12m'] < 0 , 'forecast_cons_12m'] = np.nan
churn_data.loc[churn_data['forecast_cons_year'] < 0 , 'forecast_cons_year'] = np.na
churn_data.loc[churn_data['forecast_meter_rent_12m'] < 0 , 'forecast_meter_rent_12m
churn_data.loc[churn_data['imp_cons'] < 0 , 'imp_cons'] = np.nan
```

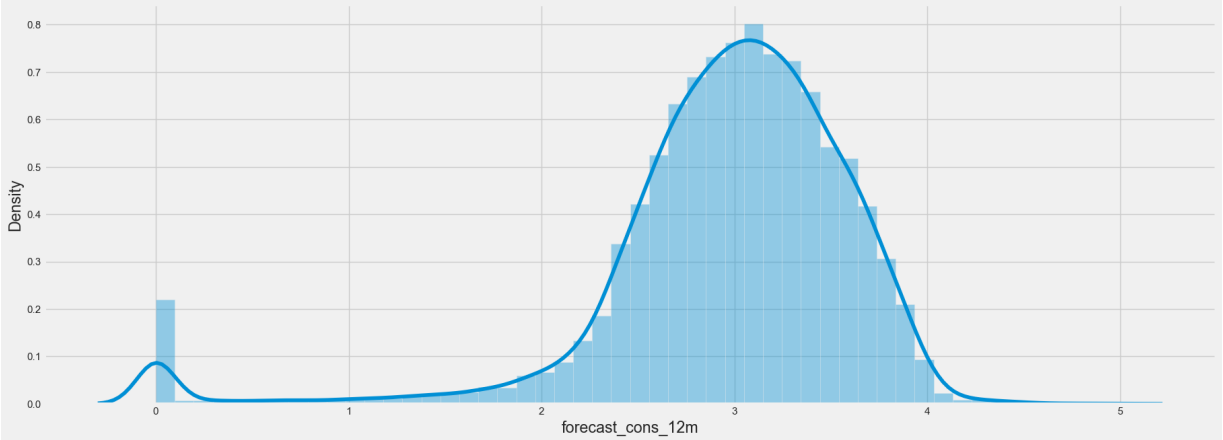
In [99]:
```
# Applying Log Transformation

churn_data['cons_12m'] = np.log10(churn_data['cons_12m']+1)
churn_data['cons_gas_12m'] = np.log10(churn_data['cons_gas_12m']+1)
churn_data['cons_last_month'] = np.log10(churn_data['cons_last_month']+1)
churn_data['forecast_cons_12m'] = np.log10(churn_data['forecast_cons_12m']+1)
churn_data['forecast_cons_year'] = np.log10(churn_data['forecast_cons_year']+1)
churn_data['forecast_meter_rent_12m'] = np.log10(churn_data['forecast_meter_rent_12
churn_data['imp_cons'] = np.log10(churn_data['imp_cons']+1)
```

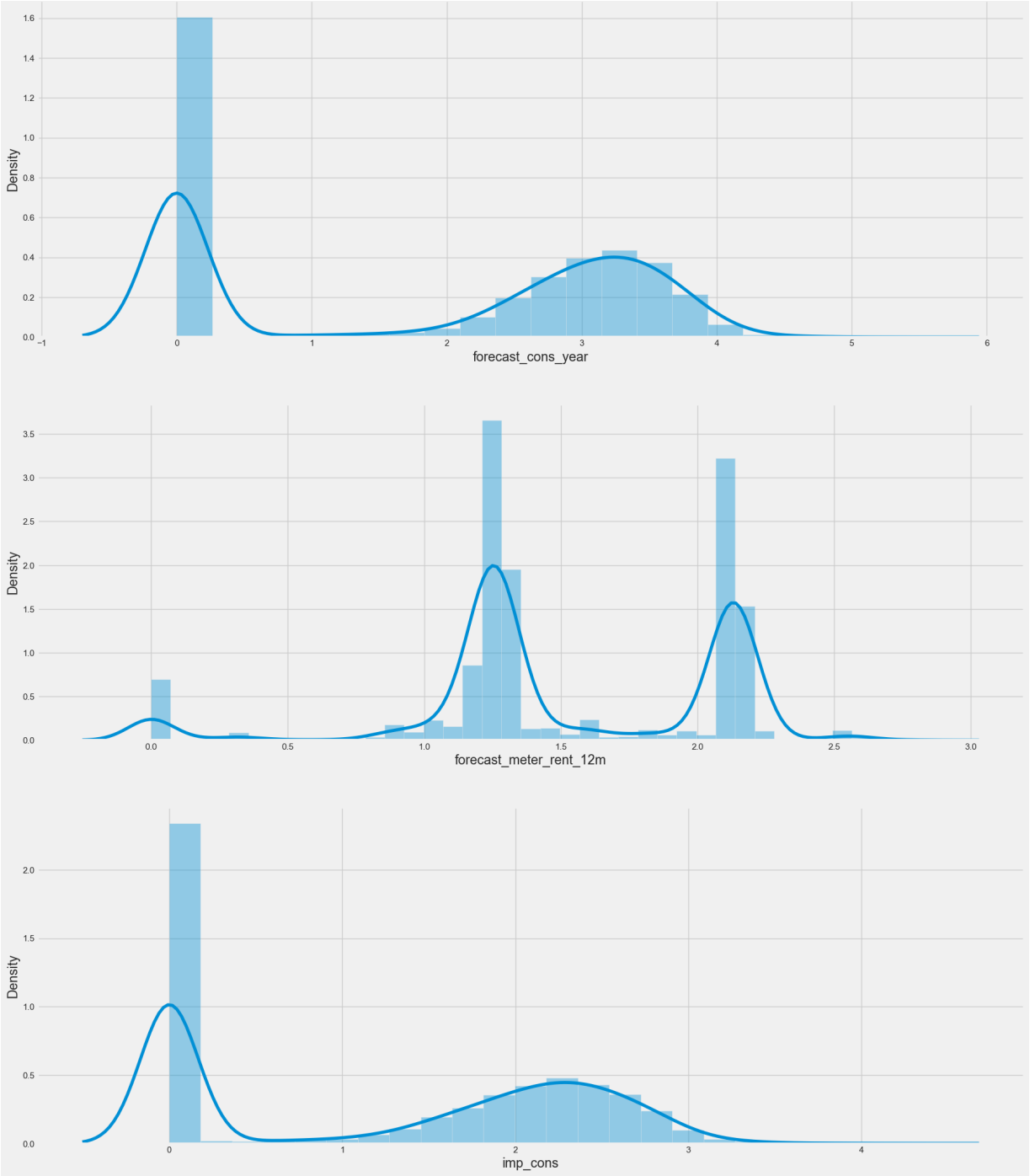
In [100…
```
fig, axs = plt.subplots(nrows=7, figsize=(20,60))
sns.distplot((churn_data['cons_12m'].dropna()), ax=axs[0])
sns.distplot((churn_data[churn_data['has_gas']==1]['cons_gas_12m'].dropna()), ax=ax
sns.distplot((churn_data['cons_last_month'].dropna()), ax=axs[2])
sns.distplot((churn_data['forecast_cons_12m'].dropna()), ax=axs[3])
sns.distplot((churn_data['forecast_cons_year'].dropna()), ax=axs[4])
sns.distplot((churn_data['forecast_meter_rent_12m'].dropna()), ax=axs[5])
sns.distplot((churn_data['imp_cons'].dropna()), ax=axs[6])
plt.show()
```


Density
cons_12m


Density
cons_gas_12m

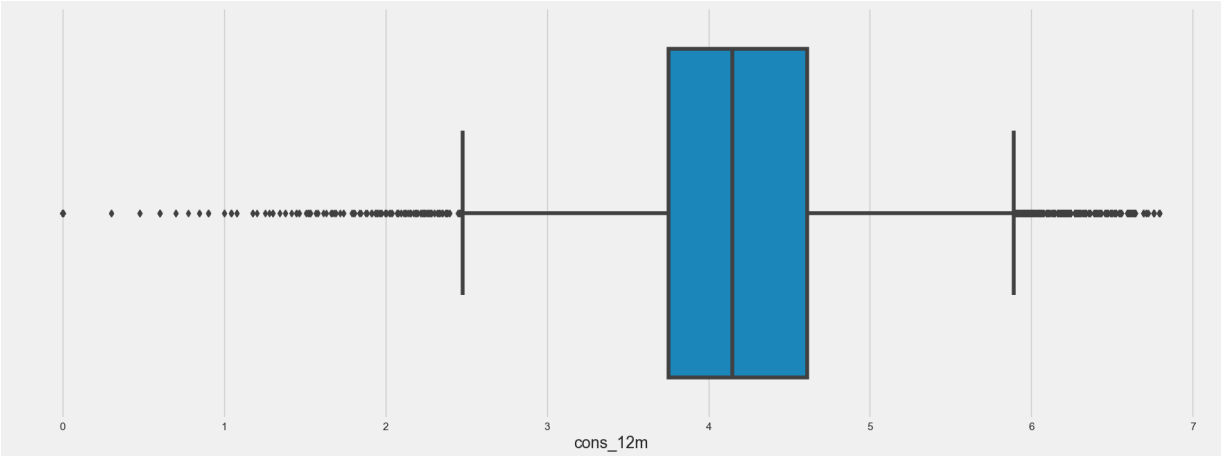

Density
cons_last_month

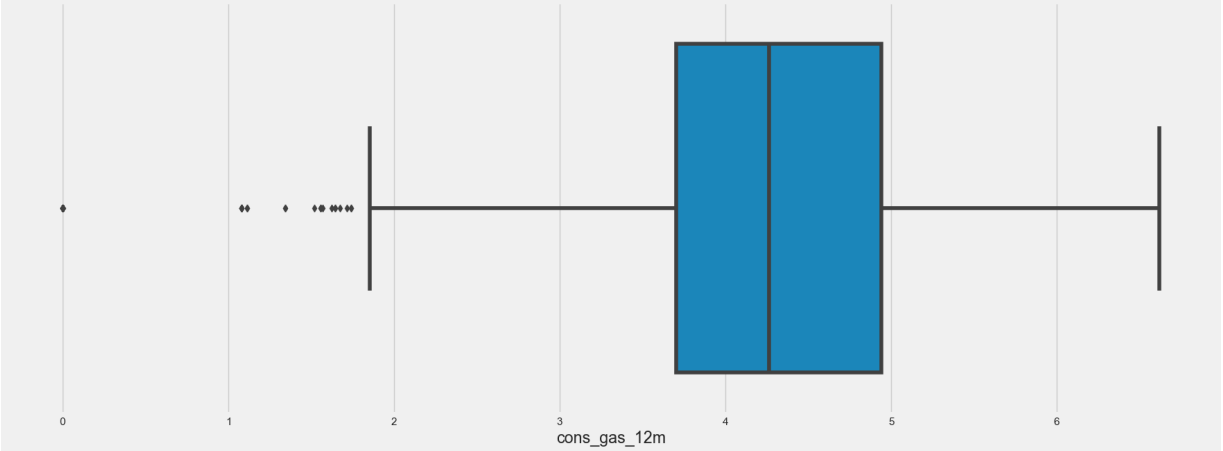

Density
forecast_cons_12m

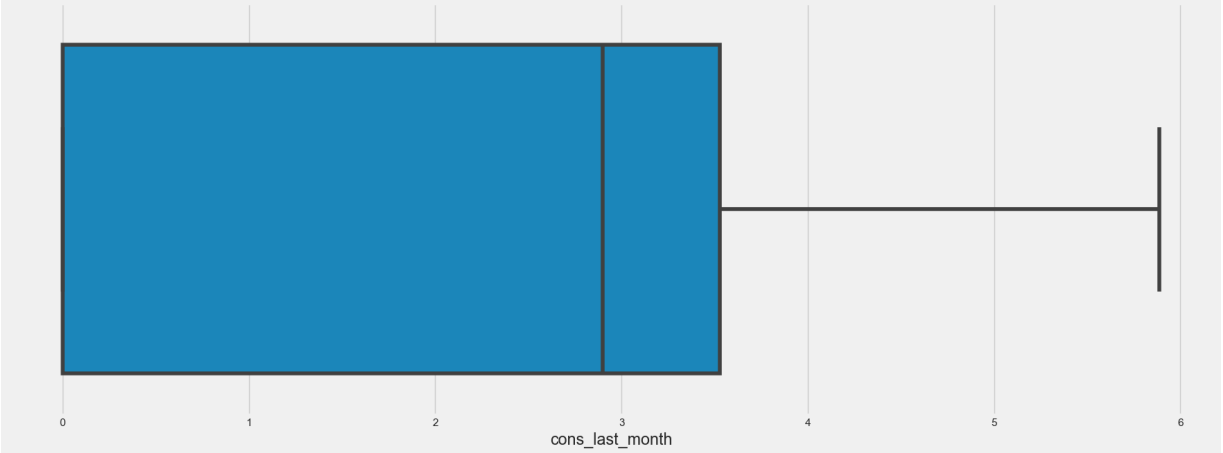


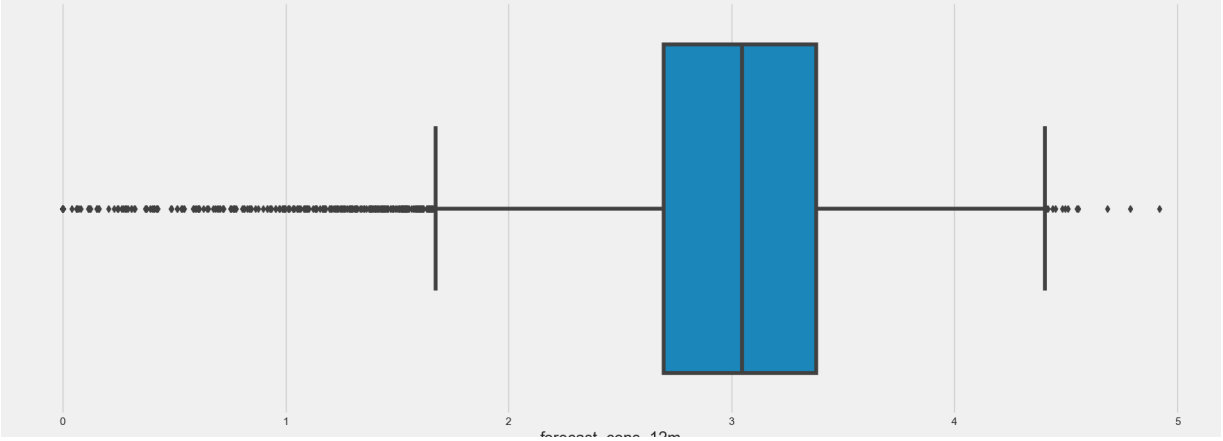
In [101…

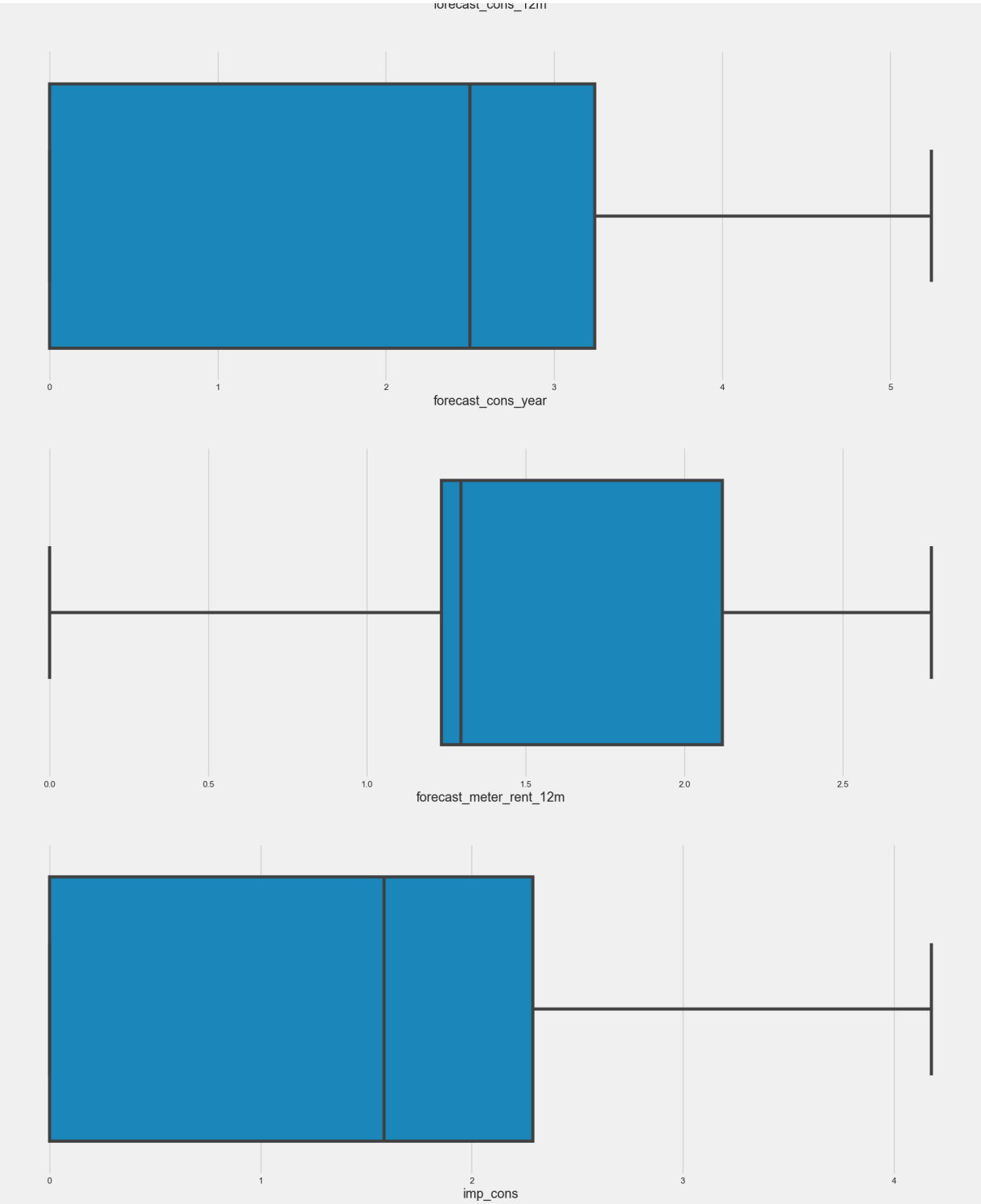
```
fig, axs = plt.subplots(nrows=7, figsize=(20,60))
sns.boxplot((churn_data['cons_12m'].dropna()), ax=axs[0])
sns.boxplot((churn_data[churn_data['has_gas']==1]['cons_gas_12m'].dropna()), ax=axs
sns.boxplot((churn_data['cons_last_month'].dropna()), ax=axs[2])
sns.boxplot((churn_data['forecast_cons_12m'].dropna()), ax=axs[3])
sns.boxplot((churn_data['forecast_cons_year'].dropna()), ax=axs[4])
sns.boxplot((churn_data['forecast_meter_rent_12m'].dropna()), ax=axs[5])
sns.boxplot((churn_data['imp_cons'].dropna()), ax=axs[6])
plt.show()
```


0
1
2
3
4
5
6
7
cons_12m


0
1
2
3
4
5
6
cons_gas_12m


0
1
2
3
4
5
6
cons_last_month


0
1
2
3
4
5



In [102…

```
churn_data.describe()
```

Out[102…

	cons_12m	cons_gas_12m	cons_last_month	forecast_cons_12m	forecast_cons_yea
count	14606.000000	14606.000000	14606.000000	14606.000000	14606.000000
mean	4.223939	0.779244	2.264646	2.962177	1.784610
std	0.884515	1.717071	1.769305	0.683592	1.584986
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	3.754023	0.000000	0.000000	2.695477	0.000000
50%	4.149727	0.000000	2.899547	3.046836	2.498311
75%	4.610285	0.000000	3.529430	3.380716	3.242231
max	6.792889	6.618528	5.887169	4.918575	5.243970

8 rows × 51 columns

From the boxplots we can still see some values are quite far from the range (outliers).

Outliers Removal

The consumption data has several outliers, Need to remove those outliers.they can negatively affect the statistical analysis and the training process of a machine learning algorithm resulting in lower accuracy

We will replace the outliers with the mean (average of the values excluding outliers).

In [103…

```
# Replace outliers with the mean values using the Z score.
# Nan values are also replaced with the mean values.

def replace_z_score(df, col, z=3):

    from scipy.stats import zscore

    temp_df = df.copy(deep=True)
    temp_df.dropna(inplace=True, subset=[col])

    temp_df["zscore"] = zscore(df[col])
    mean_=temp_df[(temp_df['zscore'] > -z) & (temp_df['zscore'] < z)][col].mean()

    df[col] = df[col].fillna(mean_)
    df['zscore']=zscore(df[col])
    no_outlier=df[(df['zscore'] < -z) | (df['zscore'] > z)].shape[0]
    df.loc[(df['zscore'] < -z) | (df['zscore'] > z) , col] = mean_

    print('Replaced : {} outliers in {}'.format(no_outlier, col))
    return df.drop(columns='zscore')
```

In [104…

```
for feat in features.columns:

    if feat!='id':
        features = replace_z_score(features, feat)
```

```
Replaced : 276 outliers in mean_year_price_off_peak_var
Replaced : 0 outliers in mean_year_price_peak_var
Replaced : 0 outliers in mean_year_price_mid_peak_var
Replaced : 120 outliers in mean_year_price_off_peak_fix
Replaced : 0 outliers in mean_year_price_peak_fix
Replaced : 0 outliers in mean_year_price_mid_peak_fix
Replaced : 122 outliers in mean_year_price_off_peak
Replaced : 0 outliers in mean_year_price_peak
Replaced : 0 outliers in mean_year_price_med_peak
```

In [105…

```
features.reset_index(drop=True, inplace=True)
```

In [106…

```
def find_outliers_iqr(df, column):

    col = sorted(df[column])

    q1, q3 = np.percentile(col, [25,75])
    iqr = q3-q1
    lower_bound = q1 - (1.5*iqr)
    upper_bound = q3 + (1.5*iqr)

    results_ouliers = {'iqr' : iqr , 'lower_bound' : lower_bound , 'upper_bound' :

    return results_ouliers
```

In [107…

```
def remove_ouliers_iqr(df, column):

    outliers = find_outliers_iqr(df,column)
    removed_outliers = df[(df[col] < outliers['lower_bound']) | (df[col] > outliers

    df = df[(df[col] > outliers['lower_bound']) | (df[col] < outliers['upper_bound'
    print('Removed {} outliers'.format(removed_outliers[0]))
    return df
```

In [108…

```
def remove_outliers_zscore(df, col, z=3):

    from scipy.stats import zscore

    df["zsscore"]=zscore(df[col])
    removed_outliers = df[(df["zscore"] < -z) | (df["zscore"] > z)].shape
    df = df[(df["zscore"] > -z) | (df["zscore"] < z)]

    print('Removed: {} otliers of {}'.format(removed_outliers[0], col))

    return df.drop(columns="zscore")
```

In [109…

```
def replace_outliers_z_score(df, col, z=3):

    from scipy.stats import zscore

    temp_df = df.copy(deep=True)
    #temp_df.dropna(inplace=True, subset=[col])

    temp_df["zscore"] = zscore(df[col])
    mean_=temp_df[(temp_df["zscore"] > -z) & (temp_df["zscore"] < z)][col].mean()
```

```
    num_outliers = df[col].isnull().sum()
    df[col] = df[col].fillna(mean_)
    df["zscore"]=zscore(df[col])
    df.loc[(df["zscore"] < -z) | (df["zscore"] > z) , col] = mean_

    print('Replaced : {} outliers in {}'.format(num_outliers, col))
    return df.drop(columns="zscore")
```

In [110…
```
churn_data.describe()
```

Out[110…

	cons_12m	cons_gas_12m	cons_last_month	forecast_cons_12m	forecast_cons_yea
count	14606.000000	14606.000000	14606.000000	14606.000000	14606.000000
mean	4.223939	0.779244	2.264646	2.962177	1.784610
std	0.884515	1.717071	1.769305	0.683592	1.584986
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	3.754023	0.000000	0.000000	2.695477	0.000000
50%	4.149727	0.000000	2.899547	3.046836	2.498311
75%	4.610285	0.000000	3.529430	3.380716	3.242231
max	6.792889	6.618528	5.887169	4.918575	5.243970

8 rows × 51 columns

In [111…
```
churn_data = replace_outliers_z_score(churn_data , 'cons_12m')
churn_data = replace_outliers_z_score(churn_data , 'cons_gas_12m')
churn_data = replace_outliers_z_score(churn_data , 'cons_last_month')
churn_data = replace_outliers_z_score(churn_data , 'forecast_cons_12m')
churn_data = replace_outliers_z_score(churn_data , 'forecast_discount_energy')
churn_data = replace_outliers_z_score(churn_data , 'forecast_meter_rent_12m')
churn_data = replace_outliers_z_score(churn_data , 'forecast_price_energy_off_peak'
churn_data = replace_outliers_z_score(churn_data , 'forecast_price_energy_peak')
churn_data = replace_outliers_z_score(churn_data , 'forecast_price_energy_peak')
churn_data = replace_outliers_z_score(churn_data , 'imp_cons')
churn_data = replace_outliers_z_score(churn_data , 'margin_gross_pow_ele')
churn_data = replace_outliers_z_score(churn_data , 'margin_net_pow_ele')
churn_data = replace_outliers_z_score(churn_data , 'net_margin')
churn_data = replace_outliers_z_score(churn_data , 'pow_max')
churn_data = replace_outliers_z_score(churn_data , 'months_activ')
churn_data = replace_outliers_z_score(churn_data , 'months_end')
churn_data = replace_outliers_z_score(churn_data , 'months_modif_prod')
churn_data = replace_outliers_z_score(churn_data , 'months_renewal')
```

```
Replaced : 0 outliers in cons_12m
Replaced : 0 outliers in cons_gas_12m
Replaced : 0 outliers in cons_last_month
Replaced : 0 outliers in forecast_cons_12m
Replaced : 0 outliers in forecast_discount_energy
Replaced : 0 outliers in forecast_meter_rent_12m
Replaced : 0 outliers in forecast_price_energy_off_peak
Replaced : 0 outliers in forecast_price_energy_peak
Replaced : 0 outliers in forecast_price_energy_peak
Replaced : 0 outliers in imp_cons
Replaced : 0 outliers in margin_gross_pow_ele
Replaced : 0 outliers in margin_net_pow_ele
Replaced : 0 outliers in net_margin
Replaced : 0 outliers in pow_max
Replaced : 0 outliers in months_activ
Replaced : 0 outliers in months_end
Replaced : 0 outliers in months_modif_prod
Replaced : 0 outliers in months_renewal
```

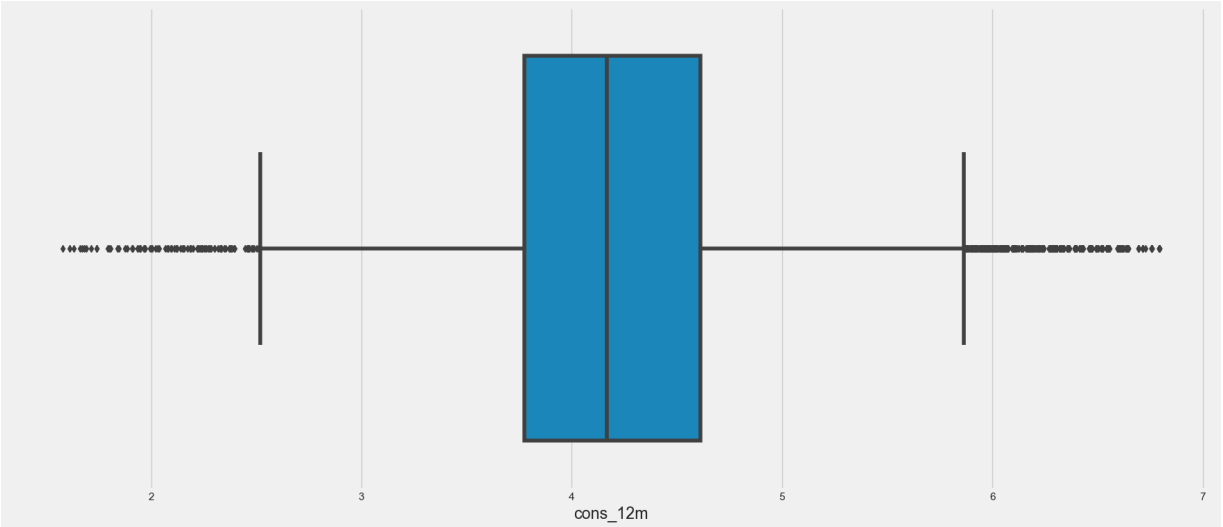
In [112…

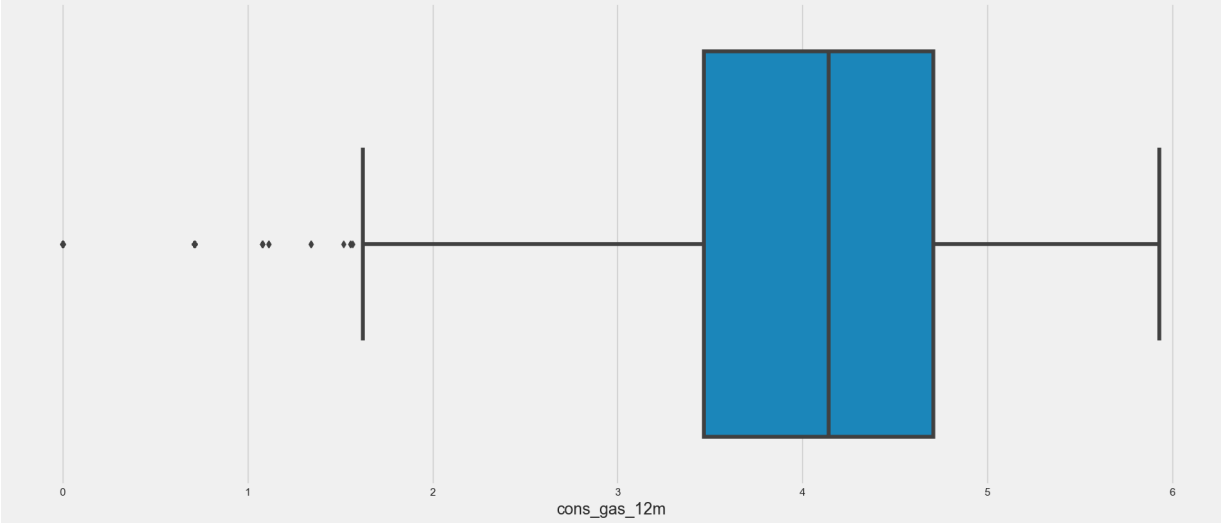
```
churn_data.reset_index(drop=True, inplace=True)
```

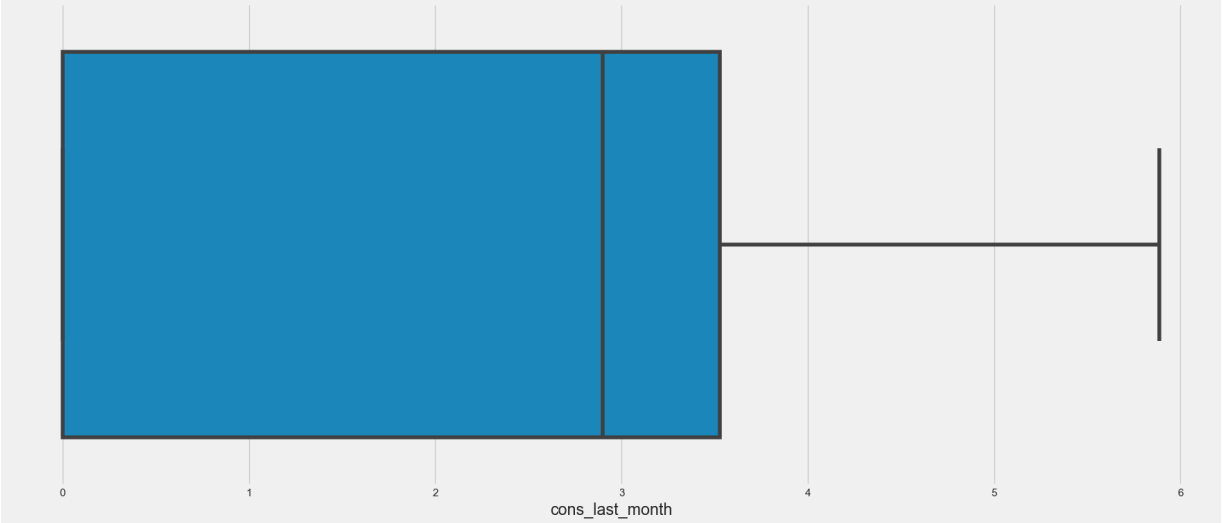
Let's see how the boxplots changed!

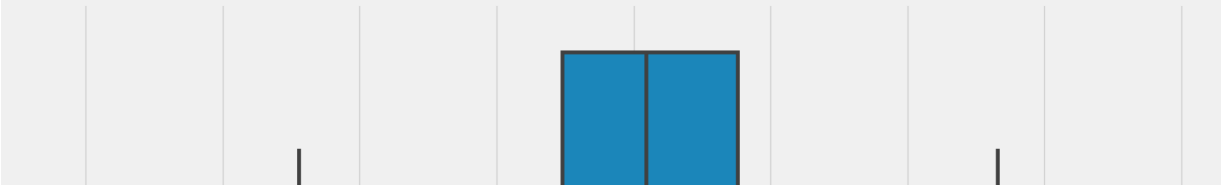
In [113…

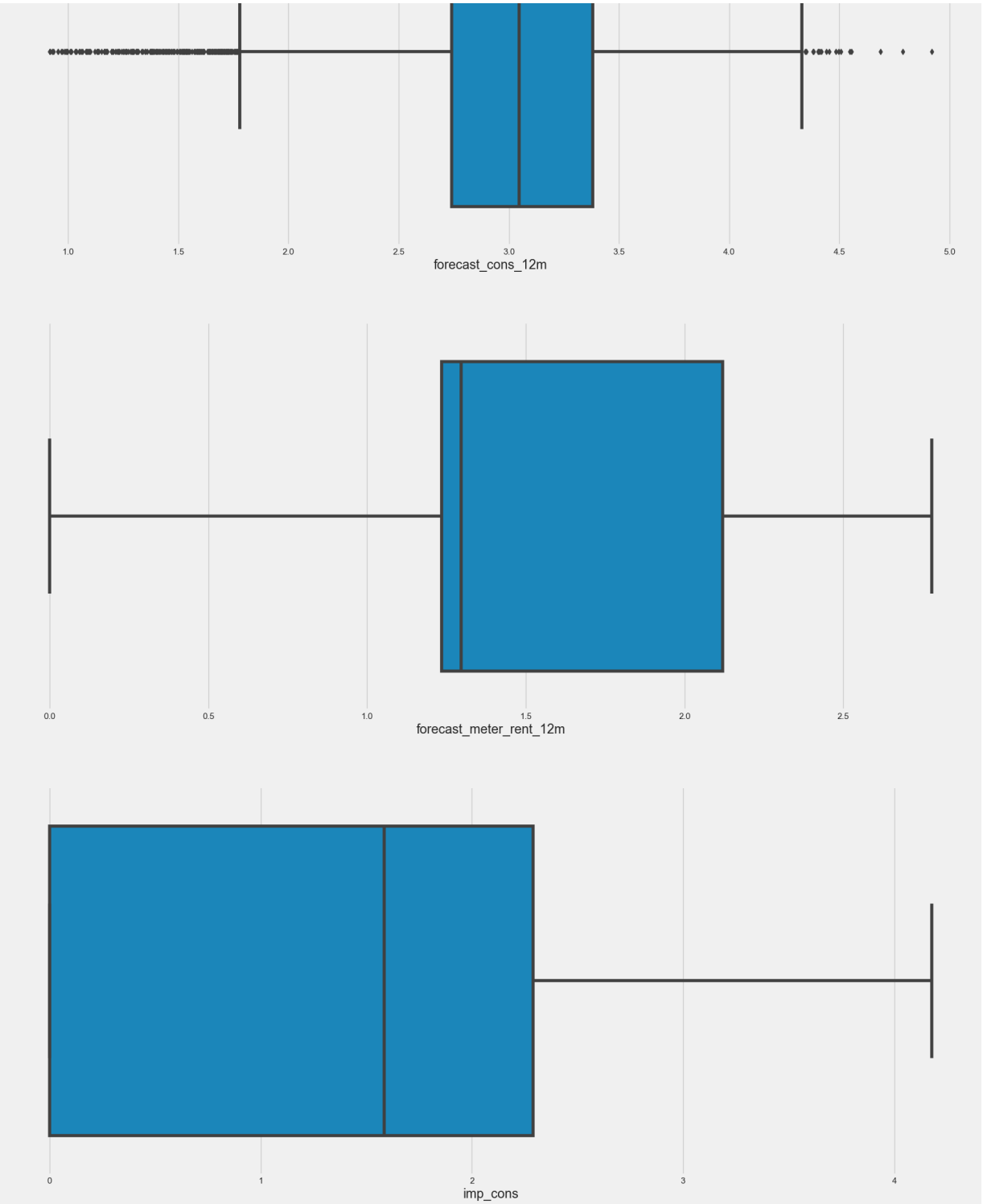
```
fig, axs = plt.subplots(nrows=6, figsize=(20,60))
sns.boxplot((churn_data['cons_12m'].dropna()), ax=axs[0])
sns.boxplot((churn_data[churn_data['has_gas']==1]['cons_gas_12m'].dropna()), ax=axs
sns.boxplot((churn_data['cons_last_month'].dropna()), ax=axs[2])
sns.boxplot((churn_data['forecast_cons_12m'].dropna()), ax=axs[3])
sns.boxplot((churn_data['forecast_meter_rent_12m'].dropna()), ax=axs[4])
sns.boxplot((churn_data['imp_cons'].dropna()), ax=axs[5])
plt.show()
```


2
3
4
5
6
7
cons_12m


0
1
2
3
4
5
6
cons_gas_12m


0
1
2
3
4
5
6
cons_last_month





In [116…

```
churn_data.describe()
```

Out[116...

	cons_12m	cons_gas_12m	cons_last_month	forecast_cons_12m	forecast_cons_yea
count	14606.000000	14606.000000	14606.000000	14606.000000	14606.000000
mean	4.268365	0.712699	2.264646	3.041639	1.784610
std	0.778083	1.610951	1.769305	0.488586	1.584986
min	1.579784	0.000000	0.000000	0.916980	0.000000
25%	3.772762	0.000000	0.000000	2.739723	0.000000
50%	4.165215	0.000000	2.899547	3.046836	2.498311
75%	4.610285	0.000000	3.529430	3.380716	3.242231
max	6.792889	5.930252	5.887169	4.918575	5.243970

8 rows × 51 columns

In [117...
```
cust_churn = pd.merge(client_df,churn_df,left_on='id', right_on='id', how='inner')
```

In [118...
```
train = pd.merge(cust_churn, price_df, on='id')
```

In [119...
```
pd.DataFrame({'Columns' : train.columns})
```

Out[119...

	Columns
0	id
1	channel_sales
2	cons_12m
3	cons_gas_12m
4	cons_last_month
5	date_activ
6	date_end
7	date_modif_prod
8	date_renewal
9	forecast_cons_12m
10	forecast_cons_year
11	forecast_discount_energy
12	forecast_meter_rent_12m
13	forecast_price_energy_off_peak
14	forecast_price_energy_peak
15	forecast_price_pow_off_peak
16	has_gas
17	imp_cons
18	margin_gross_pow_ele
19	margin_net_pow_ele
20	nb_prod_act
21	net_margin
22	num_years_antig
23	origin_up
24	pow_max
25	churn_x
26	churn_y
27	price_date
28	price_off_peak_var
29	price_peak_var

	Columns
30	price_mid_peak_var
31	price_off_peak_fix
32	price_peak_fix
33	price_mid_peak_fix