Analysis of 77095 zip code using Facebook Prophet

Imports and loading csv

In [1]:
```
from fbprophet import Prophet
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
import warnings
warnings.filterwarnings('ignore')
#Supress default INFO logging
import logging
logger = logging.getLogger()
logger.setLevel(logging.CRITICAL)
import logging, sys
logging.disable(sys.maxsize)
from fbprophet.diagnostics import cross_validation
```

In [2]:
```
df=pd.read_csv('df_zillow_77095_prepped_fbprophet.csv')
```

In [3]:
```
df.head()
```

Out[3]:

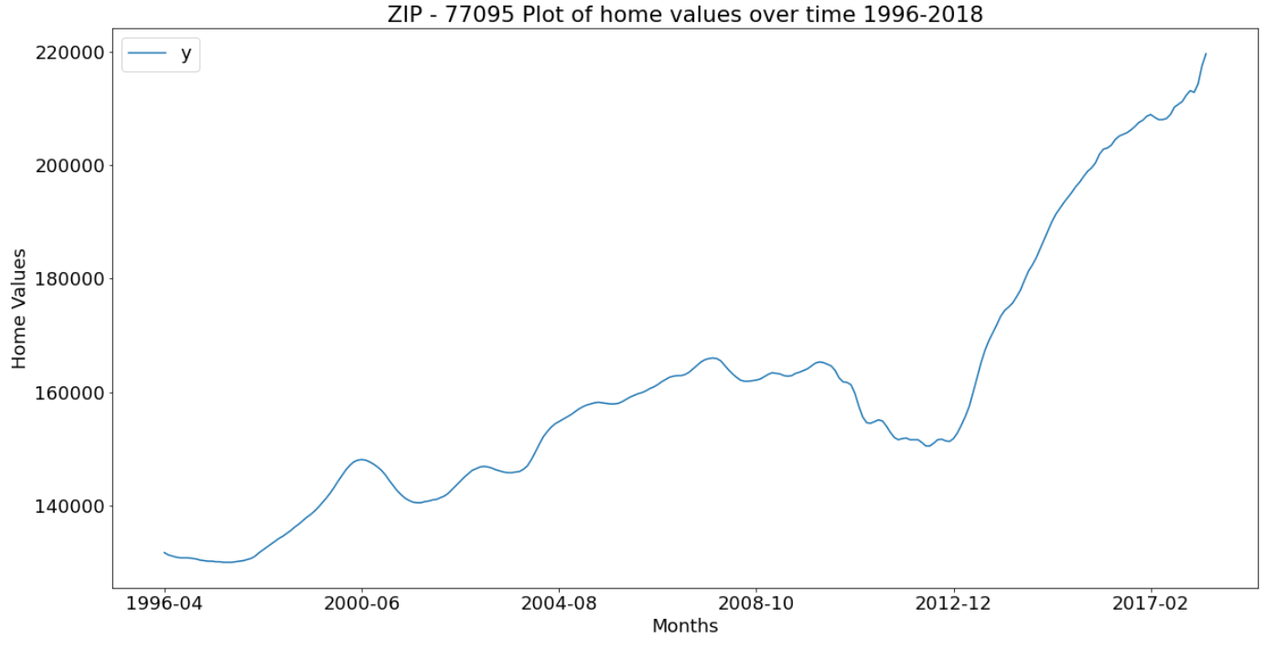
	ds	y
0	1996-04	131700.0
1	1996-05	131300.0
2	1996-06	131100.0
3	1996-07	130900.0
4	1996-08	130800.0

Plotting the specific zip code data from csv

In [4]:
```
plt.figure()
plt.rcParams.update({'font.size': 18})
ax = df.plot(title='ZIP - 77095 Plot of home values over time 1996-2018', figsize=(20,10),
ax.set_xlabel('Months')
ax.set_ylabel('Home Values')
```

Out[4]:
```
Text(0, 0.5, 'Home Values')

<Figure size 432x288 with 0 Axes>
```



Fitting and forecasting the model

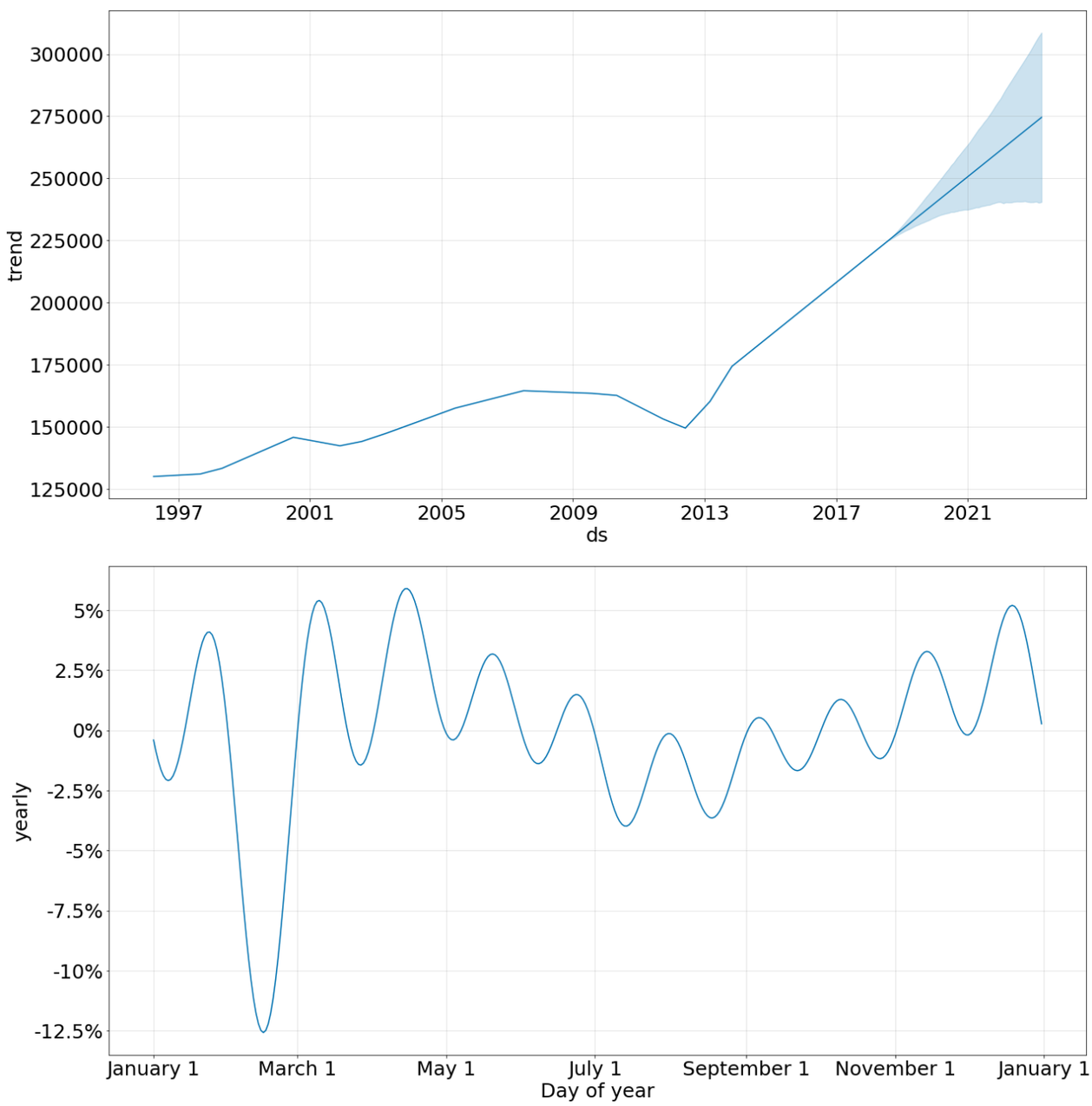
1. The length of the forecast will be 5 years into the future.
2. Periods = 60 with freq = M
    - 60 months / 12 months per year = 5 years
3. seasonality_mode = multiplicative
    - This is because additive would mean our graph will have a STEADY upward climb
    - This is not the case. There is a HUGE upward climb. Thus, multiplicative was used instead of additive.

Observations:

1. The trend shows promise, reflects the growth and demand of properties in the area.
2. The 2008 crash is reflected in the dip in home prices. This should not be confused for a cyclical occurence.
3. We cannot say much about seasonality. There is a huge upward trend.
    - Future work - maybe find stronger seasonality in daily data instead of monthly.

In [5]:
```
m = Prophet(seasonality_mode='multiplicative').fit(df)
future = m.make_future_dataframe(periods=60, freq='M')
fcst = m.predict(future)
plt.figure()
plt.rcParams.update({'font.size': 25})
fig = m.plot_components(fcst, figsize=(20,20))
```

```
<Figure size 432x288 with 0 Axes>
```



In [6]:
```
fcst[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].tail()
```

Out[6]:

	ds	yhat	yhat_lower	yhat_upper
320	2022-11-30	270510.595131	241080.183069	300463.879810
321	2022-12-31	273003.359537	241735.465323	304828.819375
322	2023-01-31	275242.979776	242166.667619	307839.911881
323	2023-02-28	268630.049374	236114.277747	300957.524942
324	2023-03-31	272495.187799	238862.717737	305894.524386

Forecast Model Diagnostics

Here I will check the accuracy of the model using cross validation

Cross validation parameters are as follows:

1. Model will be "m" from above fitted by Prophet() method
2. The initial training lengh parameter will be 5475 days or 15 years (365*15 = 5475)
    - This means cutoff will be after 15 years (1996 - 2011)
3. The horizon will be 1825 days or 5 years (365 * 5 = 1825)
    - from 2012 - 2017
4. The period is set to 180 days
    - Means it will make a prediction roughly every 6 months

In [7]:
```
cv_results = cross_validation( model = m, initial = pd.to_timedelta(5475, unit="d"),period
```

A Jupyter widget could not be displayed because the widget state could not be found. This could happen if the kernel storing the widget is no longer available, or if the widget state was not saved in the notebook. You may be able to create the widget by running the appropriate cells.

In [8]:
```
cv_results.head()
```

Out[8]:

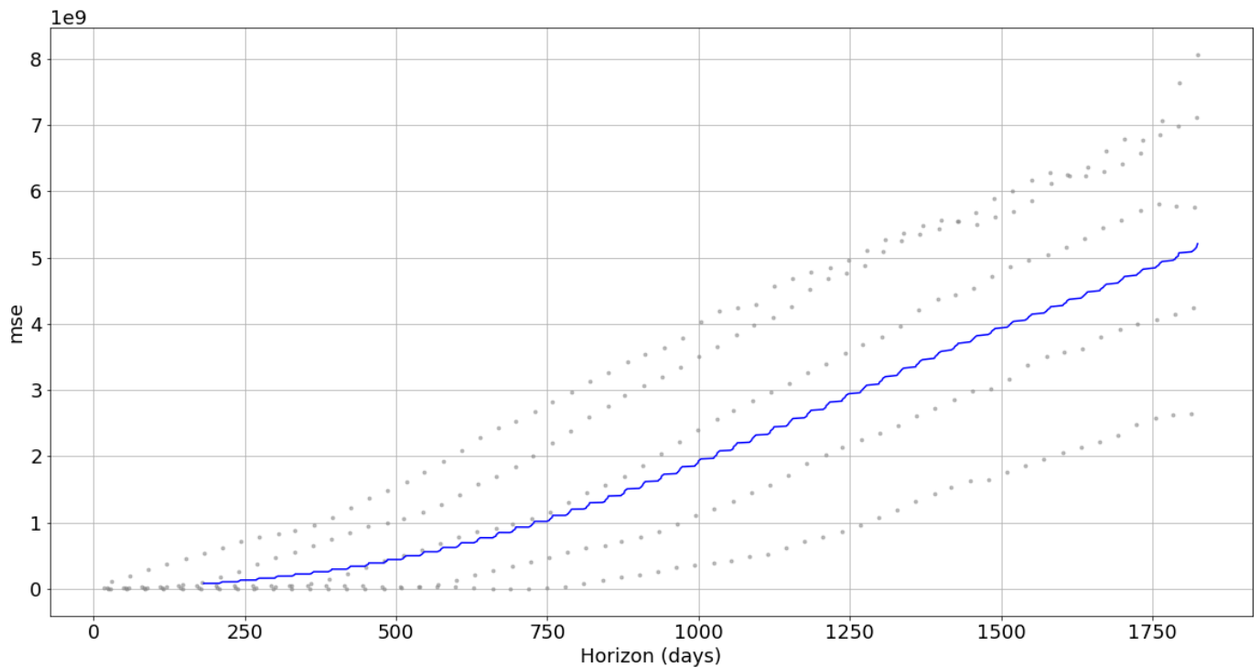
	ds	yhat	yhat_lower	yhat_upper	y	cutoff
0	2011-05-01	160012.746155	158267.987832	161810.878514	155100.0	2011-04-13
1	2011-06-01	159673.256026	157695.251943	161419.159379	154900.0	2011-04-13
2	2011-07-01	159362.357965	157613.884518	161240.955989	154000.0	2011-04-13
3	2011-08-01	159129.846232	157123.486614	161117.312003	152900.0	2011-04-13
4	2011-09-01	159011.626696	157154.455654	161079.851453	152000.0	2011-04-13

MSE observation:

1. MSE starts to increase rapidly after 500-750 days.
2. This reflects higher uncertainty the farther into the horizon

In [9]:
```
from fbprophet.plot import plot_cross_validation_metric
plt.figure()
plt.rcParams.update({'font.size': 18})
fig = plot_cross_validation_metric(cv_results, metric='mse', figsize=(20,10))
```

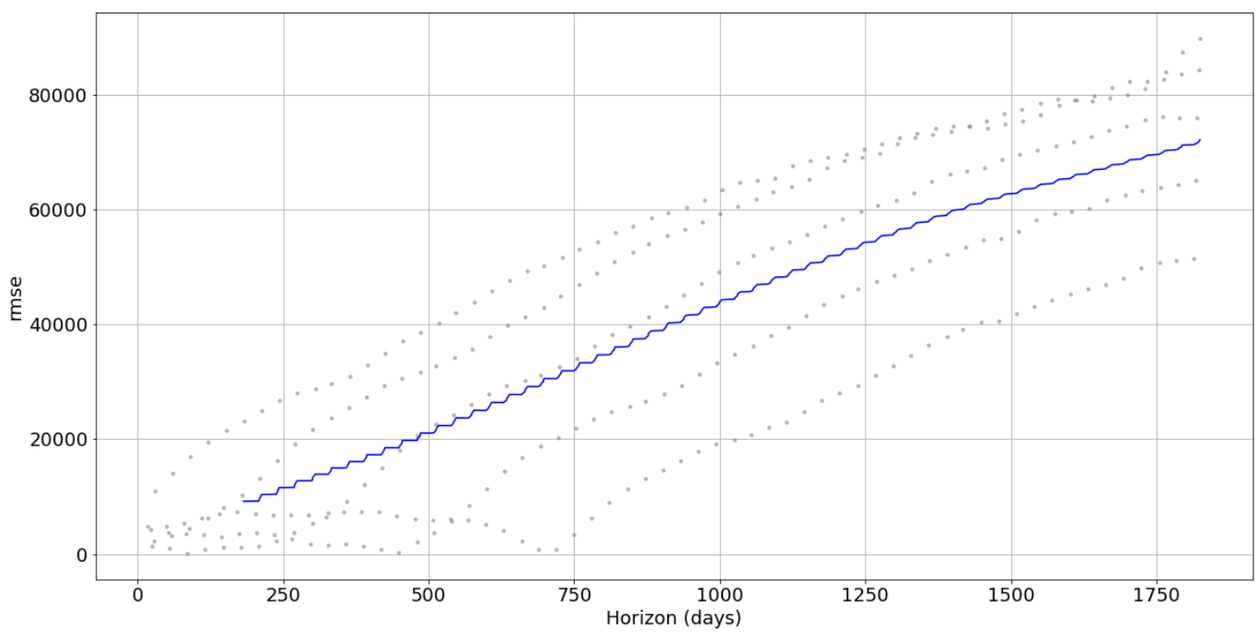
```
<Figure size 432x288 with 0 Axes>
```



RMSE Observation:

1. Similar to MSE, the error increases with longer time into horizon

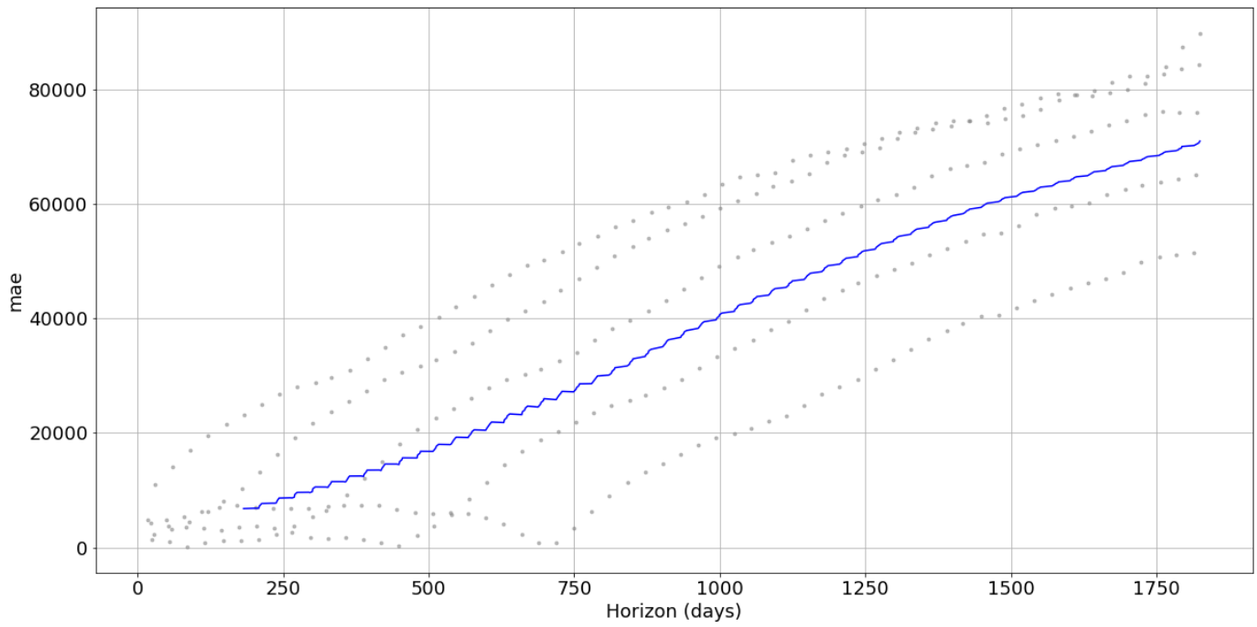
In [10]:
```
fig = plot_cross_validation_metric(cv_results, metric='rmse', figsize=(20,10))
```



MAE - Mean Absolute Error Observation:

1. Similar to MSE and RMSE, the difference starts increasing as the number of obse
rvations are increasing

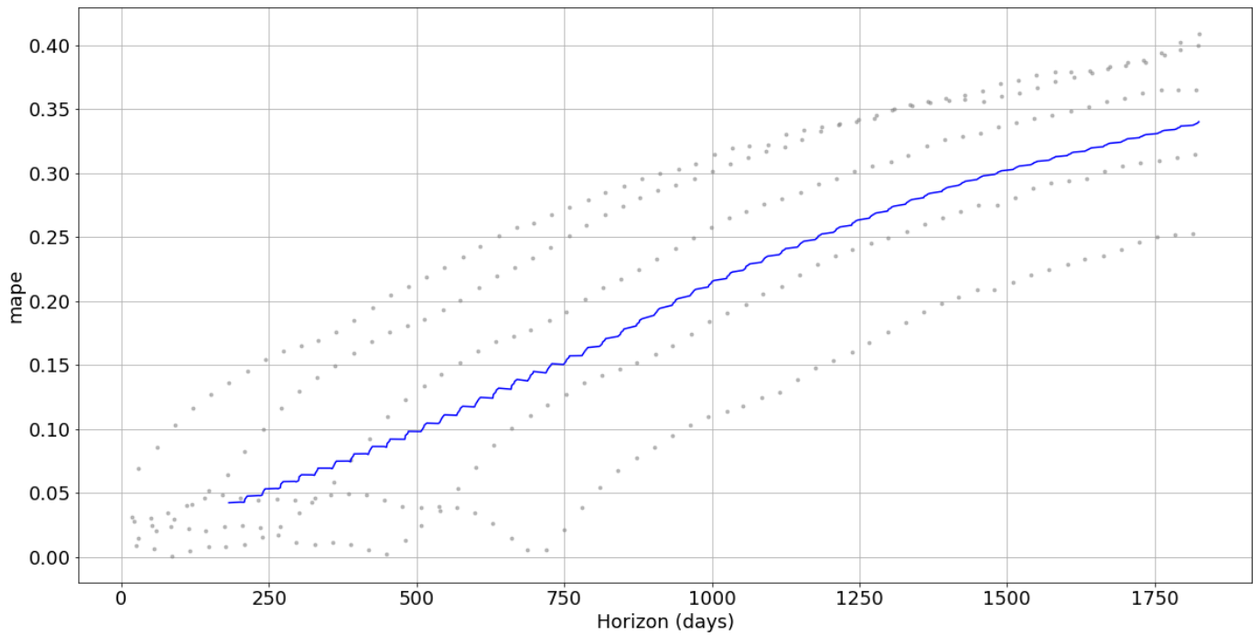
In [11]:
```
fig = plot_cross_validation_metric(cv_results, metric='mae', figsize=(20,10))
```



MAPE (Mean Average Percent Error) - Observation:

1. We see that MAPE increases over time
2. I am willing to tolerate MAPE of 0.1 to 0.2
    - This gets exceeded after about 800 days
3. We will focus on MAPE as our main diagnostic metric.
    - Shows the model was about 80% accurate at 800 days
    - Bullish prediction for the next 2-3 years
    - Supports the high upward trend we saw in the graph of all the data points for the zip code

In [12]:
```
fig = plot_cross_validation_metric(cv_results, metric='mape', figsize=(20,10))
```



Coverage Observation:

1. We see coverage decreasing over time of horizon
2. Shows 0 probability as we go past 800 days.
3. Means after about 800 days there is no probability a true value will be in the predicted range.
4. This does not fully explain anything. Just shows the values are not in the predicted range after some time.

In [13]:
```
fig = plot_cross_validation_metric(cv_results, metric='coverage', figsize=(20,10))
```