Appendix B: Prophet Comparison Model

We used the Prophet modeling package from Facebook to build Arima models using our data. We computed RMSE for comparison with the Long-Short Term Memory neural networks. Results are comparable, suggesting that LSTM has utility as a modeling approach for cryptocurrency price prediction.

In [1]:
```
from fbprophet import Prophet
import pandas as pd
import numpy as np
import math
import matplotlib as plt
from matplotlib import pyplot as plt

# Disable logging
import logging
logger = logging.getLogger()
logger.setLevel(logging.CRITICAL)
```

Part 1: Data preparation

As described in Appendix A, we're importing a dataset of Bitcoin prices, market data, semantic scores and the economic uncertainty index. The next few steps prepare the data for use with Prophet.

In [3]:
```
datafile = r'btc_new_3_24.csv'
data = pd.read_csv(datafile)
df=data
```

In [4]:
```
data.head()
```

Out[4]:

	day	epu_idx	price	volume	bidask	tpm	trans	exp_sem
0	3/24/13	126.08	68.287939	3.361108e+06	0.761886	2.203646	51335	0.24065
1	3/25/13	178.57	73.648607	6.917269e+06	0.978241	2.824132	48993	0.20230
2	3/26/13	163.29	77.090928	5.322638e+06	0.931310	2.560417	49061	0.00000
3	3/27/13	177.06	85.256510	7.356470e+06	1.033937	3.198785	53207	0.21230
4	3/28/13	72.92	90.658741	1.477020e+07	1.555560	5.049826	60989	0.20240

In [5]:
```
data = data.reset_index(drop=True)
```

In [ ]:
```
# data['lagged'] = data.price.shift(-1)
```

In [6]:
```python
# Preparing data for prophet
data.rename(columns={'day': 'ds'}, inplace=True)
data.rename(columns={'price': 'y'}, inplace=True)
```

In [7]:
```python
# view data
data.tail()
```

Out[7]:

	ds	epu_idx	y	volume	bidask	tpm	trans	exp_ser
1821	3/19/18	76.32	8390.472654	1.331577e+09	1.237513	44.369544	191528	0.09528
1822	3/20/18	79.32	8665.276738	9.671192e+08	0.931973	33.673810	195168	0.10972
1823	3/21/18	58.73	9038.338133	9.017038e+08	0.481224	30.921032	194846	0.15966
1824	3/22/18	54.22	8828.079342	9.567951e+08	0.339547	29.067163	185187	0.09225
1825	3/23/18	72.98	8574.364330	8.645390e+08	0.347265	30.230258	179818	0.11348

In [8]:
```python
# Setting ds column to Datetimeindex
# data['ds'] = pd.DatetimeIndex(data['ds'])
data['ds'] = pd.to_datetime(data['ds'])
```

In [10]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1826 entries, 0 to 1825
Data columns (total 8 columns):
ds          1826 non-null datetime64[ns]
epu_idx     1826 non-null float64
y           1826 non-null float64
volume      1826 non-null float64
bidask      1826 non-null float64
tpm         1826 non-null float64
trans       1826 non-null int64
exp_sem     1826 non-null float64
dtypes: datetime64[ns](1), float64(6), int64(1)
memory usage: 114.2 KB
```

2. Predicting based on raw data

Prediction quality: 1012.71 RMSE

In [11]:
```python
#Initialize model and fit it
m4 = Prophet()
m4.fit(data)
```

Out[11]:
```
<fbprophet.forecaster.Prophet at 0x114a55048>
```

In [12]:
```python
#build prediction ds
future_data = m4.make_future_dataframe(periods=1, freq = 'd')
```

In [13]:
```
#predict
f = m4.predict(future_data)
```

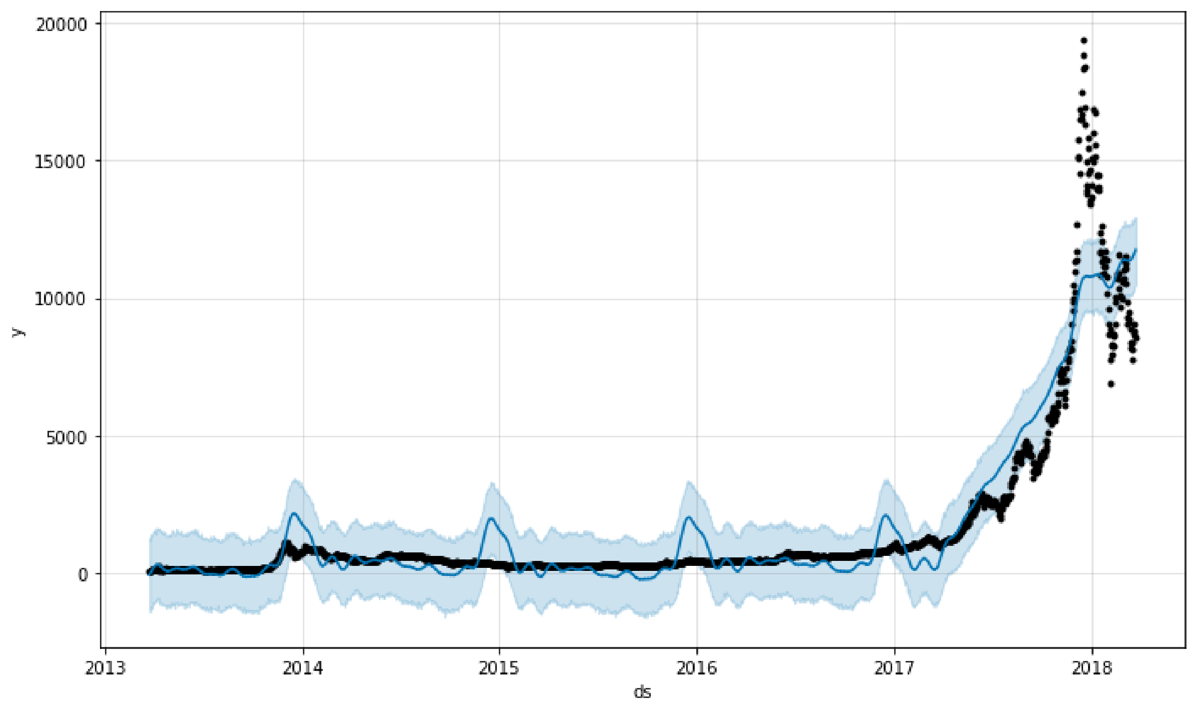
In [14]:
```
f[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].tail()
```

Out[14]:

	ds	yhat	yhat_lower	yhat_upper
1822	2018-03-20	11522.381254	10223.043170	12847.623917
1823	2018-03-21	11561.475548	10253.061927	12808.412558
1824	2018-03-22	11608.775504	10381.008110	12929.189205
1825	2018-03-23	11657.170021	10428.119677	12914.226234
1826	2018-03-24	11741.378708	10471.236299	12918.508458

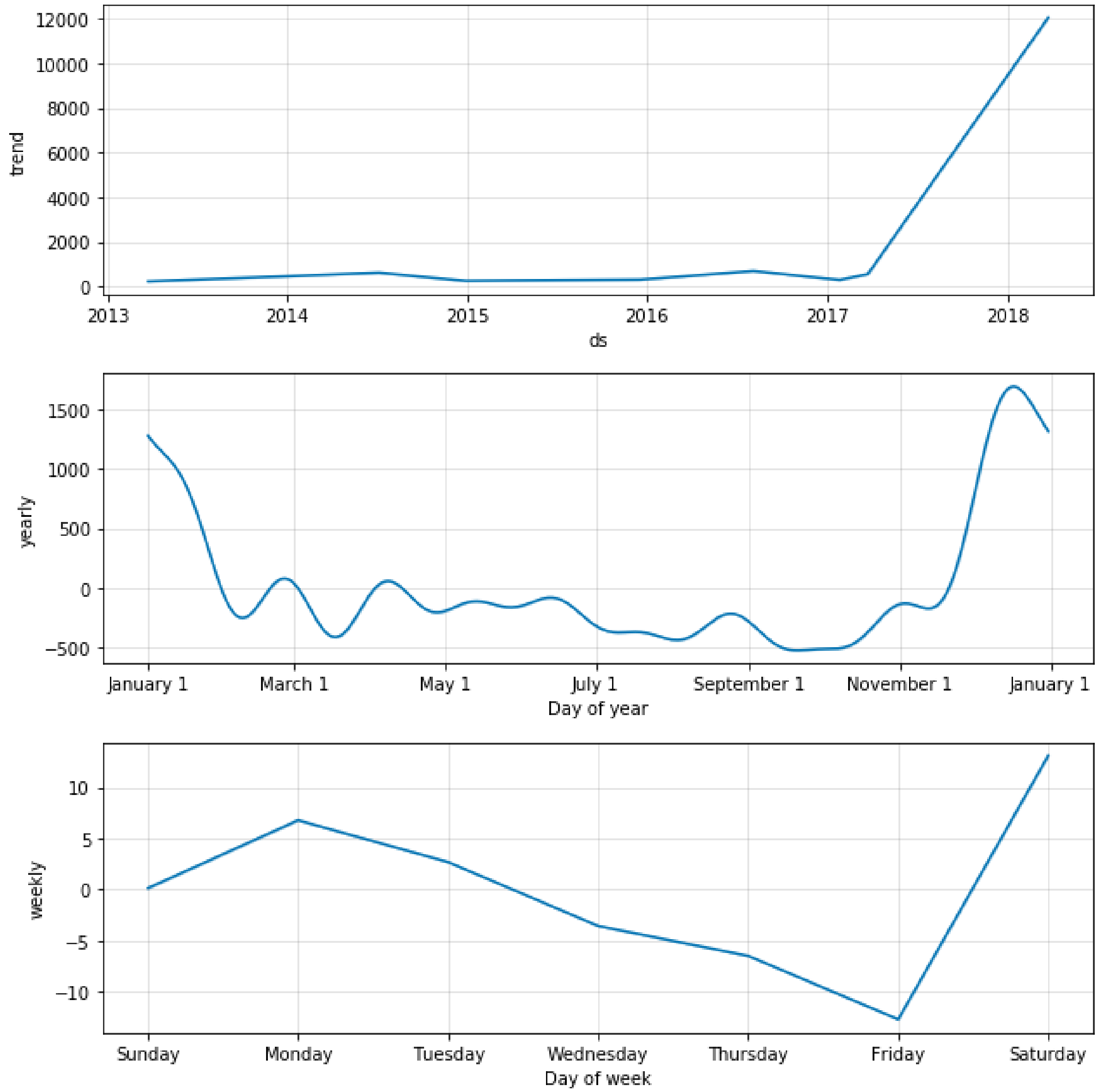
In [15]:
```
m4.plot(f)
```

Out[15]:

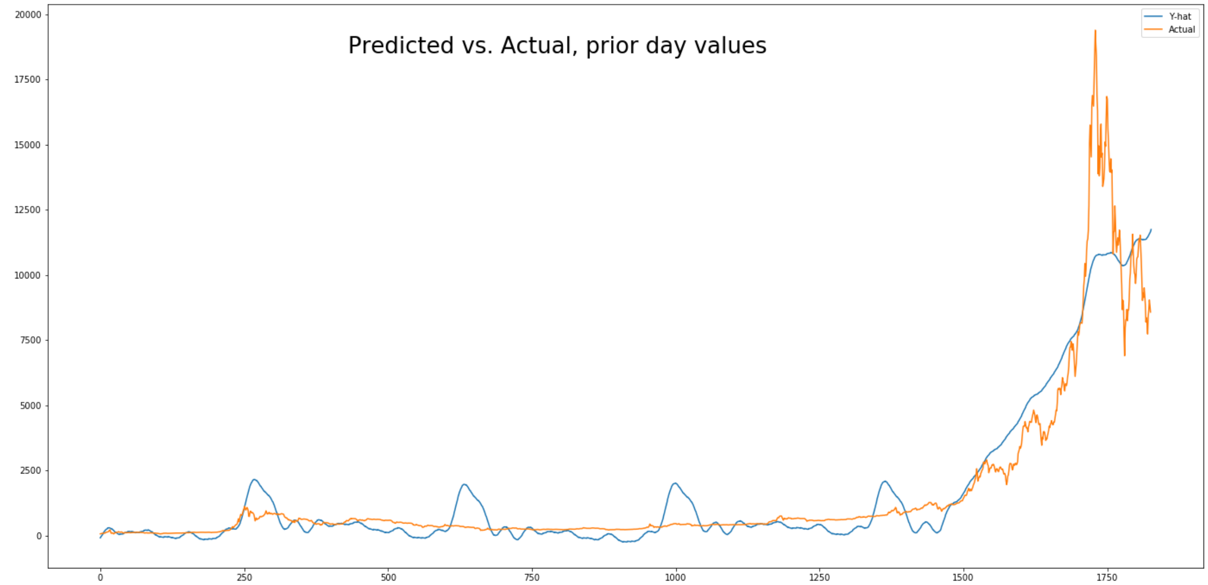


In [16]:
```
m4.plot_components(f)
```

Out[16]:



In [34]:
```
plt.figure(figsize=(24,12))
plt.plot(f['yhat'], label='Y-hat')
plt.plot(data['y'], label='Actual')
plt.legend(loc='best')
plt.text(430, 18500, 'Predicted vs. Actual, prior day values', fontsize=
26)
plt.show()
```



In [18]:
```
#Calculate accuracy
y_hat = f['yhat']
y_true = data['y']

mse = ((y_hat - y_true) ** 2).mean()
print('Prediction quality: {:.2f} MSE ({:.2f} RMSE)'.format(mse, math.sq
rt(mse)))
```

```
Prediction quality: 1025575.03 MSE (1012.71 RMSE)
```

3. Predicting based on Rolling window of 10

This approach predicts next-day price based on a rolling window of data from the 10 prior days.

Prediction quality: 296.56 RMSE

In [19]:
```
# Function to be called from the loop
def runmodel(df):
    m = Prophet()
    m.fit(df)
    future_data = m.make_future_dataframe(periods=1, freq = 'd')
    f = m.predict(future_data)
    return (f['yhat'][10])
```

In [20]:
```
# This will take some time to run.
# Looping through data and predicting based on 10 datapoint intervals.
y = []
p = []
for i in range(0,len(data)):
    if (i+11)>len(data):
        print ('Completed')
        break

    df_temp = data[i:i+10]
    y.append(runmodel(df_temp))
    p.append(data['y'][i+10])
    # print('Processed', i)
```

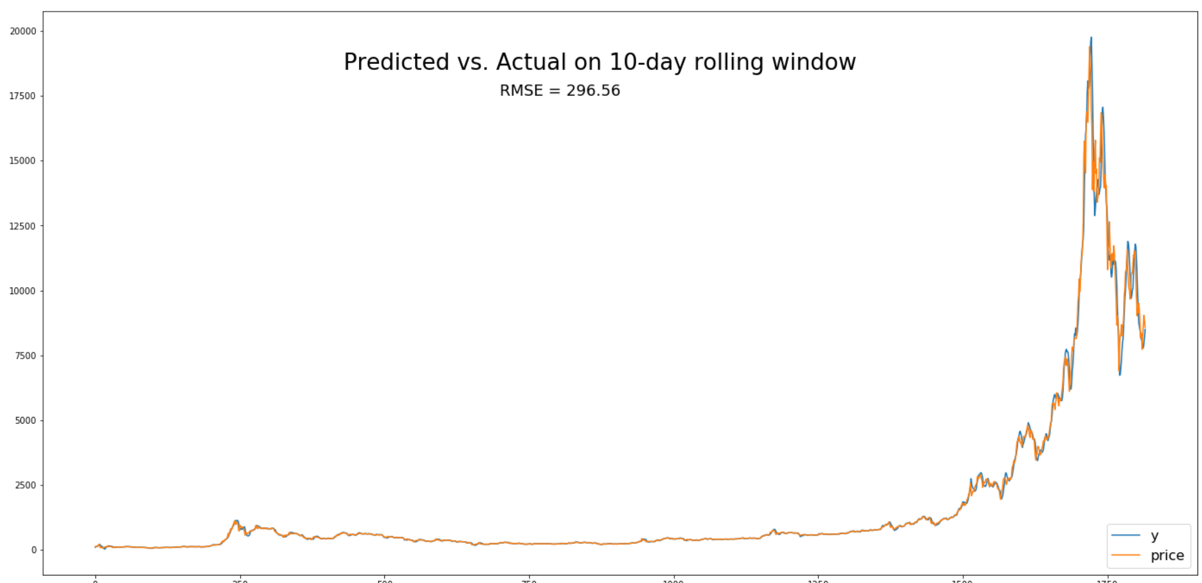
```
Completed
```

In [21]:
```
dfnew=pd.DataFrame({'y':y, 'price':p})
```

In [22]:
```
len(dfnew)
```

Out[22]:
```
1816
```

In [53]:
```
plt.figure(figsize=(24,12))
plt.plot(dfnew['y'])
plt.plot(dfnew['price'])
plt.legend(loc=4, fontsize=16)
plt.text(430, 18500, 'Predicted vs. Actual on 10-day rolling window', fo
ntsize=26)
plt.text(700, 17500, 'RMSE = 296.56', fontsize=18)
plt.show()
```



In [35]:
```
y_hat = dfnew['y']
y_true = dfnew['price']

mse = ((y_hat - y_true) ** 2).mean()
print('Prediction quality: {:.2f} MSE ({:.2f} RMSE)'.format(mse, math.sq
rt(mse)))
```

```
Prediction quality: 87946.37 MSE (296.56 RMSE)
```

4. Predicting based on log of data

Data is log-transformed prior to modeling.

Prediction quality: 655.05 RMSE

In [36]:
```
# Take a log
logdata = data
logdata['y'] = np.log(logdata['y'])
```

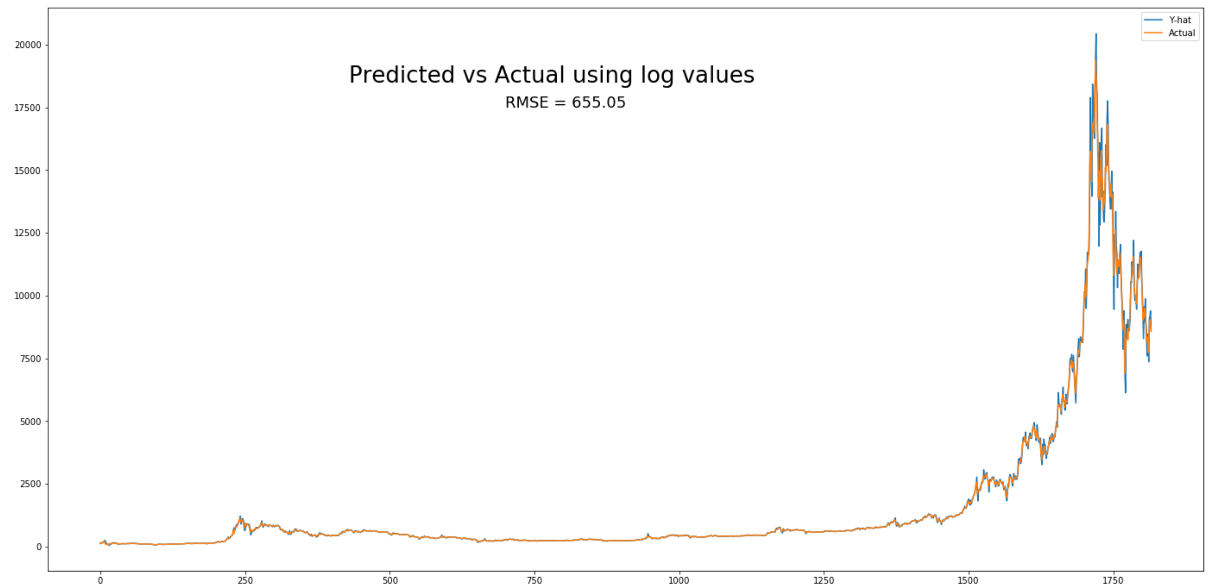
In [37]:
```
logdata.tail()
```

Out[37]:

	ds	epu_idx	y	volume	bidask	tpm	trans	exp_sem
1821	2018-03-19	76.32	9.034852	1.331577e+09	1.237513	44.369544	191528	0.095283
1822	2018-03-20	79.32	9.067079	9.671192e+08	0.931973	33.673810	195168	0.109729
1823	2018-03-21	58.73	9.109231	9.017038e+08	0.481224	30.921032	194846	0.159660
1824	2018-03-22	54.22	9.085693	9.567951e+08	0.339547	29.067163	185187	0.092254
1825	2018-03-23	72.98	9.056532	8.645390e+08	0.347265	30.230258	179818	0.113480

In [40]:
```
# Remove log and plot
y_hat = np.exp(f5['yhat'])
y_true = np.exp(logdata['y'])
```

In [50]:
```
plt.figure(figsize=(24,12))
plt.plot(y_hat, label='Y-hat')
plt.plot(y_true, label='Actual')
plt.legend(loc=4, fontsize=16)
plt.text(430, 18500, 'Predicted vs Actual using log values', fontsize=26
)
plt.text(700, 17500, 'RMSE = 655.05', fontsize=18)
plt.show()
```



In [42]:
```
# Calculate Accuracy
mse = ((y_hat - y_true) ** 2).mean()
print('Prediction quality: {:.2f} MSE ({:.2f} RMSE)'.format(mse, math.sq
rt(mse)))
```

```
Prediction quality: 429096.47 MSE (655.05 RMSE)
```

4. Predicting based on Rolling window of 10 using log

Prediction quality: 233.41 RMSE

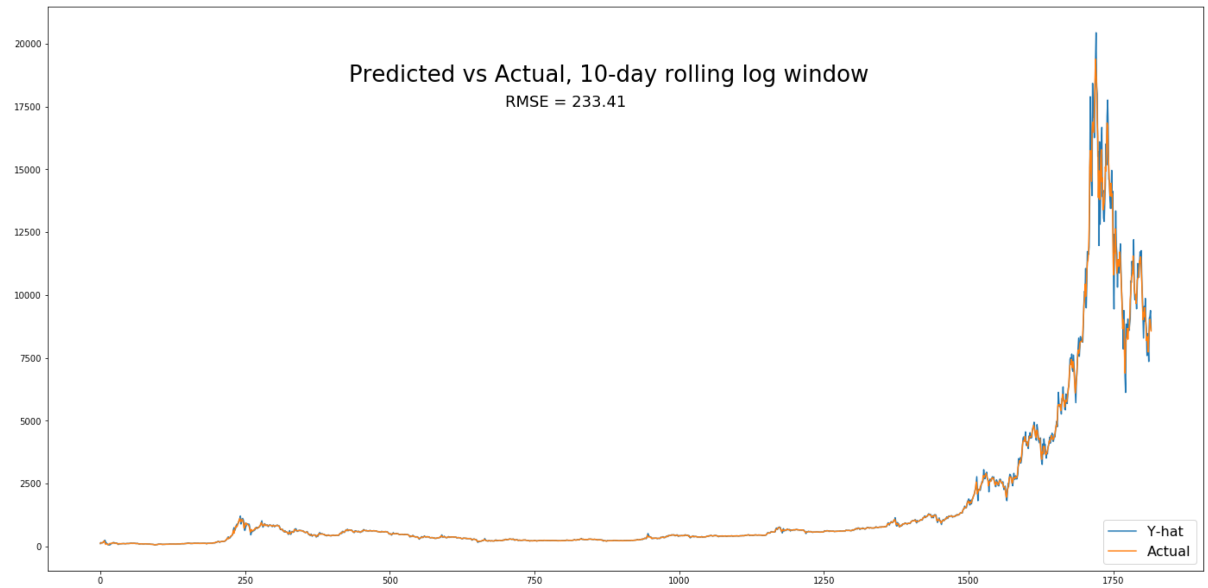
In [43]:
```
# This will take some time to run
y = []
p = []
for i in range(0,len(logdata)):
    if (i+11)>len(logdata):
        print ('Completed')
        break

    df = logdata[i:i+10]
    y.append(runmodel(df))
    p.append(logdata['y'][i+10])
    #print('Processed', i)
```

```
Completed
```

In [44]:
```
dfrolling=pd.DataFrame({'y':y, 'price':p})
```

In [45]:
```
#Remove log
y_hat = np.exp(dfrolling['y'])
y_true = np.exp(dfrolling['price'])
```

In [52]:
```
plt.figure(figsize=(24,12))
plt.plot(y_hat, label='Y-hat')
plt.plot(y_true, label='Actual')
plt.legend(loc=4, fontsize=16)
plt.text(430, 18500, 'Predicted vs Actual, 10-day rolling log window', f
ontsize=26)
plt.text(700, 17500, 'RMSE = 233.41', fontsize=18)
plt.show()
```



In [47]:
```
#Calculate accuracy
mse = ((y_hat - y_true) ** 2).mean()
print('Prediction quality: {:.2f} MSE ({:.2f} RMSE)'.format(mse, math.sq
rt(mse)))
```

```
Prediction quality: 54481.25 MSE (233.41 RMSE)
```

Code references

[https://facebook.github.io/prophet/docs/quick_start.html (https://facebook.github.io/prophet/docs/quick_start.html)](https://facebook.github.io/prophet/docs/quick_start.html)

[http://pythondata.com/stock-market-forecasting-with-prophet/ (http://pythondata.com/stock-market-forecasting-with-prophet/)](http://pythondata.com/stock-market-forecasting-with-prophet/)

[http://dacatay.com/data-science/part-5-time-series-prediction-prophet-python/ (http://dacatay.com/data-science/part-5-time-series-prediction-prophet-python/)](http://dacatay.com/data-science/part-5-time-series-prediction-prophet-python/)