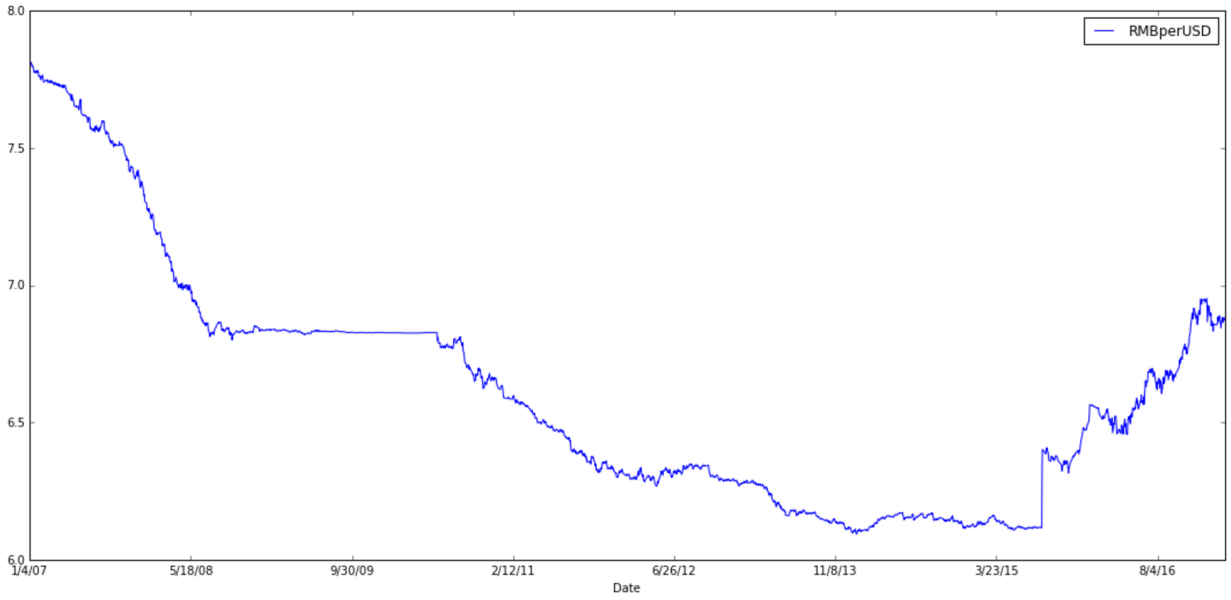
In [1]:
```
from yahoo_finance import Currency
from matplotlib.finance import quotes_historical_yahoo_ohlc
from datetime import datetime
import pandas as pd
import numpy as np
```

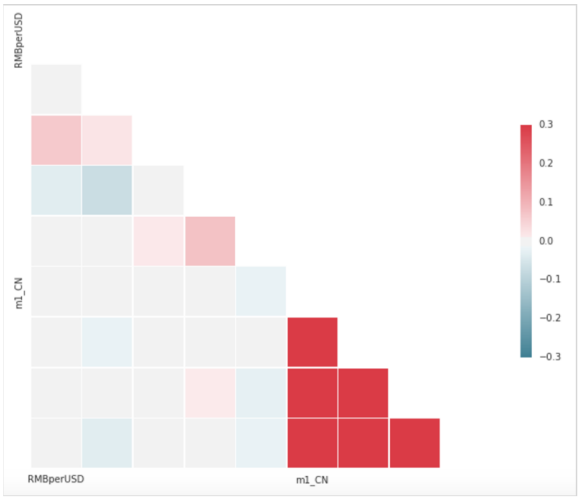
```
/Users/liang/anaconda/lib/python2.7/site-packages/matplotlib/font_manage
r.py:273: UserWarning: Matplotlib is building the font cache using fc-lis
t. This may take a moment.
  warnings.warn('Matplotlib is building the font cache using fc-list. Thi
s may take a moment.')
```

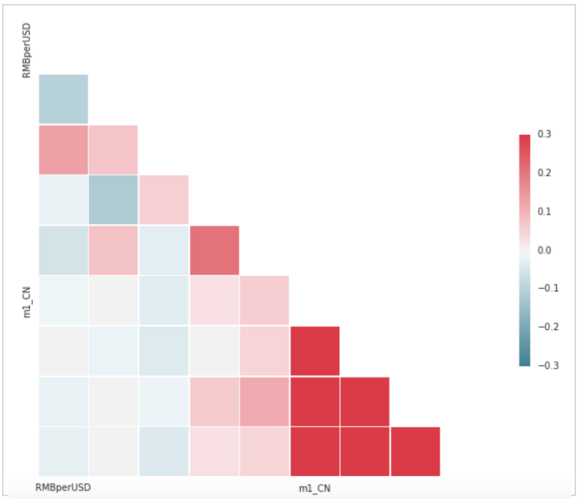
Historical Data



Time-range selection

Our time-range selection is correct

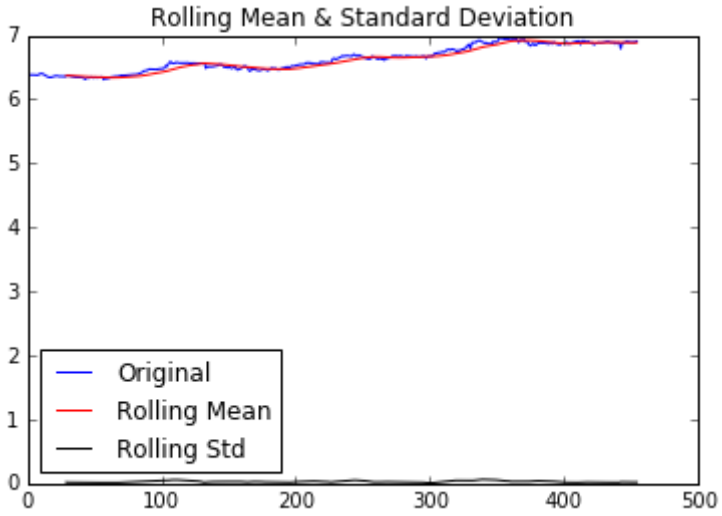




In [3]:
```
start_date = (2015, 8, 12)
end_date = datetime.utcnow().date()
rmb_usd = quotes_historical_yahoo_ohlc('CNY=X', start_date, end_date)
df = pd.DataFrame(rmb_usd)

close_rate = df[[4]]
```

Test Stationarity

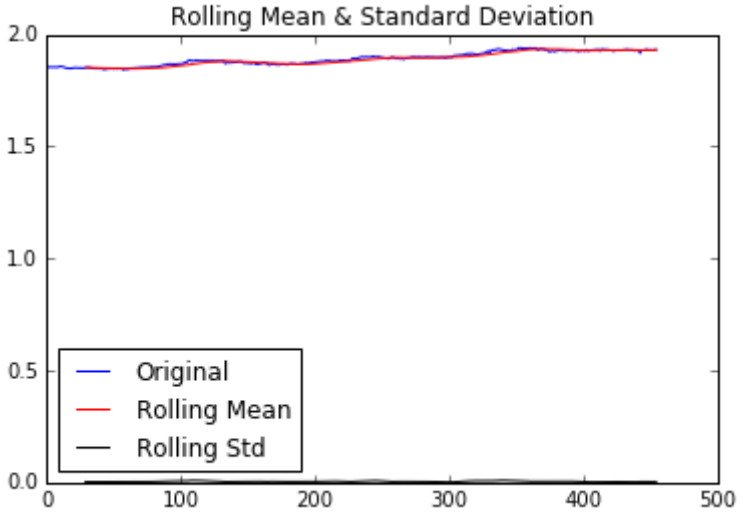
In [4]:
```
from statsmodels.tsa.stattools import adfuller
import matplotlib.pylab as plt
%matplotlib inline

def test_stationarity(timeseries):

    #Determing rolling statistics
    rolmean = timeseries.rolling(window=30).mean()
    rolstd = timeseries.rolling(window=30).std()

    #Plot rolling statistics:
    orig = plt.plot(timeseries, color='blue',label='Original')
    mean = plt.plot(rolmean, color='red', label='Rolling Mean')
    std = plt.plot(rolstd, color='black', label = 'Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation')
    plt.show(block=False)

    #Perform Dickey-Fuller test:
    print 'Results of Dickey-Fuller Test:'
    dftest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#La
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print dfoutput

test_stationarity(close_rate[4])
```




```
Results of Dickey-Fuller Test:
Test Statistic                  -0.497124
p-value                          0.892577
#Lags Used                       2.000000
Number of Observations Used    452.000000
Critical Value (5%)             -2.867956
Critical Value (1%)             -3.444900
Critical Value (10%)            -2.570187
dtype: float64
```

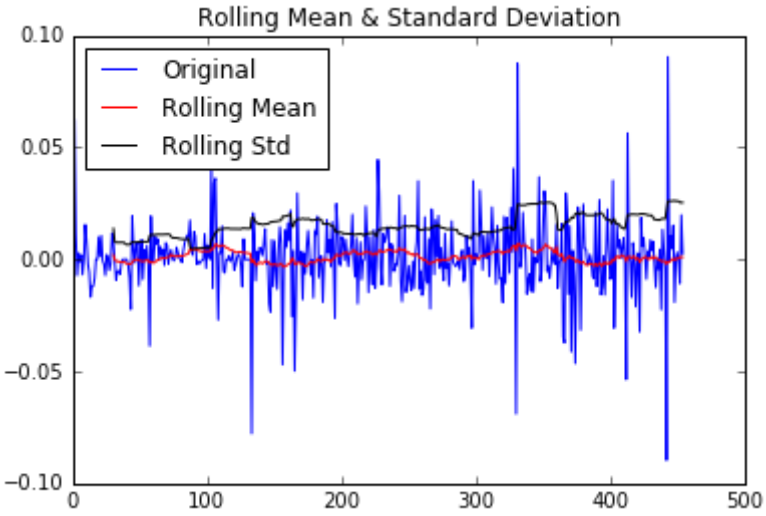
Towards Stationarity

In [5]:
```
rate_log = np.log(close_rate[4])
test_stationarity(rate_log)
```




```
Results of Dickey-Fuller Test:
Test Statistic                  -0.520478
p-value                          0.887958
#Lags Used                       2.000000
Number of Observations Used    452.000000
Critical Value (5%)             -2.867956
Critical Value (1%)             -3.444900
Critical Value (10%)            -2.570187
dtype: float64
```

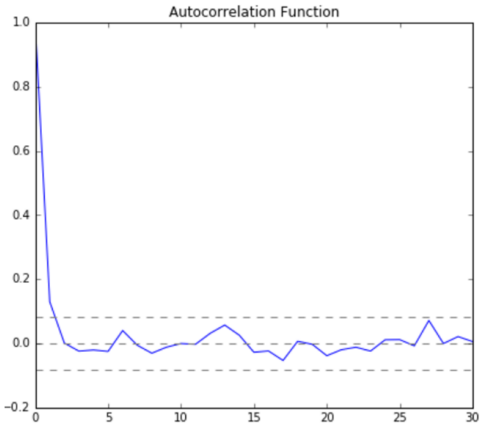
In [6]:
```
rate_log_diff = close_rate[4] - close_rate[4].shift()
rate_log_diff.dropna(inplace=True)
test_stationarity(rate_log_diff)
```

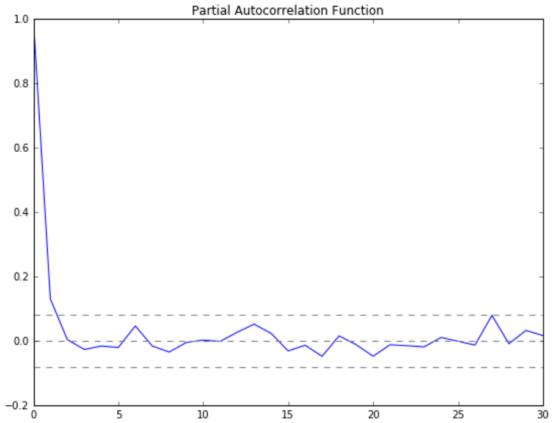



```
Results of Dickey-Fuller Test:
Test Statistic                  -19.264689
p-value                           0.000000
#Lags Used                        1.000000
Number of Observations Used     452.000000
Critical Value (5%)              -2.867956
Critical Value (1%)              -3.444900
Critical Value (10%)             -2.570187
dtype: float64
```

ARIMA

ACF & PACF





ACF and PACF decrease significantly at order 2!

Therefore we choose ARIMA model with order parameter p=2,q=2

In [8]:
```
import pyflux as pf
#import pandas as pd
#import pandas_datareader as pdr
import pandas_datareader.data as web
from datetime import datetime
#import matplotlib.pyplot as plt %matplotlib inline

cny_usd = web.DataReader('CNY=X',  'yahoo', datetime(2015,8,12), datetime(20
log_diff = pd.DataFrame(np.diff(np.log(cny_usd['Adj Close'].values)))
log_diff.index = cny_usd.index.values[1:cny_usd.index.values.shape[0]]
log_diff.columns = ['Rate Differencing']

model = pf.ARIMA(data=cny_usd, ar=2, ma=2, family=pf.Normal())
x = model.fit("MLE")
x.summary()
```

```
Normal ARIMA(2,0,2)

========================================================= =================
================================
Dependent Variable: Open                                  Method: MLE

Start Date: 2015-08-14 00:00:00                           Log Likelihood: 8
55.193
End Date: 2017-05-10 00:00:00                             AIC: -1698.3859

Number of observations: 453                               BIC: -1673.6906

==========================================================================
================================
Latent Variable                           Estimate   Std Error  z        P
>|z|    95% C.I.
========================================= ========== ========== ======== =
======= ========================
Constant                                  0.0789     0.056      1.4073
 0.1593   (-0.031 | 0.1887)
AR(1)                                     0.3744     0.2615     1.4315
 0.1523   (-0.1382 | 0.8869)
AR(2)                                     0.6144     0.2562     2.3983
 0.0165   (0.1123 | 1.1165)
MA(1)                                     0.1261     0.2447     0.5153
 0.6063   (-0.3535 | 0.6058)
MA(2)                                     -0.4147    0.0808     -5.1299
 0.0      (-0.5732 | -0.2563)
Normal Scale                              0.0332

==========================================================================
================================
```

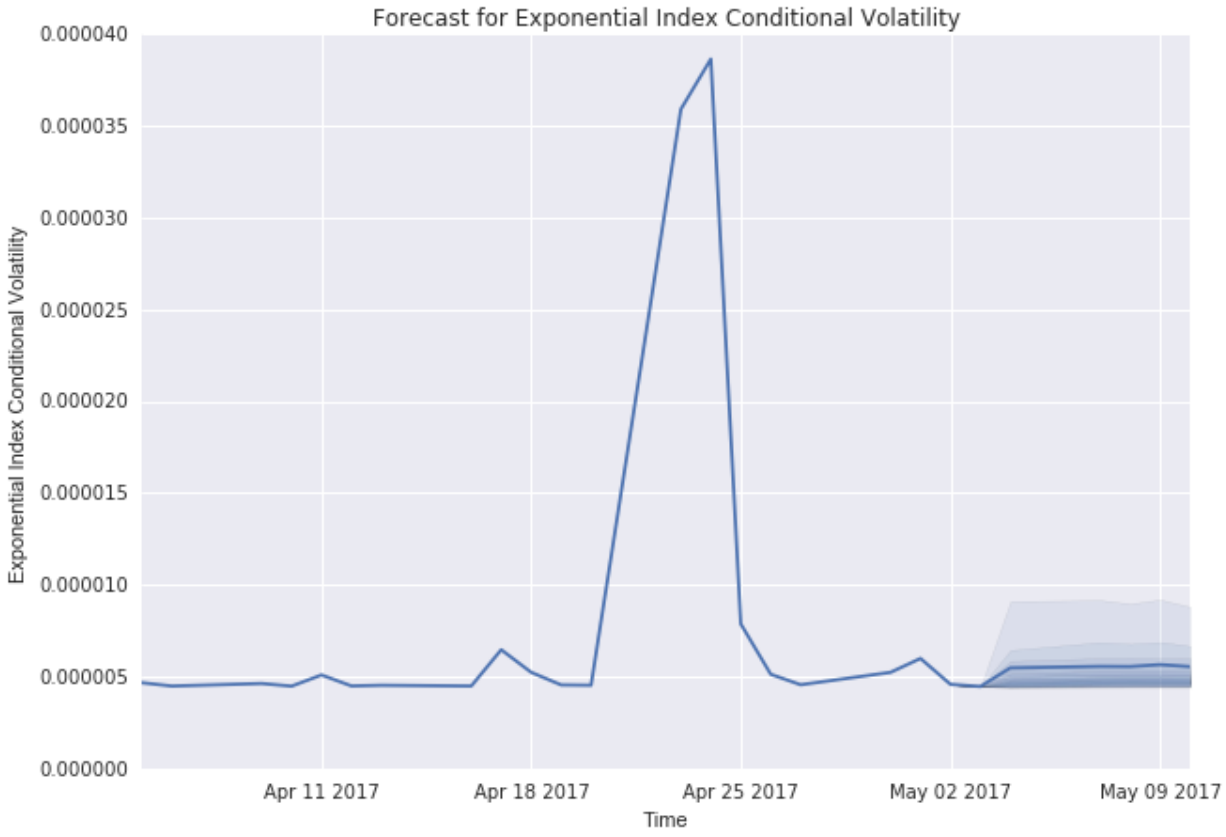
GARCH

In [23]:
```
import pyflux as pf
import pandas_datareader.data as web
from datetime import datetime

cny_usd = web.DataReader('CNY=X',  'yahoo', datetime(2015,8,12), datetime(20

log_diff = pd.DataFrame(np.diff(np.log(cny_usd['Adj Close'].values)))
log_diff.index = cny_usd.index.values[1:cny_usd.index.values.shape[0]]
log_diff.columns = ['Exponential Index']
```

In [24]:
```
garch_model = pf.GARCH(log_diff,p=1,q=1)
x = garch_model.fit()
x.summary()
```

```
GARCH(1,1)

========================================================== =================
================================
Dependent Variable: Exponential Index                     Method: MLE

Start Date: 2015-08-14 00:00:00                           Log Likelihood: 2
095.0363
End Date: 2017-05-04 00:00:00                             AIC: -4182.0727

Number of observations: 449                               BIC: -4165.6446

==========================================================================
================================
Latent Variable                           Estimate   Std Error  z        P
>|z|    95% C.I.
========================================= ========== ========== ======== =
======= ========================
Vol Constant                              0.0

q(1)                                      0.1804

p(1)                                      0.1004

Returns Constant                          0.0001     0.0021     0.0487
 0.9612   (-0.004 | 0.0042)
==========================================================================
================================
```

In [25]:
```
garch_model.plot_predict(h=6)
```



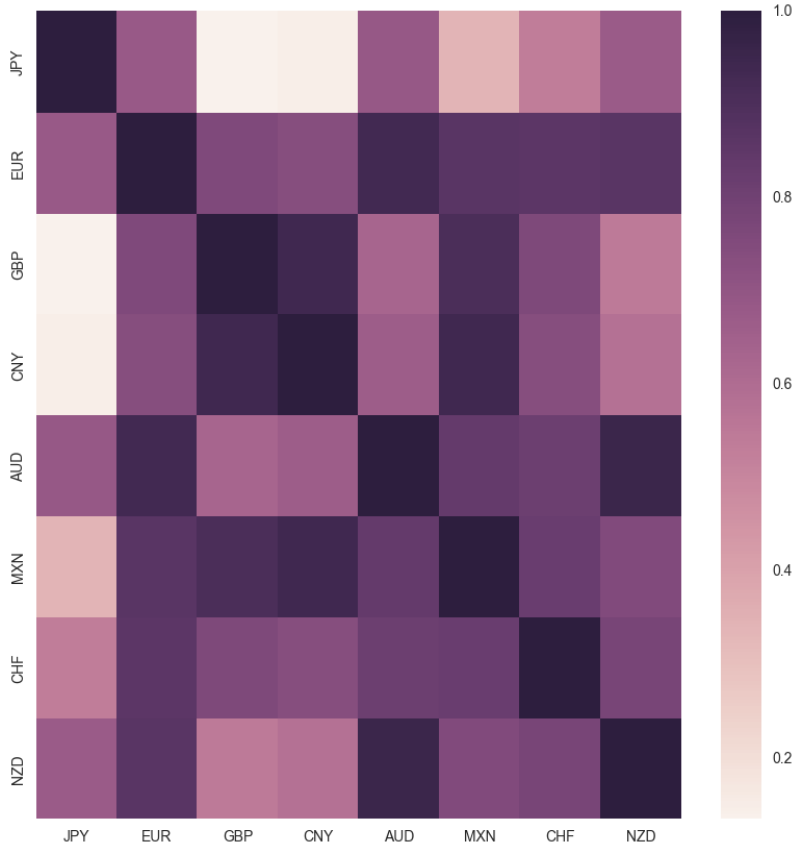
In [45]:
```
a = garch_model.predict(h=6)
##dynamic_Sample_Prediction is error is future
dynamic_Sample_Prediction = a

## dynamic_Sample_Prediction_log is error data with future error
dynamic_Sample_Prediction_log = log_diff.append(dynamic_Sample_Prediction)
dynamic_Sample_Prediction_log.drop_duplicates(inplace=True)

## dynamic_Sample_Prediction_log_cumsum is cumulate sum of all errors
dynamic_Sample_Prediction_log_cumsum = dynamic_Sample_Prediction_log.cumsum(

## add 1.81094 to all cumsum respectively
dynamic_GARCH_log = dynamic_Sample_Prediction_log_cumsum.add(1.81094)

## back to original data
dynamic_Sample_Prediction_GARCH = np.exp(dynamic_GARCH_log)

plt.figure(figsize=(15,10))
plt.plot(dynamic_Sample_Prediction_GARCH)
```

Out[45]:
```
[<matplotlib.lines.Line2D at 0x12d2bebd0>]
```

SGD (Stochastic Gradient Descent)

SGD Research Paper (https://cs.nyu.edu/media/publications/TR2013-953.pdf)

Currency Correlation



Model Comparison

SGD MSE

```
print 'Coefficients:', optim_reg.coef_
```

```
Coefficients: [ 0.05288977  0.05012294]
```

```
print 'Mean Square Error: ', np.mean((optim_model.predict(X_test1) - y_test1['CNY']) ** 2)
```

```
Mean Square Error:  0.0583584984364
```

GARCH MSE

In [47]:
```
from sklearn.metrics import mean_squared_error

true_Data = web.DataReader('CNY=X',  'yahoo', datetime(2017,5,4), datetime(2
train_Data = web.DataReader('CNY=X',  'yahoo', datetime(2015,8,12), datetime
prediction_Data = dynamic_Sample_Prediction_GARCH.tail(n=5)
mean_squared_error(true_Data['Close'], prediction_Data)
```

Out[47]:
```
0.047521002847139934
```

ARIMA MSE

```
rss('CNY=X',5)
```

```
{'optimal':     AR  Diff   MA       MSE
 4  2.0   1.0  2.0  0.000108, 'rss_table':     AR  Diff   MA       MSE
 0  1.0   1.0  1.0  0.000131
 1  1.0   1.0  2.0  0.000133
 2  1.0   1.0  3.0  0.000127
 3  2.0   1.0  1.0  0.000121
 4  2.0   1.0  2.0  0.000108
 5  2.0   1.0  3.0  0.005394
 6  3.0   1.0  1.0  0.000120
 7  3.0   1.0  2.0  0.000124
 8  3.0   1.0  3.0  0.000121, 'time': 4.235037088394165}
```

SGD < GARCH < ARIMA

Order Selection

For ARIMA, We calculated ARIMA(1,1,1), ARIMA(2,1,1)...ARIMA(2,1,2)

From *Intro to Time Series and Forecasting*, **differecing order more than 1 usually will cause overfitting**

For GARCH, We found a paper stated that GARCH(1,1) is the best

Does anything beat GARCH(1,1)? (http://www.bauer.uh.edu/rsusmel/phd/HansenLunde_Garch.pdf)

In [ ]: