Riding the Volatility Wave

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Introduction

Cryptocurrencies represent an entirely new market of traded securities. The current market capitalization is valued far past $600 billion dollars and continues to increase incrementally every day.

One of the largest and most frequently traded coins is Bitcoin, BTC. The current value of BTC doubles that of Goldman Sachs, or even Bitcoin itself, one month earlier. Whether cryptocurrencies represent a bubble or a new disruptive emerging technology, it is undeniably a very lucrative investment opportunity.

This project aims to take advantage of the present volatility in the cryptocurrency market by implementing a trading algorithm, based off of Statistical Process Controls and prior economic knowledge to indicate when current market conditions warrant a purchase of coins.

For simplicity and practicality of this project, I have limited the scope of my research to Bitcoin for two reasons: The amount of information readily available and the size of the market.

Data Sources

I was able to downloaded a free csv file from bitfinex.com cointaining all the booked trades from the bitfinex exchange throughout a 24 hour time period.

This csv file contains over several hundred thousand trades, all spanning from midnight one day to midnight the following day. Once imported into excel the respective file can be manipulated with the following code and read into a python enviroment.

The csv file has main columns of information: The volume traded, whether it was a buy or sell, the price at which the trade occured, and the timestamp.

In order to determine what the net volume traded in a period is, the buy/sell column must be correlated with the amount traded in order to account for buy(positive),sell(negative) trades. To do this I assinged each trade with a 'sell' indicator as a negative amount. This allows me to compute a net amount signed and regress it directly to the percent change in price over the same time horizon.

The main focus is to develop a working knowledge of how price changes with respect to the net volume traded by analyzing the relationship between the two respective attributes and then utilizing statistical process controls to monitor the coin's process.

From this we can develop a "buy-trigger" given the specified rules of Statistical Process Control and Bitcoin's process volatility.

Key Assumptions

This project makes three KEY assumptions:

1. The valuation of Bitcoin is a steadily increasing function which can be observed as a supply and demand model through the volume traded.

1. Any drastic change in price will eventually correct to the process mean given a short time horizon.

1. The market to buy and sell coins will continue to exist throughout the time horizon of the transaction cycle and assumes immediate market liquidity.

In [7]:

```
# Import all required packages
%matplotlib inline
import datetime
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import statsmodels.api as sm
import statsmodels.formula.api as smf
plt.style.use('ggplot')
```

Manipulating the CSV File

To be able to observe net volume vs. percent price change the following actions must be taken:

A conversion of Unix Timestamp to UTC. This will allow us to use conventional time metrics to analyze the following attributes.

The organization of the csv file into the following columns: Time, Price, Net Volume.

Converting every sell trade to a negative amount traded.

In [8]:
```
# Helper function to parse timestamp
def dateparse (time_in_secs):
    return datetime.datetime.fromtimestamp(float(time_in_secs))

# Read trade volume data, and perform initial cleaning
trade_volume = pd.read_csv('Trades_New.csv', index_col=0, parse_dates=Tru
trade_volume = trade_volume.loc[:, ~trade_volume.columns.str.contains('^U

# clean Unnamed columns
trade_volume['Amount_Signed'] = trade_volume['Amount'].where((trade_volum
del trade_volume['Amount']
del trade_volume['Type']

# Read values data
values = pd.read_csv('Values_Charts.csv')
trade_volume.head()
```

Out[8]:

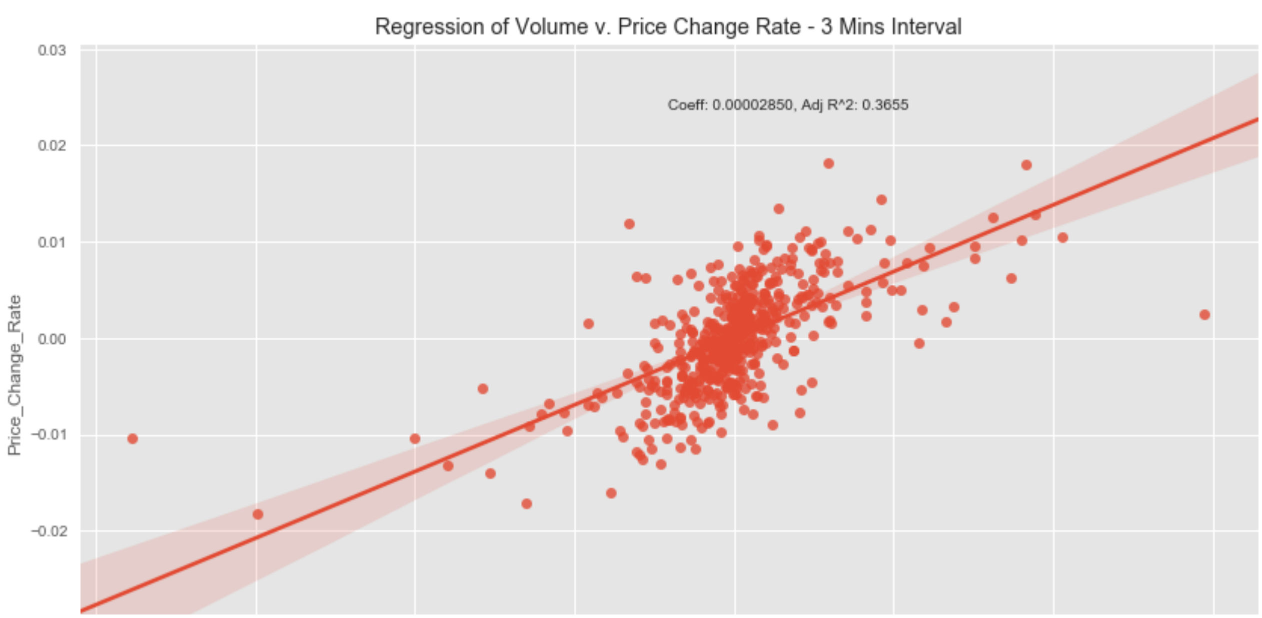
	Price	Amount_Signed
Timestamp		
2017-12-10 22:23:27	16091.00000	0.030159
2017-12-10 22:23:26	16072.60726	-0.005000
2017-12-10 22:23:26	16072.60726	-0.080000
2017-12-10 22:23:25	16071.00000	-0.100000
2017-12-10 22:23:25	16071.00000	-0.011344

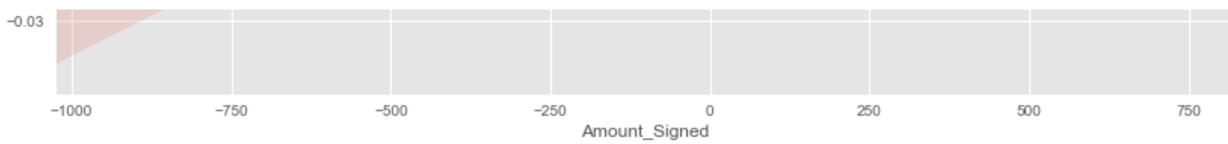
In [9]:
```
# Function to perform regression analysis on average price v. net volume,
# Given the time time interval in mins, perform regression analysis
# Outputs the regression summary and chart

def generate_regression(interval):
    global trade_volume
    trade_volume_aggr = trade_volume.copy()
    trade_volume_aggr = trade_volume.groupby([pd.Grouper(freq=str(interva
    trade_volume_aggr['Price_Obs'] = trade_volume.groupby([pd.Grouper(fre
    # print trade_volume_aggr[:10]
    trade_volume_aggr['Price_Change_Rate'] = trade_volume_aggr.pct_change

    del trade_volume_aggr['Price']
    trade_volume_aggr.to_csv("Trade_Volume_%s_Mins_Interval.csv" % str(in

    reg_res = smf.ols('Price_Change_Rate ~ Amount_Signed', data=trade_vol
    print(reg_res.summary())
    coeff = reg_res.params['Amount_Signed']
    r2_adj = reg_res.rsquared_adj

    # Plot regression, but removing outlier first
    # Keep only the ones that are within +3 to -3 standard deviations
    trade_volume_aggr_no_outlier = trade_volume_aggr[np.abs(trade_volume_
    fig, ax = plt.subplots(figsize=(14, 8))
    ax.annotate(
        'Coeff: {:.8f}, '.format(coeff) + 'Adj R^2: {:.4f}'.format(r2_adj
        xy=(.5, .9),
        xycoords=ax.transAxes)
    sns.regplot(
        x='Amount_Signed',
        y='Price_Change_Rate',
        data=trade_volume_aggr_no_outlier
    ).set_title("Regression of Volume v. Price Change Rate - %s Mins Inte
```

In [10]:
```
# Perform regression for min = 3
generate_regression(3)
```

```
                            OLS Regression Results
==============================================================================
========
Dep. Variable:      Price_Change_Rate   R-squared:
0.367
Model:                            OLS   Adj. R-squared:
0.365
Method:                 Least Squares   F-statistic:
327.0
Date:                Fri, 22 Dec 2017   Prob (F-statistic):
5.21e-58
Time:                        00:39:54   Log-Likelihood:
```

```
2203.3
No. Observations:                 567   AIC:
-4403.
Df Residuals:                     565   BIC:
-4394.
Df Model:                           1
Covariance Type:            nonrobust
======================================================================
===========
                   coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
-----------
Intercept        0.0002      0.000      0.769      0.442      -0.000
0.001
Amount_Signed  2.85e-05   1.58e-06     18.083      0.000    2.54e-05
3.16e-05
======================================================================
========
Omnibus:                      144.605   Durbin-Watson:
1.940
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
2416.727
Skew:                           0.635   Prob(JB):
0.00
Kurtosis:                      13.034   Cond. No.
133.
======================================================================
========

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

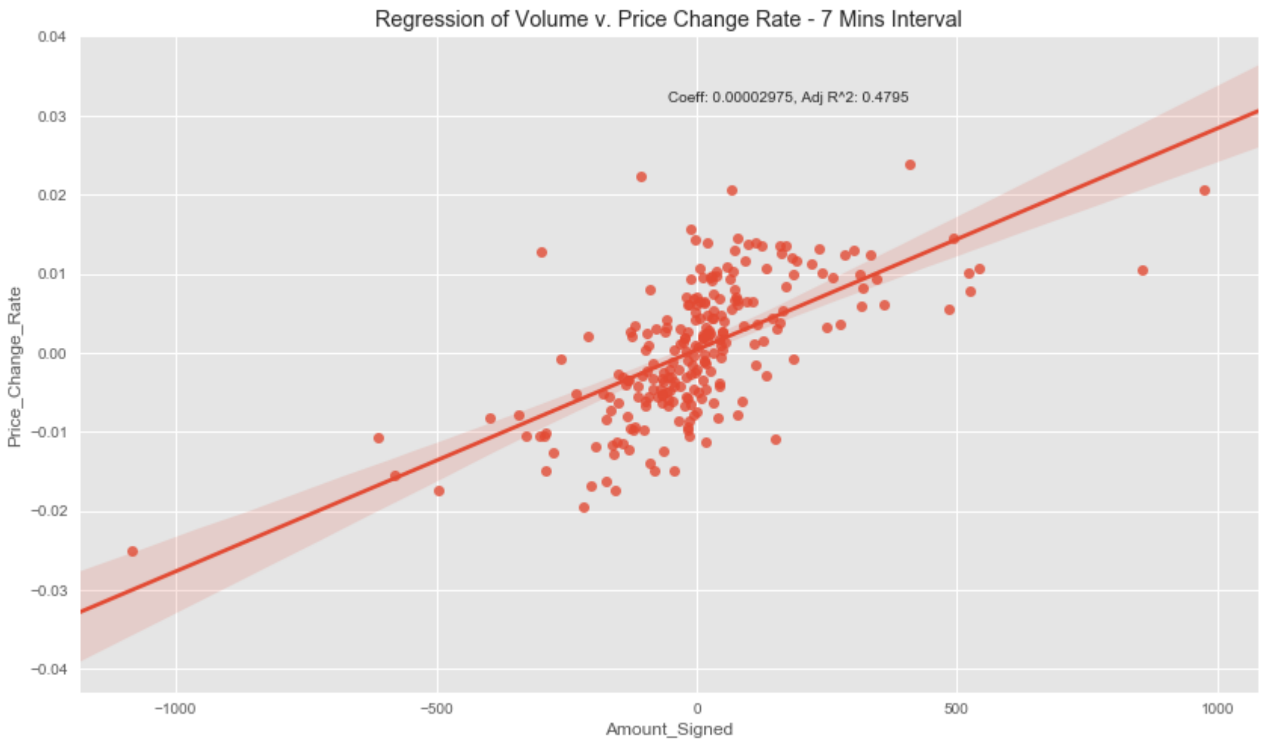




In [11]:
```
# Perform regression for min = 7
generate_regression(7)
```

```
                            OLS Regression Results
======================================================================
========
Dep. Variable:      Price_Change_Rate   R-squared:
0.482
Model:                            OLS   Adj. R-squared:
0.480
Method:                 Least Squares   F-statistic:
224.0
Date:                Fri, 22 Dec 2017   Prob (F-statistic):
2.98e-36
Time:                        00:39:55   Log-Likelihood:
880.65
No. Observations:                 243   AIC:
-1757.
Df Residuals:                     241   BIC:
-1750.
Df Model:                           1
Covariance Type:            nonrobust
======================================================================
===========
                    coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
-----------
Intercept         0.0004      0.000      0.915      0.361      -0.000
0.001
Amount_Signed  2.975e-05   1.99e-06     14.966      0.000    2.58e-05
3.37e-05
======================================================================
========
Omnibus:                        8.926   Durbin-Watson:
2.247
Prob(Omnibus):                  0.012   Jarque-Bera (JB):
10.083
Skew:                           0.341   Prob(JB):
0.00646
Kurtosis:                       3.729   Cond. No.
209.
======================================================================
========
```

```
Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

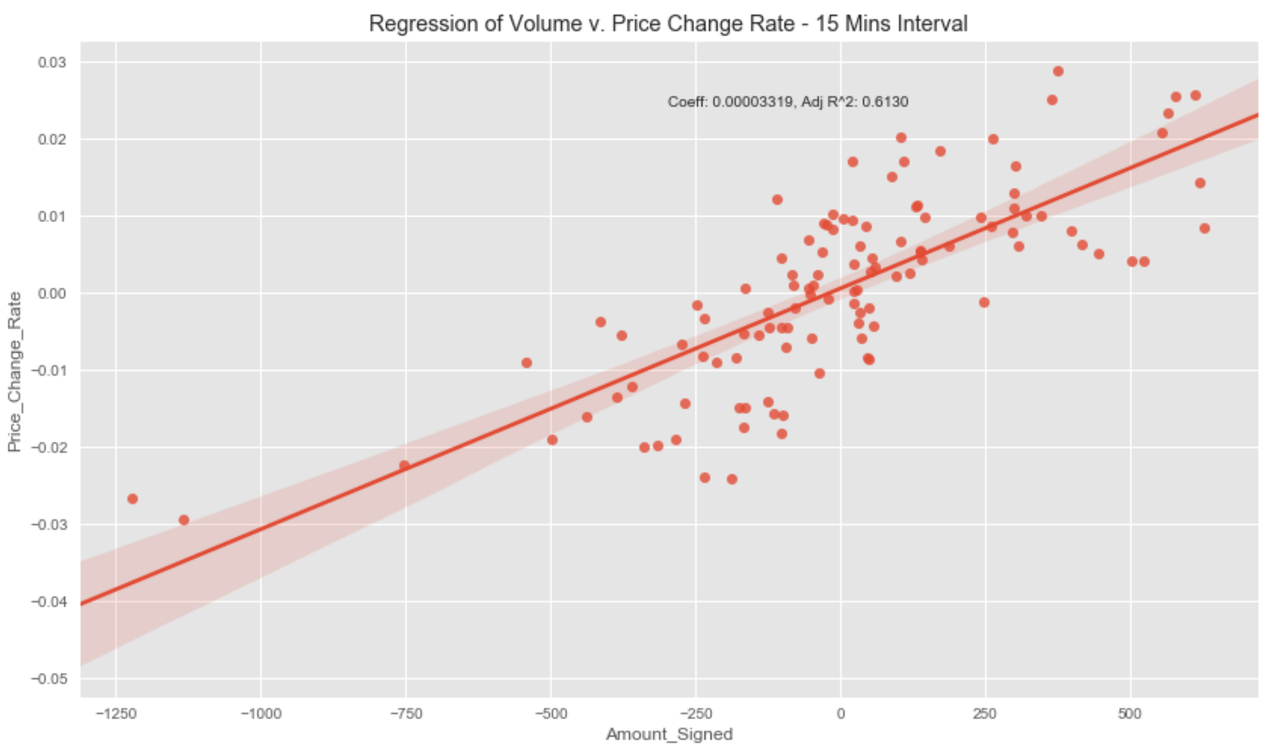


In [24]:

```
# Perform regression for min = 15
generate_regression(15)
```

```
                            OLS Regression Results
==============================================================================
========
Dep. Variable:      Price_Change_Rate   R-squared:
0.617
Model:                            OLS   Adj. R-squared:
0.613
Method:                 Least Squares   F-statistic:
178.4
Date:                Fri, 22 Dec 2017   Prob (F-statistic):
7.58e-25
Time:                        00:42:49   Log-Likelihood:
383.22
No. Observations:                 113   AIC:
-762.4
Df Residuals:                     111   BIC:
-757.0
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
===========
                    coef    std err          t      P>|t|      [0.025
```

```
0.975]
------------------------------------------------------------------------------
Intercept          0.0008      0.001      1.079      0.283      -0.001
0.002
Amount_Signed   3.319e-05   2.48e-06     13.358      0.000    2.83e-05
3.81e-05
==============================================================================
Omnibus:                        1.766   Durbin-Watson:
2.318
Prob(Omnibus):                  0.414   Jarque-Bera (JB):
1.244
Skew:                           0.205   Prob(JB):
0.537
Kurtosis:                       3.309   Cond. No.
311.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

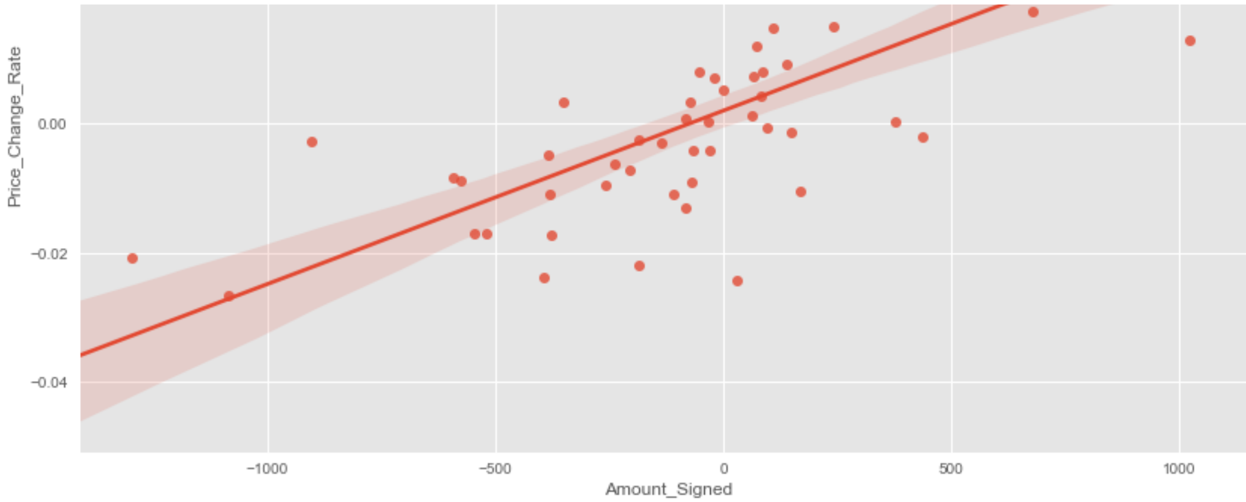


In [25]:

```
# Perform regression for min = 30
generate_regression(30)
```

```
                            OLS Regression Results
==============================================================================
```

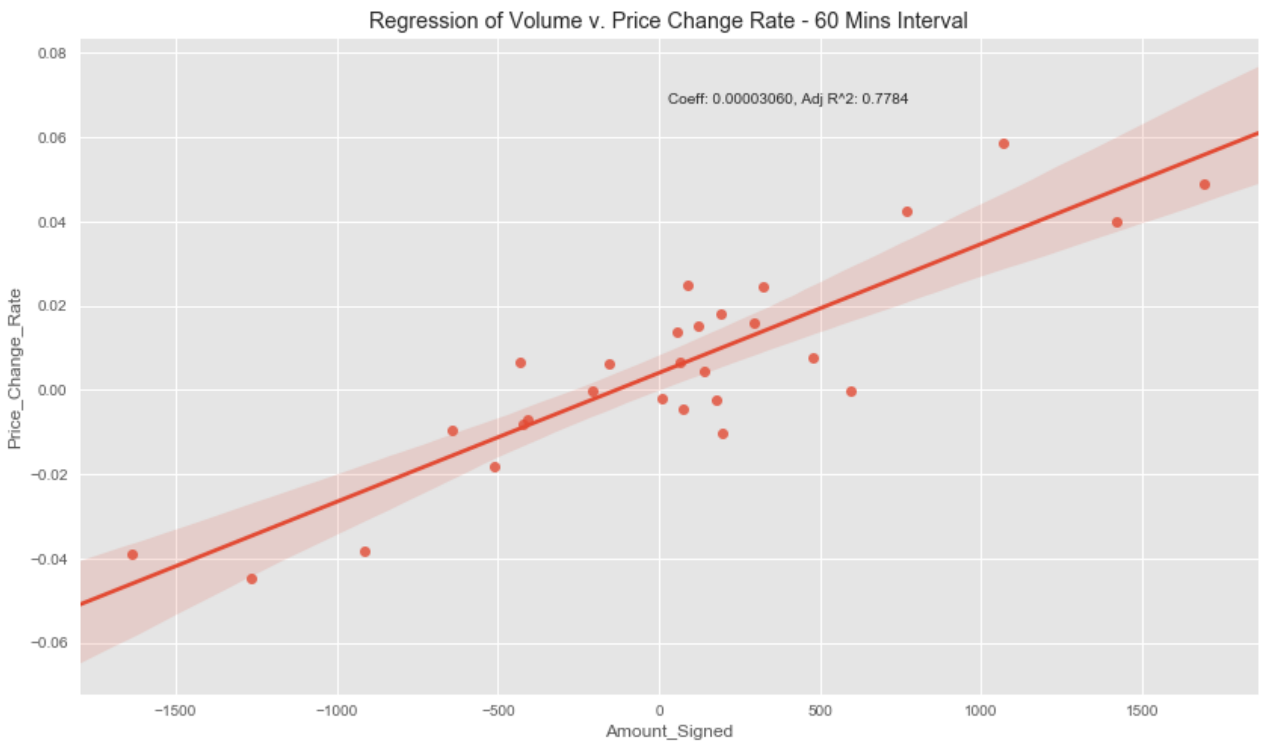
```
========
Dep. Variable:      Price_Change_Rate   R-squared:
0.629
Model:                            OLS   Adj. R-squared:
0.623
Method:                 Least Squares   F-statistic:
91.71
Date:                Fri, 22 Dec 2017   Prob (F-statistic):
3.09e-13
Time:                        00:42:52   Log-Likelihood:
179.26
No. Observations:                  56   AIC:
-354.5
Df Residuals:                      54   BIC:
-350.5
Df Model:                           1
Covariance Type:            nonrobust
======================================================================
===========
                   coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
-----------
Intercept         0.0020      0.001      1.526      0.133      -0.001
0.005
Amount_Signed  2.685e-05    2.8e-06      9.577      0.000    2.12e-05
3.25e-05
======================================================================
========
Omnibus:                        1.190   Durbin-Watson:
2.320
Prob(Omnibus):                  0.552   Jarque-Bera (JB):
0.944
Skew:                          -0.316   Prob(JB):
0.624
Kurtosis:                       2.938   Cond. No.
479.
======================================================================
========

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```



In [26]:
```
# Perform regression for min = 60
generate_regression(60)
```

```
                            OLS Regression Results
==============================================================================
========
Dep. Variable:      Price_Change_Rate   R-squared:
0.787
Model:                            OLS   Adj. R-squared:
0.778
Method:                 Least Squares   F-statistic:
95.82
Date:                Fri, 22 Dec 2017   Prob (F-statistic):
3.30e-10
Time:                        00:42:55   Log-Likelihood:
85.984
No. Observations:                  28   AIC:
-168.0
Df Residuals:                      26   BIC:
-165.3
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
===========
                    coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-----------
Intercept         0.0040      0.002      1.826      0.079      -0.001
0.009
Amount_Signed   3.06e-05   3.13e-06      9.789      0.000    2.42e-05
3.7e-05
==============================================================================
========
Omnibus:                        0.501   Durbin-Watson:
```

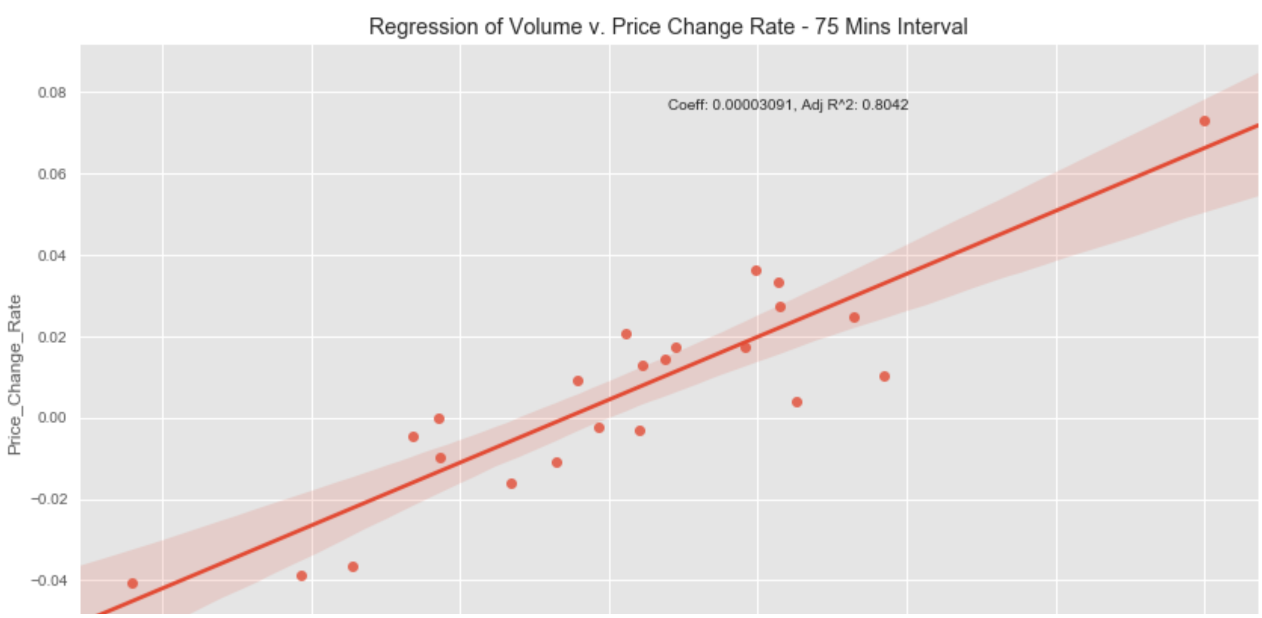
```
2.399
Prob(Omnibus):                  0.778   Jarque-Bera (JB):
0.592
Skew:                          -0.047   Prob(JB):
0.744
Kurtosis:                       2.294   Cond. No.
707.
======================================================================
========

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

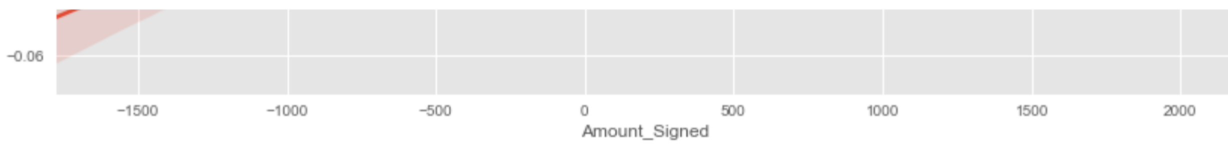


In [27]:
```
# Perform Regression for 3 hours
generate_regression(75)
```

```
                            OLS Regression Results
======================================================================
========
Dep. Variable:      Price_Change_Rate   R-squared:
0.813
Model:                            OLS   Adj. R-squared:
0.804
Method:                 Least Squares   F-statistic:
91.37
Date:                Fri, 22 Dec 2017   Prob (F-statistic):
4.25e-09
Time:                        00:43:03   Log-Likelihood:
```

```
71.086
No. Observations:                  23   AIC:
-138.2
Df Residuals:                      21   BIC:
-135.9
Df Model:                           1
Covariance Type:            nonrobust
======================================================================
===========
                   coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
-----------
Intercept        0.0044      0.002      1.810      0.085      -0.001
0.009
Amount_Signed 3.091e-05   3.23e-06      9.559      0.000    2.42e-05
3.76e-05
======================================================================
========
Omnibus:                        2.023   Durbin-Watson:
2.185
Prob(Omnibus):                  0.364   Jarque-Bera (JB):
1.458
Skew:                          -0.409   Prob(JB):
0.482
Kurtosis:                       2.077   Cond. No.
746.
======================================================================
========

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```





Regression Results

As we can see, the regression value, R squared, increases over time to its maximum regression of 78% for a one hour time horizon. One possible explanation for this is the time needed for an effecient market to factor in all the trades. Thus, the following strategy is based off of the best merger of regression results and use of chart observations.

R Chart

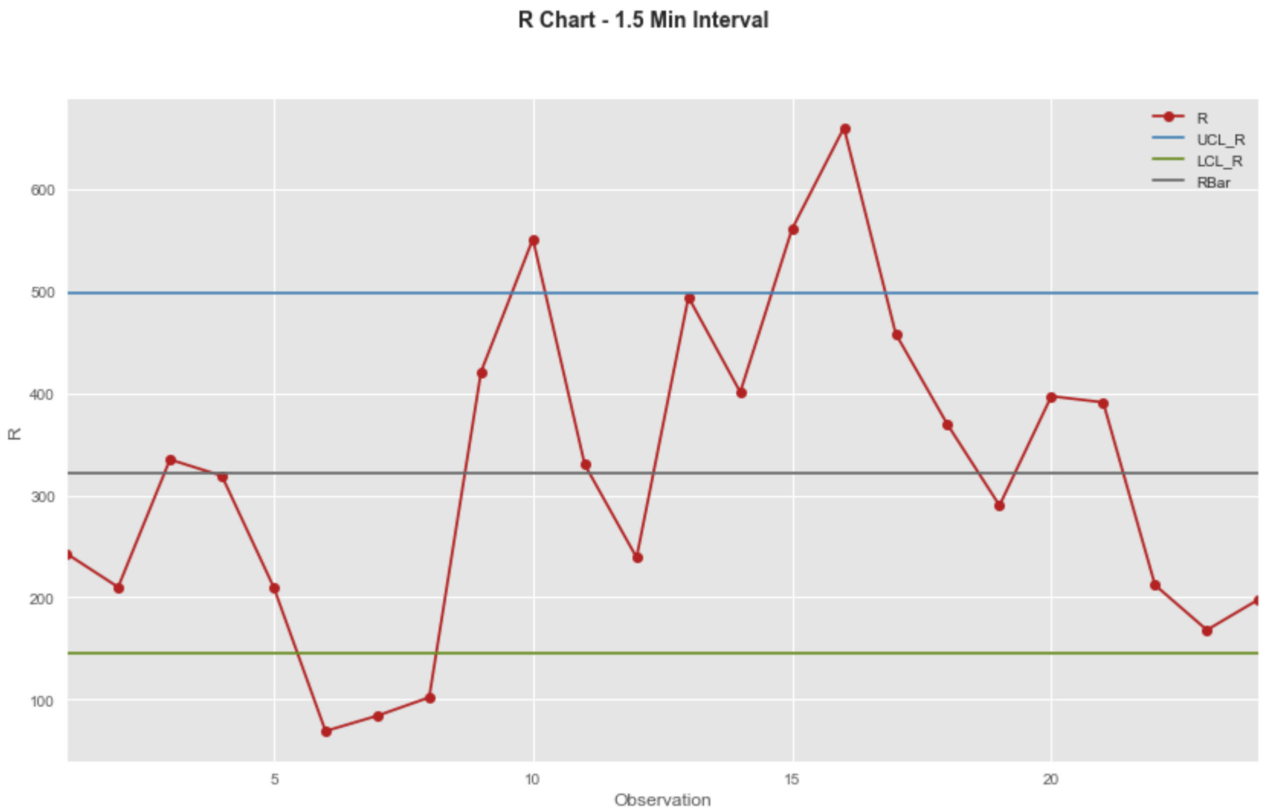
The R chart meausres how much variation there is within each subgroup observation. If the variation within the subgroups is too high, tested by the run tests, then the measurements on the X-Bar chart are meanignless and the data is insignificant. However, since this is a trading program, any significant deviation on the R chart will consequently show up on the X chart as well, potentially breaking the run rules and indicating a buy trigger.

If the measurements are in control then the observations are transferred to the X-Bar chart to check if the process is under control, if out of control, execute trades accordingly. Each subgroup is the aggregated average within a 1.5 minute time frame. Each R chart will yield 24 observations of 1.5 min, these will be later averaged and transferred to the X Chart for further process analyzation.

In [20]:
```
# Generate R Chart

r_chart = trade_volume.copy()
r_chart = trade_volume.groupby([pd.Grouper(freq='90s')]).mean()
r_chart['R'] = trade_volume.groupby([pd.Grouper(freq='90s')]).size()
r_chart = r_chart[['Price', 'R']][:24]

RBar = r_chart["R"].sum()/len(r_chart) ## mean value of range of each lot
r_chart['RBar'] = RBar
r_chart['UCL_R'] = 1.548*RBar  # upper control limit
r_chart['LCL_R'] = 0.451*RBar  # lower control limit

r_chart['idx'] = range(1, len(r_chart) + 1)
r_chart.index = r_chart['idx']

del r_chart['idx']

r_chart.to_csv('r_chart.csv')
```

```
fig, ax = plt.subplots(figsize=(14, 8))
r_chart['R'].plot(marker="o", color='firebrick')
r_chart['UCL_R'].plot(color='steelblue')
r_chart['LCL_R'].plot(color='olivedrab')
r_chart['RBar'].plot(color='dimgray')
ax.legend()
ax.set_xlabel('Observation')
ax.set_ylabel('R')
fig.suptitle('R Chart - 1.5 Min Interval', fontsize=14, fontweight='bold'
```

Out[20]: <matplotlib.text.Text at 0x113c14e10>



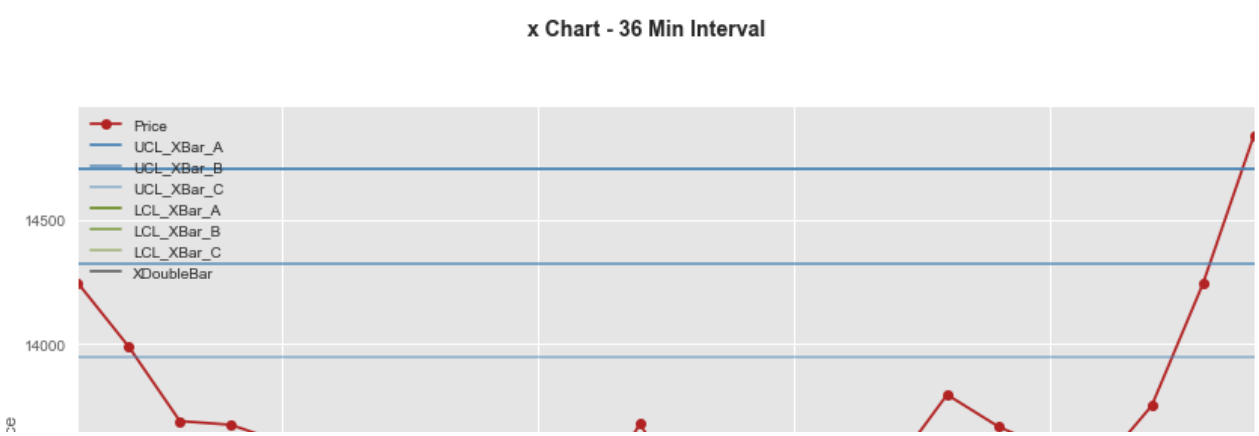
X Chart

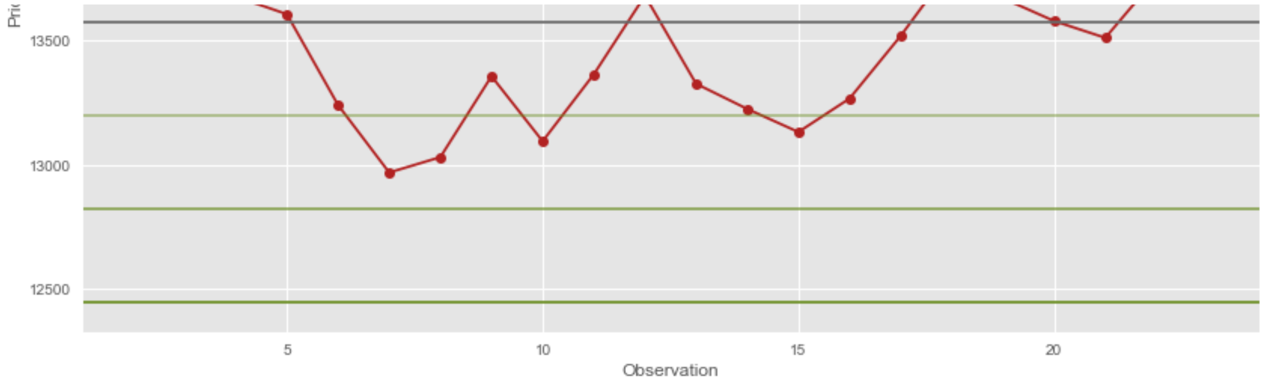
The X Bar chart measures the mean of a process based on samples taken from equal time blocks, in this case every 36 minutes. The measurements of the samples for a given period create the subgroup and are then plotted on the graph. The mean and std from the sample data are used to construct upper and lower control limits such that, under the assumption that the variation follows a normal distribution, 99.73% of observations should fall between 3 and -3 sigma. When an observation is outside these established control limits, it indicates that the mean of the process is out-of-control and an assingable cause is determined to cause such variation. For Bitcoin, any assingable cause would be represented by large amounts of volume traded, hence influencing the change in price.

In [21]:
```
# Generate X Chart
```

In [21]:
```
# Generate x chart
x_chart = trade_volume.copy()
x_chart = trade_volume.groupby([pd.Grouper(freq='2160s')]).mean()
x_chart['R'] = trade_volume.groupby([pd.Grouper(freq='2160s')]).size()
x_chart = x_chart[['Price', 'R']][:24]
RBar = x_chart["R"].sum()/len(x_chart) ## mean value of range of each lot
XDoubleBar = x_chart["Price"].sum()/len(x_chart)
x_chart['XDoubleBar'] = XDoubleBar
x_chart['UCL_XBar_A'] = XDoubleBar + (0.157 * RBar)
x_chart['UCL_XBar_B'] = XDoubleBar + (0.157 * RBar * 2/3)
x_chart['UCL_XBar_C'] = XDoubleBar + (0.157 * RBar * 1/3)
x_chart['LCL_XBar_A'] = XDoubleBar - (0.157 * RBar)
x_chart['LCL_XBar_B'] = XDoubleBar - (0.157 * RBar * 2/3)
x_chart['LCL_XBar_C'] = XDoubleBar - (0.157 * RBar * 1/3)

x_chart['idx'] = range(1, len(x_chart) + 1)
x_chart.index = x_chart['idx']

del x_chart['idx']

x_chart.to_csv('x_chart.csv')

fig, ax = plt.subplots(figsize=(14, 8))
x_chart['Price'].plot(marker="o", color='firebrick')
x_chart['UCL_XBar_A'].plot(color='steelblue', alpha=1)
x_chart['UCL_XBar_B'].plot(color='steelblue', alpha=0.75)
x_chart['UCL_XBar_C'].plot(color='steelblue', alpha=0.5)
x_chart['LCL_XBar_A'].plot(color='olivedrab', alpha=1)
x_chart['LCL_XBar_B'].plot(color='olivedrab', alpha=0.75)
x_chart['LCL_XBar_C'].plot(color='olivedrab', alpha=0.5)
x_chart['XDoubleBar'].plot(color='dimgray')

ax.legend()
ax.set_xlabel('Observation')
ax.set_ylabel('Price')

fig.suptitle('x Chart - 36 Min Interval', fontsize=14, fontweight='bold')
```

Out[21]: <matplotlib.text.Text at 0x106ea0a20>





The following instructions are the codified version of the run rules which SPC is based off of. Because this program aims to identify when the process is negatively out of control, I adapted the rules to only identify a negative trend such that if our key assumptions hold, the correction to the true mean will yield a consistent and measurable return on investment.

The run rules are listed above the respective code.

In [22]:

```
# from a given observations, decide if we should buy the stock or not
def is_buy(data_df):
    buy = False
    applied_rules = set()
    # prepare the data
    buy_data = data_df.copy()
    buy_data = trade_volume.groupby([pd.Grouper(freq='2160s')]).mean()
    buy_data['R'] = data_df.groupby([pd.Grouper(freq='2160s')]).size()
    buy_data = buy_data[['Price', 'R']][2:26]
    RBar = buy_data["R"].sum()/len(buy_data)
    ## mean value of range of each lot
    XDoubleBar = buy_data["Price"].sum()/len(buy_data)
    UCL_XBar = XDoubleBar + 0.157 * RBar
    LCL_XBar = XDoubleBar - 0.157 * RBar
    UCL_XBar_A = XDoubleBar + (0.157 * RBar)
    UCL_XBar_B = XDoubleBar + (0.157 * RBar * 2/3)
    UCL_XBar_C = XDoubleBar + (0.157 * RBar * 1/3)
    LCL_XBar_A = XDoubleBar - (0.157 * RBar)
    LCL_XBar_B = XDoubleBar - (0.157 * RBar * 2/3)
    LCL_XBar_C = XDoubleBar - (0.157 * RBar * 1/3)

    price_list = buy_data['Price'].tolist()

    buy_data['pct_chg'] = buy_data['Price'].pct_change()
    pct_chg = buy_data['pct_chg'].tolist()

    buy_data['prev'] = buy_data['pct_chg'].shift()

    # check all the rules applied
    # 1. One or more points beyond the control limits
```

```
    if (buy_data['Price'].any() < LCL_XBar):
        applied_rules.add('1')
        buy = True

    # 2. 2 out of 3 consecutive points in zone A or beyond (negative)
    for i, val in enumerate(price_list[:-2]):
        price_list_subset = price_list[i:i+3]
        price_list_a = [1 if x < LCL_XBar_B else 0 for x in price_list_su
        if sum(price_list_a) > 1:
            applied_rules.add('2')
            buy = True

    # 3. 4 out of 5 consecutive points in zone B or beyond (negative)
    for i, val in enumerate(price_list[:-4]):
        price_list_subset = price_list[i:i+5]
        price_list_b = [1 if x < LCL_XBar_C else 0 for x in price_list_su
        if sum(price_list_b) > 3:
            applied_rules.add('3')
            buy = True

    # 4. 7 or more consecutive points in zone C or beyond, at one side on
    for i, val in enumerate(price_list[:-7]):
        price_list_subset = price_list[i:i+8]
        price_list_low = [1 if x < 0 else 0 for x in price_list_subset]
        if sum(price_list_low) > 6:
            applied_rules.add('4')
            buy = True

    # 5. 7 consecutive points are in the same trend (negative)
    for i, val in enumerate(pct_chg[:-7]):
        pct_chg_subset = pct_chg[i:i+8]
        pct_chg_min = [1 if x < 0 else 0 for x in pct_chg_subset]
        if sum(pct_chg_min) > 6:
            applied_rules.add('5')
            buy = True

    # 6. 8 consecutive points with no point in zone C (negative)
    for i, val in enumerate(price_list[:-7]):
        price_list_subset = price_list[i:i+8]
        price_list_no_c = [1 if x < LCL_XBar_C else 0 for x in price_list
        if sum(price_list_no_c) > 7:
            applied_rules.add('6')
            buy = True

    # 7. 15 consecutive points in zone C
    for i, val in enumerate(price_list[:-14]):
        price_list_subset = price_list[i:i+15]
        price_list_c = [1 if x > LCL_XBar_C and x < UCL_XBar_C else 0 for
        if sum(price_list_c) > 14:
            applied_rules.add('7')
            buy = True
```

```
            buy = True

    # 8. 14 consecutive points alternating up and down
    buy_data_subset = buy_data[2:].copy()
    buy_data_subset['mult_val'] =  buy_data_subset['pct_chg'] * buy_data_
    buy_data_subset['alt'] = buy_data_subset['mult_val'].apply(lambda x:
    price_list_alt = buy_data_subset['alt'].tolist()
    for i, val in enumerate(price_list_alt[:-13]):
        price_list_subset = price_list[i:i+14]
        if sum(price_list_c) > 13:
            applied_rules.add('8')
            buy = True

    if (buy):
        print ("Action: Buy the stock.")
        print ("Rules applied: %s" % ", ".join(applied_rules))
```

In [23]:
```
# test the rules for the data
is_buy(trade_volume)
```

```
Action: Buy the stock.
Rules applied: 1, 3
```

Limitations

Because the process we are observing utilizes the previous days information, it inherently can not predict accurately whether the price will go up or down. What happened in the past does not mean the process will continue equally. Rather by using the most up to date information, the limits constructed by the R chart and X chart will be as close to the current trading day as possible.

Another limitation of this program is the rules SPC operates on. Because the rules of Statistical Process Control are originally from manufacturing and quality management, it has not been proven to be an effective strategy for valuing currency volatility.

The key assumptions innately limit the functionality of the program becaue it assumes no systematic risk to investing in bitcoin.

Conclusion

The cryptocurrency market displays a strong correlation between the net volume traded and respective change in price. While some may consider cryptocurrencies a bubble, it is undeniably a lucrative investment which can be leveraged by playing on Bitcoin's volatility and taking human intuition out of the investing strategy.