

# Cryptocurrencies Pricing Analysis

## RIHAD VARIAWA

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```
In [0]: !pip install Quandl
!pip install plotly

Collecting quandl
  Downloading https://files.pythonhosted.org/packages/ff/b9/237594fb7f236d0233bcb39a21c1d9d0c2050393762ff51b8b3b20269c/Quandl-3.4.4-py3-none-any.whl
Requirement already satisfied: requests>=2.7.0 in /usr/local/lib/python3.6/dist-packages (from quandl) (2.18.4)
Collecting inflection<0.3.1 (from quandl)
  Downloading https://files.pythonhosted.org/packages/d5/35/a6eb45b4e2356fe688261570846a0a0480e38def9c589112077f8/inflection-0.3.1.tar.gz
Collecting more-iterertools (from quandl)
  Downloading https://files.pythonhosted.org/packages/79/b1/eace304ef66bd7d3d8b2f78cc374b73ca03bc53664d781e3df3b3996cc/more_iterertools-4.3.0-py3-none-any.whl (498kB)
    100kB |#####| 51KB 4.3MB/s
Requirement already satisfied: numpy>=1.8 in /usr/local/lib/python3.6/dist-packages (from quandl) (1.14.6)
Requirement already satisfied: python-dateutil in /usr/local/lib/python3.6/dist-packages (from quandl) (2.5.3)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from quandl) (1.11.0)
Requirement already satisfied: pandas>=0.14 in /usr/local/lib/python3.6/dist-packages (from quandl) (0.22.0)
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /usr/local/lib/python3.6/dist-packages (from requests>=2.7.0->quandl) (3.0.4)
Requirement already satisfied: urllib3<1.23,>=1.21.1 in /usr/local/lib/python3.6/dist-packages (from requests>=2.7.0->quandl) (1.22)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.6/dist-packages (from requests>=2.7.0->quandl) (2018.10.15)
Requirement already satisfied: idna<2.7,>=2.5 in /usr/local/lib/python3.6/dist-packages (from requests>=2.7.0->quandl) (2.6)
Requirement already satisfied: pytz>=2011k in /usr/local/lib/python3.6/dist-packages (from pandas>=0.14->quandl) (2018.6)
Building wheels for collected packages: inflection
  Running setup.py bdist_wheel for inflection ... 0 Bdone
  Stored in directory: /root/.cache/pip/wheels/9f/5a/d3/6fc3bf6516d2a3eb7e18f9f28b472110b5925f3f258fe9211
Successfully built inflection
Installing collected packages: inflection, more-iterertools, quandl
Successfully installed inflection-0.3.1 more-iterertools-4.3.0 quandl-3.4.4
Requirement already satisfied: plotly in /usr/local/lib/python3.6/dist-packages (1.12.12)
Requirement already satisfied: requests in /usr/local/lib/python3.6/dist-packages (from plotly) (2.18.4)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from plotly) (1.11.0)
Requirement already satisfied: pytz in /usr/local/lib/python3.6/dist-packages (from plotly) (2018.6)
Requirement already satisfied: urllib3<1.23,>=1.21.1 in /usr/local/lib/python3.6/dist-packages (from requests>=2.7.0->quandl) (1.22)
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Requirement already satisfied: idna<2.7,>=2.5 in /usr/local/lib/python3.6/dist-packages (from requests>=2.7.0->quandl) (2.6)
```

```
In [0]: import os
import numpy as np
import pandas as pd
import pickle
import quandl
from datetime import datetime
```

```
In [0]: #Enable offline mode
import plotly.offline as py
import plotly.graph_objs as go
from plotly.tools import FigureFactory as FF
py.init_notebook_mode(connected=True)
```

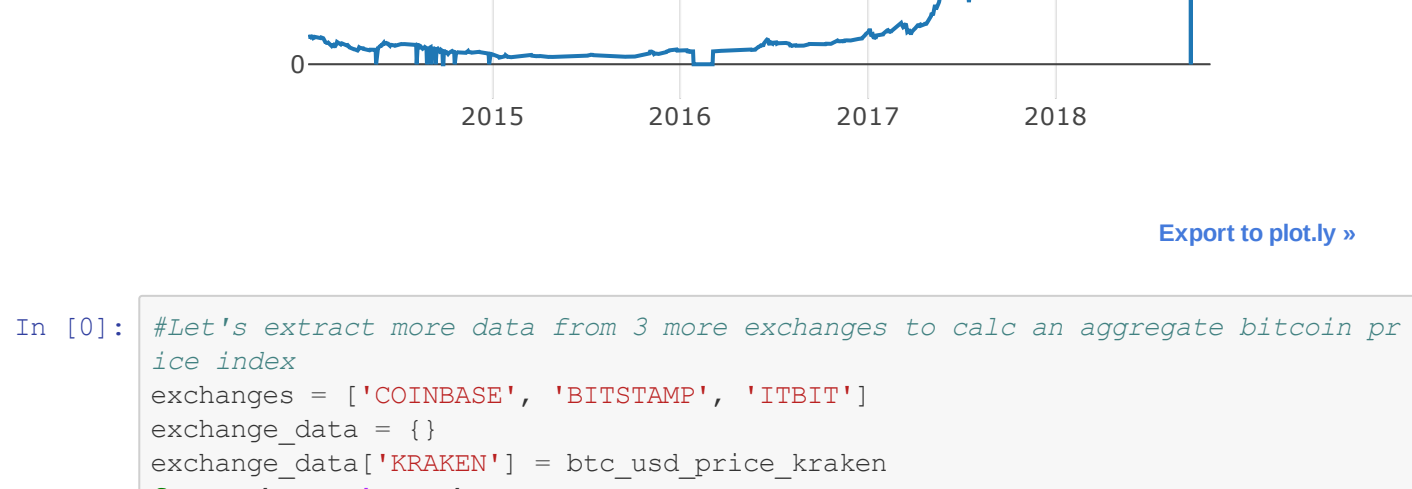
```
In [0]: #Let's get bitcoin pricing data using Quandl's bitcoin API
def get_quandl_data(quandl_id):
    cache_path = '{}.pkl'.format(quandl_id).replace('/', '-')
    try:
        f = open(cache_path, 'rb')
        df = pickle.load(f)
        print('Loaded {} from cache'.format(quandl_id))
    except (OSError, IOError) as e:
        print('Downloading {} from Quandl'.format(quandl_id))
        df = quandl.get(quandl_id, returns="pandas")
        df.to_pickle(cache_path)
        print('Cached {} as {}'.format(quandl_id, cache_path))
    return df
```

```
In [0]: #Let's get pricing data from Kraken bitcoin exchange
btc_usd_price_kraken = get_quandl_data('BCHARTS/KRAKENUSD')
Downloading BCHARTS/KRAKENUSD from Quandl
Cached BCHARTS/KRAKENUSD as BCHARTS-KRAKENUSD.pkl
```

```
In [0]: #Let's inspect the first 5 rows
btc_usd_price_kraken.head()
```

	Open	High	Low	Close	Volume (BTC)	Volume (Currency)	Weighted Price
Date							
2014-01-07	874.67040	892.06753	810.00000	810.00000	15.622378	13151.472844	841.835522
2014-01-08	810.00000	899.84281	788.00000	824.96287	19.182756	16097.329584	839.156269
2014-01-09	825.56345	870.00000	807.42084	841.86934	8.158335	6784.249982	831.572913
2014-01-10	839.99000	857.34056	817.00000	857.32056	8.024510	6780.220188	844.938794
2014-01-11	858.20000	918.05471	857.16554	899.84105	18.748285	16698.566929	890.671709

```
In [0]: #Let's visualize the data
btc_trace = go.Scatter(x=btc_usd_price_kraken.index, y=btc_usd_price_kraken['Weighted Price'])
py.iplot(btc_trace)
```



```
In [0]: #Let's extract more data from 3 more exchanges to calc an aggregate bitcoin price index
exchanges = ['COINBASE', 'BITSTAMP', 'ITBIT']
exchange_data = {}
for exchange in exchanges:
    exchange_code = 'BCHARTS/{}'.format(exchange)
    btc_exchange_df = get_quandl_data(exchange_code)
    exchange_data[exchange] = btc_exchange_df
Downloading BCHARTS/COINBASEUSD from Quandl
Cached BCHARTS/COINBASEUSD as BCHARTS-COINBASEUSD.pkl
Downloading BCHARTS/BITSTAMPUSD from Quandl
Cached BCHARTS/BITSTAMPUSD as BCHARTS-BITSTAMPUSD.pkl
Downloading BCHARTS/ITBITUSD from Quandl
Cached BCHARTS/ITBITUSD as BCHARTS-ITBITUSD.pkl
```

```
In [0]: #Let's merge all pricing data into a single df
#merge dfs on column (dataframes, labels, cols):
series_dict = {}
for index in range(len(exchange_data)):
    series_dict[index] = exchange_data[index].col
return pd.DataFrame(series_dict)
```

```
In [0]: #Let's merge all df on their 'Weighted Price' col
btc_usd_datasets = merge_dfs_on_column(list(exchange_data.values()), list(exchange_data.keys()), 'Weighted Price')
```

```
In [0]: #Let's preview last 5 rows
btc_usd_datasets.tail()
```

	BITSTAMP	COINBASE	ITBIT	KRAKEN
Date				
2018-10-25	6397.527049	6400.245236	6399.338522	6398.123113
2018-10-26	6409.420536	6403.984360	6398.979986	6404.132246
2018-10-27	6404.827196	6405.738944	6400.116561	6405.367996
2018-10-28	6402.355831	6401.989052	6402.783307	6410.208619
2018-10-29	6298.770994	6300.944994	6281.930929	6306.690944

Prices seem to be as expected. Similar across all ranges, but with slight variations based on the demand and supply of each individual bitcoin datasets.

```
In [0]: #Let's visualize how these pricing datasets compare
def df_scatter(df, title, separate_y_axis=False, y_axis_label='', scale='linear', initial_hide=False):
    label_arr = list(df)
    series_arr = list(map(lambda col: df[col], label_arr))

    layout = go.Layout(
        title=title,
        legend=dict(orientation="h"),
        xaxis=dict(type='date'),
        yaxis=dict(
            title=y_axis_label,
            showlabel=not separate_y_axis,
            type=scale
        )
    )

    y_axis_config = dict(
        overlaying='y',
        showticklabels=False,
        type=scale
    )

    visibility = 'visible'
    if initial_hide:
        visibility = 'legendonly'

    #Form trace for each series
    trace_arr = []
    for index, series in enumerate(series_arr):
        trace = go.Scatter(
            x=series.index,
            y=series,
            name=label_arr[index],
            visible=visibility
        )
        trace_arr.append(trace)

    #Add separate axis for the series
    if separate_y_axis:
        trace['yaxis1'] = 'y{}'.format(index + 1)
        layout['yaxis1'] = 'y{}'.format(index + 1)
        trace_arr.append(trace)

    fig = go.Figure(data=trace_arr, layout=layout)
    py.iplot(fig)
```

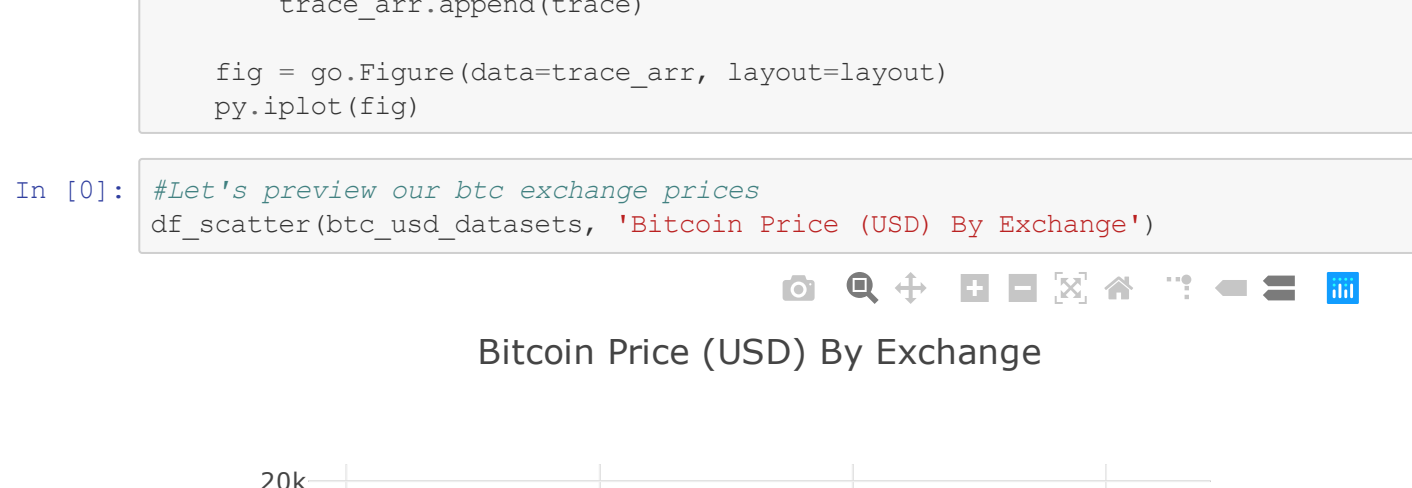
```
In [0]: #Let's preview our btc exchange prices
df_scatter(btc_usd_datasets, 'Bitcoin Price (USD) By Exchange')
```



We notice that, although the four series follow roughly the same path, there are various irregularities in each that we'll want to zero in on.

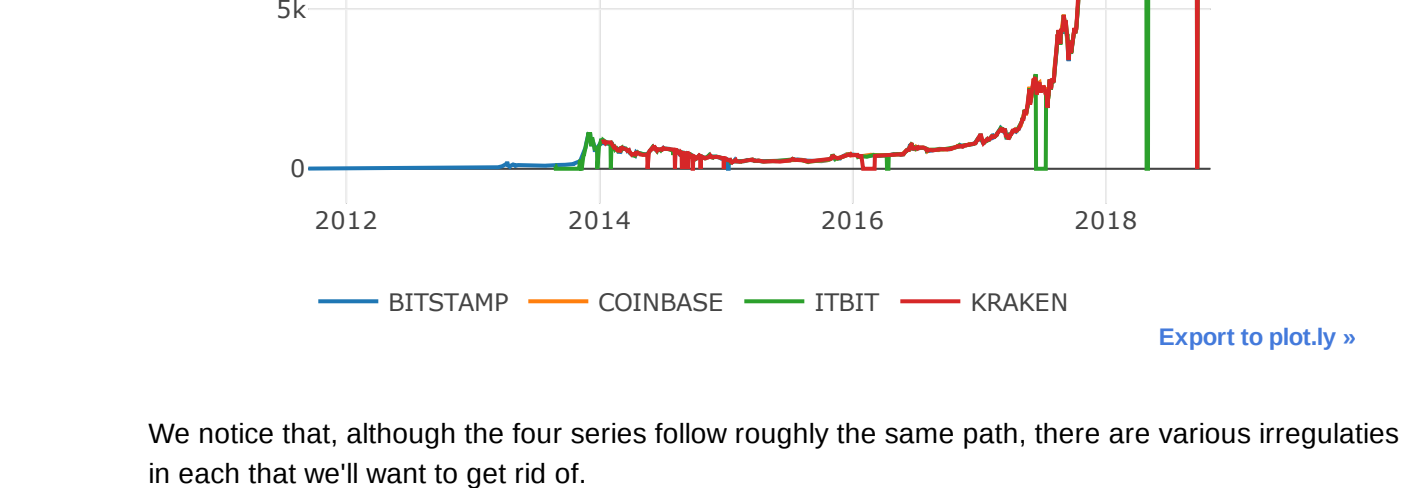
```
In [0]: #Let's remove all zero values from the df, since btc pricing has never been eq ual to zero in the timeframe we are reviewing
btc_usd_datasets.replace(0, np.nan, inplace=True)
```

```
In [0]: #Let's re-chart the df to see a cleaner chart without down-spikes
df_scatter(btc_usd_datasets, 'Bitcoin Price (USD) By Exchange')
```



```
In [0]: #Let's calc a new col containing the average btc price across all exchanges
btc_usd_datasets['avg_btc_price_usd'] = btc_usd_datasets.mean(axis=1)
```

```
In [0]: #Let's chart this col to make sure it previews ok
btc_trace = go.Scatter(x=btc_usd_datasets.index, y=btc_usd_datasets['avg_btc_price_usd'])
py.iplot(btc_trace)
```



Great!

```
In [0]: #Let's retrieve data on altcoins, (non-btc currencies) using 2 helper function s to download and cache JSON data from this API
def get_json_data(json_url, cache_path):
    try:
        f = open(cache_path, 'rb')
        df = pickle.load(f)
        print('Loaded {} from cache'.format(json_url))
    except (OSError, IOError) as e:
        print('Downloading {} from Quandl'.format(json_url))
        df = pd.read_json(json_url)
        df.to_pickle(cache_path)
        print('Cached {} as {}'.format(json_url, cache_path))
    return df
```

```
In [0]: #Let's define a function that will generate Poloniex API HTTP requests and sub sequently call our new function to save the resulting data
base_polo_url = 'https://poloniex.com/public?command=returnChartData&currencyPair={}&start={}&end={}&period={}'
start_date = datetime.strptime('2015-01-01', '%Y-%m-%d') # get data from the s tart of 2015
end_date = datetime.now() # up until today
period = 86400 # pull daily data (86,400 seconds per day)
```

```
def get_crypto_data(poloniex_pair):
    """Retrieve cryptocurrency data from poloniex"""
    json_url = base_polo_url.format(poloniex_pair, start_date.timestamp(), end _date.timestamp())
    data_df = get_json_data(json_url, poloniex_pair)
    data_df = data_df.set_index('date')
    return data_df
```

This function will take a cryptocurrency pair string (such as 'BTC\_ETH') and return a dataframe containing the historical exchange rate of the two currencies.

Most altcoins cannot be bought directly with USD; to acquire these coins individuals often buy Bitcoins and then trade the Bitcoins for altcoins on cryptocurrency exchanges.

Hence, we'll download the exchange rate to BTC for each coin, and then we'll use our existing BTC pricing data to convert this value to USD.

We'll download exchange data for nine of the top cryptocurrencies.

Ethereum, Litecoin, Ripple, Ethereum Classic, Stellar, Dash, Siacon, Monero, and NEM.

```
In [0]: altcoins = ['ETH', 'LTC', 'XRP', 'BTC', 'STR', 'DASH', 'SC', 'XMR', 'XEM']
for altcoin in altcoins:
    coinpair = 'BTC_{}'.format(altcoin)
    crypto_data_df = get_crypto_data(coinpair)
    altcoin_data[altcoin] = crypto_data_df
```

```
Downloading https://poloniex.com/public?command=returnChartData&currencyPair=BTC_ETH&start=1420070400.0&end=1540889085.14896&period=86400 at BTC_ETH
Cached https://poloniex.com/public?command=returnChartData&currencyPair=BTC_ETH&start=1420070400.0&end=1540889085.14896&period=86400 at BTC_ETH
Downloading https://poloniex.com/public?command=returnChartData&currencyPair=BTC_LTC&start=1420070400.0&end=1540889085.14896&period=86400 at BTC_LTC
Cached https://poloniex.com/public?command=returnChartData&currencyPair=BTC_LTC&start=1420070400.0&end=1540889085.14896&period=86400 at BTC_LTC
Downloading https://poloniex.com/public?command=returnChartData&currencyPair=BTC_XRP&start=1420070400.0&end=1540889085.14896&period=86400 at BTC_XRP
Cached https://poloniex.com/public?command=returnChartData&currencyPair=BTC_XRP&start=1420070400.0&end=1540889085.14896&period=86400 at BTC_XRP
Downloading https://poloniex.com/public?command=returnChartData&currencyPair=BTC_STR&start=1420070400.0&end=1540889085.14896&period=86400 at BTC_STR
Cached https://poloniex.com/public?command=returnChartData&currencyPair=BTC_STR&start=1420070400.0&end=1540889085.14896&period=86400 at BTC_STR
Downloading https://poloniex.com/public?command=returnChartData&currencyPair=BTC_DASH&start=1420070400.0&end=1540889085.14896&period=86400 at BTC_DASH
Cached https://poloniex.com/public?command=returnChartData&currencyPair=BTC_DASH&start=1420070400.0&end=1540889085.14896&period=86400 at BTC_DASH
Downloading https://poloniex.com/public?command=returnChartData&currencyPair=BTC_SC&start=1420070400.0&end=1540889085.14896&period=86400 at BTC_SC
Cached https://poloniex.com/public?command=returnChartData&currencyPair=BTC_SC&start=1420070400.0&end=1540889085.14896&period=86400 at BTC_SC
Downloading https://poloniex.com/public?command=returnChartData&currencyPair=BTC_XMR&start=1420070400.0&end=1540889085.14896&period=86400 at BTC_XMR
Cached https://poloniex.com/public?command=returnChartData&currencyPair=BTC_XMR&start=1420070400.0&end=1540889085.14896&period=86400 at BTC_XMR
Downloading https://poloniex.com/public?command=returnChartData&currencyPair=BTC_XEM&start=1420070400.0&end=1540889085.14896&period=86400 at BTC_XEM
Cached https://poloniex.com/public?command=returnChartData&currencyPair=BTC_XEM&start=1420070400.0&end=1540889085.14896&period=86400 at BTC_XEM
```

Now we have a dictionary with 9 dataframes, each containing the historical daily average exchange prices between the altcoin and Bitcoin.

```
In [0]: #Let's preview the last 5 rows for the Ethereum price table
altcoin_data['ETH'].tail()
```

	close	high	low	open	quoteVolume	volume	weightedAverage
date							
2018-10-26	0.031345	0.031675	0.031145	0.031225	5385.568022	168.798551	0.031343
2018-10-27	0.031434	0.031450	0.031303	0.031345	3191.663487	100.133646	0.031373
2018-10-28	0.031630	0.031651	0.031391	0.031434	3145.438601	99.212066	0.031542
2018-10-29	0.031030	0.031011	0.030867	0.031029	8618.249836	269.317134	0.031250
2018-10-30	0.031060	0.031086	0.030980	0.031020	1249.165185	38.757839	0.031027

```
In [0]: #Let's combine this btc pricing dataframes with our btc pricing index to directly calc historical USD values for each altcoin
for altcoin in altcoin_data.keys():
    altcoin_data[altcoin]['price_usd'] = altcoin_data[altcoin]['weightedAverage'] * btc_usd_datasets['avg_btc_price_usd']
```

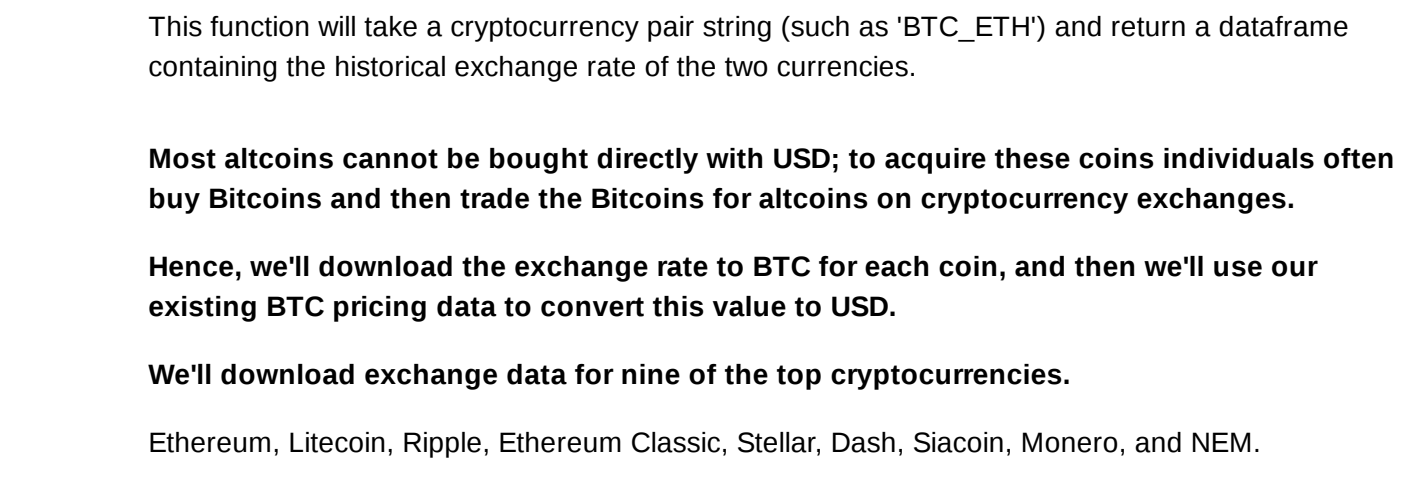
Here, we've created a new column in each altcoin dataframe with the USD prices for that coin.

```
In [0]: #Let's create a combined df of USD prices for each cryptocurrency
combined_df = merge_dfs_on_column(list(altcoin_data.values()), list(altcoin_data.keys()), 'price_usd')
```

```
In [0]: #Let's add btc prices as a final col to the combined df
combined_df['BTC'] = btc_usd_datasets['avg_btc_price_usd']
```

Now we should have a single dataframe containing daily USD prices for the ten cryptocurrencies that we're examining.

```
In [0]: #Let's chart all currencies against each other
df_scatter(combined_df, 'Cryptocurrency Prices (USD)', separate_y_axis=False, y_axis_label='Coin Value (USD)', scale='log')
```



FANTASTIC!

This graph provides a pretty solid "big picture" of how the exchange rates for each currency have varied over the past few years.

```
In [0]: #Let's perform Correlation Analysis, since cryptocurrency exchange prices, des pite their different values and volatility, look alighly correlated
#Testing my correlation hypothesis using Pandas, computes a Pearson correlation coefficient for each col in the df against each other col
#Note, computing correlations directly on non-stationary time series can give bias correlation values
combined_df_2016 = combined_df[combined_df.index.year == 2016]
combined_df_2016.pct_change().corr(method='pearson')
```

	DASH	ETC	ETH	LTC	SC	STR	XEM	XMR
DASH	1.000000	0.003992	0.122695	-0.021294	0.026602	0.058063	0.014571	0.021537
ETC	0.003992	1.000000	-0.181991	-0.131079	-0.008066	-0.102654	-0.080938	-0.105896
ETH	0.122695	-0.181991	1.000000	-0.064652	0.169642	0.050593	0.043205	0.087216
LTC	-0.021294	-0.131079	-0.064652	1.000000	0.021253	0.113523	0.160667	0.129475
SC	0.026602	-0.008066	0.169642	0.021253	1.000000	0.143252	0.106153	0.047910
STR	0.058063	-0.102654	0.050593	0.113523	0.143252	1.000000	0.043205	0.027998
XEM	0.014571	-0.105896	0.043205	0.160667	0.106153	0.043205	1.000000	0.016438
XMR	0.021537	-0.105896	0.087216	0.129475	0.047910	0.027998	0.016438	1.000000
XRP	0.088057	-0.054095	0.085436	0.053712	0.021098	0.032016	0.013126	0.027649
BTC	-0.014040	-0.170538	-0.006502	0.750174	0.035116	0.073075	0.027674	0.127520

These are strongly correlated are all over the place. Coefficients close to 1 or -1 mean that the series are strongly correlated or inversely correlated respectively, and coefficients close to zero mean that the values are not correlated, and fluctuate independently of each other.

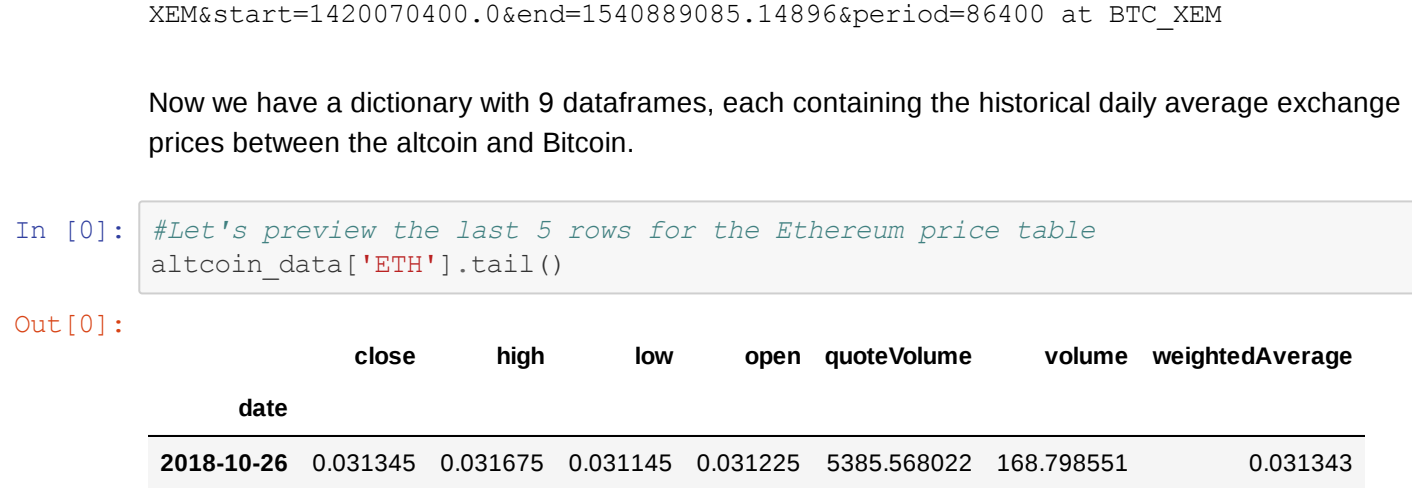
```
In [0]: #Let's visualize these results
def correlation_heatmap(df, title, absolute_bounds=True):
    """Plot a correlation heatmap for the entire dataframe"""
    heatmap = go.Heatmap(
        z=df.corr(method='pearson').as_matrix(),
        x=df.columns,
        y=df.columns,
        colorbar=dict(title='Pearson Coefficient',)
    )

    layout = go.Layout(title=title)

    if absolute_bounds:
        heatmap['zmax'] = 1.0
        heatmap['zmin'] = -1.0

    fig = go.Figure(data=[heatmap], layout=layout)
    py.iplot(fig)
```

```
In [0]: correlation_heatmap(combined_df_2016.pct_change(), "Cryptocurrency Correlation s in 2016")
```



Here, the dark red values represent strong correlations (note that each currency is, obviously, strongly correlated with itself), and the dark blue values represent strong inverse correlations. All of the light blue/gray values in-between represent varying degrees of weak/non-existent correlations.

Essentially, it shows that there was little statistically significant linkage between how the prices of different cryptocurrencies fluctuated during 2016.

```
In [0]: #Let's test the hypothesis that cryptos have become more correlated in recent years
combined_df_2017 = combined_df[combined_df.index.year == 2017]
combined_df_2017.pct_change().corr(method='pearson')
```

	DASH	ETC	ETH	LTC	SC	STR	XEM	XMR
DASH	1.000000	0.387555	0.505911	0.340153	0.291424	0.130308	0.325966	0.498418
ETC	0.387555	1.000000	0.601437	0.427602	0.298406	0.210387	0.399220	0.545632
ETH	0.505911	0.601437	1.000000	0.437609	0.373078	0.259399	0.398250	0.545632
LTC	0.340153	0.427602	0.437609	1.000000	0.391441	0.370589	0.370908	0.437204
SC	0.291424	0.298406	0.373078	0.391441	1.000000	0.402366	0.331350	0.378644
STR	0.130308	0.210387	0.259399	0.370589	0.402366	1.000000	0.339502	0.327488
XEM	0.325966	0.399220	0.398250	0.370908	0.339502	0.339502	1.000000	0.336076
XMR	0.498418	0.545632	0.545632	0.437204	0.378644	0.327488	0.336076	1.000000
XRP	0.091146	0.114780	0.121350	0.323905	0.243872	0.509828	0.268168	0.226636
BTC	0.307065	0.410545	0.416771	0.420465	0.235218	0.320957	0.329431	0.409183

These are somewhat more significant correlation coefficients. Strong enough to use as the sole basis for an investment? Certainly not.

```
In [0]: correlation_heatmap(combined_df_2017.pct_change(), "Cryptocurrency Correlation s in 2017")
```

