

607 Project

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Motivation

Cryptocurrency is a digital currency that is created and managed through the use of cryptography, which is an advanced type of encryption technique. Bitcoin was one of the earliest forms of cryptocurrency and since then, many other types of cryptocurrencies have been created. I first heard about Bitcoin back in 2013, when I was a financially struggling college student, and I thought 80 Dollars per coin was a bit too much. Today, one bitcoin is about 100 times that amount.

Below is the index for November 19th 2017 from <https://www.coindesk.com>

Today's Open: \$8,033.94 Today's High: \$8,049.12 Today's Low: \$8,021.33 Today's Closed: \$8,034.42

*Update: Since the time this proposal was written, Bitcoin has increased dramatically. Below is the index for December 9th 2017 from <https://www.coindesk.com>

Today's Open: \$16,057.15 Today's High: \$16,291.68 Today's Low: \$15,538.25

Even though Bitcoin seems like a great investment, many investors remain skeptical. The main reason is bitcoin and other cryptocurrencies are virtual currencies that are not backed by anything. Since there are a limited amount of bitcoin(20 million), the market purely fluctuates on demand, making it extremely volatile. This gives spectators reason to believe it is a bubble. Currently, many new investors, attracted by its potential, are entering the market, increasing its value significantly, but this can change if the demand drops. Currently there are many theories out there, but for now, I wanted to see how volatile bitcoin is compared to other currencies.

Obtain the Data

Bitcoin API from Quandl

Since bitcoin is the most widely known cryptocurrency, there is a lot of data available for it. I was able to find an API for Bitcoin's historical data.

```
#Daily Bitcoin exchange rate (BTC vs. USD) on Bitstamp from 09/13/2011 to 12/09/2017
Quandl.api_key('mxcqtzYcf5Co4fbG3WAX')
Bitcoin <- Quandl('BCHARTS/BITSTAMPUSD', start_date='2011-01-01', end_date='2017-12-07')
head(Bitcoin )
```

##	Date	Open	High	Low	Close	Volume (BTC)
## 1	2017-12-07	13623.00	16615.62	13085.90	16599.99	25787.677
## 2	2017-12-06	11676.99	13700.00	11659.80	13623.50	19784.873
## 3	2017-12-05	11613.07	11850.00	11384.25	11677.00	11875.034
## 4	2017-12-04	11250.00	11613.07	10850.00	11613.07	13621.482
## 5	2017-12-03	10875.68	11800.01	10513.16	11250.00	14238.526
## 6	2017-12-02	10840.45	11200.00	10637.69	10872.00	9267.161
##	Volume (Currency) Weighted Price					
## 1		382694044	14840.19			
## 2		250560790	12664.26			
## 3		138370076	11652.18			

```
## 4      154122918      11314.70
## 5      160176290      11249.50
## 6      101270084      10927.84
```

```
tail(Bitcoin)
```

```
##      Date Open High  Low Close Volume (BTC) Volume (Currency)
## 2273 2011-09-18 4.87 4.92 4.81 4.92      119.81280          579.8431
## 2274 2011-09-17 4.87 4.87 4.87 4.87         0.30000           1.4610
## 2275 2011-09-16 4.82 4.87 4.80 4.85        39.91401          193.7631
## 2276 2011-09-15 5.12 5.24 5.00 5.13        80.14080          408.2590
## 2277 2011-09-14 5.58 5.72 5.52 5.53        61.14598          341.8548
## 2278 2011-09-13 5.80 6.00 5.65 5.97        58.37138          346.0974
##      Weighted Price
## 2273      4.839576
## 2274      4.870000
## 2275      4.854515
## 2276      5.094272
## 2277      5.590798
## 2278      5.929231
```

Main Competitors

The second tier of cryptocurrencies in terms of popularity include Ethereum, Litecoin. I was interested in those two, plus a couple more, Dash and Bitcoin cash. I was able to find a csv file on the historical data from the website: <https://coinmetrics.io/data-downloads/>

I saved the csv files in Github.

```
Bc_cash <- read.csv("https://raw.githubusercontent.com/mikegankhuyag/607-Projects/master/Final/bch.csv")
Dash <- read.csv("https://raw.githubusercontent.com/mikegankhuyag/607-Projects/master/Final/dash.csv", l
Ethereum <- read.csv("https://raw.githubusercontent.com/mikegankhuyag/607-Projects/master/Final/eth.csv")
Litecoin <- read.csv("https://raw.githubusercontent.com/mikegankhuyag/607-Projects/master/Final/ltc.csv")
head(Bc_cash)
```

```
##      date txVolume.USD. txCount marketcap.USD. price.USD.
## 1 7/31/2017    2406864986    183998           0      294.46
## 2 8/1/2017     906913244    230867           0      380.01
## 3 8/2/2017     603435293     76537      6302360000    452.66
## 4 8/3/2017      83677447      7416      7392030000    364.05
## 5 8/4/2017     218502200     20909      5969720000    233.05
## 6 8/5/2017     263414318     26517      3809330000    213.15
##      exchangeVolume.USD. generatedCoins      fees
## 1          1075960          1837.5 138.116822
## 2          65988800          1812.5 194.868866
## 3          416207000          1112.5  51.706019
## 4          161518000           87.5   6.288903
## 5          185038000          437.5  20.234731
## 6          144043000          237.5  21.324498
```

```
head(Dash)
```

```
##      date txVolume.USD. txCount marketcap.USD. price.USD.
## 1 2/14/2014    150641.42     3421       702537   0.374024
## 2 2/15/2014     78256.18     3663       1092120   0.314865
## 3 2/16/2014     96549.99     3236       1085280   0.406976
```

```
## 4 2/17/2014      367922.18      2766      1360260      1.450000
## 5 2/18/2014      838488.30      2631      3960320      1.040000
## 6 2/19/2014      675559.38      2551      3497850      0.941647
##   exchangeVolume.USD. generatedCoins      fees
## 1              15422              33849 3.355010
## 2              21119              33235 3.739035
## 3              28017              30944 5.238558
## 4             178618              20713 2.473010
## 5             160779              15940 2.827082
## 6             60551              13548 2.363510
```

```
head(Ethereum)
```

```
##           date txVolume.USD. txCount marketcap.USD. price.USD.
## 1  8/7/2015           0           0           0  2.770000
## 2  8/8/2015      1513209      2016      167911000  0.753325
## 3  8/9/2015      1180418      2807      42637600  0.701897
## 4  8/10/2015      825663      1298      43130000  0.708448
## 5  8/11/2015      1787874      1999      42796500  1.070000
## 6  8/12/2015      1812412      4945      64018400  1.220000
##   exchangeVolume.USD. generatedCoins      fees
## 1              164329      27075.47  0.00000
## 2              674188      27437.66 37.31841
## 3              532170      27943.44 68.09997
## 4              405283      27178.28 14.09895
## 5             1463100      27817.34 31.16514
## 6             2150620      28027.81 11.31145
```

```
head(Litecoin)
```

```
##           date txVolume.USD. txCount marketcap.USD. price.USD.
## 1  4/28/2013      39038951      8847      73773400      4.35
## 2  4/29/2013      48283929      9408      74952700      4.38
## 3  4/30/2013      38686090      9092      75726800      4.30
## 4  5/1/2013      33849471      9205      73901200      3.80
## 5  5/2/2013      58715299      8927      65242700      3.37
## 6  5/3/2013      13752345      8290      58607400      3.04
##   exchangeVolume.USD. generatedCoins      fees
## 1              0              32800 511.0816
## 2              0              31500 634.1212
## 3              0              32450 597.0982
## 4              0              31600 755.4951
## 5              0              31450 689.1598
## 6              0              28300 551.3278
```

New Comers

I was interested in two coins that are currently valued really low, Ripple and Tether. I was able to find the historical data on <https://coinmarketcap.com>. Since I couldn't download it, I decided to scrape the data.

```
Rip <- read_html("https://coinmarketcap.com/currencies/ripple/historical-data/?start=20130428&end=20171231")
Tet <- read_html("https://coinmarketcap.com/currencies/tether/historical-data/?start=20130428&end=20171231")
```

```
Ripp <- html_text(html_nodes(Rip, "td"))
Rippl <- matrix(Ripp, ncol = 7, byrow = TRUE)
```

```
Ripple <- data.frame(Rippl[2:1588,], stringsAsFactors = TRUE)
colnames(Ripple) <- c("Date", "Open", "High", "Low", "Close", "Volume", "Market Cap")
head(Ripple)
```

```
##           Date      Open      High      Low      Close      Volume
## 1 Dec 08, 2017 0.223636 0.278673 0.222168 0.252125 660,172,000
## 2 Dec 07, 2017 0.232623 0.233760 0.221340 0.222823 275,205,000
## 3 Dec 06, 2017 0.245416 0.245705 0.227742 0.232544 274,526,000
## 4 Dec 05, 2017 0.253598 0.253988 0.245234 0.246101 174,591,000
## 5 Dec 04, 2017 0.252919 0.255362 0.247160 0.253571 104,650,000
## 6 Dec 03, 2017 0.255530 0.263072 0.247391 0.252558 134,710,000
##           Market Cap
## 1 8,663,460,000
## 2 9,011,630,000
## 3 9,507,190,000
## 4 9,815,990,000
## 5 9,768,480,000
## 6 9,869,310,000
```

```
Teth <- html_text(html_nodes(Tet, "td"))
Tethe <- matrix(Teth, ncol = 7, byrow = TRUE)
```

```
Tether <- data.frame(Tethe[2:1013,], stringsAsFactors = TRUE)
colnames(Tether) <- c("Date", "Open", "High", "Low", "Close", "Volume", "Market Cap")
head(Tether)
```

```
##           Date      Open      High      Low      Close      Volume      Market Cap
## 1 Dec 08, 2017      1.04 1.06 0.986563 1.02 1,993,030,000 843,587,000
## 2 Dec 07, 2017      1.01 1.08      1.00 1.03 1,671,610,000 819,775,000
## 3 Dec 06, 2017 0.999760 1.02 0.995840 1.01 1,281,490,000 813,822,000
## 4 Dec 05, 2017      1.00 1.01 0.996458 1.00 814,146,000 816,872,000
## 5 Dec 04, 2017      1.00 1.01 0.992132 1.00 668,510,000 816,012,000
## 6 Dec 03, 2017      1.00 1.03 0.985320 1.00 946,749,000 814,847,000
```

Cleaning the data

I want all the to be in the same format as the Bitcoin API. For the CSV files, I first wanted to reorder the data since it starts from the earliest point.

```
Bc_cash <- Bc_cash[130:1,]
Dash <- Dash[1393:1,]
Ethereum <- Ethereum[854:1,]
Litecoin <- Litecoin[1685:1,]
```

The Bitcoin API is in a YYYY-MM-DD format. So I needed to change that all the dates to that format.

```
Bc_cash$date <- as.Date(Bc_cash$date, format = "%m/%d/%Y")
Ethereum$date <- as.Date(Ethereum$date, format = "%m/%d/%Y")
Dash$date <- as.Date(Dash$date, format = "%m/%d/%Y")
Litecoin$date <- as.Date(Litecoin$date, format = "%m/%d/%Y")
```

Change column name 'date' to 'Date'

```
colnames(Bc_cash)[1] <- "Date"
colnames(Ethereum)[1] <- "Date"
```

```
colnames(Dash)[1] <- "Date"
colnames(Litecoin)[1] <- "Date"
```

Since the two scraped data is from a html website, all of it needs to be reformatted.

```
Tether[,2:5] %<>%
  mutate_each(funs(if(is.factor(.)) as.character(.) else .)) %<>%
  mutate_each(funs(if(is.character(.)) as.numeric(.) else .))
Ripple[,2:5] %<>%
  mutate_each(funs(if(is.factor(.)) as.character(.) else .)) %<>%
  mutate_each(funs(if(is.character(.)) as.numeric(.) else .))
```

Also, change the date format to YYYY-MM-DD format.

```
Tether$Date <- as.Date(Tether$Date, format = "%b %d, %Y")
Ripple$Date <- as.Date(Ripple$Date, format = "%b %d, %Y")
```

Combining the data

Now that all of our data is in consistent format, lets get all the variables needed for analysis.

I want to average out the highs and lows to get one price for the day.

```
require(magrittr)
Bitcoin %<>% mutate(bitcoin_price = (High + Low)/2,
  bitcoin_gain = Close - Open)
Ripple %<>% mutate(ripple_price = (High + Low)/2,
  ripple_gain = Close - Open)
Tether %<>% mutate(tether_price = (High + Low)/2,
  tether_gain = Close - Open)
```

Selecting the data we need.

```
Bitcoin_data <- select(Bitcoin, Date, bitcoin_price)
Ripple_data <- select(Ripple, Date, ripple_price)
Tether_data <- select(Tether, Date, tether_price)
Ethereum_data <- select(Ethereum, Date, price.USD.)
Dash_data <- select(Dash, Date, price.USD.)
Bc_cash_data <- select(Bc_cash, Date, price.USD.)
Litecoin_data <- select(Litecoin, Date, price.USD.)
```

Since, all of our data is in the same format, we join them using the 'Date' field as the identifier. Bitcoin data has the most rows, so I used it as the left part of left join.

```
cryptocurrencies <-
left_join(
left_join(
left_join(
left_join(
  left_join(
    left_join(Bitcoin_data, Ripple_data, "Date"),
    Tether_data, "Date"),
    Ethereum_data, "Date"),
    Dash_data, "Date"),
    Bc_cash_data, "Date"),
    Litecoin_data, "Date")
```

```
colnames(cryptocurrencies) <- c("Date","bitcoin_price","ripple_price","tether_price",
                                "ethereum_price", "dash_price","bc_cash_price","litecoin_price")
head(cryptocurrencies)
```

```
##      Date bitcoin_price ripple_price tether_price ethereum_price
## 1 2017-12-07      14850.76    0.2275500      1.040000         434.41
## 2 2017-12-06      12679.90    0.2367235      1.007920         428.59
## 3 2017-12-05      11617.12    0.2496110      1.003229         463.28
## 4 2017-12-04      11231.53    0.2512610      1.001066         470.20
## 5 2017-12-03      11156.58    0.2552315      1.007660         465.85
## 6 2017-12-02      10918.85    0.2549870      1.007805         463.45
##  dash_price bc_cash_price litecoin_price
## 1      697.90      1330.93          98.29
## 2      700.07      1430.10         100.35
## 3      756.36      1501.85         102.40
## 4      774.01      1576.92         104.24
## 5      768.88      1559.93         101.26
## 6      778.43      1434.98         100.28
```

Since the prices of the currencies between each other have huge differences, it would be hard to compare them. I decided to calculate the relative change between them.

I created another table with the previous day's price, added 1 to the day and did a left join to match the day.

```
Prior_day <- cryptocurrencies[2:2278,]
Prior_day$Date <- as.Date(Prior_day$Date)+1
colnames(Prior_day) <- c("Date","yes_bitcoin_price","yes_ripple_price","yes_tether_price",
                        "yes_ethereum_price", "yes_dash_price","yes_bc_cash_price","yes_litecoin_price")

r_cryptocurrencies <- left_join(cryptocurrencies, Prior_day, by = "Date")
r_cryptocurrencies <- select(r_cryptocurrencies, Date, bitcoin_price, yes_bitcoin_price, ripple_price, yes_ripple_price,
                            ethereum_price, yes_ethereum_price, dash_price, yes_dash_price, bc_cash_price, yes_bc_cash_price,
                            litecoin_price, yes_litecoin_price)
head(r_cryptocurrencies)
```

```
##      Date bitcoin_price yes_bitcoin_price ripple_price yes_ripple_price
## 1 2017-12-07      14850.76      12679.90    0.2275500    0.2367235
## 2 2017-12-06      12679.90      11617.12    0.2367235    0.2496110
## 3 2017-12-05      11617.12      11231.53    0.2496110    0.2512610
## 4 2017-12-04      11231.53      11156.58    0.2512610    0.2552315
## 5 2017-12-03      11156.58      10918.85    0.2552315    0.2549870
## 6 2017-12-02      10918.85      10160.00    0.2549870    0.2491330
##  tether_price yes_tether_price ethereum_price yes_ethereum_price
## 1      1.040000      1.007920         434.41         428.59
## 2      1.007920      1.003229         428.59         463.28
## 3      1.003229      1.001066         463.28         470.20
## 4      1.001066      1.007660         470.20         465.85
## 5      1.007660      1.007805         465.85         463.45
## 6      1.007805      1.006522         463.45         466.54
##  dash_price yes_dash_price bc_cash_price yes_bc_cash_price litecoin_price
## 1      697.90      700.07      1330.93      1430.10          98.29
## 2      700.07      756.36      1430.10      1501.85         100.35
## 3      756.36      774.01      1501.85      1576.92         102.40
## 4      774.01      768.88      1576.92      1559.93         104.24
## 5      768.88      778.43      1559.93      1434.98         101.26
## 6      778.43      797.53      1434.98      1462.68         100.28
```

```
##   yes_litecoin_price
## 1                100.35
## 2                102.40
## 3                104.24
## 4                101.26
## 5                100.28
## 6                 99.00
```

Calculate relative change

```
r_cryptocurrencies %<>% mutate(bitcoin_change = ((bitcoin_price - yes_bitcoin_price)/yes_bitcoin_price)*
                                ripple_change = ((ripple_price - yes_ripple_price)/yes_ripple_price)*100,
                                tether_change = ((tether_price - yes_tether_price)/yes_tether_price)*100,
                                ethereum_change = ((ethereum_price - yes_ethereum_price)/yes_ethereum_price)*100,
                                dash_change = ((dash_price - yes_dash_price)/yes_dash_price)*100,
                                bc_cash_change = ((bc_cash_price - yes_bc_cash_price)/yes_bc_cash_price)*100,
                                litecoin_change = ((litecoin_price - yes_litecoin_price)/yes_litecoin_price)*100)
```

Create a new table with just the relative changes.

```
relative_change <- select(r_cryptocurrencies, "Date", ends_with("change"))
relative_change_ <- relative_change

relative_change_[is.na(relative_change_ <- relative_change)] <- 0
head(relative_change_)
```

```
##      Date bitcoin_change ripple_change tether_change ethereum_change
## 1 2017-12-07    17.1204820   -3.87519617    3.18279229    1.3579412
## 2 2017-12-06     9.1483478   -5.16303368    0.46759015   -7.4879123
## 3 2017-12-05     3.4331015   -0.65668767    0.21606967   -1.4717142
## 4 2017-12-04     0.6718006   -1.55564654   -0.65438739    0.9337770
## 5 2017-12-03     2.1773365    0.09588724   -0.01443731    0.5178552
## 6 2017-12-02     7.4689469    2.34974893    0.12756806   -0.6623226
##   dash_change bc_cash_change litecoin_change
## 1  -0.3099690   -6.934480    -2.0528151
## 2  -7.4422233   -4.777441    -2.0019531
## 3  -2.2803323   -4.760546    -1.7651573
## 4   0.6672042    1.089151     2.9429192
## 5  -1.2268284    8.707438     0.9772637
## 6  -2.3948942   -1.893784     1.2929293
```

Round the percentages

```
relative_change_$bitcoin_change <- round(relative_change_$bitcoin_change, 4)
relative_change_$ripple_change <- round(relative_change_$ripple_change ,4)
relative_change_$tether_change <- round(relative_change_$tether_change ,4)
relative_change_$ethereum_change <- round(relative_change_$ethereum_change ,4)
relative_change_$dash_change <- round(relative_change_$dash_change ,4)
relative_change_$bc_cash_change <- round(relative_change_$bc_cash_change ,4)
relative_change_$litecoin_change <- round(relative_change_$litecoin_change ,4)
```

Analysis

Relative Change

Tidy the data for analysis. The mean relative change shows the average changes.

```
tidy_change <- (gather(relative_change_, key= Currency, "relative_change", desc("Date")))
tidy_change %>% filter(relative_change !=0, is.finite(relative_change) == TRUE) %>%
  group_by(Currency) %>% summarise(mean = mean(relative_change), count = n())
```

```
## # A tibble: 7 x 3
##       Currency      mean count
##       <chr>      <dbl> <int>
## 1 bc_cash_change 1.97931085  129
## 2 bitcoin_change -0.05745514  2249
## 3 dash_change    0.98085324  1360
## 4 ethereum_change 0.93719399   849
## 5 litecoin_change 0.44710412  1602
## 6 ripple_change  0.44249058  1581
## 7 tether_change  0.02202607   399
```

From the data, we can see that Bitcoin prices has a negative relative change. This might be due to some skews in our data. Lets limit high percentage changes.

```
tidy_change <- (gather(relative_change_, key= Currency, "relative_change", desc("Date")))
tidy_change %>% filter(relative_change !=0, is.finite(relative_change) == TRUE, relative_change < 50, r
  group_by(Currency) %>% summarise(mean = mean(relative_change), count = n())
```

```
## # A tibble: 7 x 3
##       Currency      mean count
##       <chr>      <dbl> <int>
## 1 bc_cash_change 1.16503465   127
## 2 bitcoin_change 0.41088594  2233
## 3 dash_change    0.57381055  1355
## 4 ethereum_change 0.90714835   846
## 5 litecoin_change 0.22708623  1598
## 6 ripple_change  0.29571635  1578
## 7 tether_change  0.02202607   399
```

We see that when we limit the relative changes between -50 and 50, there is significant changes to the mean, but not the count.

```
tidy_change <- (gather(relative_change_, key= Currency, "relative_change", desc("Date")))
tidy_change %>% filter(relative_change !=0, is.finite(relative_change) == TRUE, relative_change < 10, r
  group_by(Currency) %>% summarise(mean = mean(relative_change), count = n())
```

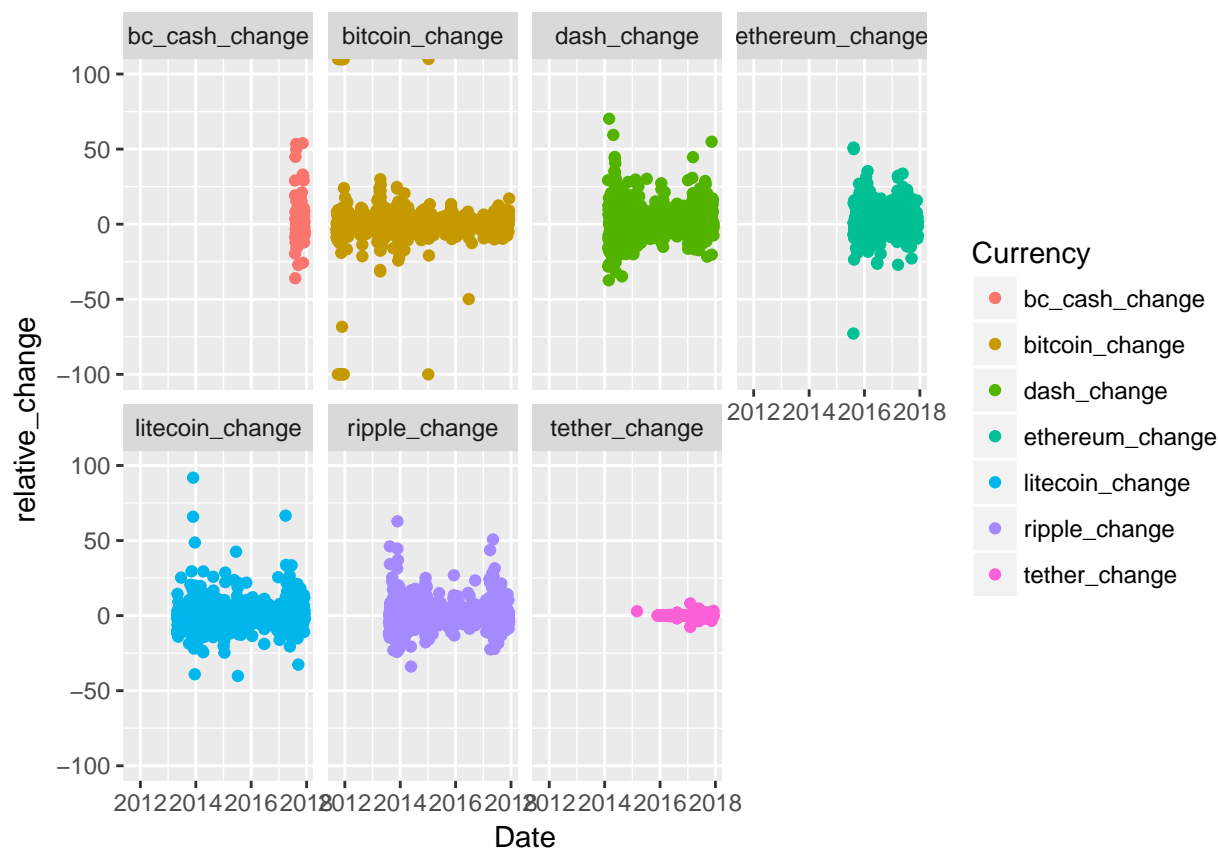
```
## # A tibble: 7 x 3
##       Currency      mean count
##       <chr>      <dbl> <int>
## 1 bc_cash_change -0.71430515    97
## 2 bitcoin_change  0.36466306  2152
## 3 dash_change    -0.12132624  1189
## 4 ethereum_change -0.12964241   738
## 5 litecoin_change -0.08903114  1461
## 6 ripple_change  -0.14734908  1465
## 7 tether_change  0.02202607   399
```


When we limit the relative change to between -10 and 10, most of the mean is negative. This means for 5/7 observations, the increases are due to high shifts in the market in the day, but most days, they are losing value. This is opposite for Bitcoin, which is increasing on most days and its losses come from large drops in the market. For Tether, the market looks surprisingly stable. This may be due to it being a small player in the market.

Let's visualize the relative changes.

```
ggplot(data = tidy_change[which(tidy_change$relative_change != 0),]) +
  geom_point(mapping = aes(x = Date, y = relative_change, color = Currency, fill = Currency), position = "jitter") +
  facet_wrap(~ Currency, nrow = 2) +
  ylim(-100, 100)
```

Warning: Removed 11 rows containing missing values (geom_point).



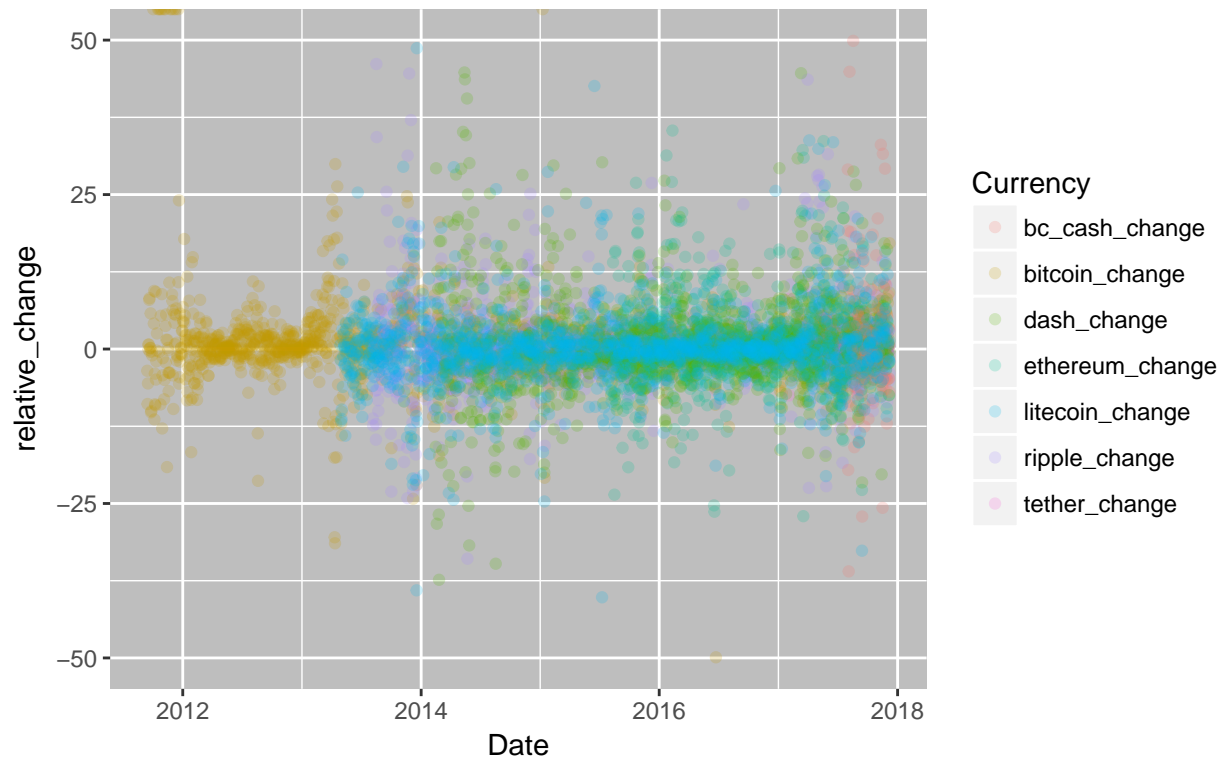
From the visualization, we can see that the spread is very large for most of the currencies with exception to tether. Visualizing the relative changes together.

```
ggplot(data = tidy_change[which(tidy_change$relative_change != 0),]) +
  geom_point(mapping = aes(x = Date, y = relative_change, color = Currency, fill = Currency), alpha = 1/5, position = "jitter") +
  ylim(-50, 50) +
  theme(panel.background = element_rect(fill = 'gray')) +
  ggtitle("Cryptocurrencies from 2011 to 2017", subtitle = "Relative Changes")
```

Warning: Removed 33 rows containing missing values (geom_point).

Cryptocurrencies from 2011 to 2017

Relative Changes



Gain to Loss Ratio

Let's dive deeper into how the currencies fluctuate and look at gain to loss ratio. Categorize for each relative change percentage to 'gain', 'loss' or 'no change'.

```
tidy_change$lost_gain <- ifelse(tidy_change$relative_change > 0, "gain",
                                ifelse(tidy_change$relative_change == 0, "no, change", "loss"))
tidy_change[sample(nrow(iris), 10), ]
```

##	Date	Currency	relative_change	lost_gain
## 81	2017-09-18	bitcoin_change	7.5544	gain
## 69	2017-09-30	bitcoin_change	3.0746	gain
## 102	2017-08-28	bitcoin_change	-1.3231	loss
## 27	2017-11-11	bitcoin_change	-5.3339	loss
## 60	2017-10-09	bitcoin_change	4.3199	gain
## 82	2017-09-17	bitcoin_change	-1.8633	loss
## 73	2017-09-26	bitcoin_change	2.5388	gain
## 51	2017-10-18	bitcoin_change	-4.9985	loss
## 43	2017-10-26	bitcoin_change	5.0117	gain
## 78	2017-09-21	bitcoin_change	-4.8734	loss

Untidy the data for analysis

```
#All
ratio<- tidy_change %>% group_by(Currency) %>% count(lost_gain)
gain_loss_ratio <- ratio %>% spread(lost_gain, n) %>% mutate(ratio = gain/loss)
gain_loss_ratio <- select(gain_loss_ratio,Currency,ratio)
```

```

#Limit -100 to 100
ratio100<- tidy_change %>% filter(relative_change < 100, relative_change > -100) %>% group_by(Currency)
gain_loss_ratio100 <- ratio100 %<>% spread(lost_gain, n) %<>% mutate(ratio100 = gain/loss)
gain_loss_ratio100 <- select(gain_loss_ratio100,Currency,ratio100)

#Limit -10 to 10
ratio1<- tidy_change %>% filter(relative_change < 10, relative_change > -10) %>% group_by(Currency) %>%
gain_loss_ratio1 <- ratio1 %<>% spread(lost_gain, n) %<>% mutate(ratio10 = gain/loss)
gain_loss_ratio1 <- select(gain_loss_ratio1,Currency,ratio10)

All_ratios <- inner_join(gain_loss_ratio,inner_join(gain_loss_ratio100,gain_loss_ratio1,by = "Currency"))
All_ratios$Currency <- c("Bitcoin Cash", "Bitcoin", "Dash", "Ethereum","Litecoin","Ripple","Tether")
All_ratios

```

```

## # A tibble: 7 x 4
## # Groups:   Currency [?]
##   Currency    ratio ratio100 ratio10
##   <chr>      <dbl>    <dbl>    <dbl>
## 1 Bitcoin Cash 0.8970588 0.8970588 0.7017544
## 2 Bitcoin 1.2507463 1.2520161 1.2510460
## 3 Dash 0.9209040 0.9180791 0.8405573
## 4 Ethereum 0.9698376 0.9698376 0.8403990
## 5 Litecoin 0.9418182 0.9406061 0.9023438
## 6 Ripple 0.8843862 0.8831943 0.8381430
## 7 Tether 1.1336898 1.1336898 1.1336898

```

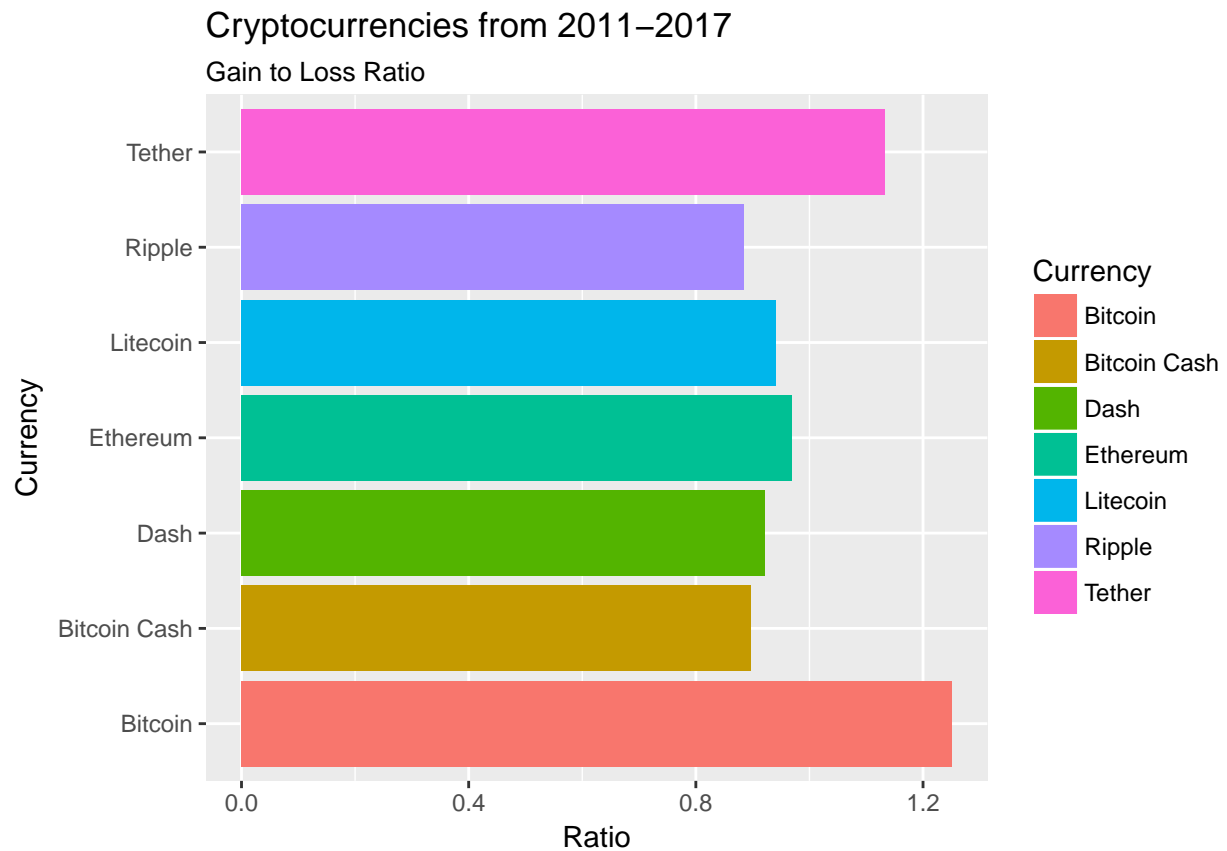
The gain to loss ratio table shows that Bitcoin has the highest ratio with over +25% margin over total losses. 2ND is Tether with a +12% margin over total losses. The rest have more losses than gains in their history.

Lets visualize the results.

```

ratio_bar <- ggplot(All_ratios, mapping = aes(y= ratio,x= Currency, fill=Currency)) +
  geom_bar(stat = "identity") +
  ggtitle("Cryptocurrencies from 2011-2017", subtitle = "Gain to Loss Ratio")+
  labs(y= "Ratio")
ratio_bar + coord_flip()

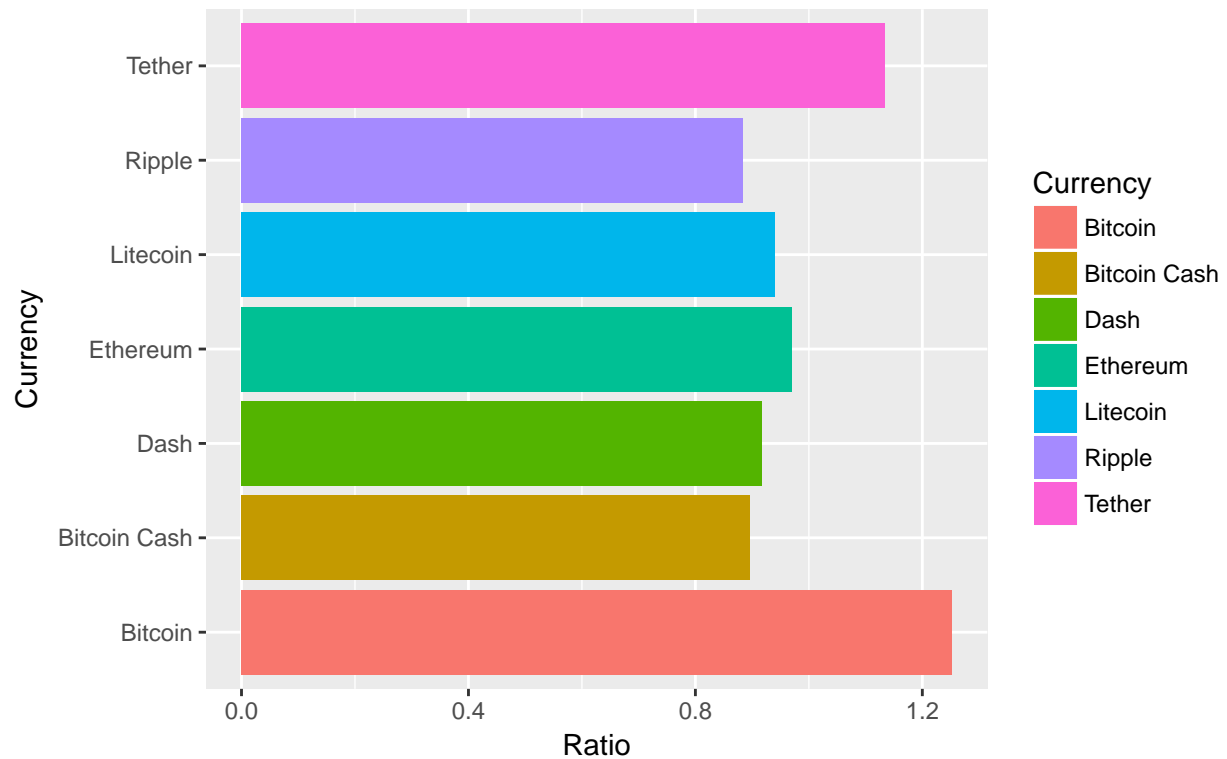
```



```
ratio_bar100 <- ggplot(All_ratios, mapping = aes(y= ratio100,x= Currency, fill=Currency)) +
  geom_bar(stat = "identity") +
  ggtitle("Cryptocurrencies from 2011-2017", subtitle = "Gain to Loss Ratio: Relative Change Limit (-100%)") +
  labs(y= "Ratio")
ratio_bar100 + coord_flip()
```

Cryptocurrencies from 2011–2017

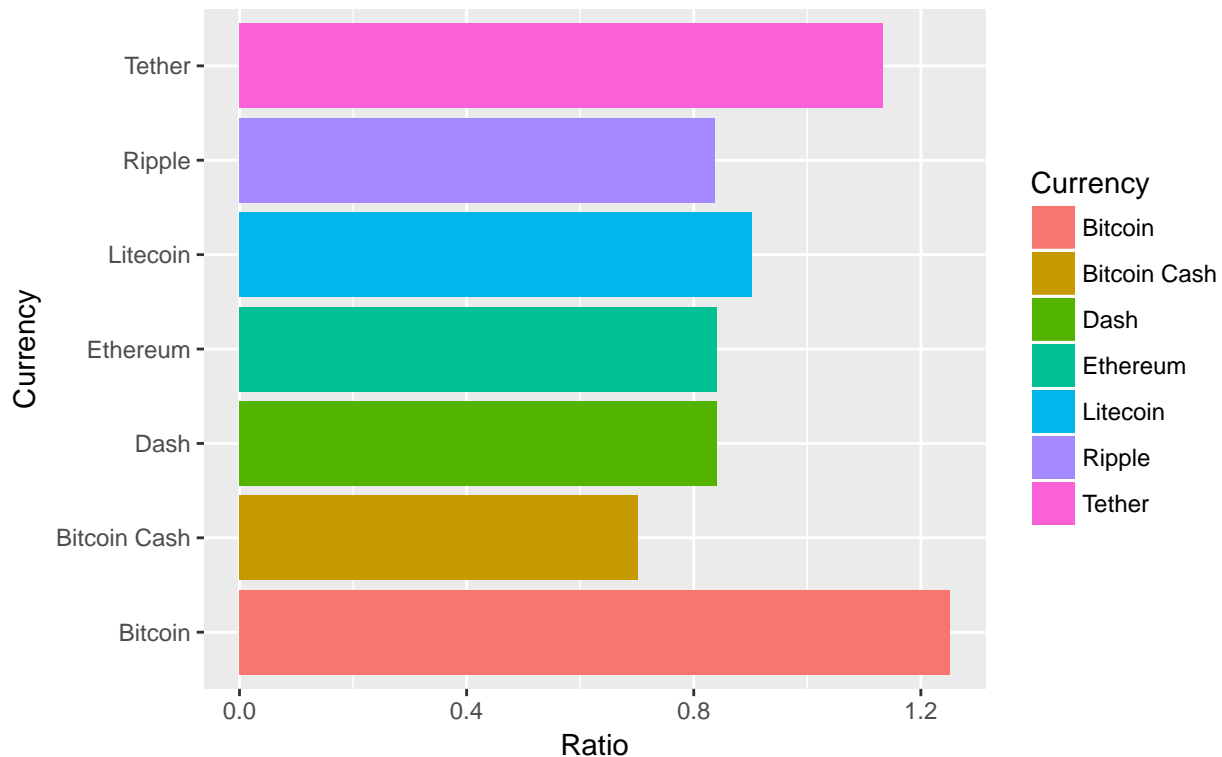
Gain to Loss Ratio: Relative Change Limit (–100:100)



```
ratio_bar1 <- ggplot(All_ratios, mapping = aes(y= ratio10,x= Currency, fill=Currency))+  
  geom_bar(stat = "identity") +  
  ggtitle("Cryptocurrencies from 2011-2017", subtitle = "Gain to Loss Ratio: Relative Change Limit (–100:100)") +  
  labs(y= "Ratio")  
ratio_bar1 + coord_flip()
```

Cryptocurrencies from 2011–2017

Gain to Loss Ratio: Relative Change Limit (–10:10)



When we compare the overall gains to losses, we can see that there is a significant drop for Ripple, Litecoin, Ethereum, Dash and Bitcoin cash.

Probability

Lets look at the probability of currencies increasing on a given day, based on the count of gains and losses.

```
gain_loss_counts <- tidy_change %>% group_by(Currency, lost_gain) %>% summarise(n=n())
gain_loss_counts <- spread(gain_loss_counts, lost_gain, n)
gain_loss_counts <- mutate(gain_loss_counts, probability = (gain/(gain+loss)))
probability <- select(gain_loss_counts, Currency, probability)

gain_loss_counts100 <- tidy_change %>% filter(relative_change < 100, relative_change > -100) %>%
  group_by(Currency, lost_gain) %>% summarise(n=n())
gain_loss_counts100 <- spread(gain_loss_counts100, lost_gain, n)
gain_loss_counts100 <- mutate(gain_loss_counts100, probability100 = (gain/(gain+loss)))
probability100 <- select(gain_loss_counts100, Currency, probability100)

gain_loss_counts10 <- tidy_change %>% filter(relative_change < 10, relative_change > -10) %>%
  group_by(Currency, lost_gain) %>% summarise(n=n())
gain_loss_counts10 <- spread(gain_loss_counts10, lost_gain, n)
gain_loss_counts10 <- mutate(gain_loss_counts10, probability10 = (gain/(gain+loss)))
probability10 <- select(gain_loss_counts10, Currency, probability10)

All_probability <- inner_join(probability, inner_join(probability100, probability10, by = "Currency"), by = "Currency")
All_probability$Currency <- c("Bitcoin Cash", "Bitcoin", "Dash", "Ethereum", "Litecoin", "Ripple", "Tether")
```

```
All_probability
```

```
## # A tibble: 7 x 4
## # Groups:   Currency [?]
##   Currency probability probability100 probability10
##   <chr>      <dbl>          <dbl>          <dbl>
## 1 Bitcoin Cash  0.4728682      0.4728682      0.4123711
## 2 Bitcoin      0.5557029      0.5559534      0.5557621
## 3 Dash         0.4794118      0.4786451      0.4566863
## 4 Ethereum     0.4923439      0.4923439      0.4566396
## 5 Litecoin     0.4850187      0.4846971      0.4743326
## 6 Ripple       0.4693232      0.4689873      0.4559727
## 7 Tether       0.5313283      0.5313283      0.5313283
```

The probability table shows that Bitcoin has the highest chance of increase on a given day with 55% and that stays consistent when outliers are removed. Second is Tether with 53%. The rest is in the 47%-49% range, but decreases when outliers are removed. out of the remaining 5, Litecoin is most consistent, dropping from 48.5% to 47.4%.

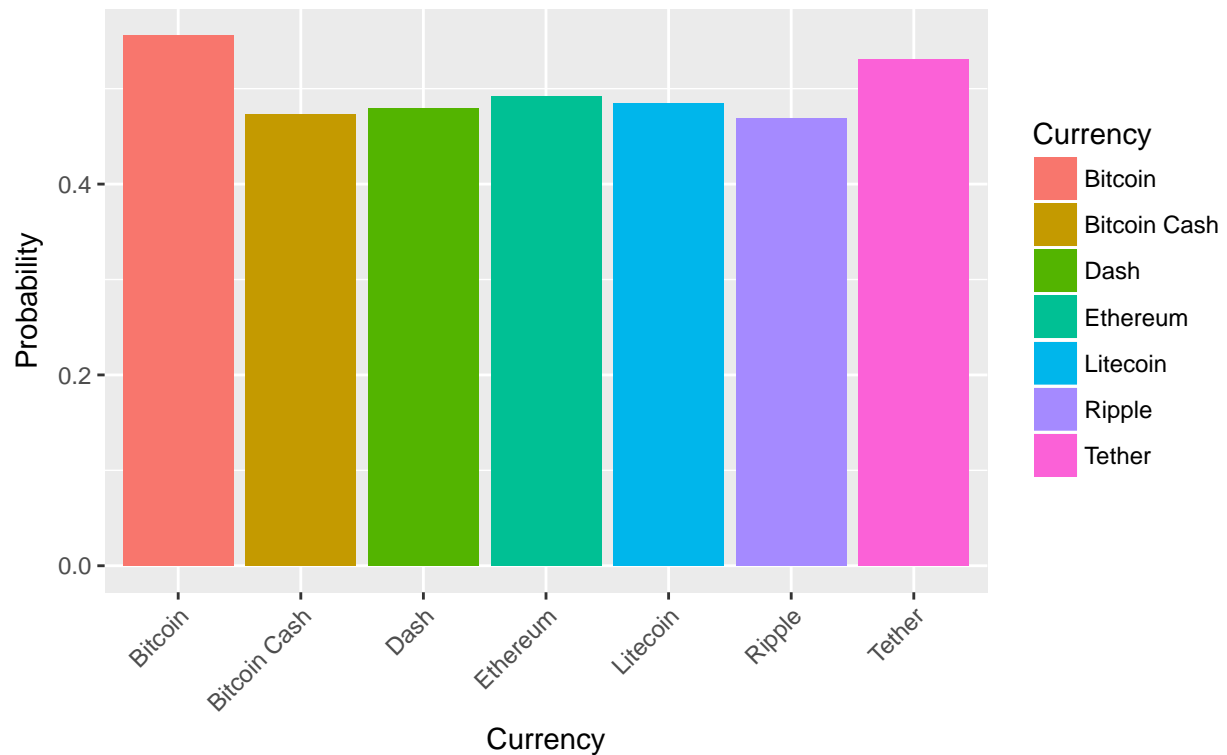
Lets visualize the results.

```
facet_wrap(~All_ratios,nrow = 3)
```

```
## <ggproto object: Class FacetWrap, Facet>
##   compute_layout: function
##   draw_back: function
##   draw_front: function
##   draw_labels: function
##   draw_panels: function
##   finish_data: function
##   init_scales: function
##   map: function
##   map_data: function
##   params: list
##   render_back: function
##   render_front: function
##   render_panels: function
##   setup_data: function
##   setup_params: function
##   shrink: TRUE
##   train: function
##   train_positions: function
##   train_scales: function
##   super: <ggproto object: Class FacetWrap, Facet>
probability_bar <- ggplot(All_probability, mapping = aes(y=probability,x= Currency, fill=Currency)) +
  geom_bar(stat = "identity") +
  ggtitle("Cryptocurrencies from 2011-2017", subtitle = "Probability of Increase within a day")+
  labs(y= "Probability") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
probability_bar
```

Cryptocurrencies from 2011–2017

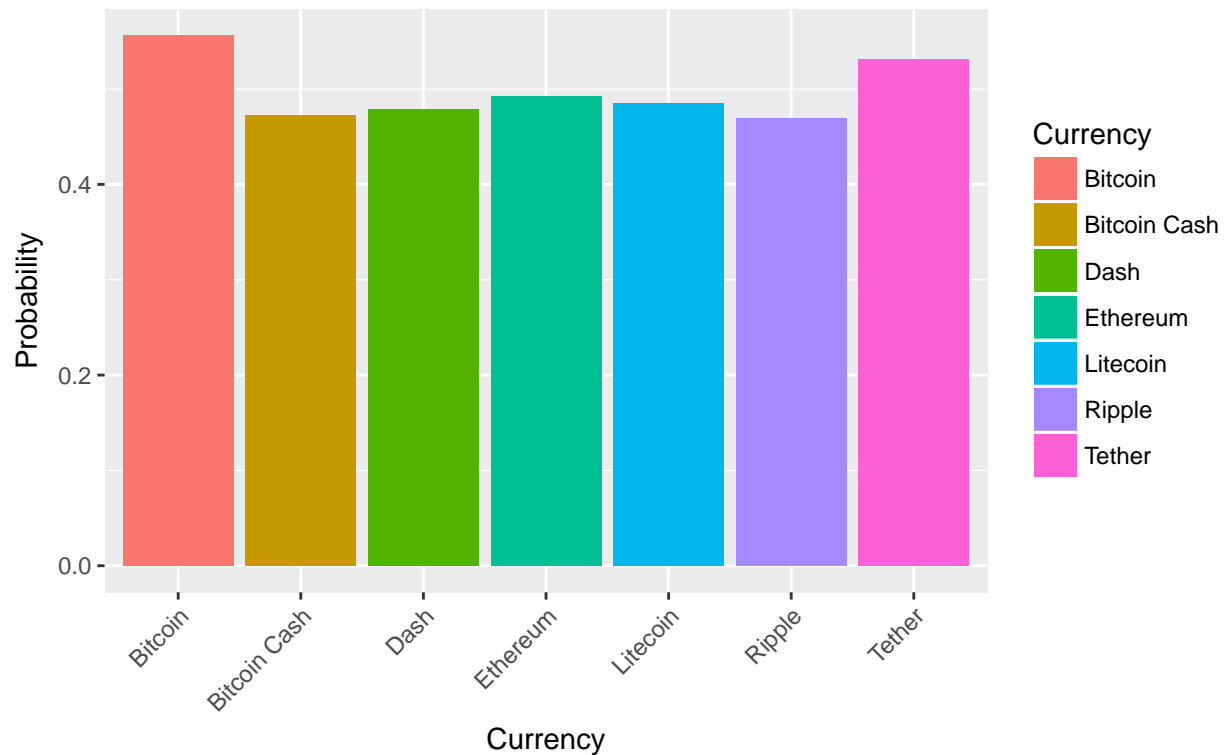
Probability of Increase within a day



```
probability_bar100 <- ggplot(All_probability, mapping = aes(y= probability100,x= Currency, fill=Currency)) +  
  geom_bar(stat = "identity") +  
  ggtitle("Cryptocurrencies from 2011-2017", subtitle = "Probability of Increase within a day: Relative") +  
  labs(y= "Probability") +  
  theme(axis.text.x = element_text(angle = 45, hjust = 1))  
probability_bar100
```


Cryptocurrencies from 2011–2017

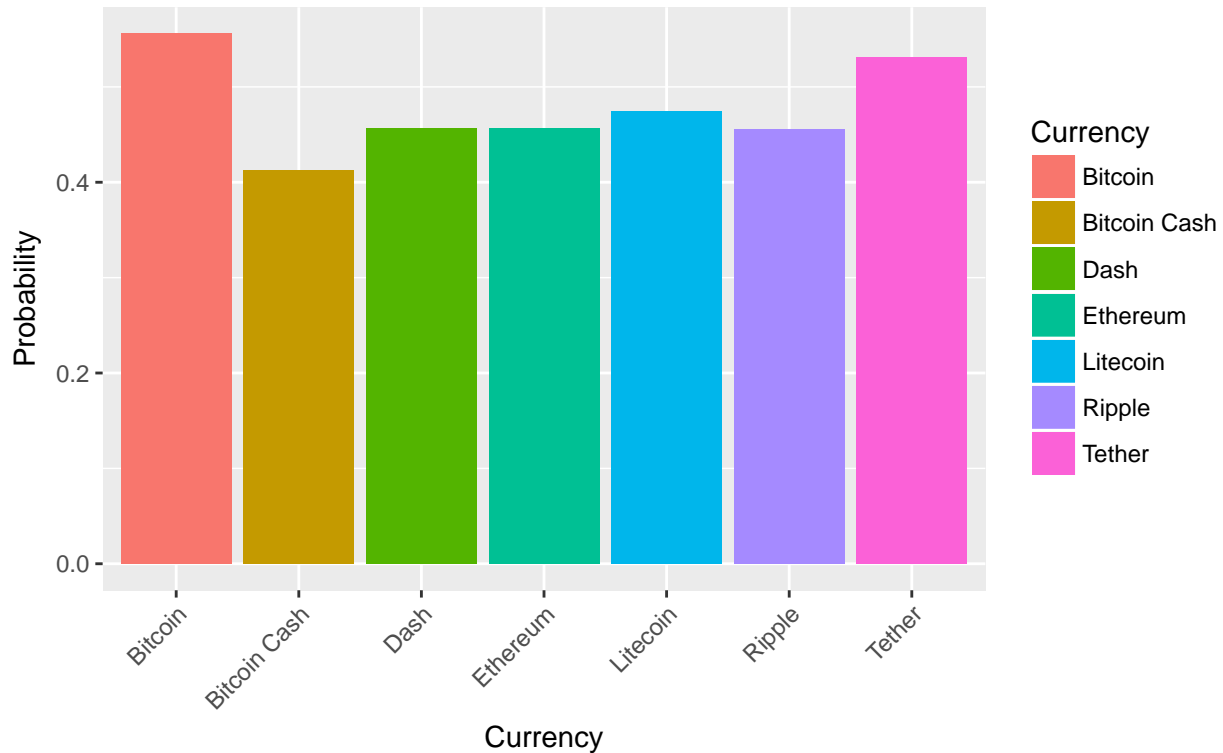
Probability of Increase within a day: Relative Change Limit (–100:100)



```
probability_bar1 <- ggplot(All_probability, mapping = aes(y=probability10,x= Currency, fill=Currency))+  
  geom_bar(stat = "identity") +  
  ggtitle("Cryptocurrencies from 2011-2017", subtitle = "Probability of Increase within a day: Relative  
  labs(y= "Probability")+  
  theme(axis.text.x = element_text(angle = 45, hjust = 1))  
probability_bar1
```

Cryptocurrencies from 2011–2017

Probability of Increase within a day: Relative Change Limit (–10:10)



Conclusion

Based on the day to day relative change of the currencies, we have some insight on how the market fluctuates. We saw that the relative change showed that there was an inverse relationship between Bitcoin and most of the currencies. Bitcoin Cash, Dash, Ethereum, Litecoin, and Ripple's decrease most days with few large increases making up for the losses. While Bitcoin and Tether increase most days, with large drops evening it out.

When we looked at the gain to loss ratio, Bitcoin and Tether had a surplus in increases over losses, while the other 5 had a ratio of below 1. This supports the previous conclusion that there are more gains than losses and when we look at probabilities of this. We see that Bitcoin and Tether have a chance of increase more than 50% in a given day.

For someone that is interested in investing in Cryptocurrency, based on the analysis above, their best bet would be to invest in Bitcoin since. Since there isn't much more information on Tether, more in depth research needs to be done for a conclusion. If someone is looking to invest in another currency, the data tells us that Litecoin has the highest upside.

Overall, since the market moves so fast, a day to day analysis might not be enough to come up with an accurate assumption.