Altcoin-Bitcoin Arbitrage

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Abstract

We give an algorithm and source code for a cryptoasset statistical arbitrage alpha based on a mean-reversion effect driven by the leading momentum factor in cryptoasset returns discussed in `https://ssrn.com/abstract=3245641`. Using empirical data, we identify the cross-section of cryptoassets for which this altcoin-Bitcoin arbitrage alpha is significant and discuss it in the context of liquidity considerations as well as its implications for cryptoasset trading.

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1 Introduction

There is a sizable proliferation of cryptoassets,[4] whose number according to `https://coinmarketcap.com` was 2,116 as of January 18, 2019. Just as with stocks (and other asset classes), there appear to be underlying common factors for cryptoasset returns, at least on shorter-horizons [Kakushadze, 2018].[5] Thus, the leading common factor in the daily close-to-close cryptoasset returns is the prior day's momentum ("mom"), and on average the subsequent open-to-close return is negatively correlated with mom. So, there is a mean-reversion effect in daily cryptoasset returns.

Can we utilize this mean-reversion effect to construct a trading signal (alpha)? The mean-reversion here is cross-sectional, so such an alpha would (ideally) involve a sizable cross-section of cryptoassets. In the case of stocks one can construct a dollar-neutral mean-reversion strategy by going long a sizable number of stocks with the investment level I_L and simultaneously shorting a sizable number of stocks with the investment level I_S, with $I_S = I_L$ (so we have dollar-neutrality), which is a standard long-short statistical arbitrage strategy. Alternatively, one can go long a sizable number of stocks with the investment level I_L and simultaneously short an index futures with the investment level I_S (again, $I_S = I_L$), e.g., S&P 500 futures, in which case we have a dollar-neutral so-called S&P 500 outperformance strategy.

We can attempt to do something similar with cryptoassets. However, shorting a sizable number of cryptoassets is not practicable. We can short Bitcoin futures[6] instead. The long position then can be in a sizable number of cryptoassets other than Bitcoin, i.e., altcoins. We then have a Bitcoin outperformance strategy, which we refer to as altcoin-Bitcoin arbitrage.[7] So, the idea is simple. We maintain a short Bitcoin position with the investment level I_S (so we do not trade Bitcoin). The long position consists of a cross-section of altcoins, which changes daily based on their mom values, so we either establish or liquidate long altcoin positions, but never short them. We discuss some simple trading rules for altcoin positions in Section 2.

The next question is whether the alpha is "tradable". The main considerations are transaction costs and liquidity. In this note we focus on liquidity considera-

[4] For the purposes of this note, cryptoassets include digital cryptography-based assets such as cryptocurrencies (e.g., Bitcoin), as well various other digital "coins" and "tokens" (minable as well as non-minable), that have data on `https://coinmarketcap.com`.

[5] [Kakushadze, 2018] extends short-horizon equity factors [Kakushadze, 2015] to cryptoassets.

[6] For a discussion on Bitcoin futures, see, e.g., [Hale *et al*, 2018].

[7] For some cryptoasset investment and trading related literature, see, e.g., [Alessandretti *et al*, 2018], [Amjad and Shah, 2017], [Baek and Elbeck, 2014], [Bariviera *et al*, 2017], [Bouoiyour *et al*, 2016], [Bouri *et al*, 2017], [Brandvold *et al*, 2015], [Brière, Oosterlinck and Szafarz, 2015], [Cheah and Fry, 2015], [Cheung, Roca and Su, 2015], [Ciaian, Rajcaniova and Kancs, 2015], [Colianni, Rosales and Signorotti, 2015], [Donier and Bouchaud, 2015], [Dyhrberg, 2015], [Eisl, Gasser and Weinmayer, 2015], [ElBahrawy *et al*, 2017], [Gajardo, Kristjanpoller and Minutolo, 2018], [Garcia and Schweitzer, 2015], [Georgoula *et al*, 2015], [Harvey, 2016], [Jiang and Liang, 2017], [Kim *et al*, 2016], [Kristoufek, 2015], [Lee, Guo and Wang, 2018], [Li *et al*, 2018], [Liew and Hewlett, 2017], [Liew, Li and Budavári, 2018], [Nakano, Takahashi and Takahashi, 2018], [Ortisi, 2016], [Shah and Zhang, 2014], [Van Alstyne, 2014], [Vo and Yost-Bremm, 2018], [Wang and Vergne, 2017].

tions. Does this alpha work across essentially all cryptoassets, or is its performance correlated with their liquidity? We address this question empirically in Section 3. We briefly conclude in Section 4. Appendix A gives R source code for building the portfolio and backtesting it.[8] Tables and figures summarize our backtesting results.

2 Alpha

2.1 Setup and Data

Cryptoassets trade continuously, 24/7.[9] Thus, "open" on any given day means the price right after midnight (UTC time), while "close" on any given day means the price right before midnight (UTC time), so the open on a given day is almost the same as the close of the previous day. All prices (open, close, high, low), volume and market cap are measured in dollars. The index $i = 1, \dots, N$ labels N different cryptoassets cross-sectionally, while the index $s = 0, 1, 2, \dots$ labels the dates, with $s = 0$ corresponding to the most recent date in the time series. So: P^C_{is} (or, equivalently, $P^C_{i,s}$) is the close price for the cryptoasset labeled by i on the day labeled by s; P^O_{is} is the open price; P^H_{is} is the high price; P^L_{is} is the low price; V_{is} is the daily dollar volume; C_{is} is the market cap.[10] All our data was freely downloaded (see below).

We define daily open-to-close log-returns (or "continuously compounded" returns), which we use to define the mom factor as in [Kakushadze, 2018] (see below):

$$R_{is} = \ln\left(P^C_{is}/P^O_{is}\right) \tag{1}$$

For small values it is approximately the same as the standard ("single-period") return defined as

$$\widetilde{R}_{is} = P^C_{is}/P^O_{is} - 1 \tag{2}$$

For computing portfolio P&L, return, Sharpe ration [Sharpe, 1994], etc., we use $\widetilde{R}_{is}$.

2.2 Momentum

There are various ways to define the momentum factor (mom). For our purposes here, we will define it as in [Kakushadze, 2018]:

$$\beta^{\text{mom}}_{is} = R_{i,s+1} \tag{3}$$

This definition is 100% out-of-sample: we use β^{mom}_{is} for trading on the date labeled by s, and β^{mom}_{is} is computed using quantities from the prior date labeled by $s+1$.

[8] The source code given in Appendix A hereof is not written to be "fancy" or optimized for speed or in any other way. Its sole purpose is to illustrate the algorithms described in the main text in a simple-to-understand fashion. Some important legalese is relegated to Appendix B.

[9] Assuming no special circumstances such as trading halts.

[10] High, low and volume are measured between the open and the close of a given day.

2.3 Trading Signal

The trading signal (alpha) α_{is} for altcoins is defined as follows:

$$\alpha_{is} = \theta\left(-\beta_{is}^{\text{mom}}\right) \tag{4}$$

where the Heaviside function $\theta(x) = 1$ if $x > 0$, and $\theta(x) = 0$ if $x \leq 0$. So, we establish a new long altcoin position, or maintain an existing long altcoin position, if mom is negative. If mom is nonnegative, then we do not establish a new altcoin position, and liquidate an existing long altcoin position. All altcoin positions are long or null. Meanwhile, we continuously maintain a constant short Bitcoin position.[11]

2.4 Altcoin Weights

Let us assume that the constant short Bitcoin position has the investment level I_S. Let the total investment level of our long altcoin position be I_L. To have a dollar-neutral portfolio, we must set $I_L = I_S$. Let H_{is} be the individual altcoin dollar holdings. Let us use the labels $i = 2, \dots, N$ for altcoins, while $i = 1$ will correspond to Bitcoin. We can define the altcoin weights as $w_{is} = H_{is}/I_L$. Then we have ($w_{is} \geq 0$):

$$\sum_{i=2}^{N} w_{is} = 1 \tag{5}$$

The simplest choice for the weights is to have equal weights for all altcoins with nonzero signals:

$$w_{is} = \frac{1}{n_s}\,\alpha_{is} \tag{6}$$

$$n_s = \sum_{i=2}^{N} \alpha_{is} \tag{7}$$

Other weighting schemes are possible, e.g., by suppressing the weights by volatility:

$$w_{is} = \gamma_s\,\frac{\alpha_{is}}{\sigma_{is}} \tag{8}$$

$$w_{is} = \widetilde{\gamma}_s\,\frac{\alpha_{is}\,|\beta_{is}^{\text{mom}}|}{\sigma_{is}^2} \tag{9}$$

$$\dots \tag{10}$$

Here σ_{is} is historical volatility (e.g., the standard deviation of the returns $R_{is'}$ computed over d previous days $s' = s+1, \dots, s+d$, or the hlv factor defined in [Kakushadze, 2018], etc.), while the normalization coefficients γ_s,$\widetilde{\gamma}_s$ are fixed via Eq. (5). In our backtests (see below) we focus on equally weighted portfolios (6).

[11] Technically, this should be short Bitcoin futures, but we assume a short Bitcoin position.

3 Backtests

3.1 Estimation Period and Universe

We downloaded[12] the data from `https://coinmarketcap.com` for all 2,116 cryptoassets as of January 19, 2019 (so the most recent date in the data is January 18, 2019), and 2,115 cryptoassets had downloadable data, albeit for many various fields were populated with "?", which we converted into NAs. In our backtests (see below), we only kept cryptoassets with non-NA price (open, close, high, low), volume and market cap data, with an additional filter that no null volume was allowed either.[13]

Cboe Bitcoin Futures (symbol XBT)[14] started trading on December 10, 2017. So, technically speaking, backtesting the strategy before that time might not be particularly meaningful.[15] Still, although we primarily focus on the 1-year backtest (looking back from January 18, 2019), for comparison and completeness purposes we also run 2-, 3-, 4- and 5-year lookback backtests. For the 1-year backtest we have 417 cryptoassets with historical data, while for the 2-, 3-, 4- and 5-year backtests we have 121, 67, 44 and 13 cryptoassets, respectively.[16] For the 1-year backtest we further break up the universe of the 416 altcoins (which together with Bitcoin make up the aforesaid 417 cryptoassets) into market cap tiers A,B,C,D,E,F. Thus, the alpha based on tier A on any given day goes long only the altcoins whose market cap on the previous day ranks 2 to 30 among all cryptoassets. Similarly, for tiers B,C,D,E,F the corresponding market cap rank ranges are: 31-60, 61-100, 101-200, 201-300, 301-417. In fact, based on our results (see below), running a backtest for the full universe of all 416 altcoins would obscure the liquidity effect (see below).

3.2 Results

For various universes mentioned above, Table 1 summarizes the market cap, the 20-day average daily volume, and the daily "turnover" defined as the market cap

[12] R source code for data downloads is given in Appendix A of [Kakushadze, 2018]. This code still works with two minor tweaks. First, the line `u <- c(x[22:28])` in the function `crypto.data()` now reads `u <- c(x[22:27])` due to a formatting change on `https://coinmarketcap.com`. Second, in the function `crypto.hist.prc()`, right after the line `shared.write.table(x, file, T)`, one should now include the following (or similar) line: `Sys.sleep(max(rnorm(1, 10, 2), 5))` (which spaces downloads at random intervals). This is due to the apparent change at `https://coinmarketcap.com`, which averts "rapid-fire" (i.e., continuous serial) downloads.

[13] This is to avoid stale prices. Further, 2 cryptoassets had apparently "artifact" stale prices during some periods, so they were also excluded from the corresponding backtests (see below).

[14] Which is the actual investment vehicle we implicitly assume for our short Bitcoin position.

[15] Especially considering the effect Bitcoin futures arguably had on Bitcoin (and other cryptoassets) – see, e.g., [Hale *et al*, 2018]. For a nontechnical discussion, see, e.g., [Kelleher, 2018].

[16] These counts include Bitcoin. Also, these counts exclude the aforesaid 2 cryptoassets with apparently "artifact" stale prices during some periods. Finally, in 2-year and longer backtests the cryptoasset "Circuit of Value Coin" (symbol COVAL) is excluded as it had an extraordinarily large positive return in a short time period and including it would misleadingly "rosy-up" the results.

divided by the 20-day average daily volume. Table 2 and Figures 1-10 summarize the backtest results. These results suggest that the altcoin-Bitcoin arbitrage alpha is a low-liquidity effect. It simply is not there for higher liquidity altcoins. However, the alpha – which hinges on the mean-reversion effect based on the prior day's momentum (mom) – is real. Thus, if for the universe 1E (see Tables 1 and 2) we reverse the signal, we get ROC = -235.16% and Sharpe = -7.18, and if we go long all altcoins with equal weights in this universe (irrespective of mom),[17] we get ROC = -26.56% and Sharpe = -1.34. Conversely, if we reverse the signal for, say, the universe 1A, we do not get a positive return. Therefore, the altcoin-Bitcoin arbitrage alpha appears to be a real effect owing to low liquidity of the altcoins for which it is present. Put differently, the alpha exists as it cannot be arbitraged away.

4 Concluding Remarks

So, the altcoin-Bitcoin arbitrage alpha we discuss above is essentially is "a low-liquidity premium" in altcoin returns. In practice, to arbitrage it, one must account for trading costs – both transaction costs and market impact. For low-liquidity altcoins the market impact can quickly become prohibitive when attempting to execute sizable trades. In fact, for the 2-year, 3-year, 4-year and 5-year lookbacks (where the number of altcoins with historical data is smaller) the naïve pickup in the performance is due to the fact that most of the altcoins in these universes, even though they have been around for a while, are lower-cap, lower-liquidity cryptoassets (which is a telltale sign for persistence), with the notable exception of XRP (Ripple), which is what "Max" in the market cap corresponds to in Table 1 for these universes.

Can the altcoin-Bitcoin arbitrage alpha – or the momentum indicator on which it is based – be useful outside outright arbitraging it (which may be challenging due to the liquidity considerations)? Perhaps. In a sideways cryptoasset market, this indicator could be used as a guide for executing trades for lower-liquidity altcoins in other contexts. Thus, statistically, we expect that there is a mean-reversion effect, and if its yesterday's momentum is positive, today an altcoin (on average) is expected to trade lower, and if its yesterday's momentum is negative, today said altcoin (on average) is expected to trade higher. This can then conceivably be used as a "shorter-horizon" (daily) execution signal for longer-horizon trades. It should be mentioned, however, that the aforesaid alpha is a statistical effect, which is expected to work better for a sizable cross-section of altcoins, so using it as a "shorter-horizon" execution signal for such sizable cross-sections of altcoins would make more sense than for a single (or a few) altcoin(s). In this regard, let us mention [Liew, Li and Budavári, 2018], whose conclusion is that forecasting (using machine learning techniques) short-horizon single-cryptoasset returns (for the top 100 cryptoassets by market cap) appears to be challenging. This also bodes well with our findings here.

[17] In this case we have a quasi-static (the altcoin universe can change with market cap fluctuations) dollar-neutral portfolio, which is obtained by setting $\alpha_{is} \equiv 1$ ($i = 2, \dots, N$) in Eq. (6).

A R Source Code: Trading Signal

In this appendix we give R (R Project for Statistical Computing, `https://www.r-project.org/`) source code for computing the altcoin-Bitcoin arbitrage trading signal. The sole function `crypto.arb()` reads the aggregated data files `cr.prc.txt` (close price), `cr.open.txt` (open price), `cr.high.txt` (high price), `cr.low.txt` (low price), `cr.vol.txt` (dollar volume), `cr.cap.txt` (market cap), `cr.name.txt` (names of the cryptoassets in the same order as all the other files), and `cr.mnbl.txt` (1 if the name is minable, otherwise 0) generated by the function `crypto.prc.files()` of [Kakushadze, 2018] (also, see fn.12 hereof). Internally, `crypto.arb()` computes the `av` (average volume), `size` (market cap), `mom` (momentum), `hlv` (intraday volatility) factors of [Kakushadze, 2018] and the trading signal based on `mom` (together with the trading universe based on `size`). The inputs of `crypto.arb()` are `days` (the length of the selection period used in fixing the cryptoasset universe by applying the aforesaid non-NA data and non-zero volume filters, which period is further "padded" – see below), `back` (the length of the skip period, i.e., how many days to skip in the selection period before the lookback period),[18] `lookback` (the length of the lookback period over which the backtest is run), `d.r` (the extra "padding" added to the selection period plus one day, so the moving averages can be computed out-of-sample; we take `d.r = 20`), `d.v` (the `av` moving average length; we take `d.v = 20`), `d.i` (the `hlv` moving average length; we take `d.i = 20`), `ix.upper` (the rank of the highest market cap (as of the previous day) altcoin to include in the trading universe), and `ix.lower` (the rank of the lowest market cap (as of the previous day) altcoin to include in the trading universe). The function `crypto.arb()` internally computes and plots/outputs the daily P&L and annualized ROC and Sharpe ratio.

```
crypto.arb <- function (days = 365, back = 0, lookback = days,
   d.r = 20, d.v = 20, d.i = 20, ix.lower = NA, ix.upper = 2)
{
   read.prc <- function(file, header = F, make.numeric = T)
   {
      x <- read.delim(file, header = header)
      x <- as.matrix(x)
      if(make.numeric)
         mode(x) <- "numeric"
      return(x)
   }

   calc.mv.avg <- function(x, days, d.r)
   {
      if(d.r == 1)
         return(x[, 1:days])
```

[18] In our backtests we always set `back = 0`. Also note that `mnbl` and `av` are not used internally.

```
   y <- matrix(0, nrow(x), days)
   for(i in 1:days)
      y[, i] <- rowMeans(x[, i:(i + d.r - 1)], na.rm = T)

   return(y)
}

prc <- read.prc("cr.prc.txt")
cap <- read.prc("cr.cap.txt")
high <- read.prc("cr.high.txt")
low <- read.prc("cr.low.txt")
vol <- read.prc("cr.vol.txt")
open <- read.prc("cr.open.txt")
mnbl <- read.prc("cr.mnbl.txt")
name <- read.prc("cr.name.txt", make.numeric = F)

d <- days + d.r + 1
prc <- prc[, 1:d]
cap <- cap[, 1:d]
high <- high[, 1:d]
low <- low[, 1:d]
vol <- vol[, 1:d]
open <- open[, 1:d]

take <- rowSums(is.na(prc)) == 0 & rowSums(is.na(cap)) == 0 &
   rowSums(is.na(high)) == 0 & rowSums(is.na(low)) == 0 &
   rowSums(is.na(vol)) == 0 & rowSums(is.na(open)) == 0 &
   rowSums(vol == 0) == 0

ret <- log(prc[take, -d] / prc[take, -1])
ret.d <- prc[take, -d] / prc[take, -1] - 1
prc <- prc[take, -1]
cap <- cap[take, -1]
high <- high[take, -1]
low <- low[take, -1]
vol <- vol[take, -1]
open <- open[take, -1]
mnbl <- mnbl[take, 1]
name <- name[take, 1]

if(back > 0)
{
   ret <- ret[, (back + 1):ncol(ret)]
```

```
   ret.d <- ret[, (back + 1):ncol(ret)]
   prc <- prc[, (back + 1):ncol(prc)]
   cap <- cap[, (back + 1):ncol(cap)]
   high <- high[, (back + 1):ncol(high)]
   low <- low[, (back + 1):ncol(low)]
   vol <- vol[, (back + 1):ncol(vol)]
   open <- open[, (back + 1):ncol(open)]
}
days <- lookback

av <- log(calc.mv.avg(vol, days, d.v))
hlv <- (high - low)^2 / prc^2
hlv <- 0.5 * log(calc.mv.avg(hlv, days, d.i))
take <- rowSums(!is.finite(hlv)) == 0 ### removes stale prices

av <- av[take, ]
hlv <- hlv[take, ]
mom <- log(prc[take, 1:days] / prc[take, 1:days + 1])
size <- log(cap)[take, 1:days]
ret <- ret[take, 1:days]
ret.d <- ret.d[take, 1:days]
mnbl <- mnbl[take]
name <- name[take]

pnl <- rep(0, days)
for(i in days:1)
{
   x <- -sign(mom[, i]) ### momentum based trading signal
   ### x[] <- 1 ### no signal
   ### x <- -x ### reverse signal

   sort.size <- sort(size[, i], decreasing = T)
   if(is.na(ix.lower))
      ix.lower <- length(sort.size)
   take <- size[, i] >= sort.size[ix.lower] &
      size[, i] <= sort.size[ix.upper] ### cap tier based universe

   x[!take] <- 0
   x[1] <- 0
   if(days > 365)
      x[name == "Circuits of V..." ] <- 0 ### removes COVAL

   x[x < 0] <- 0
```

```
    ### ss <- exp(hlv[, i]) ### hlv based volatility
    ### ss can be computed e.g.  as 20-day historical return volatility
    ### x <- x / ss ### volatility-suppressed signal
    ### x <- x * abs(mom[, i]) / ss^2 ### alternative suppression
    x <- x / sum(abs(x))
    x <- x * ret.d[, i]
    x <- sum(x) - ret.d[1, i]
    if(!is.finite(x))
      x <- 0
    pnl[i] <- x
  }
  pnl1 <- pnl
  pnl <- pnl[days:1]
  pnl <- cumsum(pnl)
  plot(1:days, pnl, type = "l",
    col = "green", xlab = "days", ylab = "P&L")

  roc <- round(mean(pnl1) * 365 / 2 * 100, 2) ### annualized ROC
  sr <- round(mean(pnl1) / sd(pnl1) * sqrt(365), 2) ### annualized Sharpe
  print(roc)
  print(sr)
}
```

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Table 1: Summaries for market cap (Cap), 20-day average daily volume (ADV), and "turnover" (Tvr) defined as Cap divided by ADV. All quantities are as of January 18, 2019. The suffix in the first column is the number of lookback years (and the Cap tier for the 1-year lookback – see Subsection 3.1). Qu = quartile. See Table 2 for the numbers of altcoins in each trading universe. The 1A quantities include Bitcoin (along with 29 altcoins).

Quantity	Min	1st Qu	Median	Mean	3rd Qu	Max
Cap.1A	1.19e+08	1.85e+08	5.13e+08	3.71e+09	1.86e+09	6.43e+10
ADV.1A	1.35e+06	9.90e+06	3.56e+07	5.03e+08	2.05e+08	5.18e+09
Tvr.1A	8.48e-03	2.92e-02	5.97e-02	1.93e-01	2.08e-01	1.93e+00
Cap.1B	3.75e+07	4.45e+07	5.77e+07	6.94e+07	9.85e+07	1.16e+08
ADV.1B	4.04e+04	6.59e+05	1.91e+06	3.76e+06	3.57e+06	2.08e+07
Tvr.1B	9.94e-04	9.90e-03	3.02e-02	5.15e-02	5.23e-02	3.01e-01
Cap.1C	1.66e+07	2.00e+07	2.42e+07	2.50e+07	2.81e+07	3.71e+07
ADV.1C	1.29e+03	3.22e+05	5.23e+05	1.90e+06	1.34e+06	1.75e+07
Tvr.1C	7.78e-05	1.20e-02	2.30e-02	6.80e-02	6.19e-02	5.85e-01
Cap.1D	4.38e+06	5.98e+06	7.62e+06	8.72e+06	1.10e+07	1.63e+07
ADV.1D	3.67e+02	4.10e+04	1.79e+05	7.94e+05	5.29e+05	3.14e+07
Tvr.1D	5.40e-05	6.03e-03	2.40e-02	1.12e-01	6.38e-02	4.83e+00
Cap.1E	1.02e+06	1.43e+06	2.20e+06	2.34e+06	2.96e+06	4.37e+06
ADV.1E	4.00e+02	3.60e+03	1.16e+04	1.14e+05	4.56e+04	3.04e+06
Tvr.1E	1.45e-04	2.00e-03	5.49e-03	4.56e-02	2.48e-02	1.02e+00
Cap.1F	8.82e+03	1.60e+05	4.22e+05	4.37e+05	7.15e+05	1.02e+06
ADV.1F	1.10e+01	4.97e+02	1.47e+03	4.50e+04	8.13e+03	3.54e+06
Tvr.1F	1.38e-04	1.87e-03	5.28e-03	1.09e-01	2.18e-02	9.38e+00
Cap.2	2.44e+04	1.09e+06	4.70e+06	3.00e+08	2.49e+07	1.35e+10
ADV.2	7.70e+01	4.30e+03	2.72e+04	3.75e+07	3.98e+05	2.75e+09
Tvr.2	7.78e-05	2.34e-03	8.75e-03	3.24e-02	2.35e-02	5.03e-01
Cap.3	6.70e+04	1.24e+06	5.07e+06	5.05e+08	2.21e+07	1.35e+10
ADV.3	8.30e+01	7.06e+03	3.64e+04	6.14e+07	2.37e+05	2.75e+09
Tvr.3	7.64e-04	2.33e-03	8.32e-03	2.67e-02	2.36e-02	2.75e-01
Cap.4	6.70e+04	2.34e+06	8.30e+06	4.60e+08	3.62e+07	1.35e+10
ADV.4	8.30e+01	8.88e+03	7.95e+04	2.99e+07	3.85e+05	5.27e+08
Tvr.4	7.64e-04	2.25e-03	9.47e-03	2.72e-02	2.32e-02	2.75e-01
Cap.5	1.31e+06	4.57e+06	1.27e+07	1.31e+09	8.23e+07	1.35e+10
ADV.5	3.07e+03	1.88e+04	6.18e+04	8.67e+07	4.53e+06	5.27e+08
Tvr.5	1.05e-03	2.33e-03	9.12e-03	3.64e-02	1.86e-02	2.75e-01

Table 2: Backtest results. Lookback is the number of years (and the Cap tier for the 1-year lookback – see Subsection 3.1). The second column labeled "rank" determines which altcoins are allowed to be included in the long portfolio on a given day: "rank" refers to the range of the rank of the market cap on the previous day among all cryptoassets (with a few cryptoassets excluded as set forth in fn.16 hereof). ROC = annualized return-on-capital (which is given by $365 \times \mathrm{P}/(I_L + I_S)$, where P is the average daily P&L, I_L and I_S are the total long and short investment levels, and $I_L = I_S$ for dollar-neutrality). Sharpe = annualized Sharpe ratio (which is given by $\sqrt{365} \times P/S$, where S is the standard deviation of daily P&Ls).

Lookback	rank	ROC (%)	Sharpe
1A	2-30	-44.25	-1.81
1B	31-60	-59.29	-1.99
1C	61-100	-24.78	-0.83
1D	101-200	11.26	0.43
1E	201-300	124.43	4.93
1F	301-417	459.08	14.65
2	2-121	174.7	4.2
3	2-67	222.75	4.06
4	2-44	191.43	4.34
5	2-13	62.27	1.28

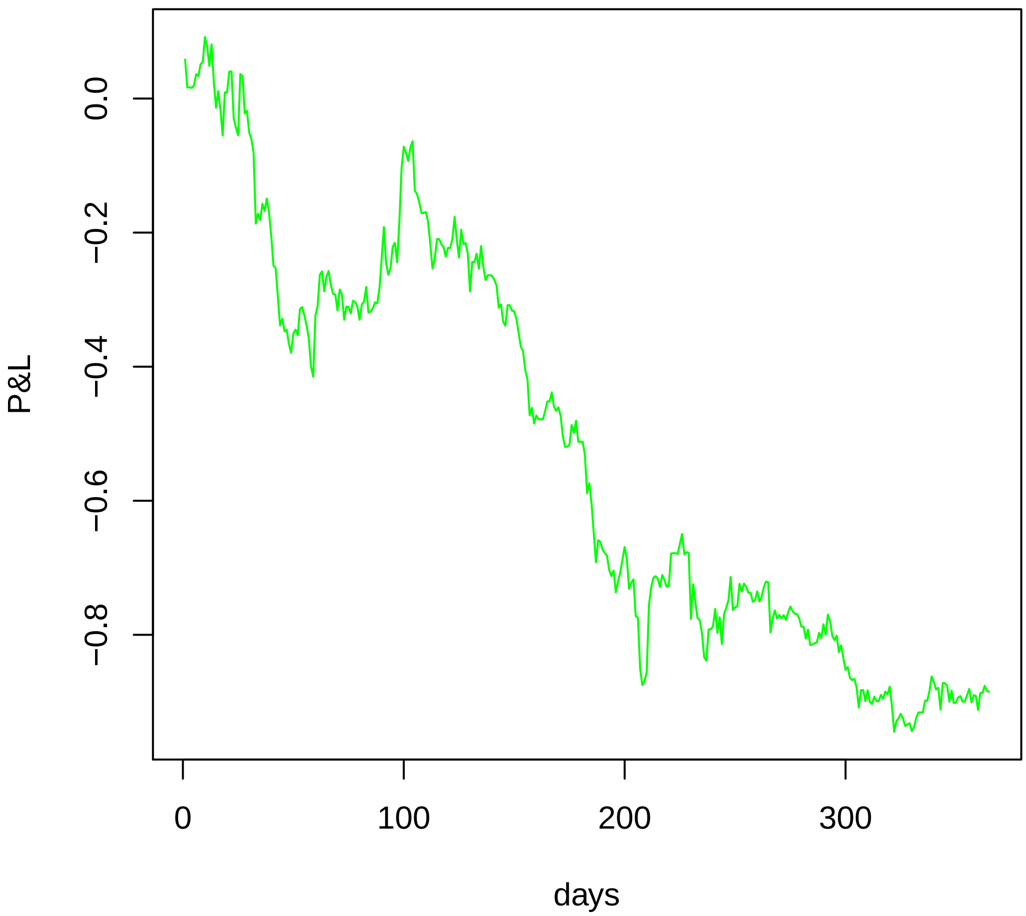

Figure 1: P&L (in the units where the short Bitcoin position is normalized to 1) for the lookback 1A portfolio (see Table 2).

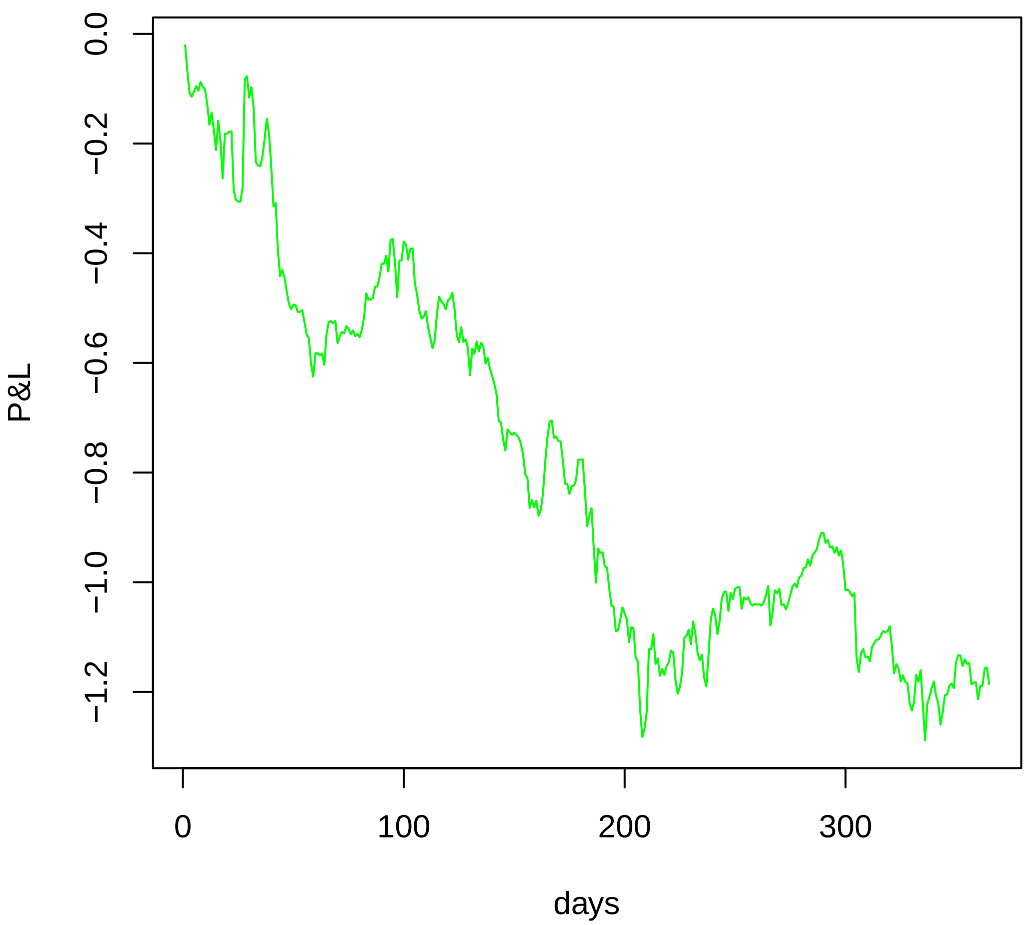

Figure 2: P&L (in the units where the short Bitcoin position is normalized to 1) for the lookback 1B portfolio (see Table 2).

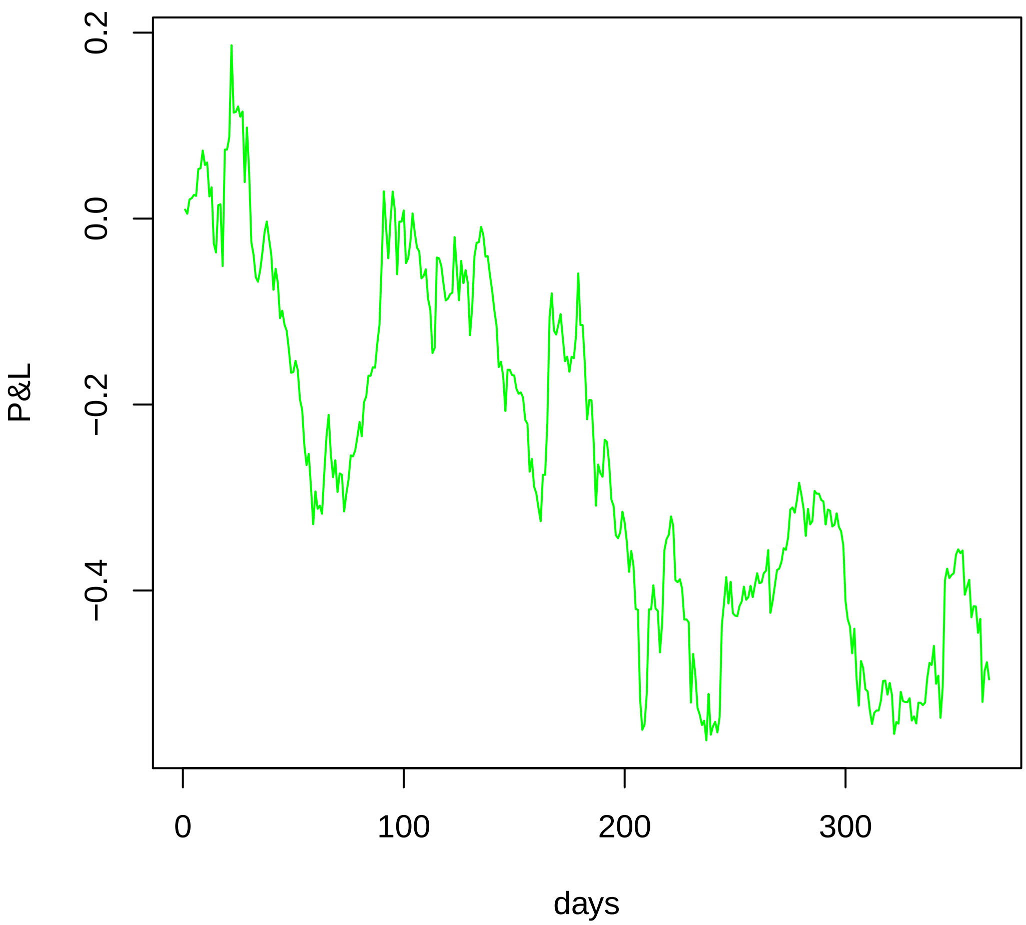

Figure 3: P&L (in the units where the short Bitcoin position is normalized to 1) for the lookback 1C portfolio (see Table 2).

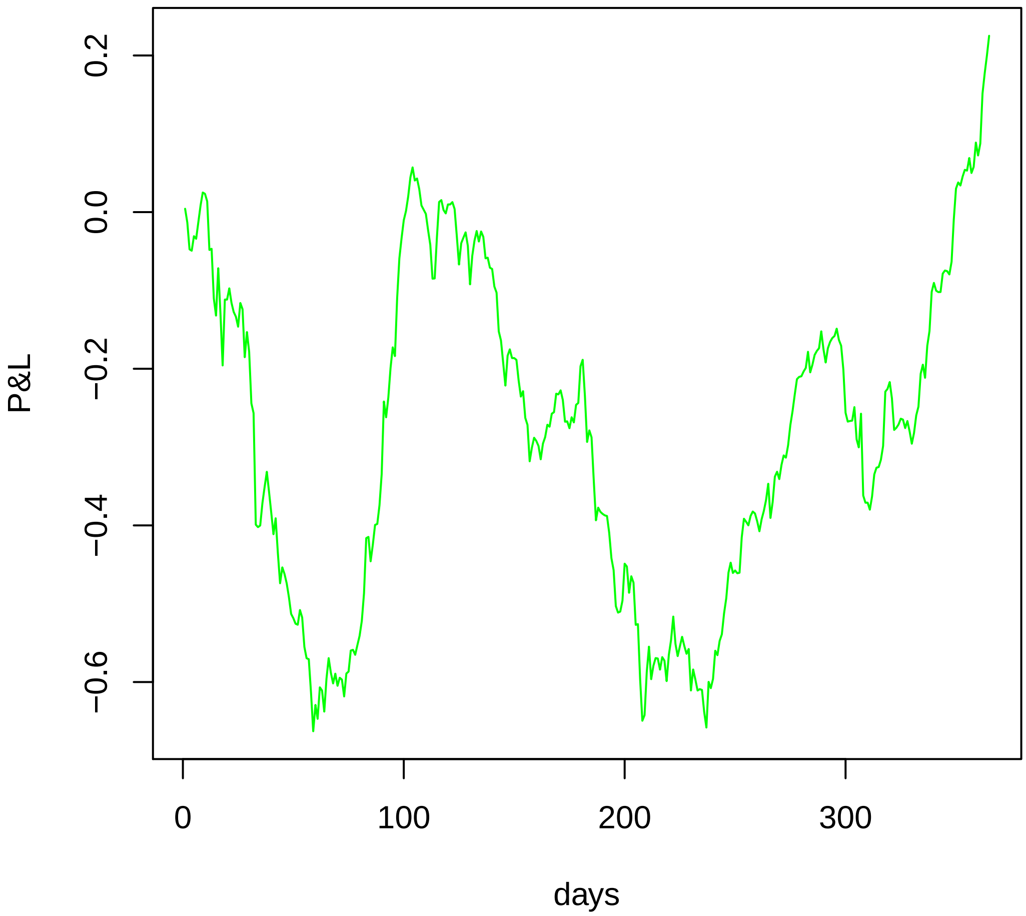

Figure 4: P&L (in the units where the short Bitcoin position is normalized to 1) for the lookback 1D portfolio (see Table 2).

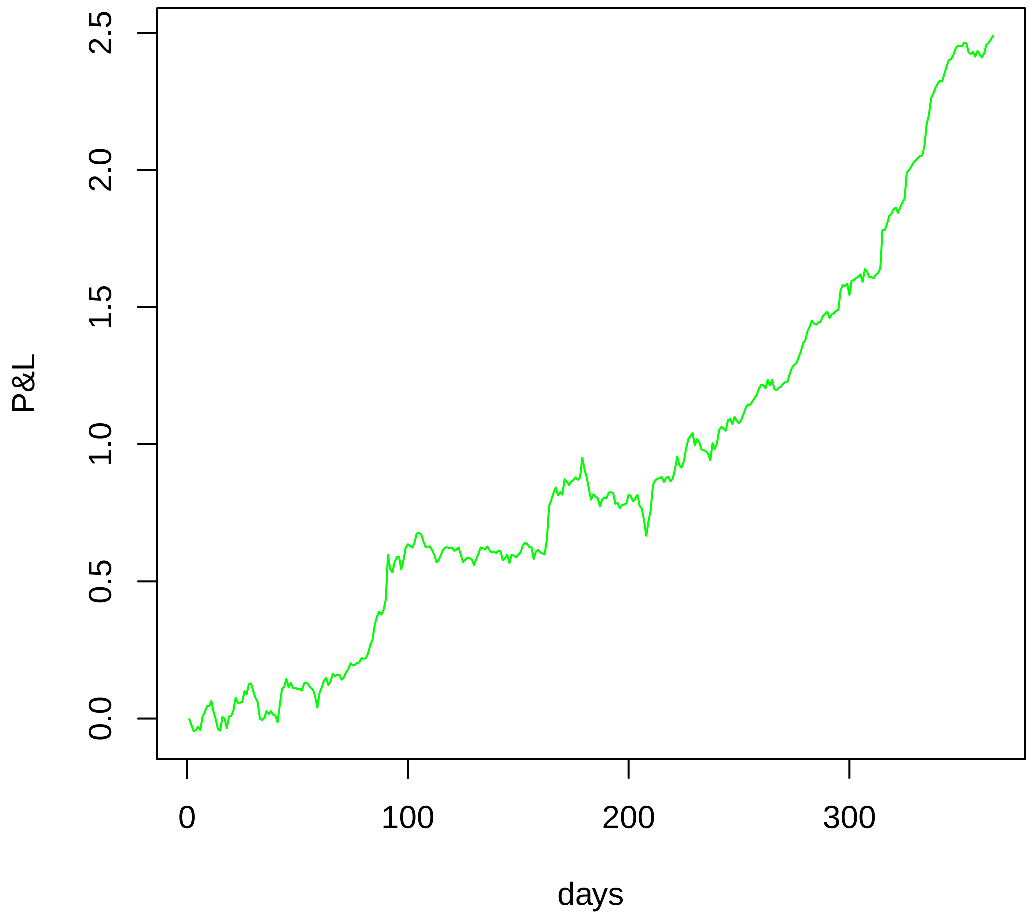

Figure 5: P&L (in the units where the short Bitcoin position is normalized to 1) for the lookback 1E portfolio (see Table 2).

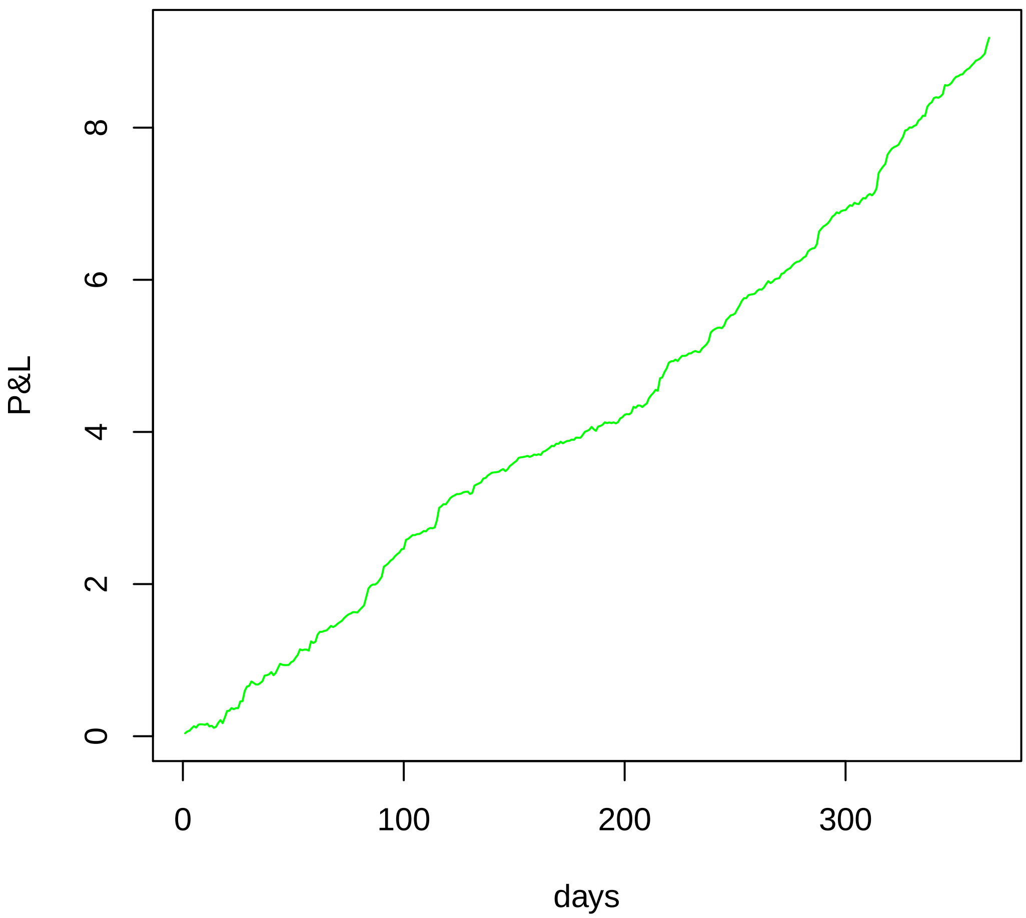

Figure 6: P&L (in the units where the short Bitcoin position is normalized to 1) for the lookback 1F portfolio (see Table 2).

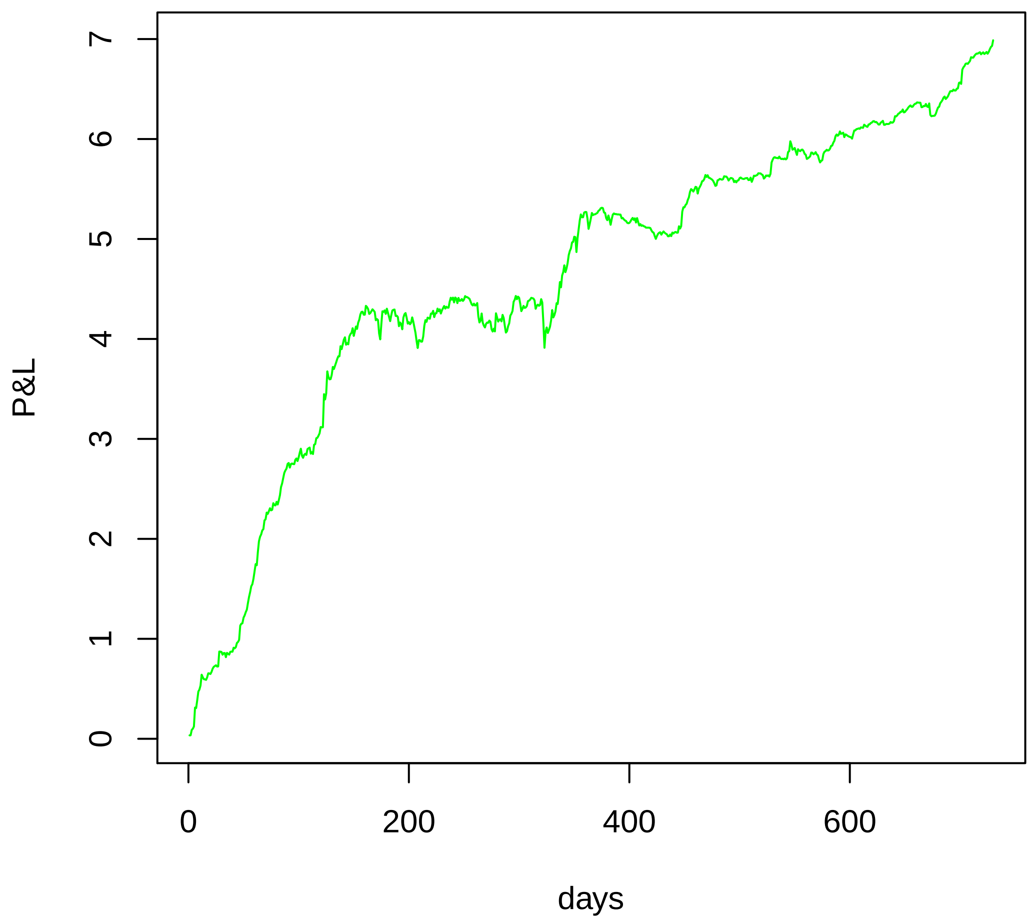

Figure 7: P&L (in the units where the short Bitcoin position is normalized to 1) for the lookback 2 portfolio (see Table 2).

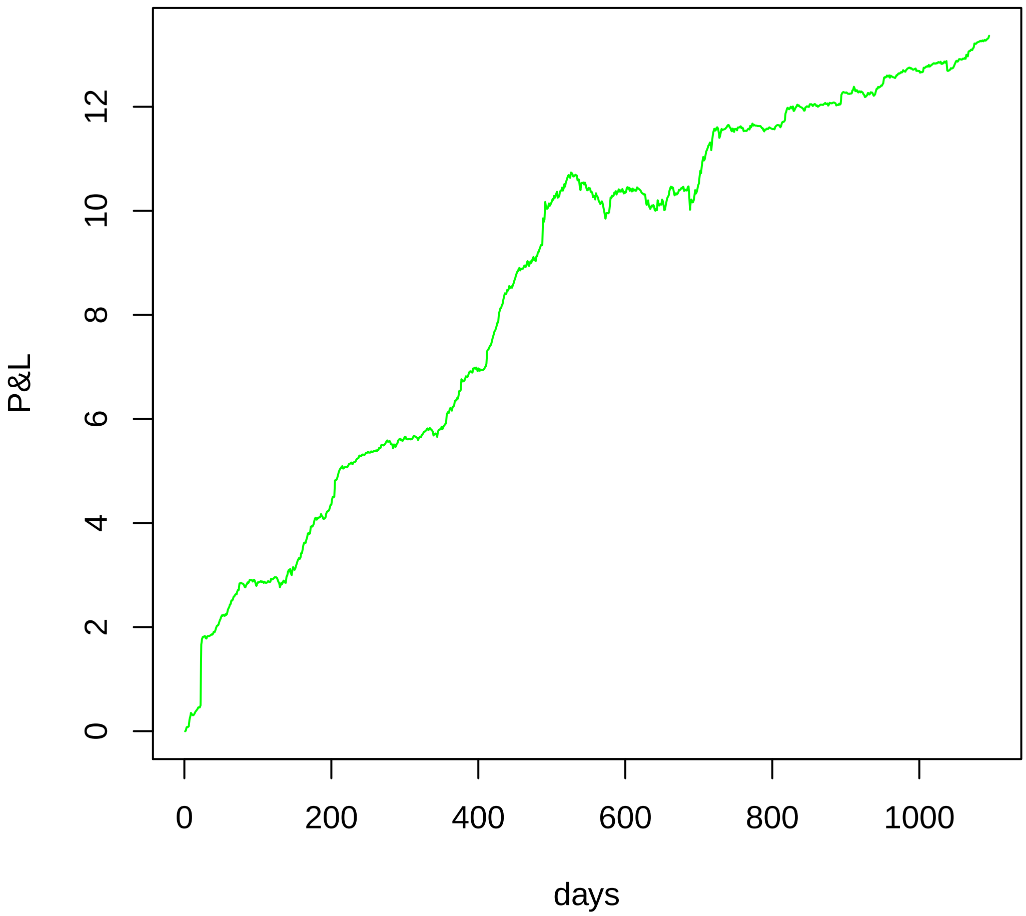

Figure 8: P&L (in the units where the short Bitcoin position is normalized to 1) for the lookback 3 portfolio (see Table 2).

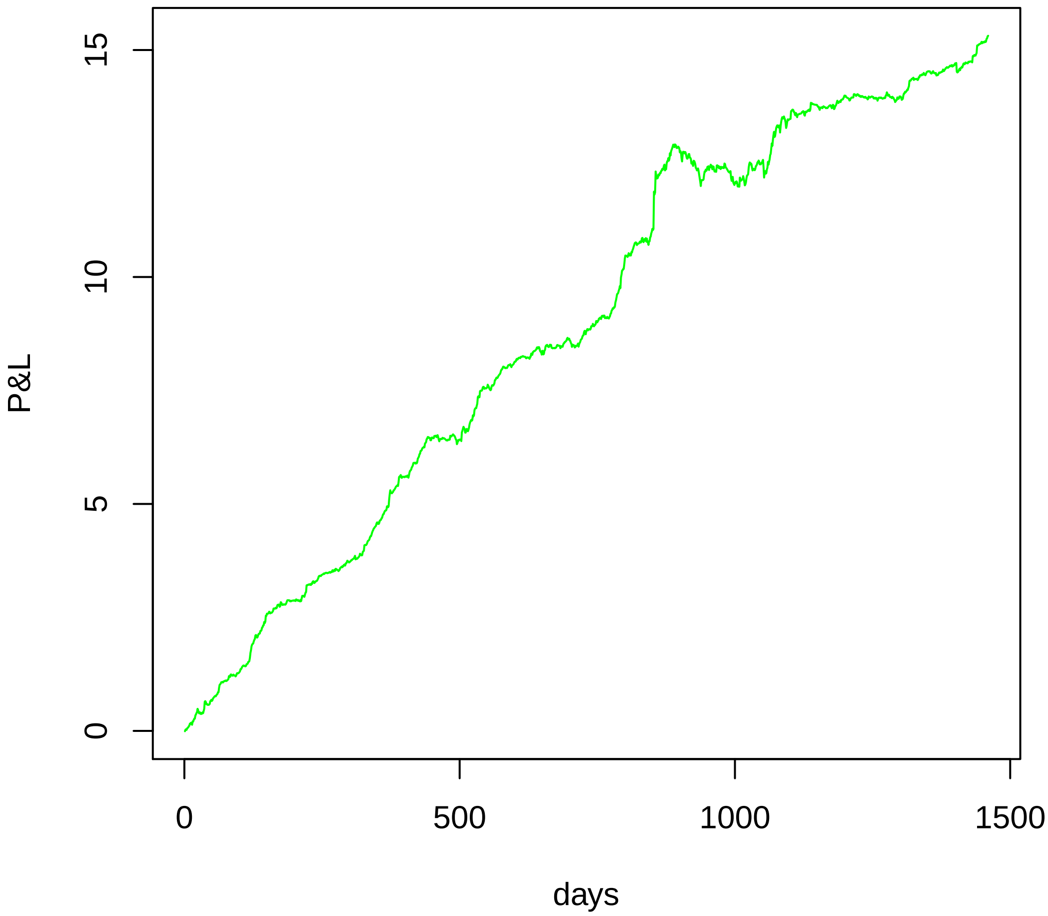

Figure 9: P&L (in the units where the short Bitcoin position is normalized to 1) for the lookback 4 portfolio (see Table 2).

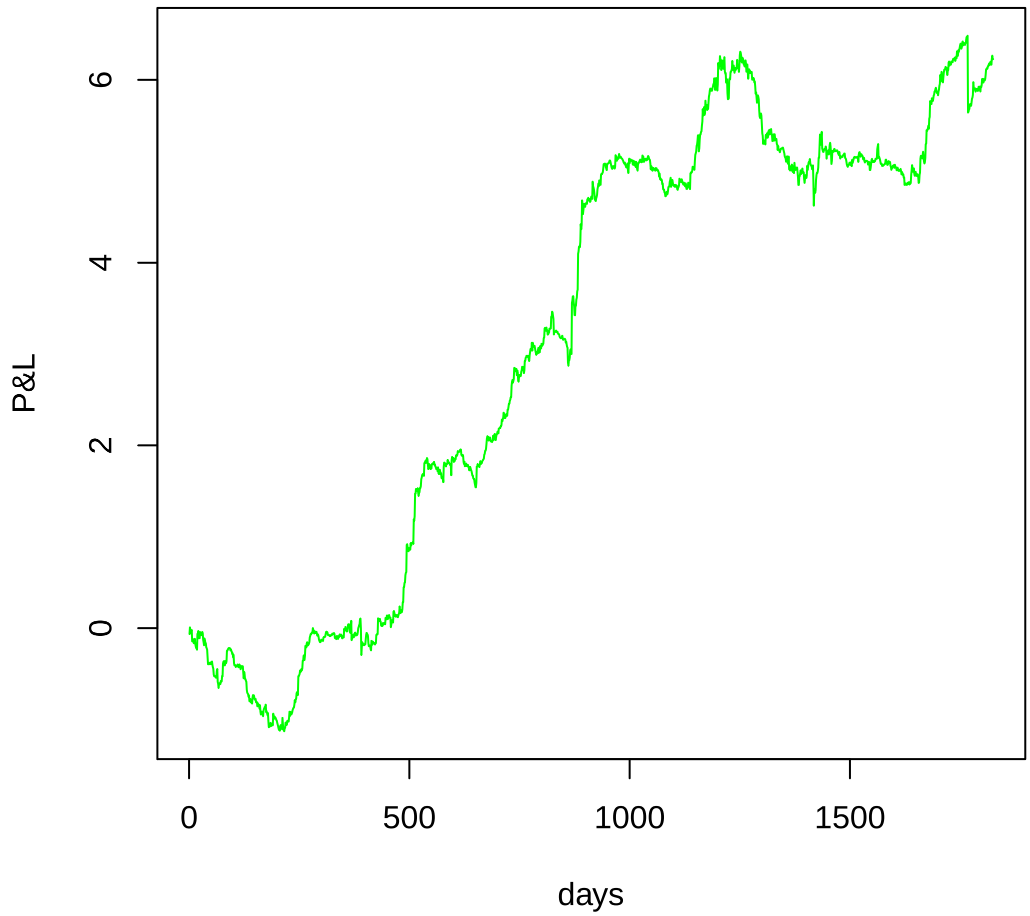

Figure 10: P&L (in the units where the short Bitcoin position is normalized to 1) for the lookback 5 portfolio (see Table 2).