eCommerce - Time Series with Montecarlo Simulation (CAPM and Efficient Porfolio) [.pdf]

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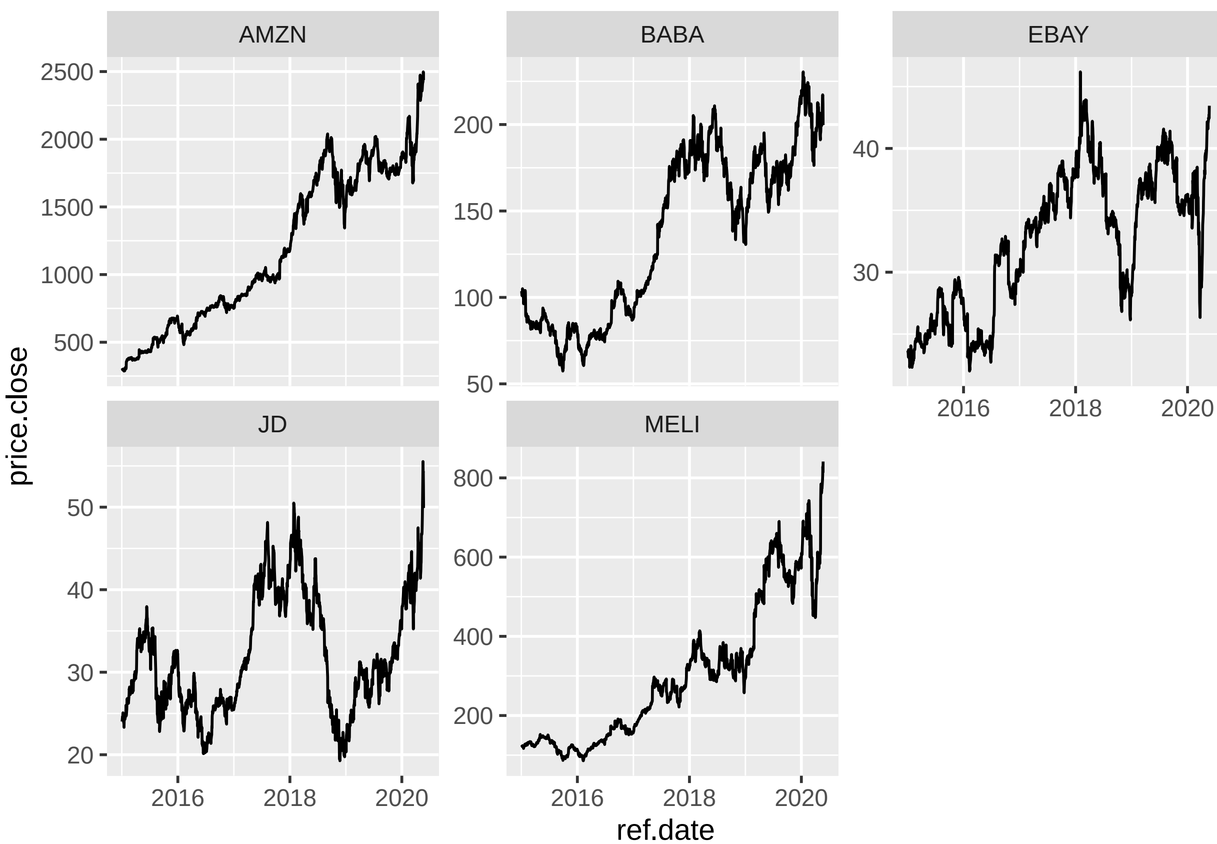
Mon May 25, 2020. 21:28:28. Buenos Aires, Argentina.

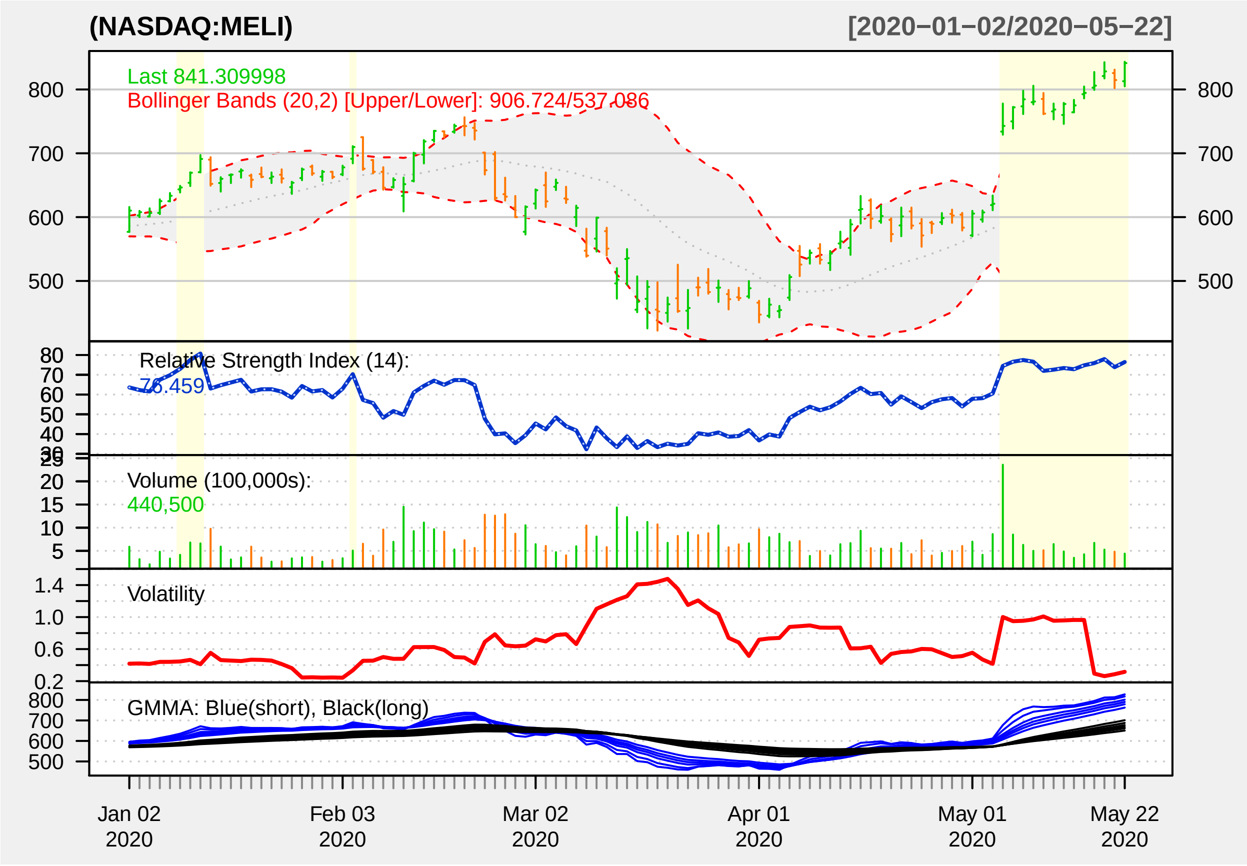
This is a BONUS Lab in R

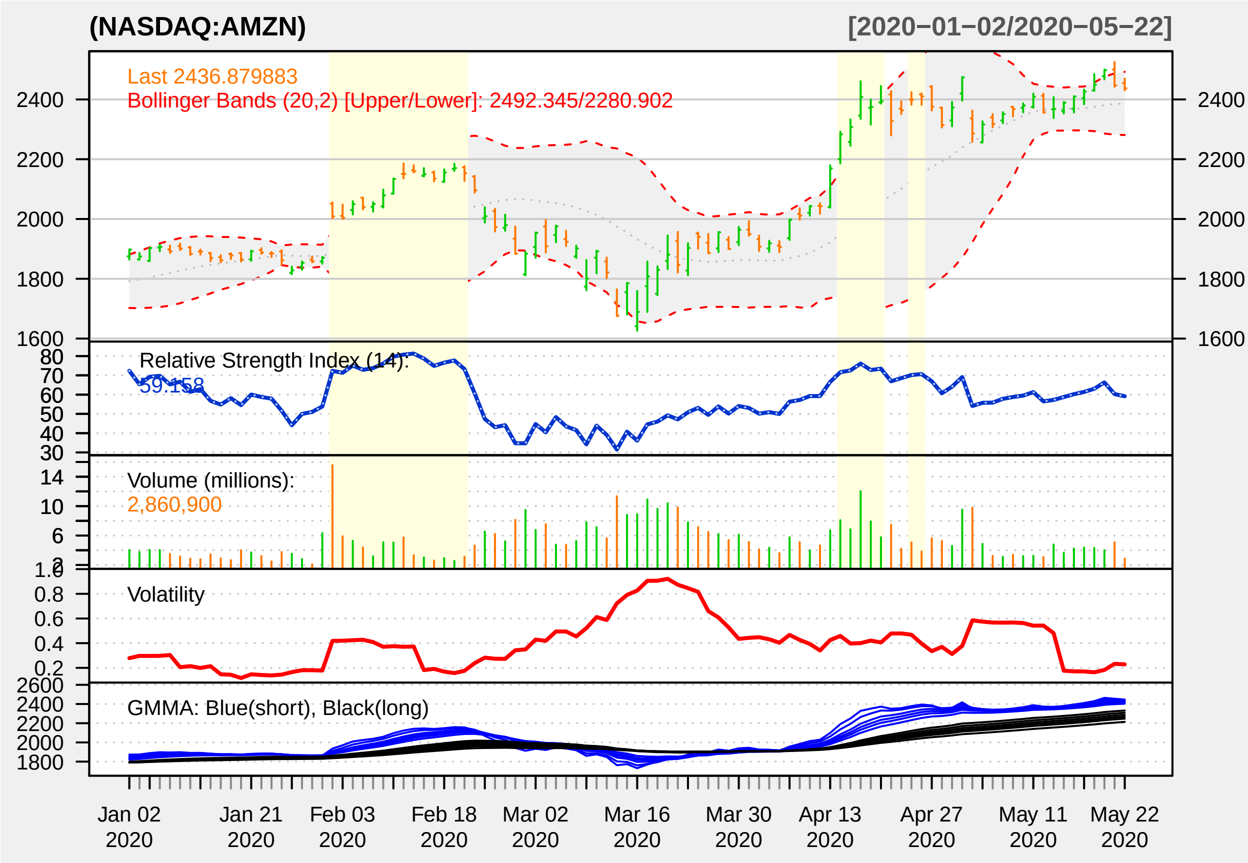
We will apply Montecarlo Simulations and Efficient Portfolio Management theory to Financial Time Series to determine how much of 5 Global eCommerce stocks we should buy for our investment portfolio. Namly, we will be looking at:

Mercado Libre (Latam), Amazon and Ebay (USA/Europe), Alibaba & JD.com (Asia/China)

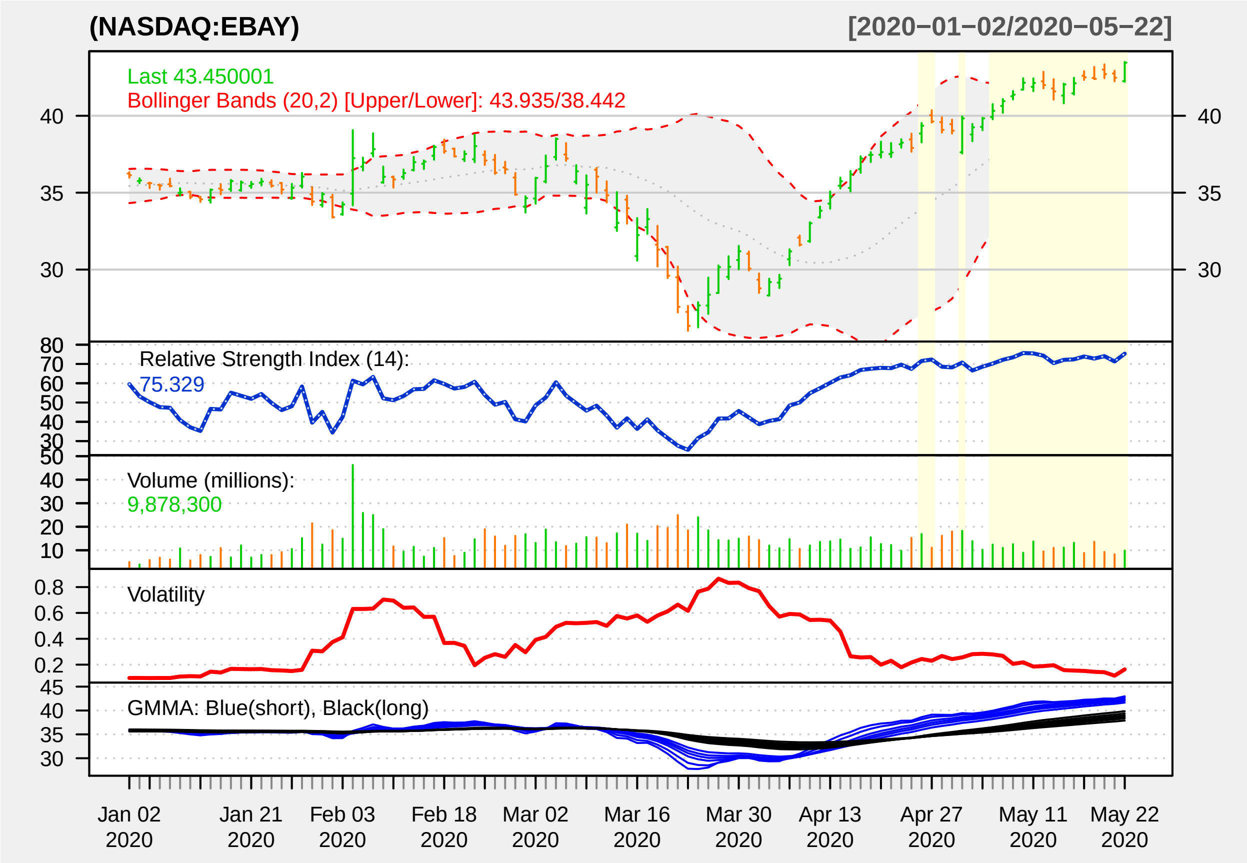


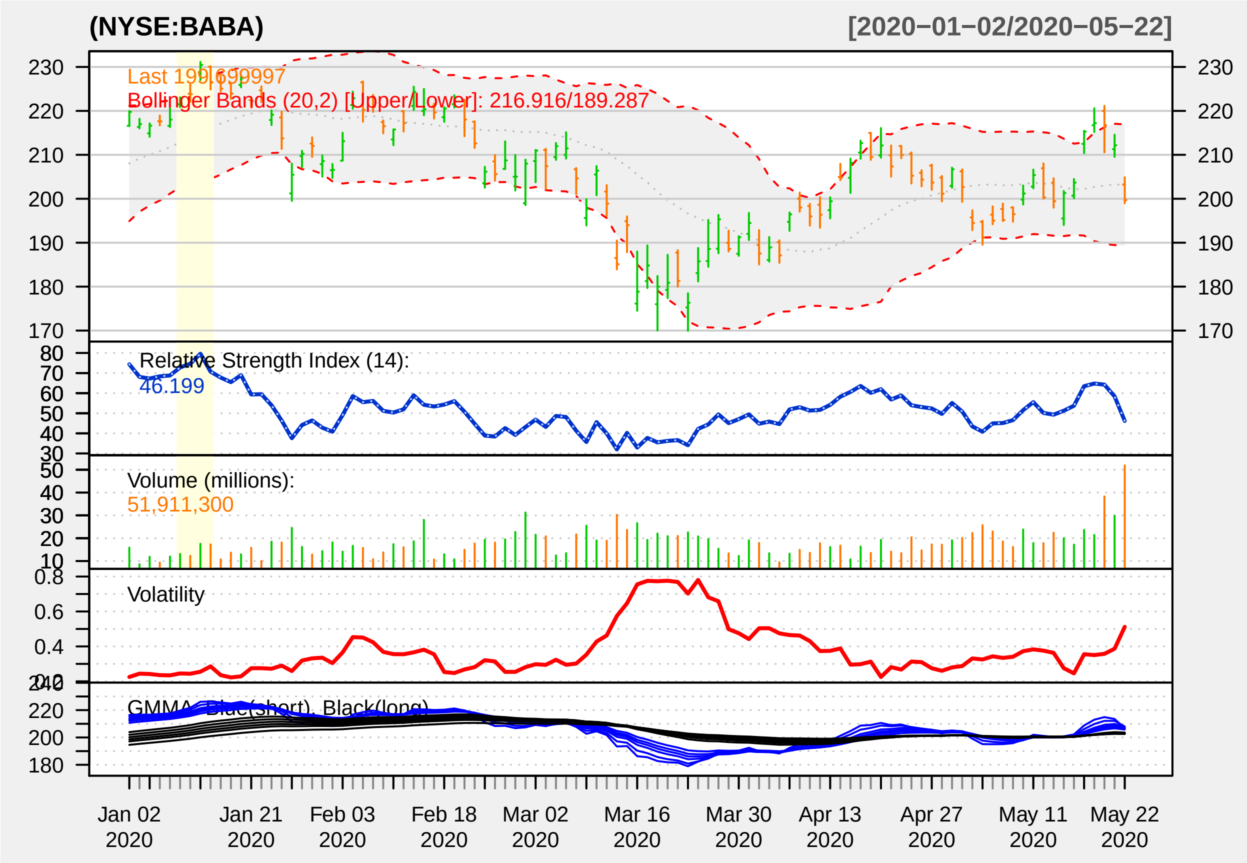
Technical charts in more detail

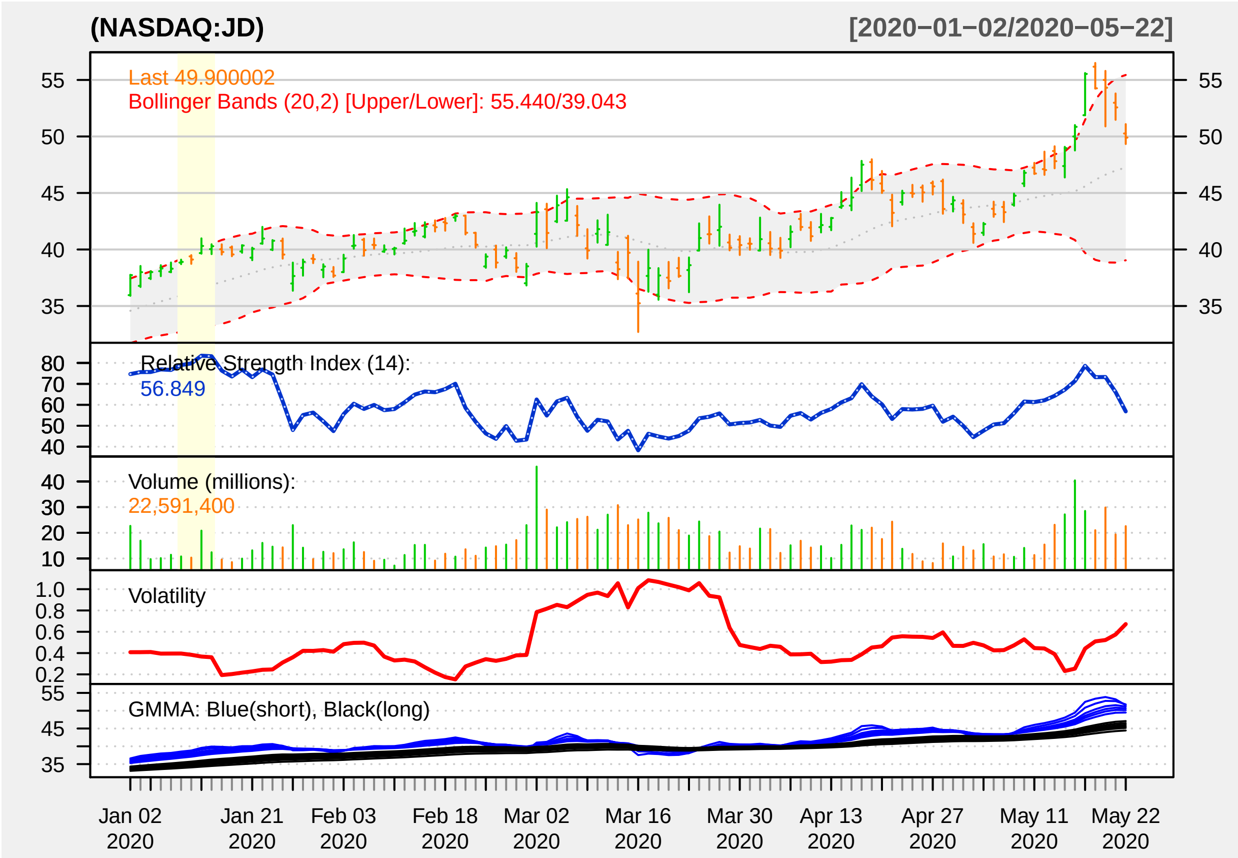




(NASDAQ:AMZN)
[2020−01−02/2020−05−22]
Last 2436.879883
Bollinger Bands (20,2) [Upper/Lower]: 2492.345/2280.902
Relative Strength Index (14):
59.158
Volume (millions):
2,860,900
Volatility
GMMA: Blue(short), Black(long)
Jan 02 2020
Jan 21 2020
Feb 03 2020
Feb 18 2020
Mar 02 2020
Mar 16 2020
Mar 30 2020
Apr 13 2020
Apr 27 2020
May 11 2020
May 22 2020


(NASDAQ:EBAY)
[2020−01−02/2020−05−22]
Last 43.450001
Bollinger Bands (20,2) [Upper/Lower]: 43.935/38.442
Relative Strength Index (14):
75.329
Volume (millions):
9,878,300
Volatility
GMMA: Blue(short), Black(long)
Jan 02 2020
Jan 21 2020
Feb 03 2020
Feb 18 2020
Mar 02 2020
Mar 16 2020
Mar 30 2020
Apr 13 2020
Apr 27 2020
May 11 2020
May 22 2020


(NYSE:BABA)
[2020−01−02/2020−05−22]
Last 199.699997
Bollinger Bands (20,2) [Upper/Lower]: 216.916/189.287
Relative Strength Index (14):
46.199
Volume (millions):
51,911,300
Volatility
GMMA - Blue(short), Black(long)
Jan 02 2020
Jan 21 2020
Feb 03 2020
Feb 18 2020
Mar 02 2020
Mar 16 2020
Mar 30 2020
Apr 13 2020
Apr 27 2020
May 11 2020
May 22 2020



Source: Yahoo Finance + All things R.

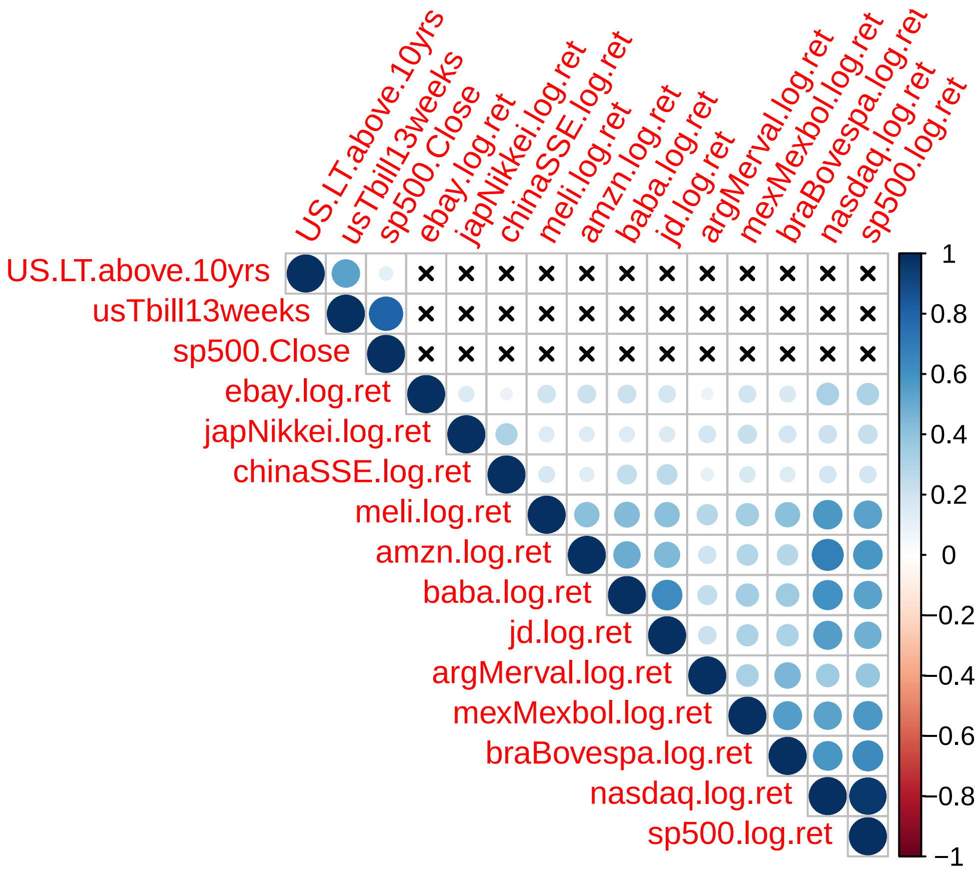
Correlation of stock returns, fx rates, market index log returns, and risk free rates.

Individual assets and the market move in correlation and covariance with many additional financial and economical factors, each with its respective volatilities. I run a wide analysis on the mayor indexes and other possible influential players for each of the companies, countries and mayor markets where these companies operate.

As we can see from the graph below, as expected, the mayor influences on these eCommerce companies performance are: each other, of course, the market indexes of the US, the index for the markets in their countries of origin, and the indexes of the mayor markets they operate in.

All companies under our current coverage are traded in the US stock markets. Beyond this first introductory analysis and going forward, for our purposes of risk management and portfolio management, we will work with three key economic factors:

1) The US short term 13 week T bill;
2) the US cost of long term 10 year bonds; and
3) The S&P 500 value.



Notes: "X" marks denote a pairwise correlation rejected at a 0.05 sig.level.
Sources of variables: Yahoo Finance.

Capital Asset Pricing Model per company

Lets begin by looking at how our individual stock prices and performance are tied to the US market. We will use historical returns starting on January of 2018 for MELI, AMZN, EBAY, BABA and JD.

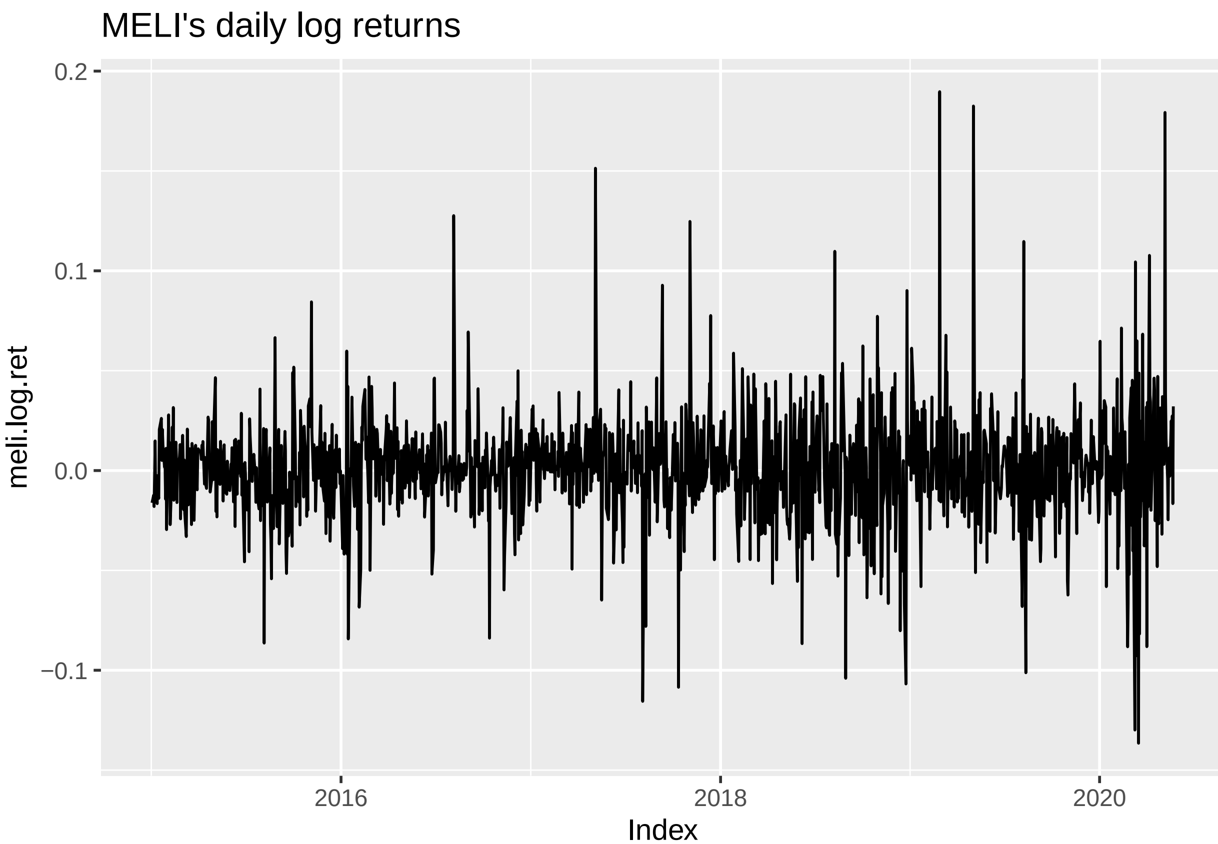
Looking at daily arithmetic returns for each stock and the S&P500 minus the daily closing interest rate of the 10 year US treasury Bond, which we use as the risky free return, we compute each stock's and the S&P500's excess return. We then compare each of their excess returns versus the excess return of the market, represented by the S&P 500 index.

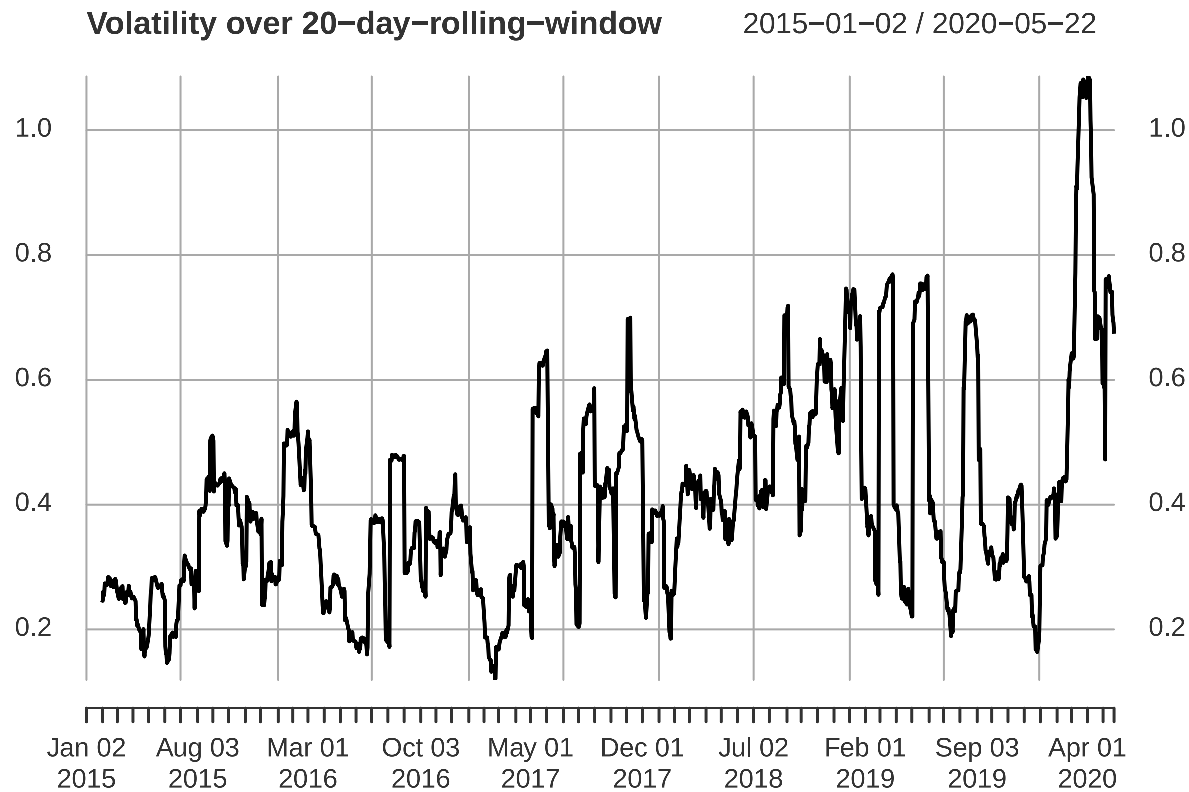
With alphas very close to zero, all stocks are fairly priced.

	MELI	AMZN	EBAY	BABA	JD
Beta	1.24	0.95	0.83	0.93	1.09
Alpha	0.00353	0.000976	-0.000135	-0.000253	0.00137
Over/Under Priced	Under-priced	Neutral	Over-priced	Over-priced	Under-priced
Market Risk Exposure	27.67%	34.21%	5.27%	28.91%	24.67%
Expected Excess Returns	-0.16%	0.08%	0.18%	0.09%	-0.04%

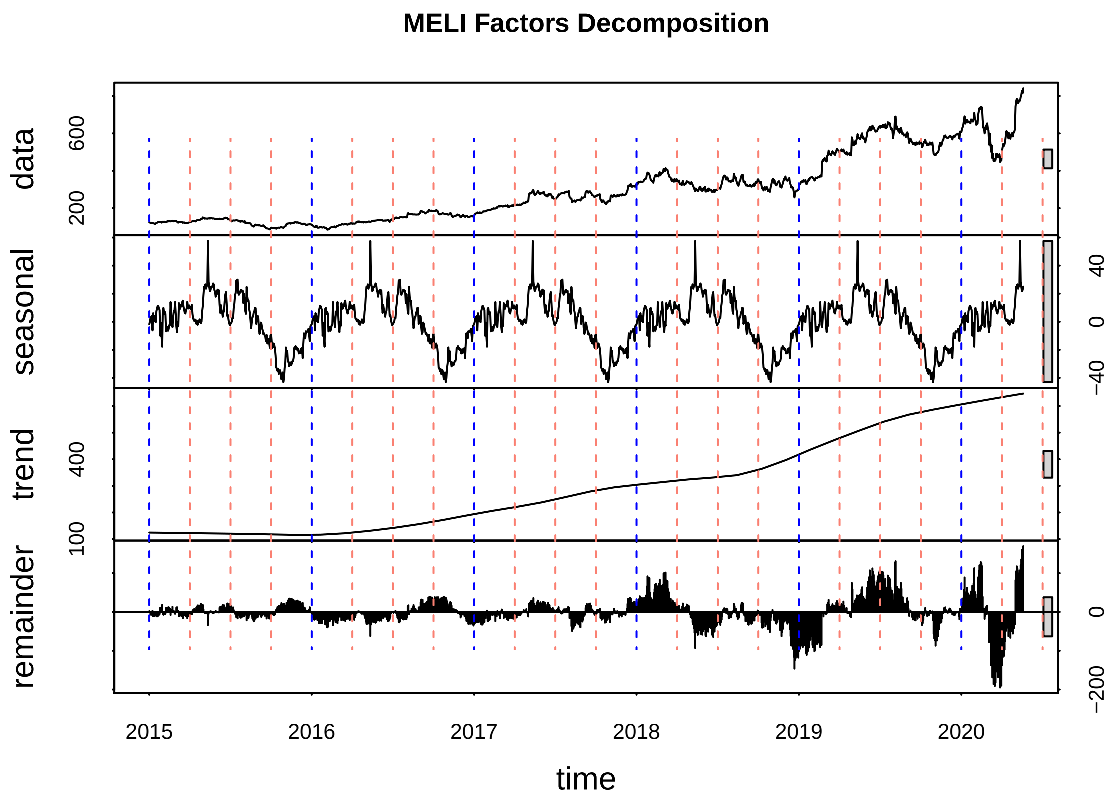
Decomposing MELI: Trend and Seasonality

Decompose trend and seasonal factros with Seasonal Decomposition of Time Series by Loess






```
## Call:
## stl(x = meli.ts[, "MELI.Adjusted"], s.window = "periodic", robust = T)
##
## Time.series components:
##     seasonal             trend            remainder
## Min.   :-43.12100   Min.   :115.7779   Min.   :-194.86784
## 1st Qu.: -8.93257   1st Qu.:130.4136   1st Qu.: -18.23794
## Median :  1.89781   Median :275.5146   Median :  -3.20217
## Mean   :  0.49560   Mean   :302.0769   Mean   :  -1.72015
## 3rd Qu.: 11.04145   3rd Qu.:427.1541   3rd Qu.:  17.23930
## Max.   : 57.57213   Max.   :646.8118   Max.   : 169.48420
## IQR:
##     STL.seasonal STL.trend STL.remainder data
##      19.97        296.74     35.48        234.78
##    %   8.5        126.4      15.1         100.0
##
## Weights:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.0000  0.8158  0.9452  0.8186  0.9887  1.0000
##
## Other components: List of 5
## $ win  : Named num [1:3] 13571 379 253
## $ deg  : Named int [1:3] 0 1 1
## $ jump : Named num [1:3] 1358 38 26
## $ inner: int 1
## $ outer: int 15
```



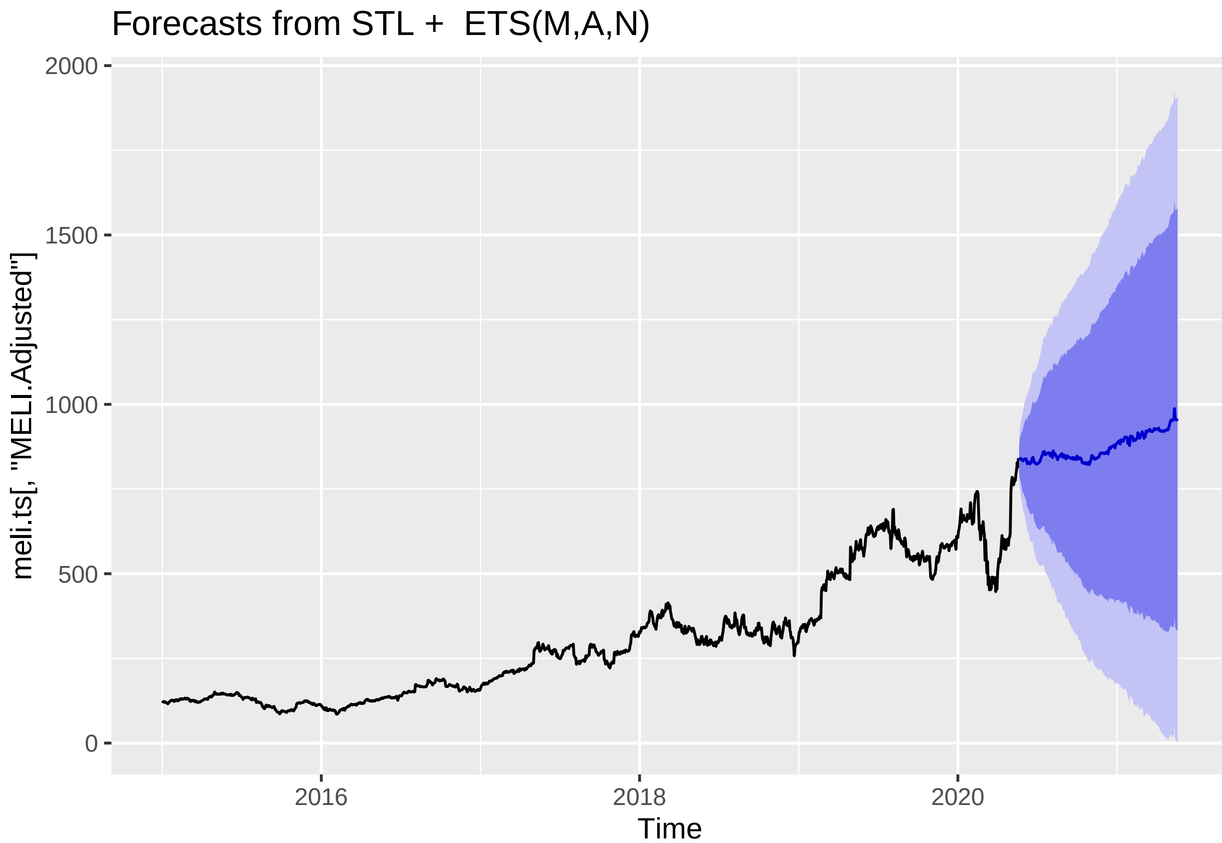
Projections for MELI

Note: I will always be suing seed 123 so that everyone's randomizer can be set equally to reproduce the same or as close to the same results at any time the same data is used.

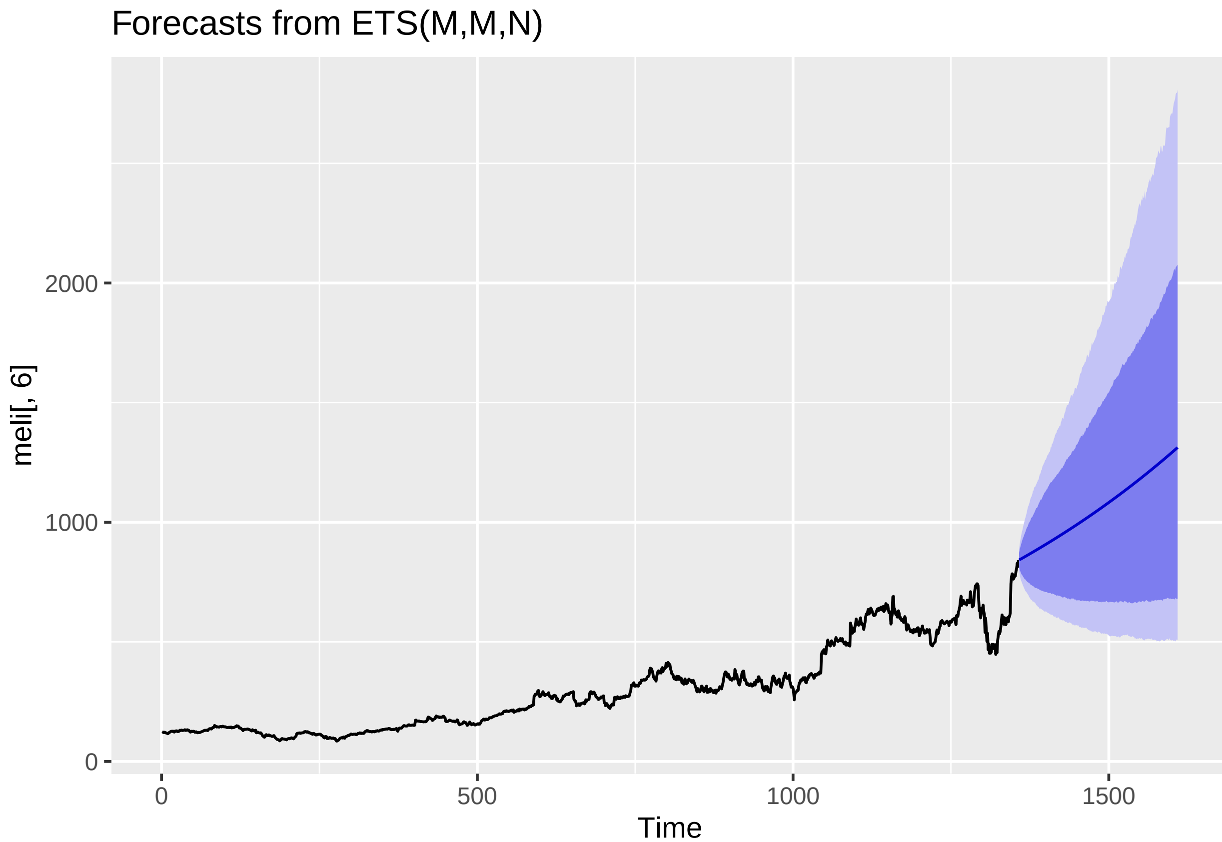
Forecast using STL (Seasonal Decomposition of Time Series by Loess)

1 year is approximately 252 business/trading days, so we will forecast 252 periods ahead.

There are 3 similar methods (stl, stlm, and stlf), we will use stl.


Forecasts from STL + ETS(M,A,N)
2000
1500
1000
500
0
meli.ts[, "MELI.Adjusted"]
2016
2018
2020
Time

Forecast using ETS (Exponential smoothing state space model)



COMPARE ACCURACY with Diebold-Mariano test for predictive accuracy

Usage dm.test(e1, e2, alternative=c("two.sided","less","greater"), h=1, power=1)

Arguments e1 Forecast errors from method 1.

e2 Forecast errors from method 2.

A character string specifying the alternative hypothesis, must be one of "two.sided" (default), "greater" or "less". You can specify just the initial letter.

The forecast horizon used in calculating e1 and e2 is determined with h.

The power used in the loss function. Usually 1 or 2. The choice of power is entirely due to the loss function. If we lose x dollars if the forecast error is x - then our loss function is linear and we should use the option power = 1. If we lose x^2 dollars when the forecast error is x, then we should use power = 2.

Details The null hypothesis is that the two methods have the same forecast accuracy.

For alternative="two.sided", the alternative hypothesis is that method 1 and method 2 have different levels of accuracy

For alternative="less", the alternative hypothesis is that method 2 is less accurate than method 1.

For alternative="greater", the alternative hypothesis is that method 2 is more accurate than method 1.

A smaller p-value means that there is stronger evidence in favor of the alternative hypothesis

STLM vs. ETS

```
##
##  Diebold-Mariano Test
##
## data:  stl.forecast.meli$residualsets.forecast.meli$residuals
## DM = 3.2091, Forecast horizon = 252, Loss function power = 1, p-value =
## 0.001363
## alternative hypothesis: two.sided
```

p-value is very low, H0 rejected, stl and ets have different levels of accuracy.

```
##
##  Diebold-Mariano Test
##
## data:  stl.forecast.meli$residualsets.forecast.meli$residuals
## DM = 3.2091, Forecast horizon = 252, Loss function power = 1, p-value =
## 0.0006813
## alternative hypothesis: greater
```

p-value = is very low, H0 rejected: ets IS MORE accurate than stl.

```
##
##  Diebold-Mariano Test
##
## data:  stl.forecast.meli$residualsets.forecast.meli$residuals
## DM = 3.2091, Forecast horizon = 252, Loss function power = 1, p-value =
## 0.9993
## alternative hypothesis: less
```

p-value = 1, H0 accepted: ets IS NOT LESS accurate than stl.

So ETS is more accurate than STL in this case.

Montecarlo Simulations for Price Projections

Lets use MONTECARLO simulations now adn run 20,000 simulations 252 trading days into the future.

Alternatively to auto.arima which can take very long and be very heavy on computational resources, there is the option to use auto ARFIMA out of the rugarcch library.

The Rugarch package is one of the more robust R libraries for financial data analysis and forecating.

It allows to forecast more than just prices, specifically volatility which is very importat for VaR estimations at the time to decide what porfoloio allocations are on the efficient fontier and which allocations will give us less than optimal returns for a given level of risk.

Even more so, it can accept streaming data and build it into the models, but we will not cover that here - it is just nice to know.

Sources: http://www.unstarched.net/r-examples/rugarch/a-short-introduction-to-the-rugarch-package/ https://palomar.home.ece.ust.hk/MAFS6010R_lectures/Rsession_time_series_modeling.html

```
##   AR MA Mean ARFIMA       AIC converged
## 1  0  0    1      0 -4.325384         1
## 2  1  0    1      0 -4.324285         1
## 3  0  1    1      0 -4.324267         1
## 4  0  2    1      0 -4.323525         1
## 5  2  0    1      0 -4.323488         1
## 6  1  0    0      0 -4.323148         1
```

So ARMA(0,0) model WITH a mean

Parameters for ARIMA(p,d,q)

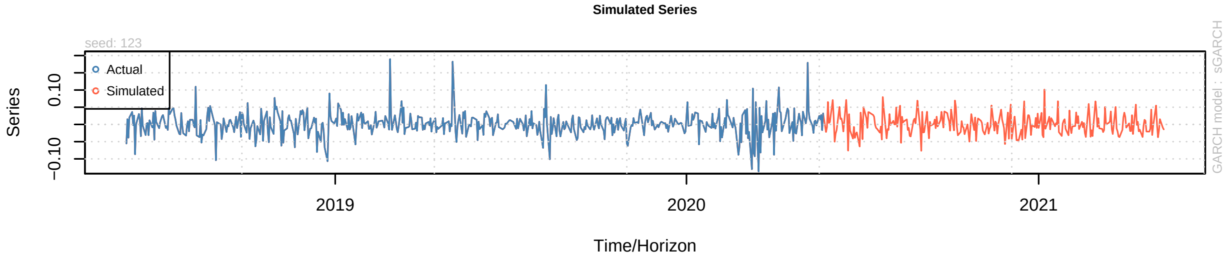
If convergence problems arise:

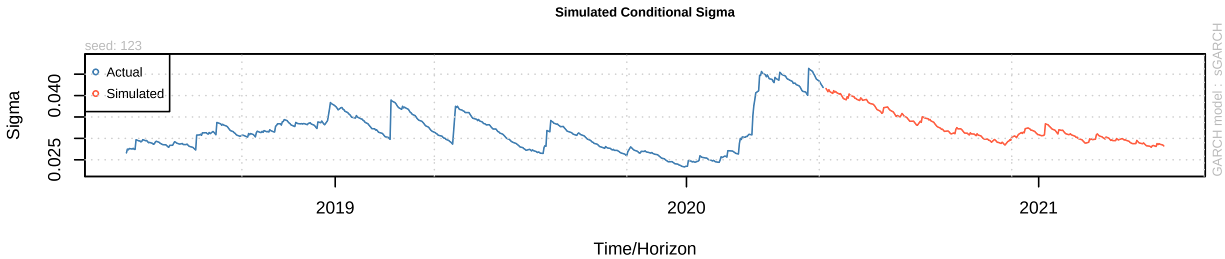
In choosing ARMA(p,q) the theory of difference equations suggests that we should choose ARMA(p+1,p), which gives rise to a solution of the difference equation with p+1 terms. You can of course have some zero orders

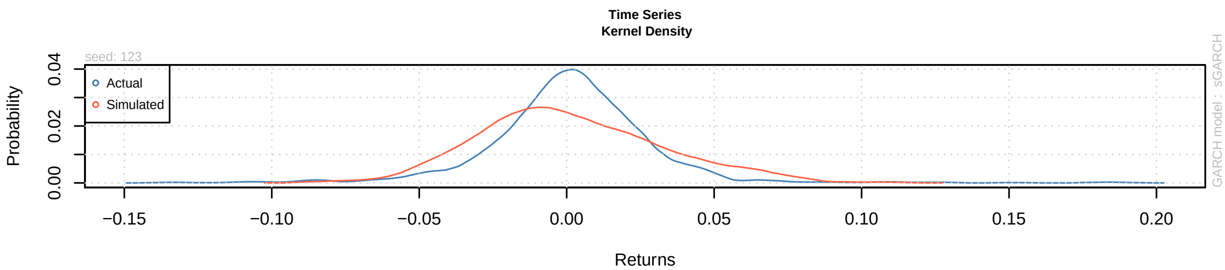
This is explained in my book H. D. Vinod, "Hands-On Intermediate Econometrics Using R: Templates for Extending Dozens of Practical Examples." (2008) World Scientific Publishers: Hackensack, NJ. (http://www.worldscibooks.com/economics/6895.html)

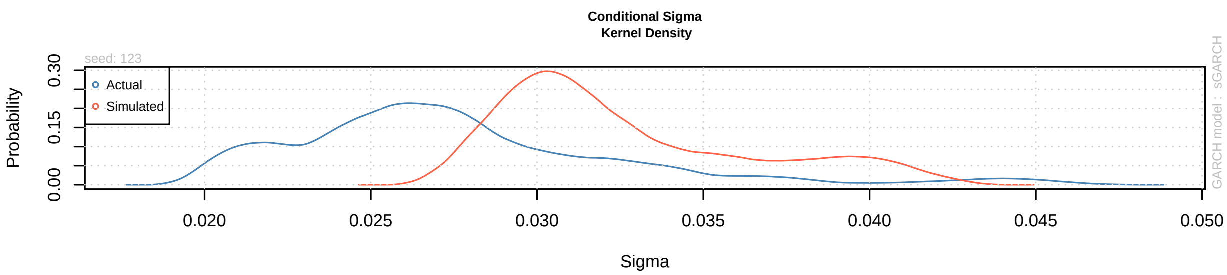
No convergence problems so we will use p and q with/without mean as estimated:

Run 20,000 simulations, 252 trading days into the future. Set seed 123 to be able to reproduce same results.

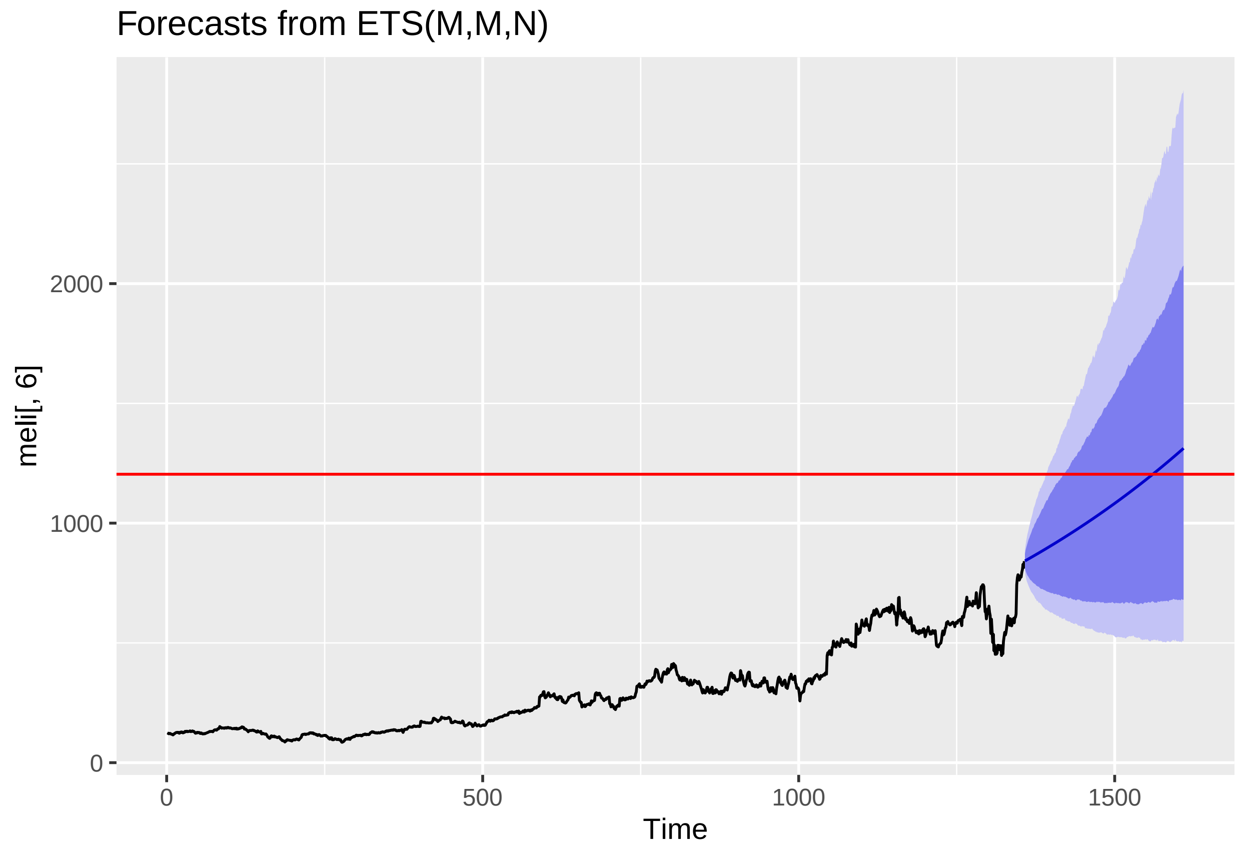






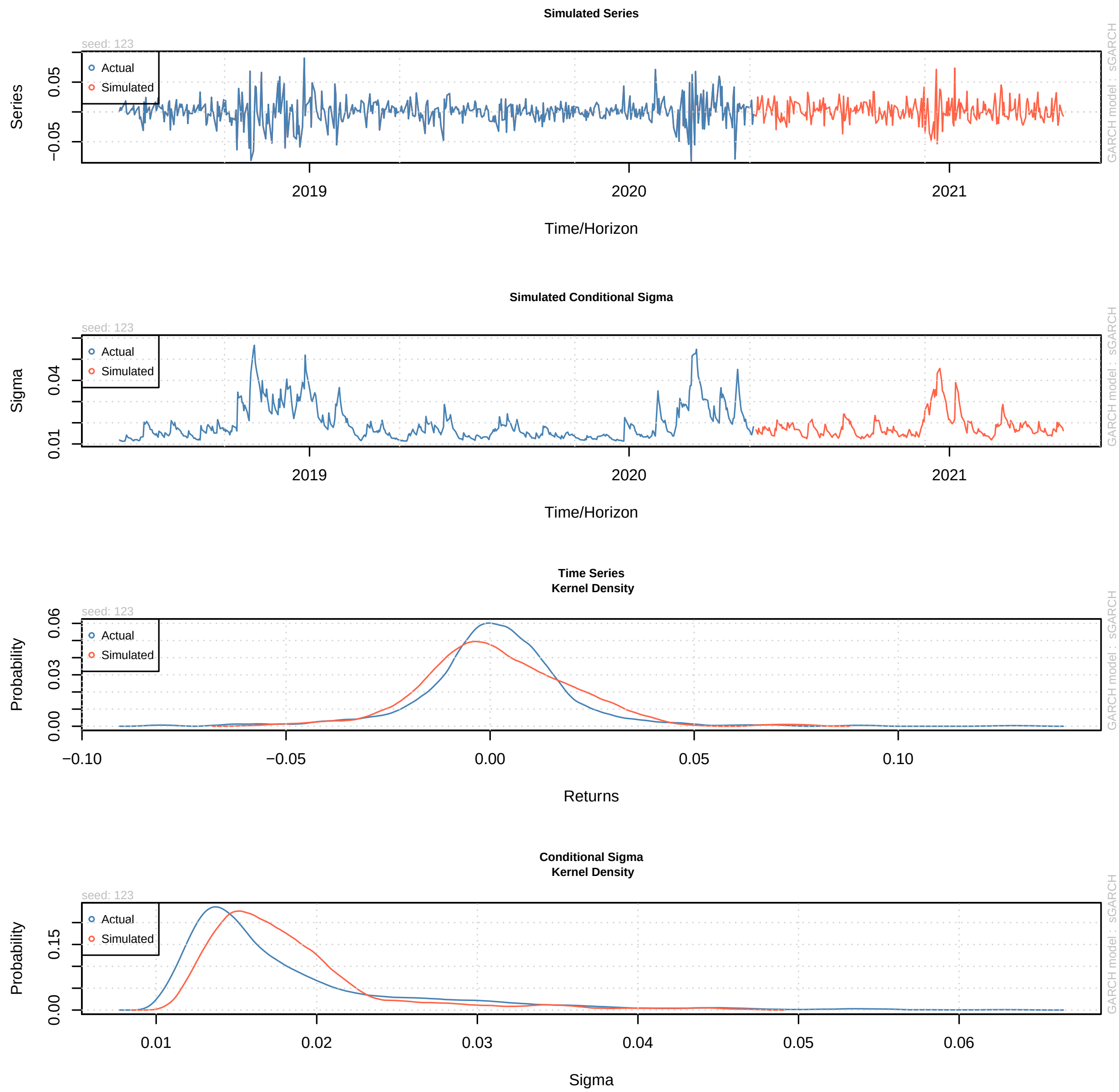


1 year (252 trading days approx.) target price for MERCADO LIBRE in USD 1204.26, (43.14% change compared to the last closing price of USD 841.31)

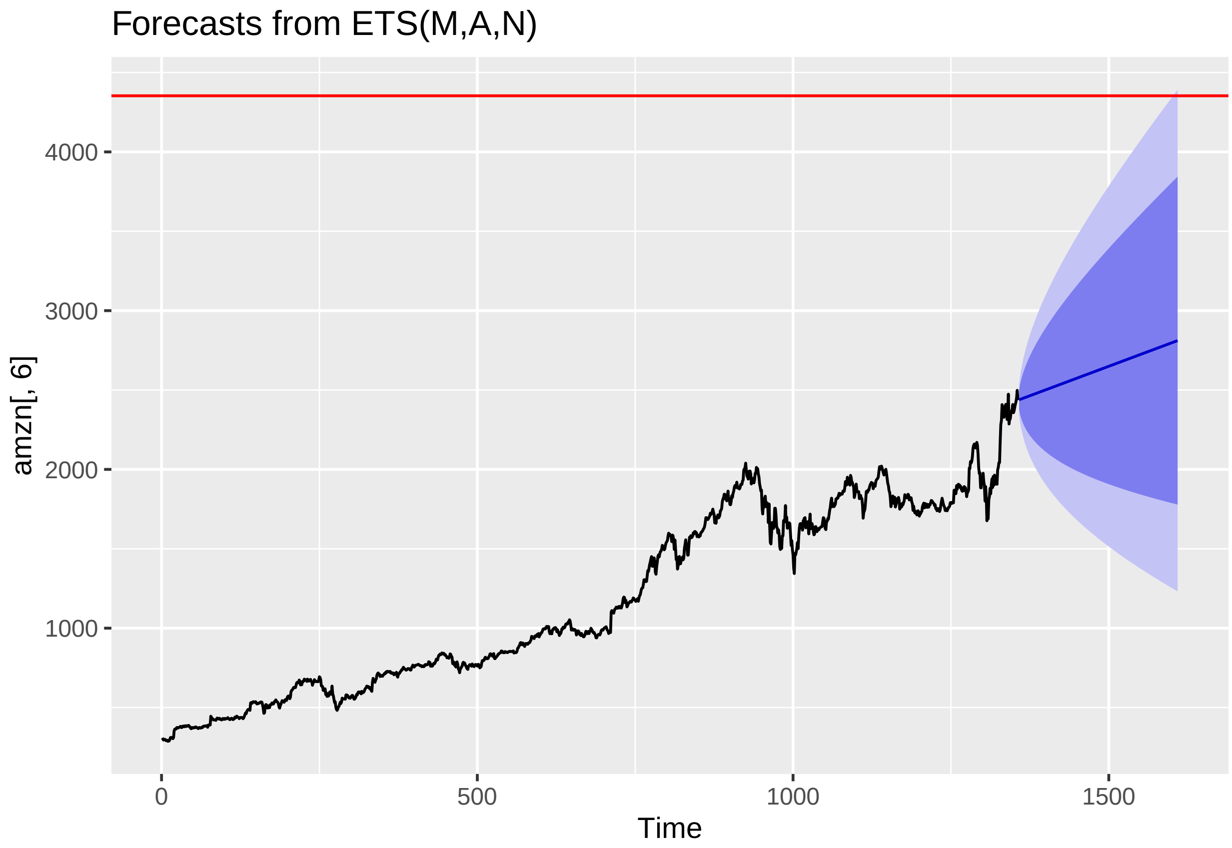


Makes sense!

Projections for AMAZON

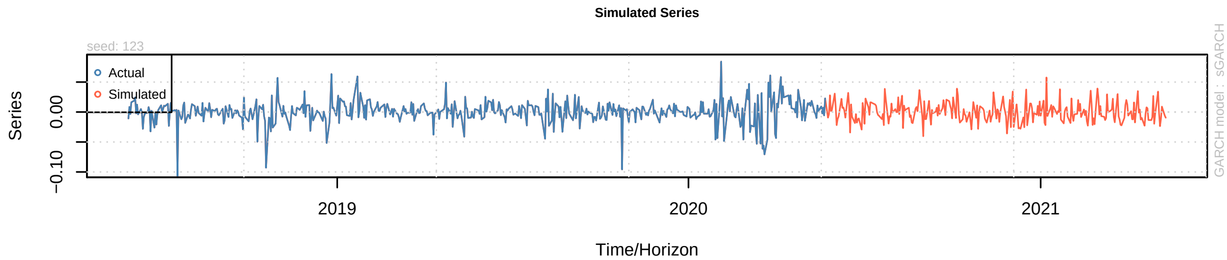


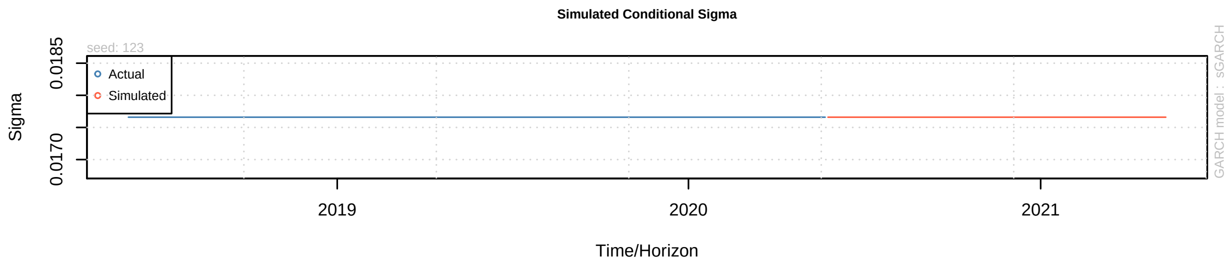
1 year (252 trading days approx.) target price for AMAZON in USD 4353.44, (78.65% change compared to the last closing price of USD 2436.88)

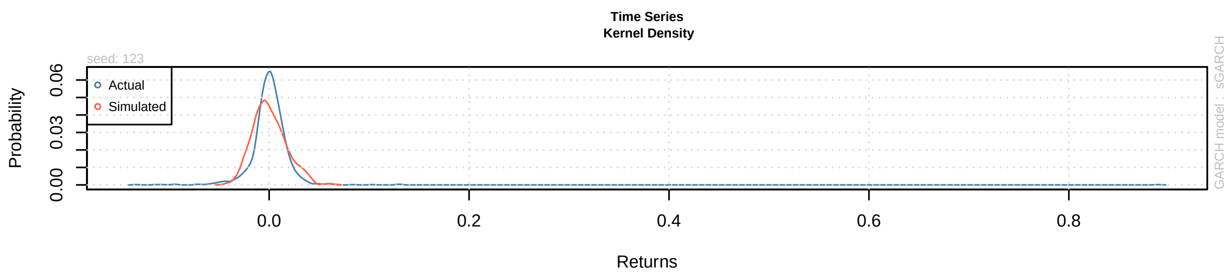


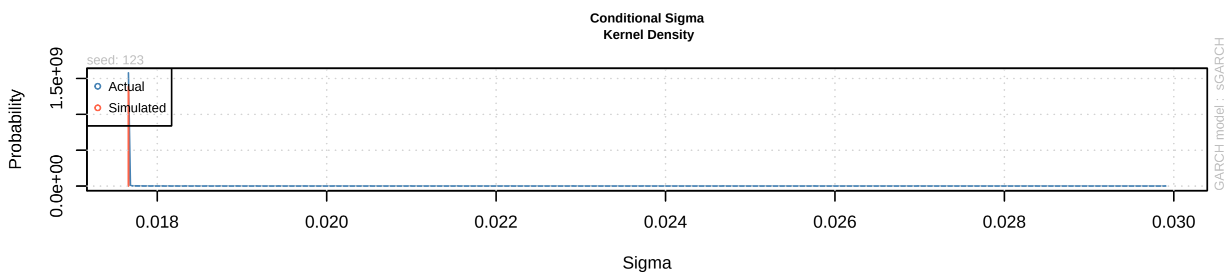
Seems a little TOO bullish, but we have enough simulations on variation for the VaR that we will do further down.

Projections for EBAY

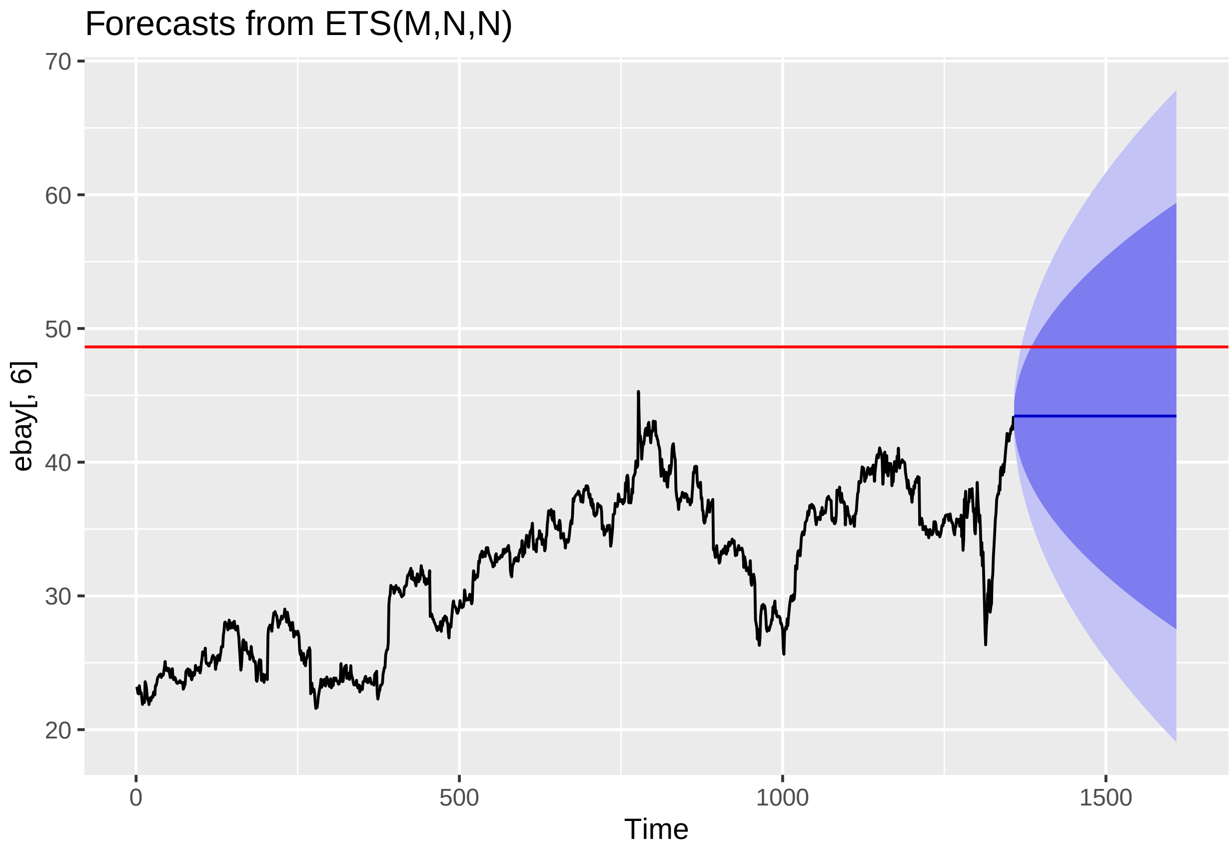






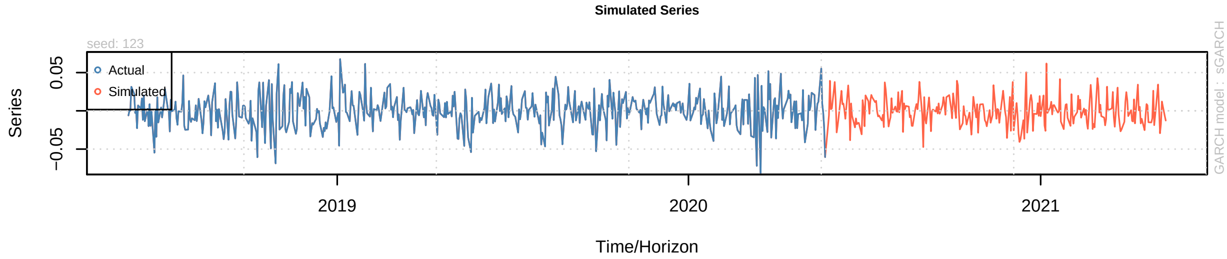


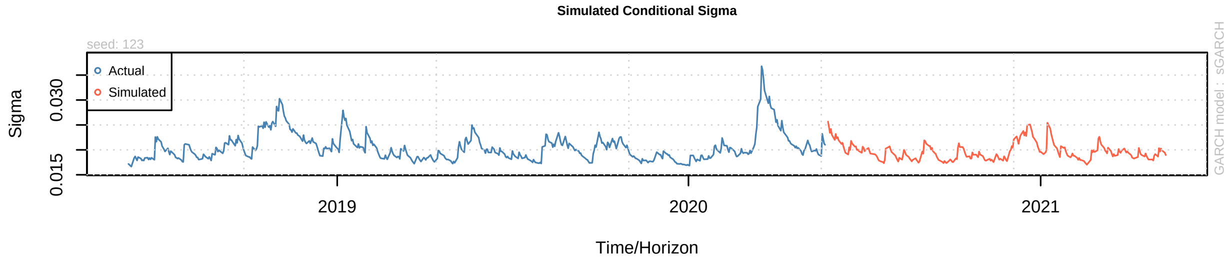
1 year (252 trading days approx.) target price for EBAY in USD 48.62, (11.9% change compared to the last closing price of USD 43.45)

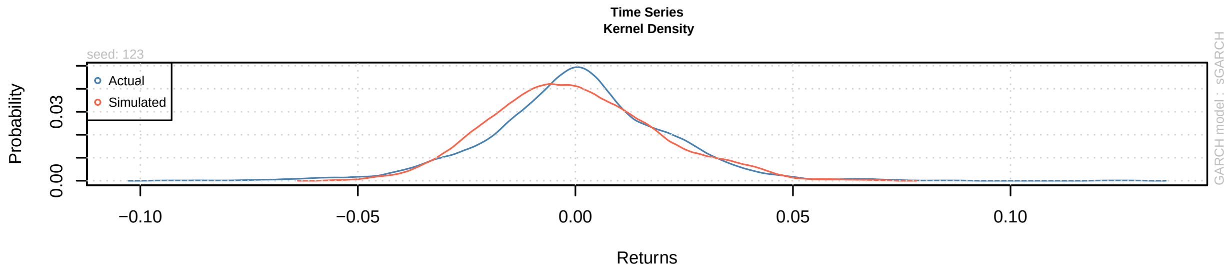


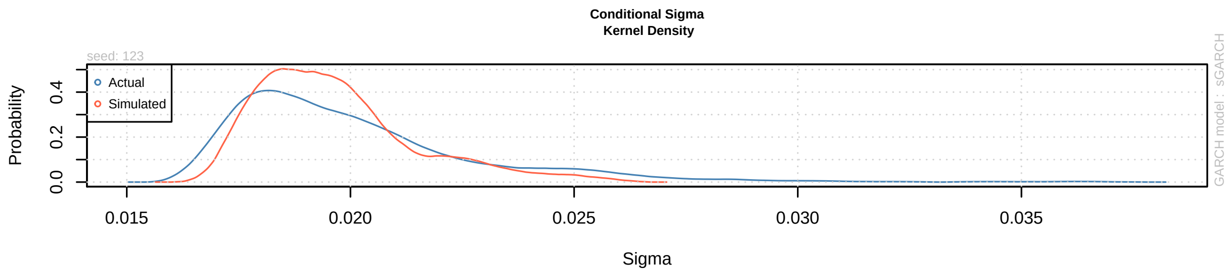
Makes sense, although the conditional sigma looks flat, we can double check that with the VaR excersise.

Projections for ALIBABA

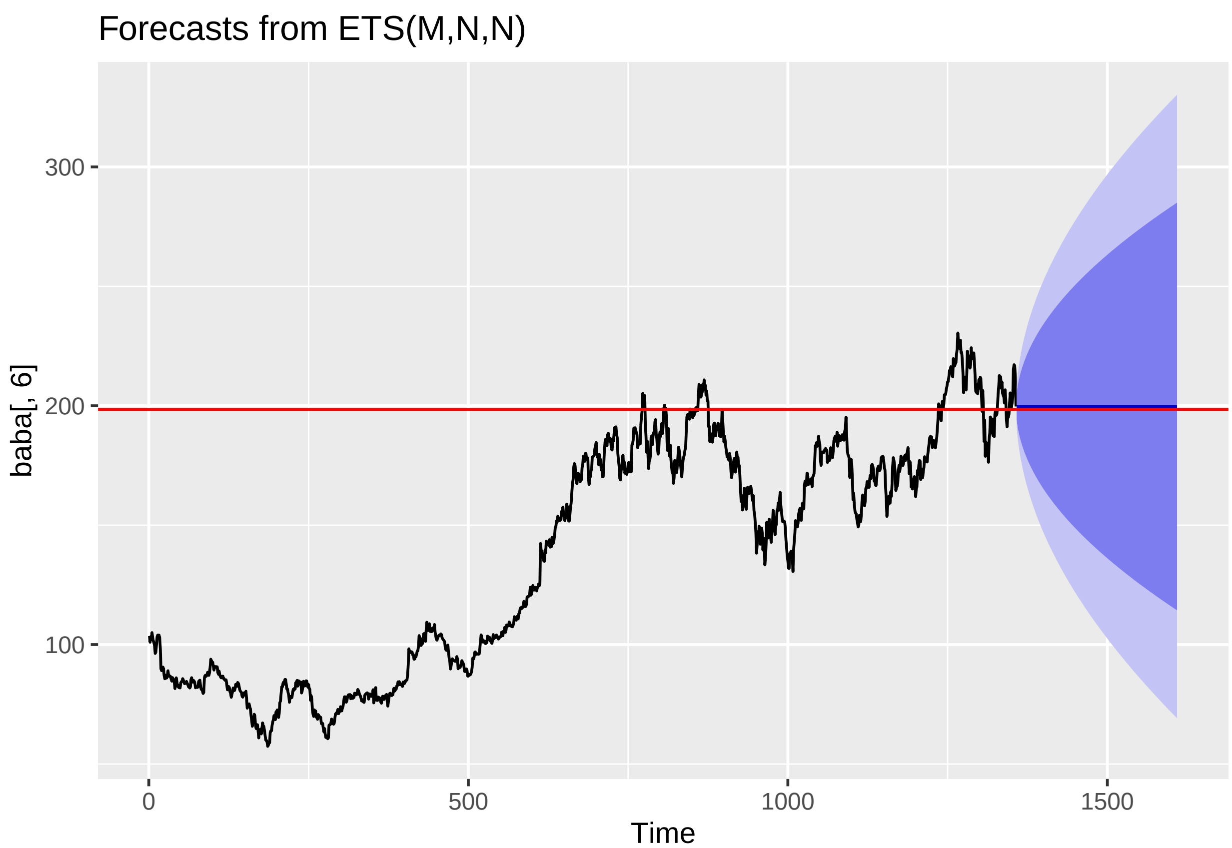






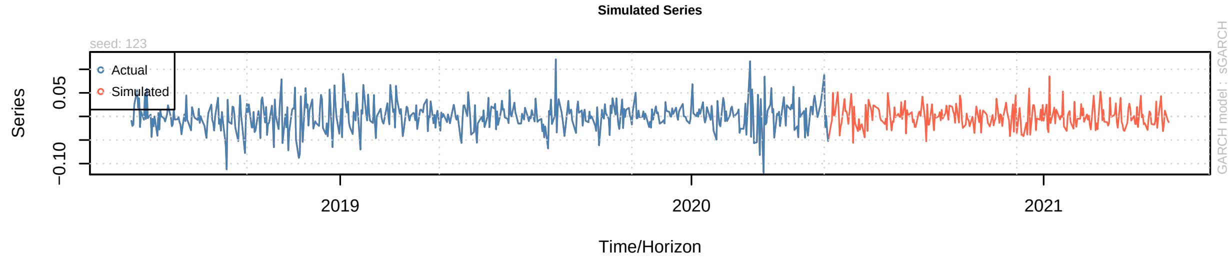


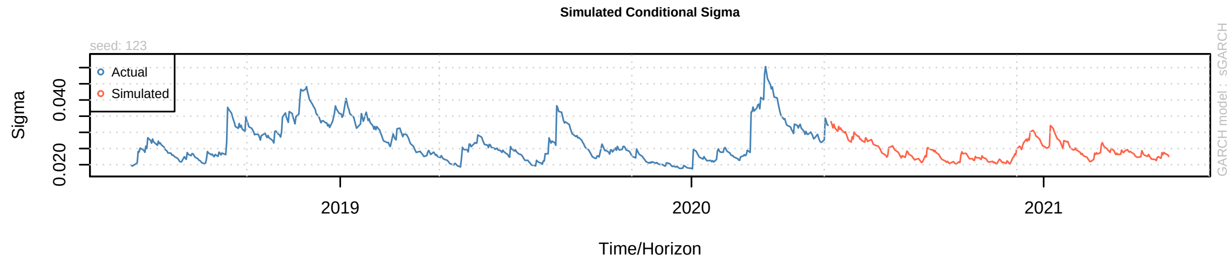
1 year (252 trading days approx.) target price for ALIBABA in USD 198.46, (-0.62% change compared to the last closing price of USD 199.7)

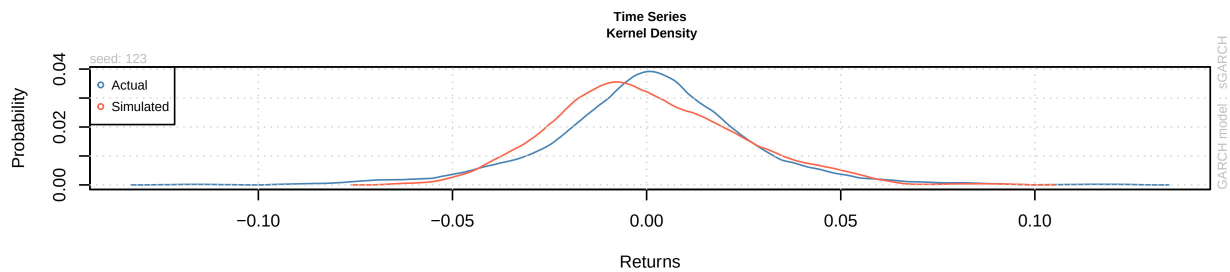


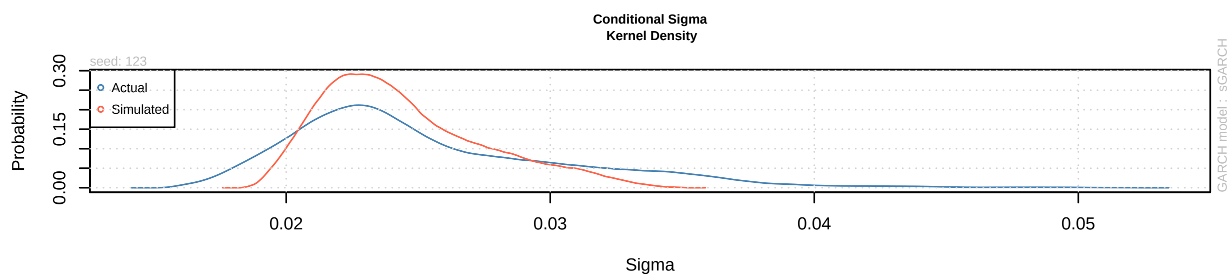
Makes sense!

Projections for JD.com

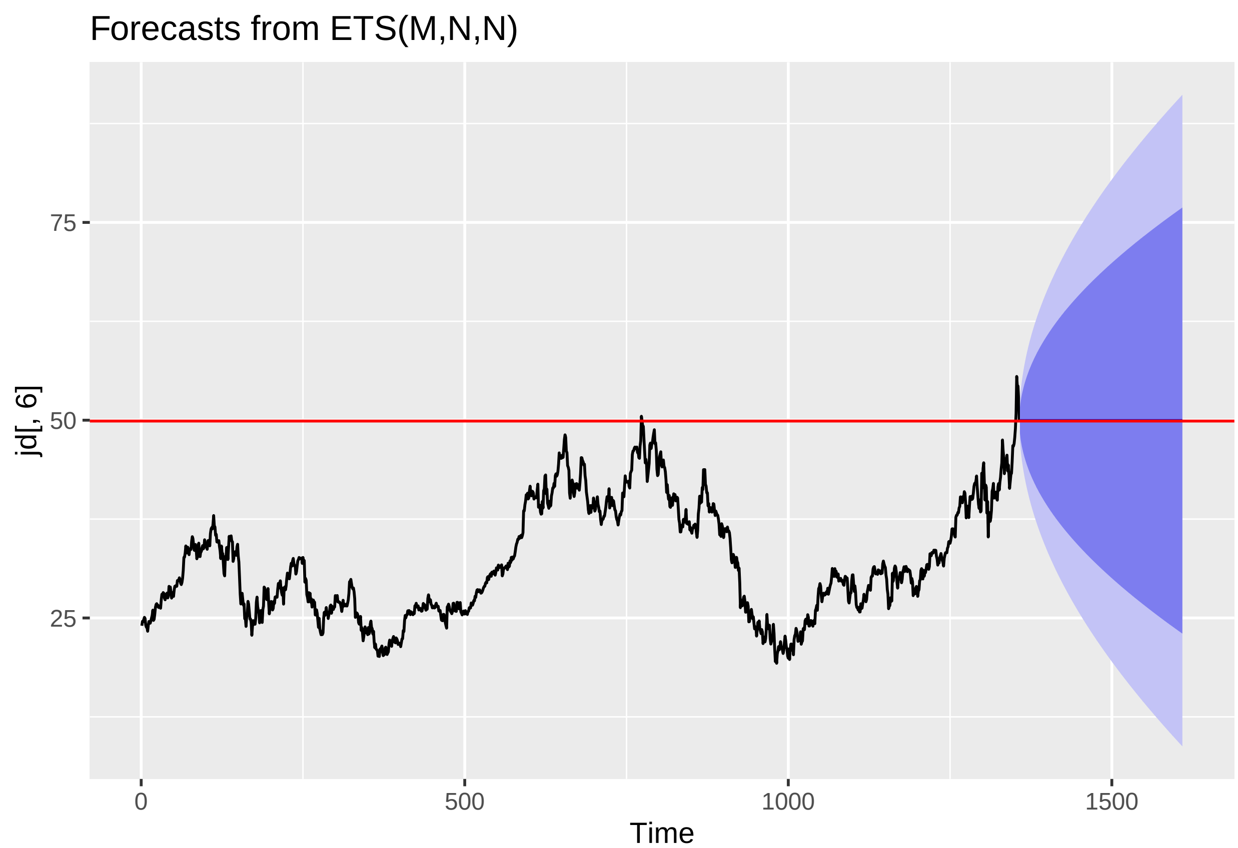








1 year (252 trading days approx.) target price for JD.com in USD 49.89, (-0.01% change compared to the last closing price of USD 49.9)



Makes sense!

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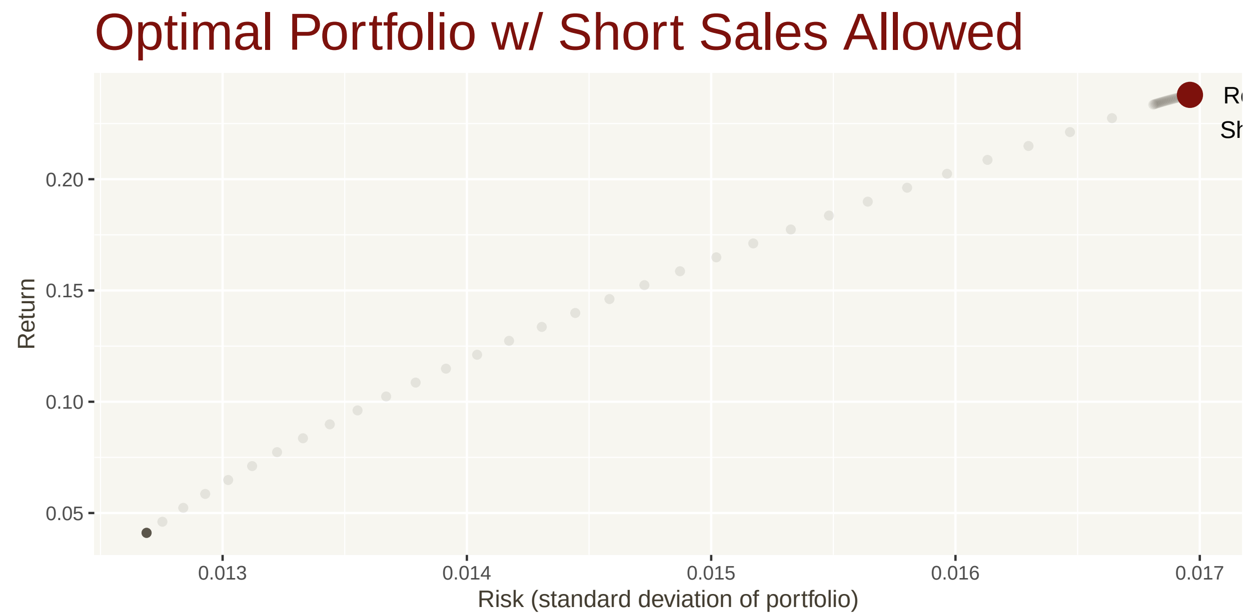
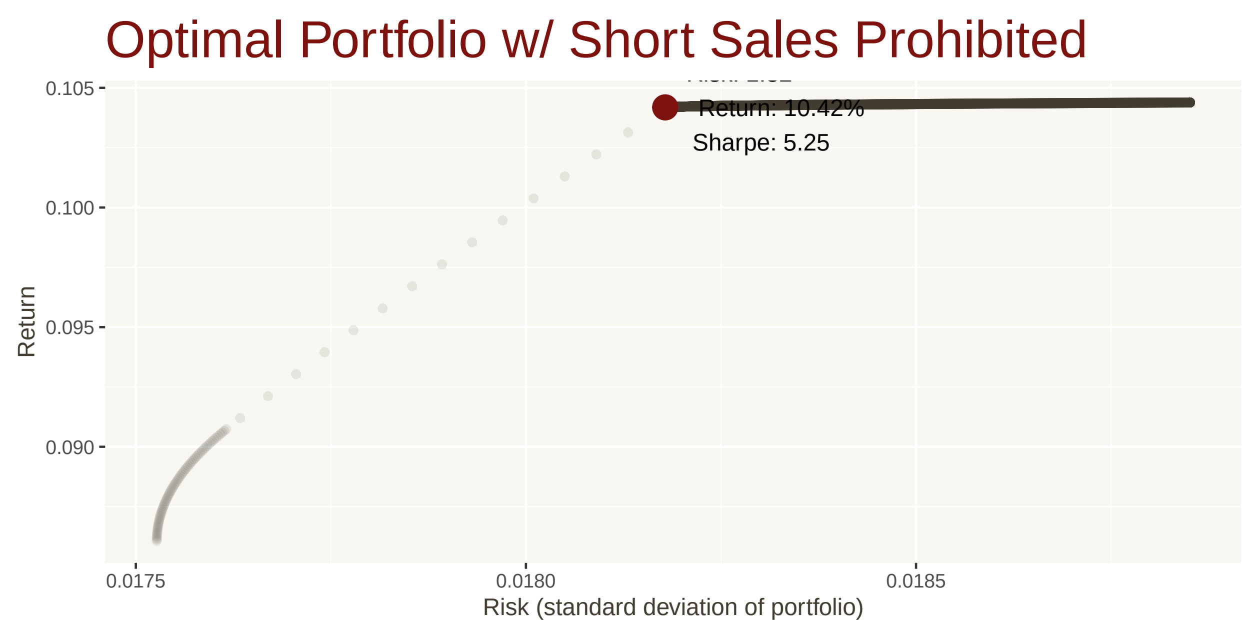
eCommerce porfolio allocation with and without short selling

The optimal or efficient portfolio mixes that follow were formulated using:
. Projected daily prices based on the simulations for all companies that we discussed earlier.
. Computing arithmetic daily returns of said projected prices.
. Limitation on the maximum portfolio participation of any single stock to not go above a ceiling of 40% long, and not below 20% short. I chose these constraints for arbitrary reasons: a rule of thumb of twice the amount of an equal weights portfolio (100% divided by 5) for long and no more than once the balanced portfolio for short positions.
. Sharpe ratio calculated using stocks daily simple returns in excess of risk free rate. . 13 week US Treasury Bill Risk Free rate

	MELI	AMZN	EBAY	BABA	JD
Weights w/ Short Sales Allowed	-0.01	1.04	-0.01	-0.01	-0.01
Weights w/ Short Sales Prohibited	0.25	0.25	0.25	0.08	0.17





Portfolio and Components' Value-at-Risk (VaR) and Expected Shortfall (ES)

Key points to keep in mind:
. VaR and ES are approximation measures to the worst that could happen (max losses) on one single day out of twenty (5%).
. ES looks at the entire first five percent quantile of the low end of the return distribution tail so its larger than VaR.
. With positive correlation, asset prices tend to move together and this increases the volatility.
. Without short sales, it is impossible to go above the expected return of the stock with the highest expected return.

. When short sales are allowed, there is no upper bound on the expected return nor on the risk. And the projected fall for Alibaba, a company with a market cap above 100B, should not be for the long run. A short sale strategy should be combined with a stop-loss limit order.

	Total	MELI	EBAY	AMZN	JD	BABA
VaR(5%) - Short Sales Allowed	-23.77%	0.14%	-23.95%	0.04%	0%	0%
VaR(5%) - Short Sales Prohibited	-10.39%	-3.55%	-5.76%	-1.11%	0.02%	0.01%
ES(5%) - Short Sales Allowed	-23.79%	0.14%	-23.97%	0.04%	0%	0%
ES(5%) - Short Sales Prohibited	-10.42%	-3.56%	-5.76%	-1.12%	0.02%	0%

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