



Presentazione Progetto BISF

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Titoli utilizzati

settore tecnologico

 Meta

Alphabet

settore militare

Raytheon

LOCKHEED MARTIN 

settore bancario

BANK OF AMERICA 

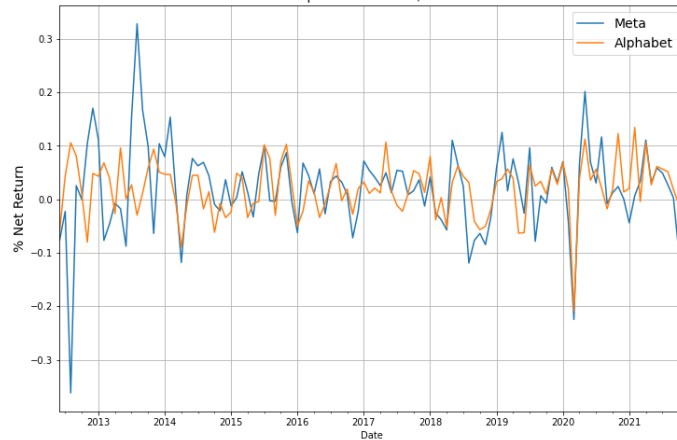
JPMORGAN CHASE & CO.

Statistiche descrittive

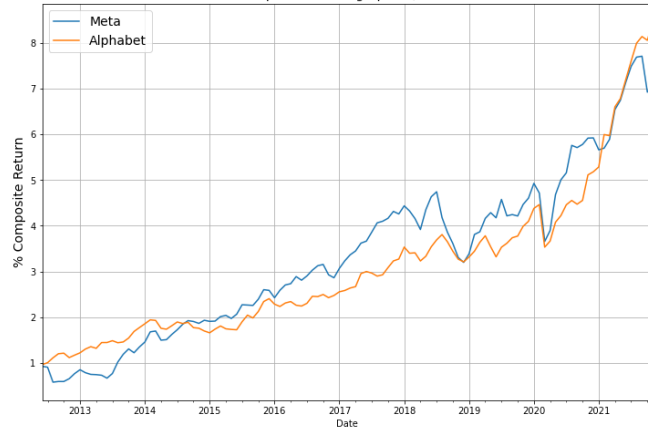
Rendimenti semplici e composti

titoli tecnologici

Simple net return FB/GOOG

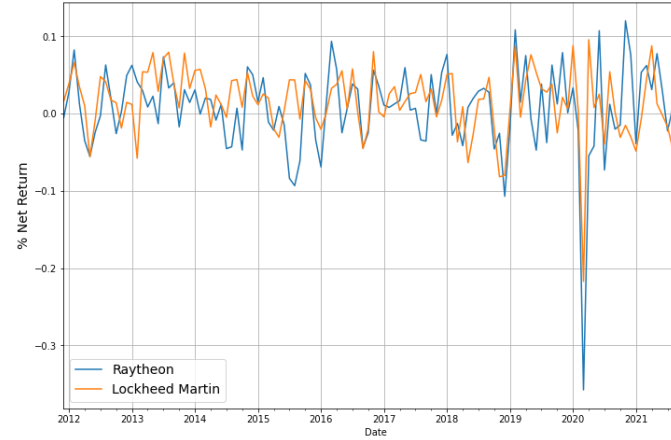


Composite Return graph FB/GOOG

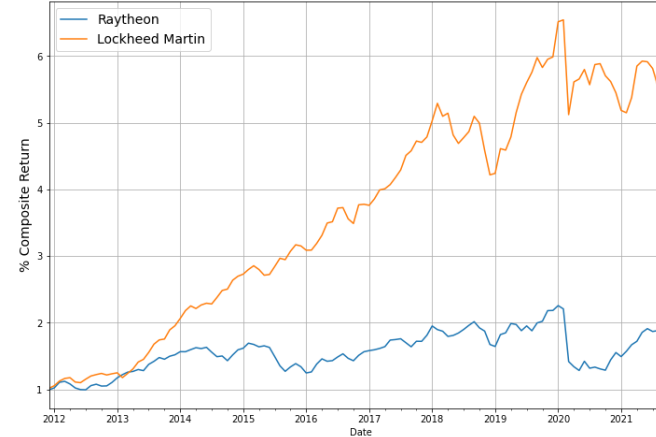


titoli militari

Simple net return RTX/LMT

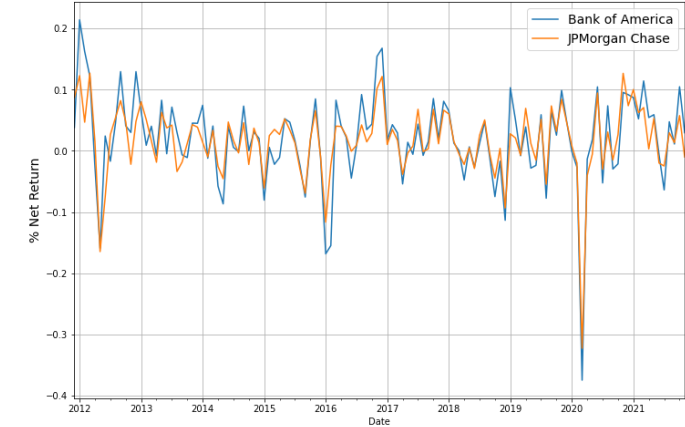


Composite Return graph RTX/LMT

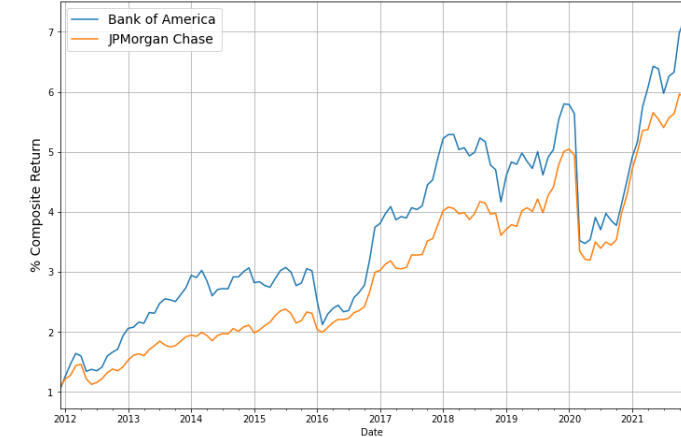


titoli bancari

Simple net return BAC/JPM

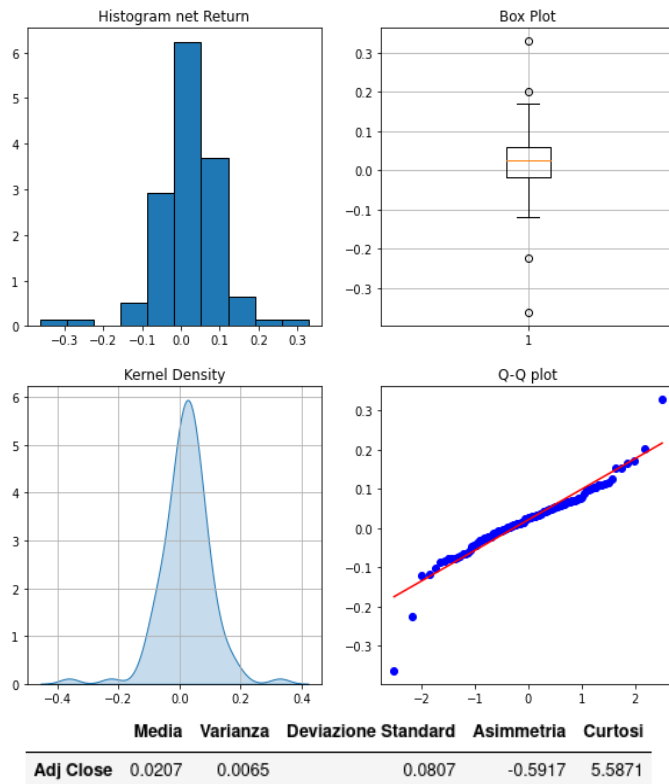


Composite Return graph BAC/JPM



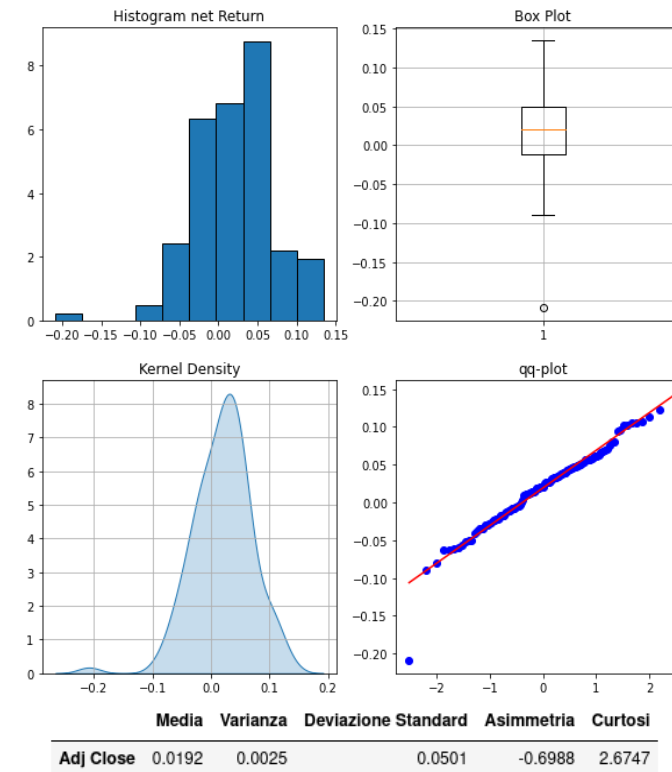
Grafici diagnostici e statistiche – FB/GOOG

Meta (FB)



Volatilità: 36,44%

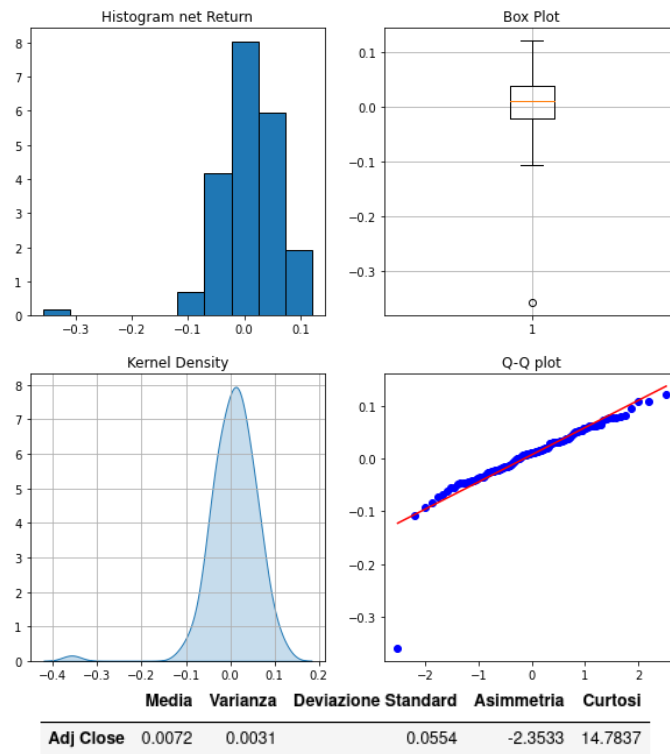
Alphabet (GOOG)



Volatilità: 25,11%

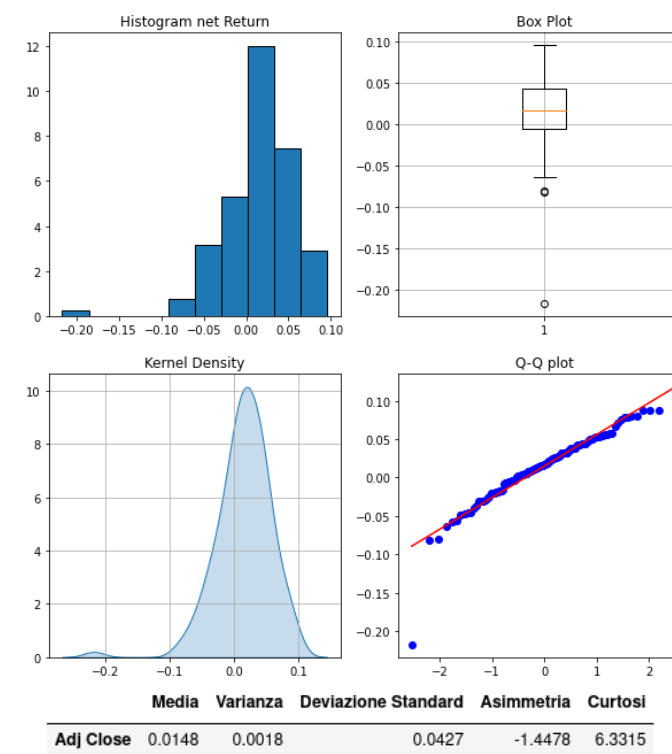
Grafici diagnostici e statistiche – RTX/LMT

Raytheon (RTX)



Volatilità: 25,49%

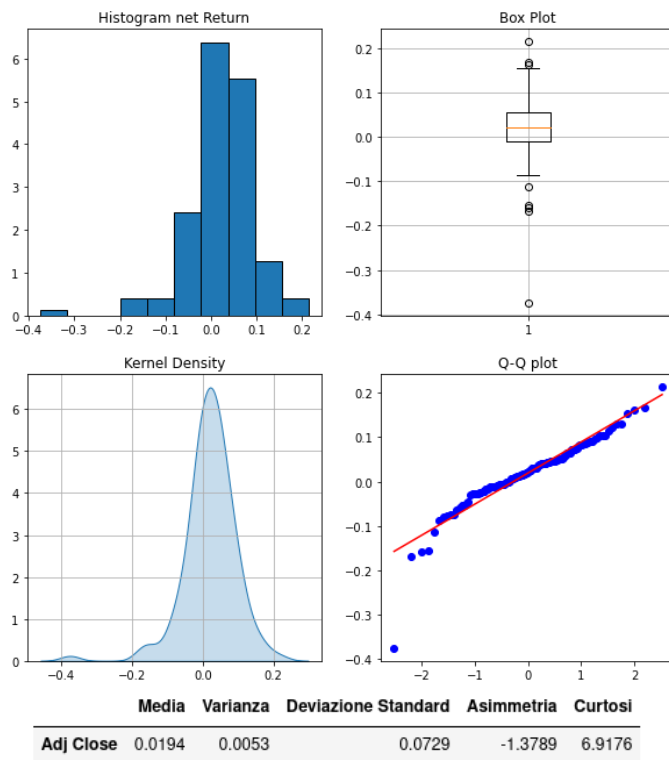
Lockheed Martin (LMT)



Volatilità: 21,1%

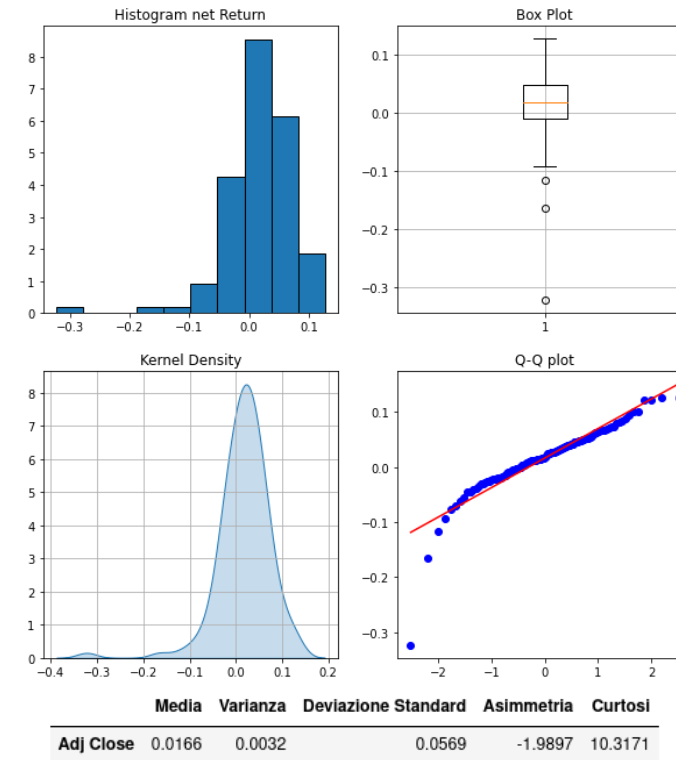
Grafici diagnostici e statistiche – BAC/JPM

Bank of America (BAC)



Volatilità: 31,74%

JPMorgan Chase (JPM)

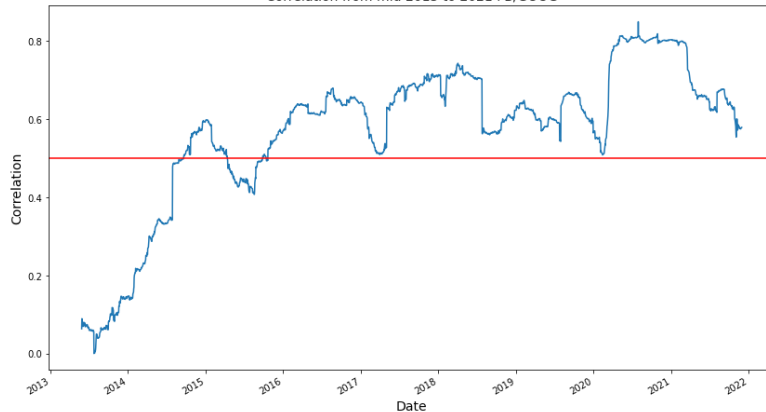


Volatilità: 27,04%

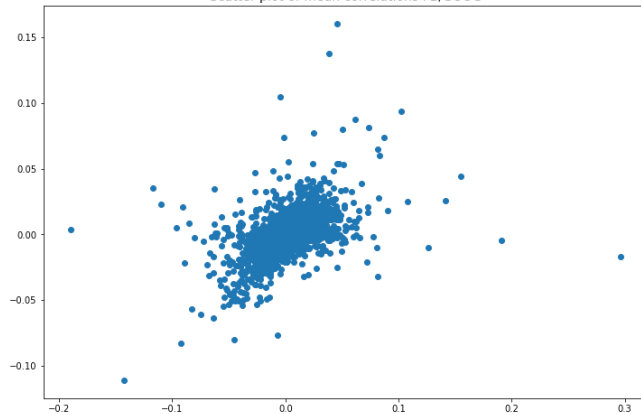
Correlazione e dispersione

titoli tecnologici

Correlation from mid 2013 to 2021 FB/GOOG

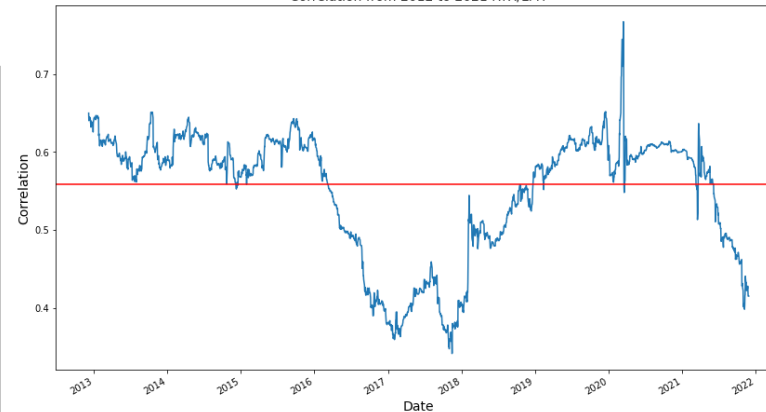


Scatter plot of mean correlations FB/GOOG

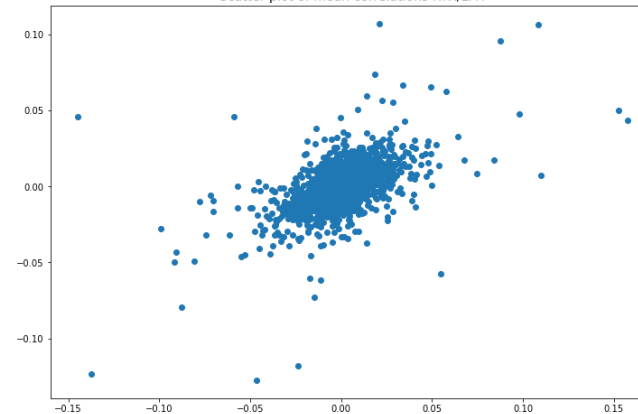


titoli militari

Correlation from 2012 to 2021 RTX/LMT

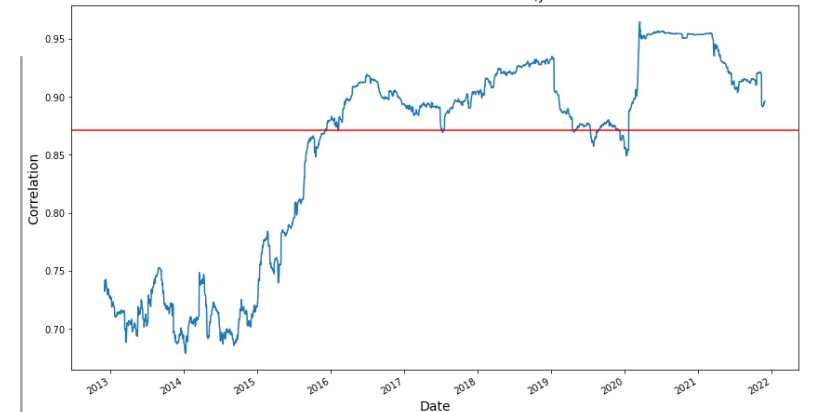


Scatter plot of mean correlations RTX/LMT

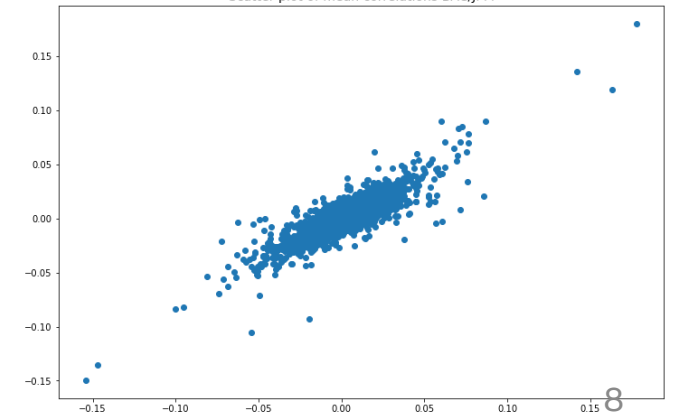


titoli bancari

Correlation from 2012 to 2021 BAC/PM



Scatter plot of mean correlations BAC/PM



Modelli di Previsione

Mediante modello ARIMA

Il modello di previsione ARIMA

ARIMA (AutoRegressive Integrated Moving Averages) è un modello statistico autoregressivo integrato a media mobile che ci permette di effettuare predizioni sui trend futuri in una serie storica (utilizzando dati passati).

Questo modello essendo composto da 3 parti (definite dal nome), necessita in input tre variabili:

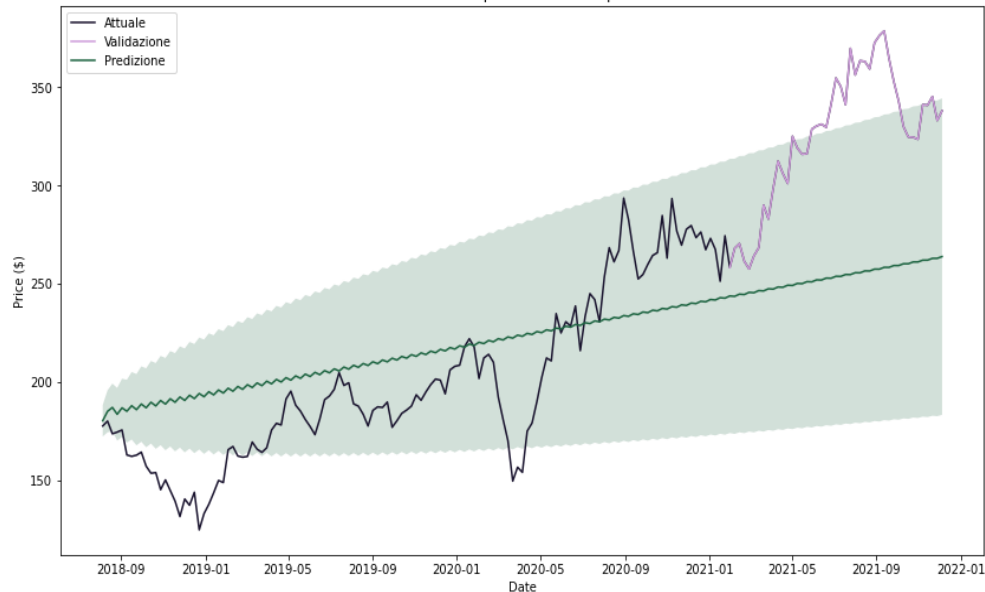
- p = *lag order*
- d = *grado di differenziazione*
- q = *ordine della media mobile*

La scelta accurata di queste tre variabili è fondamentale per ottenere risultati con margine di errore inferiore.

Predizioni con ARIMA – FB/GOOG

predizione per Meta (FB)

Facebook stock price - actual vs. predicted



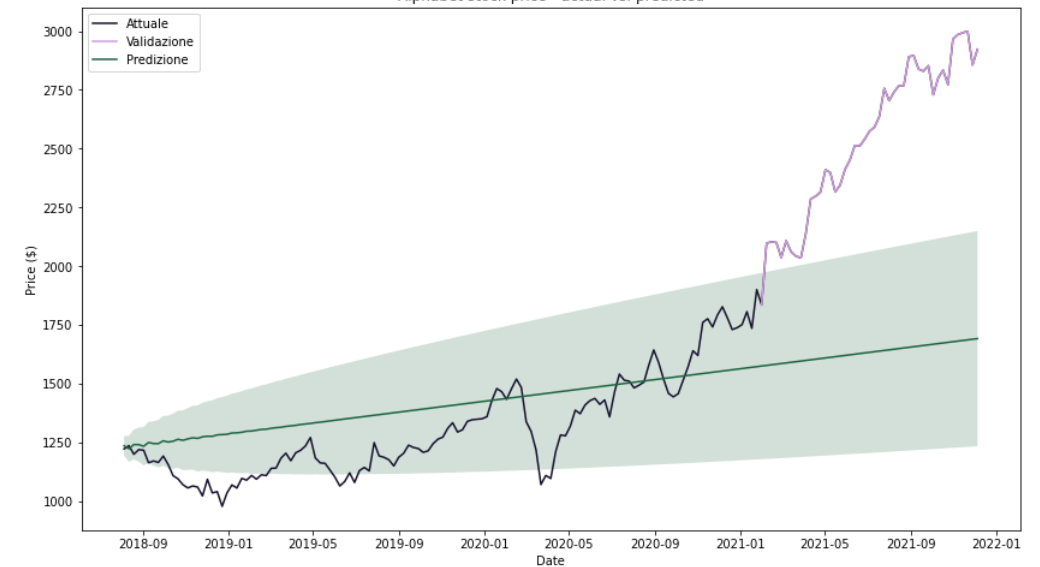
parametri stimati (p, d, q)

SARIMAX Results

Dep. Variable:	y	No. Observations:	324
Model:	SARIMAX(3, 1, 1)	Log Likelihood	-912.383
Date:	Tue, 24 May 2022	AIC	1836.767
Time:	16:34:12	BIC	1859.433
Sample:	0	HQIC	1845.815
	- 324		
Covariance Type:	opg		

predizione per Alphabet (GOOG)

Alphabet stock price - actual vs. predicted



parametri stimati (p, d, q)

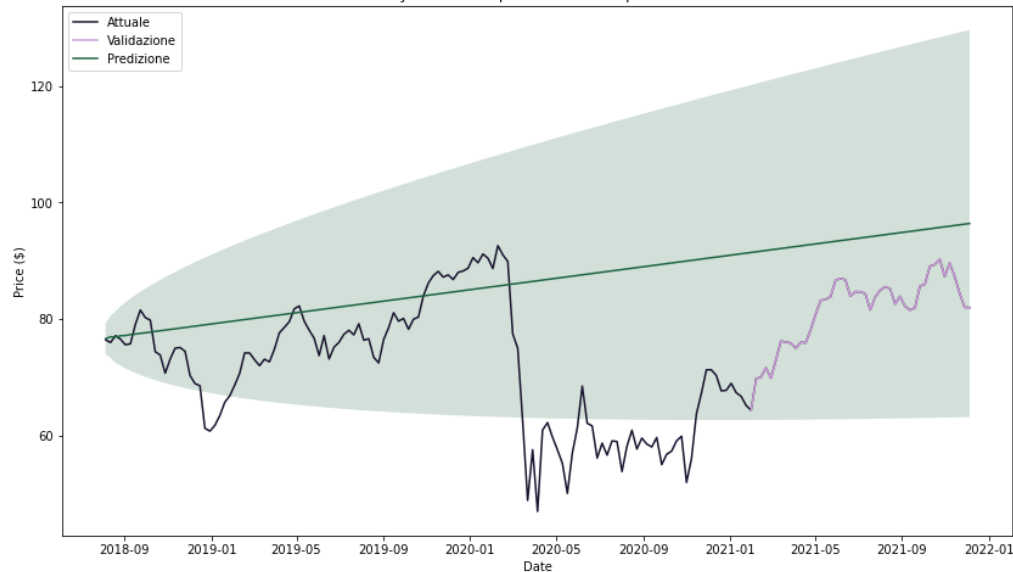
SARIMAX Results

Dep. Variable:	y	No. Observations:	348
Model:	SARIMAX(3, 1, 2)	Log Likelihood	-1546.650
Date:	Tue, 24 May 2022	AIC	3107.301
Time:	16:39:05	BIC	3134.246
Sample:	0	HQIC	3118.029
	- 348		
Covariance Type:	opg		

Predizioni con ARIMA – RTX/LMT

predizione per Raytheon (RTX)

Raytheon stock price - actual vs. predicted



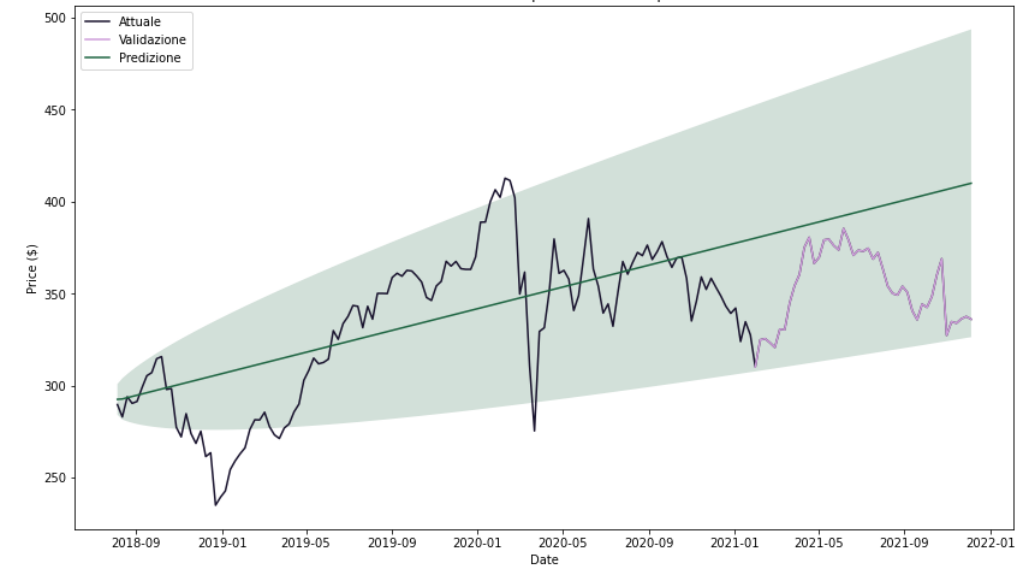
parametri stimati (p, d, q)

SARIMAX Results

Dep. Variable:	y	No. Observations:	348
Model:	SARIMAX(1, 1, 1)	Log Likelihood	-596.913
Date:	Tue, 24 May 2022	AIC	1201.826
Time:	16:49:36	BIC	1217.224
Sample:	0	HQIC	1207.957
	- 348		
Covariance Type:	opg		

predizione per Lockheed Martin (LMT)

Lockheed Martin stock price - actual vs. predicted



parametri stimati (p, d, q)

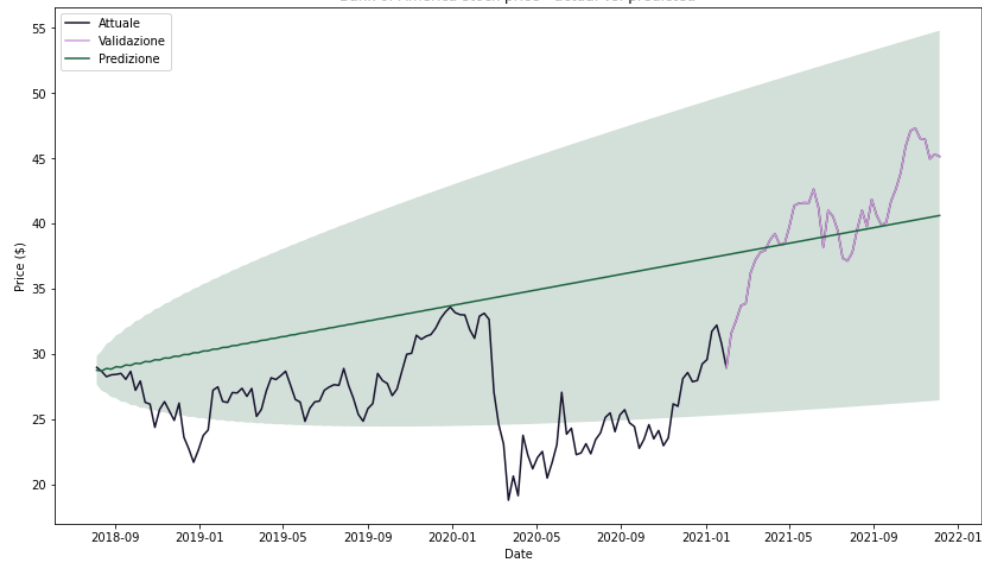
SARIMAX Results

Dep. Variable:	y	No. Observations:	348
Model:	SARIMAX(0, 1, 2)	Log Likelihood	-994.125
Date:	Tue, 24 May 2022	AIC	1996.251
Time:	16:57:17	BIC	2011.648
Sample:	0	HQIC	2002.381
	- 348		
Covariance Type:	opg		

Predizioni con ARIMA – BAC/JPM

predizione per Bank of America (BAC)

Bank of America stock price - actual vs. predicted



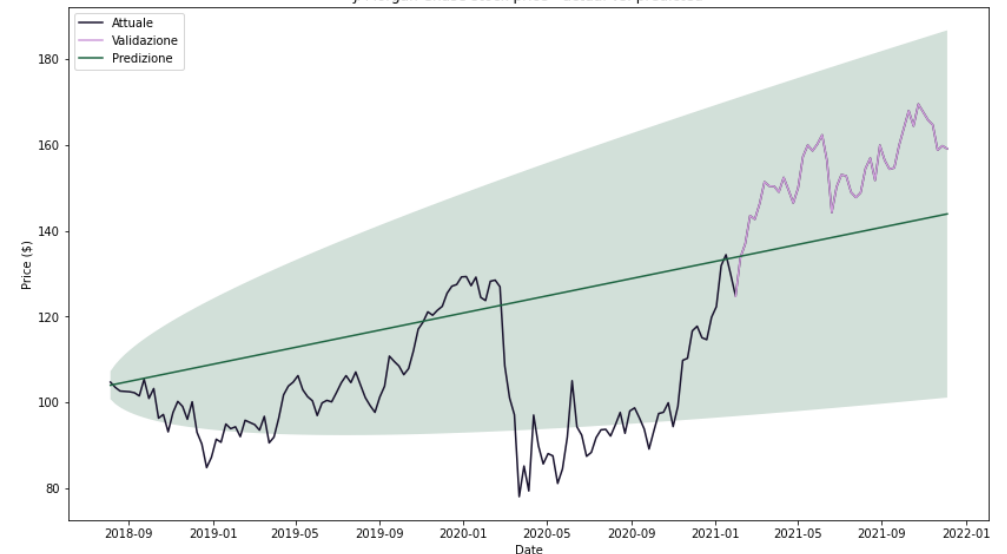
parametri stimati (p, d, q)

SARIMAX Results

Dep. Variable:	y	No. Observations:	348
Model:	SARIMAX(1, 1, 1)	Log Likelihood	-288.497
Date:	Tue, 24 May 2022	AIC	584.994
Time:	17:14:17	BIC	600.392
Sample:	0	HQIC	591.125
	- 348		
Covariance Type:	opg		

predizione per JPMorgan Chase (JPM)

JPMorgan Chase stock price - actual vs. predicted



parametri stimati (p, d, q)

SARIMAX Results

Dep. Variable:	y	No. Observations:	348
Model:	SARIMAX(0, 1, 0)	Log Likelihood	-666.058
Date:	Tue, 24 May 2022	AIC	1336.117
Time:	17:27:36	BIC	1343.815
Sample:	0	HQIC	1339.182
	- 348		
Covariance Type:	opg		

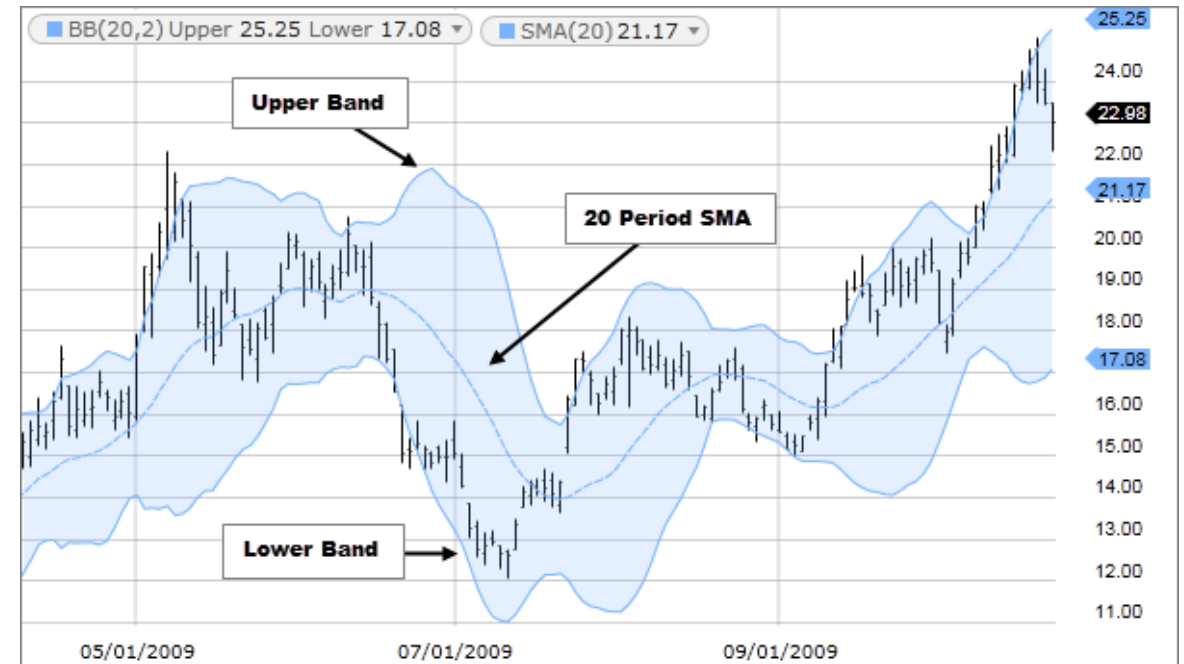
Strategie di trading

Mediante Bollinger's Bands

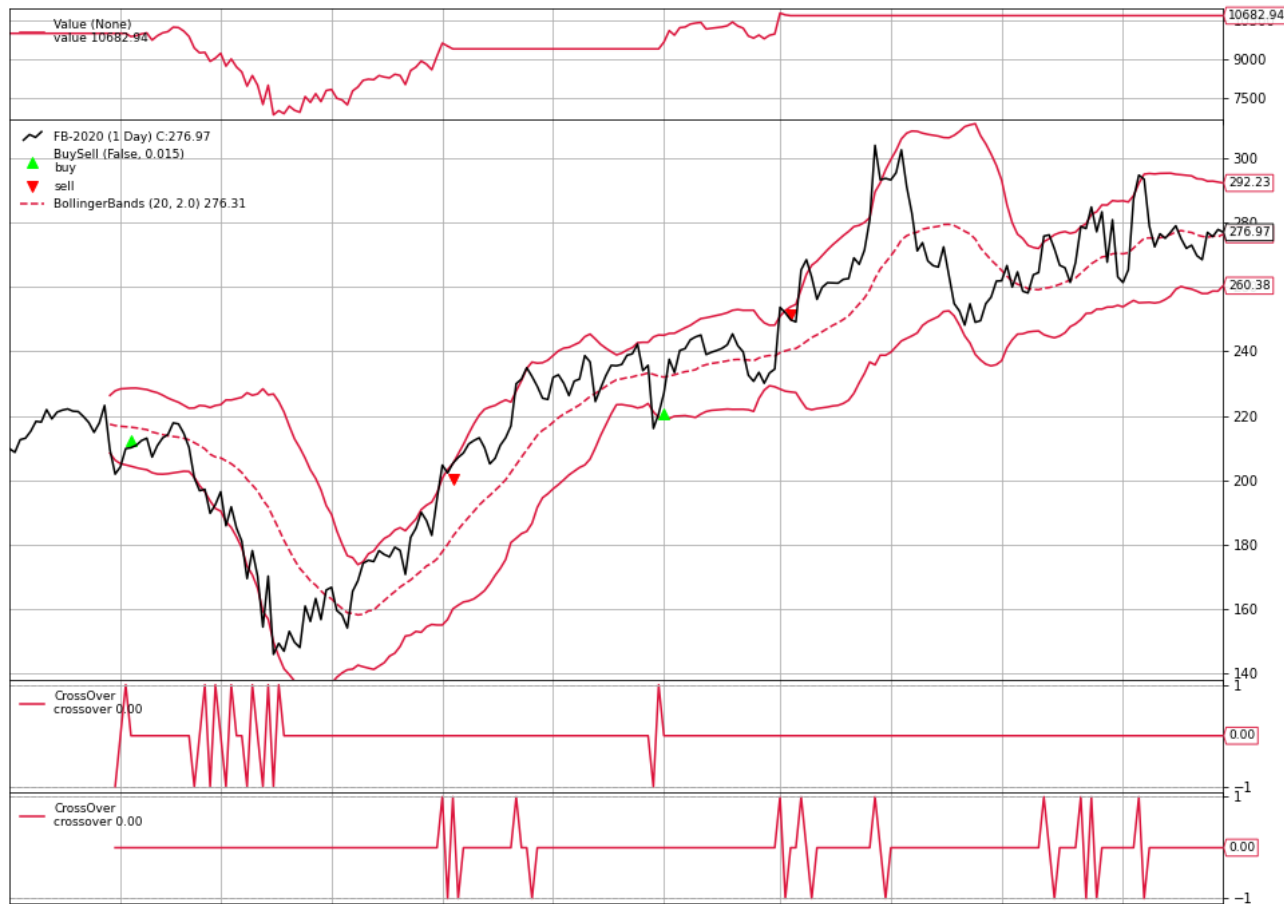
Strategia con Bollinger's Band (BB)

La Bollinger's Band è uno strumento analitico costituito da un insieme di linee che si trovano rispettivamente due deviazioni standard sopra e sotto (positivamente e negativamente) la media mobile semplice (SMA) relativa ad il prezzo di un titolo.

La strategia con le BB prevede che in caso di 'breakout' cioè superamento della linea superiore o inferiore, venga generato un trading signal. (senza short selling)



Backtest strategia BB su FB



Starting Portfolio Value: 10000.00

2020-02-05, BUY CREATED --- Size: 47, Cash: 10000.00, Open: 212.51, Close: 210.11

2020-02-05, BUY EXECUTED --- Price: 212.51, Cost: 9987.97, Commission: 9.99

2020-05-04, SELL CREATED --- Size: 47

2020-05-04, SELL EXECUTED --- Price: 200.20, Cost: 9987.97, Commission: 9.41

2020-05-04, OPERATION RESULT --- Gross: -578.57, Net: -597.97

2020-06-30, BUY CREATED --- Size: 42, Cash: 9402.03, Open: 220.59, Close: 227.07

2020-06-30, BUY EXECUTED --- Price: 220.59, Cost: 9264.78, Commission: 9.26

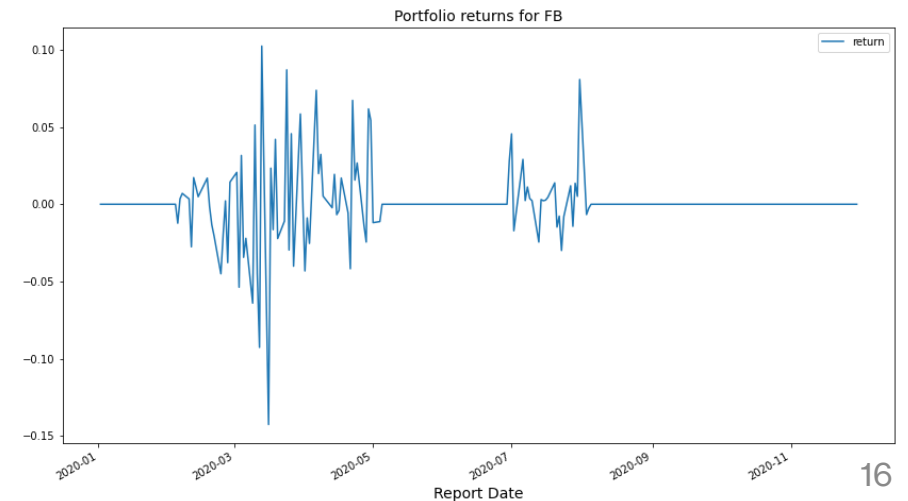
2020-08-04, SELL CREATED --- Size: 42

2020-08-04, SELL EXECUTED --- Price: 251.56, Cost: 9264.78, Commission: 10.57

2020-08-04, OPERATION RESULT --- Gross: 1300.74, Net: 1280.91

Final Portfolio Value: 10682.94

Rendimento annuale (periodo 2020): +7.4%



CAPM

Capital Asset Pricing Model

Il CAPM ed il modello Fama-French

- Il CAPM (Capital Asset Pricing Model) descrive la relazione tra il rischio sistematico (o di mercato) e i rendimenti aspettati di una *security*. *Interpretando i valori dell'indice β si può avere una idea del livello di sensitività dell'indice rispetto al mercato.*
- Il modello Fama-French a 3 fattori estende il CAPM aggiungendo altri due indici beta (o fattori) utili per spiegare l'eccesso di ritorno di un asset o portfolio.

$$E(r_i) - r_f = \alpha + \beta_{mkt}MKT + \beta_{smb}SMB + \beta_{hml}HML$$

Esposizione con Fama-Frech – FB/GOOG

Esposizione per FB

OLS Regression Results

Dep. Variable:	excess_rtn	R-squared:	0.194
Model:	OLS	Adj. R-squared:	0.172
Method:	Least Squares	F-statistic:	8.851
Date:	Thu, 26 May 2022	Prob (F-statistic):	2.63e-05
Time:	15:09:13	Log-Likelihood:	112.20
No. Observations:	114	AIC:	-216.4
Df Residuals:	110	BIC:	-205.5
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.0100	0.009	1.089	0.278	-0.008	0.028
mkt	1.1343	0.231	4.910	0.000	0.676	1.592
smb	-0.0631	0.366	-0.172	0.863	-0.789	0.662
hml	-0.4505	0.286	-1.578	0.117	-1.016	0.115

Omnibus:	27.694	Durbin-Watson:	1.867
Prob(Omnibus):	0.000	Jarque-Bera (JB):	104.260
Skew:	0.716	Prob(JB):	2.29e-23
Kurtosis:	7.461	Cond. No.	43.8

Esposizione per GOOG

OLS Regression Results

Dep. Variable:	excess_rtn	R-squared:	0.392
Model:	OLS	Adj. R-squared:	0.376
Method:	Least Squares	F-statistic:	24.92
Date:	Thu, 26 May 2022	Prob (F-statistic):	1.63e-12
Time:	15:23:11	Log-Likelihood:	191.82
No. Observations:	120	AIC:	-375.6
Df Residuals:	116	BIC:	-364.5
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.0068	0.005	1.400	0.164	-0.003	0.016
mkt	1.0504	0.122	8.637	0.000	0.810	1.291
smb	-0.5393	0.196	-2.752	0.007	-0.927	-0.151
hml	-0.1268	0.154	-0.825	0.411	-0.431	0.178

Omnibus:	6.136	Durbin-Watson:	2.133
Prob(Omnibus):	0.047	Jarque-Bera (JB):	7.037
Skew:	0.309	Prob(JB):	0.0296
Kurtosis:	4.012	Cond. No.	44.4

Dove:

- **mkt**: Market factor
- **smb**: Size factor
- **hml**: Value factor

Esposizione con Fama-Frech – RTX/LMT

Esposizione per RTX

OLS Regression Results						
=====						
Dep. Variable:	excess_rtn	R-squared:	0.606			
Model:	OLS	Adj. R-squared:	0.595			
Method:	Least Squares	F-statistic:	59.36			
Date:	Thu, 26 May 2022	Prob (F-statistic):	2.50e-23			
Time:	15:28:18	Log-likelihood:	210.65			
No. Observations:	120	AIC:	-413.3			
Df Residuals:	116	BIC:	-402.1			
Df Model:	3					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

Intercept	-0.0067	0.004	-1.612	0.110	-0.015	0.002
mkt	1.2293	0.104	11.824	0.000	1.023	1.435
smb	-0.0075	0.168	-0.045	0.964	-0.339	0.324
hml	0.4470	0.131	3.401	0.001	0.187	0.707
=====						
Omnibus:	12.722	Durbin-Watson:	2.189			
Prob(Omnibus):	0.002	Jarque-Bera (JB):	26.871			
Skew:	0.361	Prob(JB):	1.46e-06			
Kurtosis:	5.203	Cond. No.	44.4			
=====						

Esposizione per LMT

OLS Regression Results

Dep. Variable:	excess_rtn	R-squared:	0.383
Model:	OLS	Adj. R-squared:	0.367
Method:	Least Squares	F-statistic:	24.01
Date:	Thu, 26 May 2022	Prob (F-statistic):	3.70e-12
Time:	15:34:07	Log-Likelihood:	210.71
No. Observations:	120	AIC:	-413.4
Df Residuals:	116	BIC:	-402.3
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.0046	0.004	1.103	0.272	-0.004	0.013
mkt	0.8730	0.104	8.402	0.000	0.667	1.079
smb	-0.5501	0.167	-3.285	0.001	-0.882	-0.218
hml	-0.0070	0.131	-0.053	0.958	-0.267	0.253

Omnibus:	4.739	Durbin-Watson:	2.122
Prob(Omnibus):	0.094	Jarque-Bera (JB):	4.429
Skew:	-0.469	Prob(JB):	0.109
Kurtosis:	3.085	Cond. No.	44.4

Dove:

- **mkt**: Market factor
- **smb**: Size factor
- **hml**: Value factor

Esposizione con Fama-Frech – BAC/JPM

Esposizione per BAC

OLS Regression Results						
=====						
Dep. Variable:	excess_rtn	R-squared:	0.604			
Model:	OLS	Adj. R-squared:	0.593			
Method:	Least Squares	F-statistic:	58.87			
Date:	Thu, 26 May 2022	Prob (F-statistic):	3.34e-23			
Time:	15:37:12	Log-Likelihood:	178.26			
No. Observations:	120	AIC:	-348.5			
Df Residuals:	116	BIC:	-337.4			
Df Model:	3					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

Intercept	0.0073	0.005	1.356	0.178	-0.003	0.018
mkt	1.3409	0.136	9.847	0.000	1.071	1.611
smb	0.2108	0.219	0.961	0.339	-0.224	0.645
hml	1.0896	0.172	6.330	0.000	0.749	1.431
=====						
Omnibus:	10.439	Durbin-Watson:	2.198			
Prob(Omnibus):	0.005	Jarque-Bera (JB):	17.075			
Skew:	0.375	Prob(JB):	0.000196			
Kurtosis:	4.689	Cond. No.	44.4			

Esposizione per JPM

OLS Regression Results

Dep. Variable:	excess_rtn	R-squared:	0.691
Model:	OLS	Adj. R-squared:	0.683
Method:	Least Squares	F-statistic:	86.28
Date:	Thu, 26 May 2022	Prob (F-statistic):	2.06e-29
Time:	15:44:25	Log-Likelihood:	221.60
No. Observations:	120	AIC:	-435.2
Df Residuals:	116	BIC:	-424.1
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.0058	0.004	1.541	0.126	-0.002	0.013
mkt	1.1199	0.095	11.802	0.000	0.932	1.308
smb	0.0163	0.153	0.107	0.915	-0.287	0.319
hml	1.0124	0.120	8.440	0.000	0.775	1.250

Omnibus:	10.230	Durbin-Watson:	2.123
Prob(Omnibus):	0.006	Jarque-Bera (JB):	20.512
Skew:	-0.256	Prob(JB):	3.51e-05
Kurtosis:	4.959	Cond. No.	44.4

Dove:

- **mkt**: Market factor
- **smb**: Size factor
- **hml**: Value factor

Portfolio Optimization

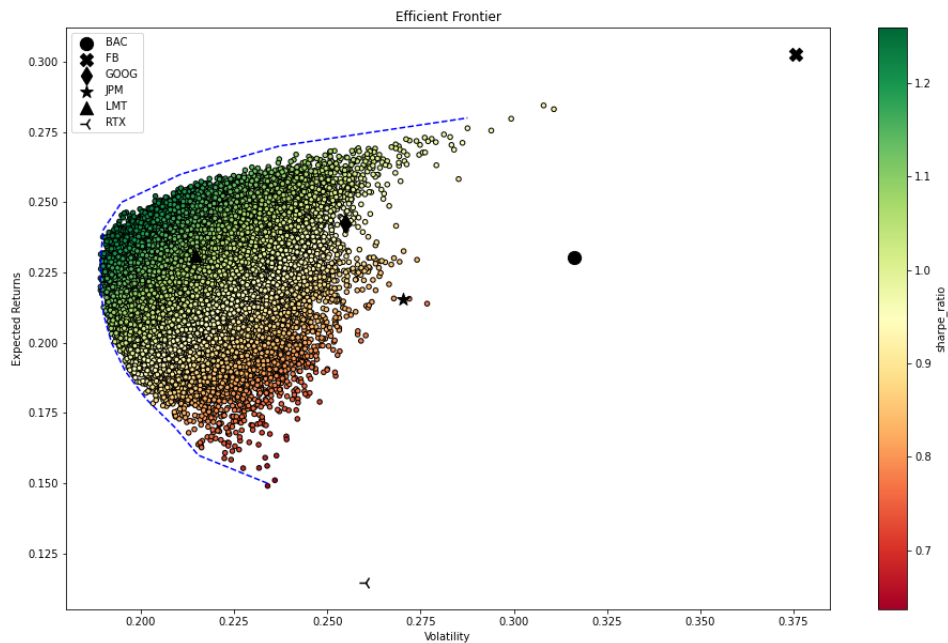
Costruzione di portafoglio

Portfolio optimization e Monte Carlo

- La Modern Portfolio Theory **MPT** è il principio fondamentale che sta dietro alla allocazione degli asset in un portfolio, tale principio si basa sulla *diversificazione* dei titoli per cercare di aumentare il profitto e di ridurre il rischio.
- Le simulazioni di Monte Carlo ci permettono di ottenere un set di portafogli ottimali grazie alla generazione in maniera random di un elevato numero di portafogli, tale metodo lo si può utilizzare sia con dati passati ma anche con dati di previsione.

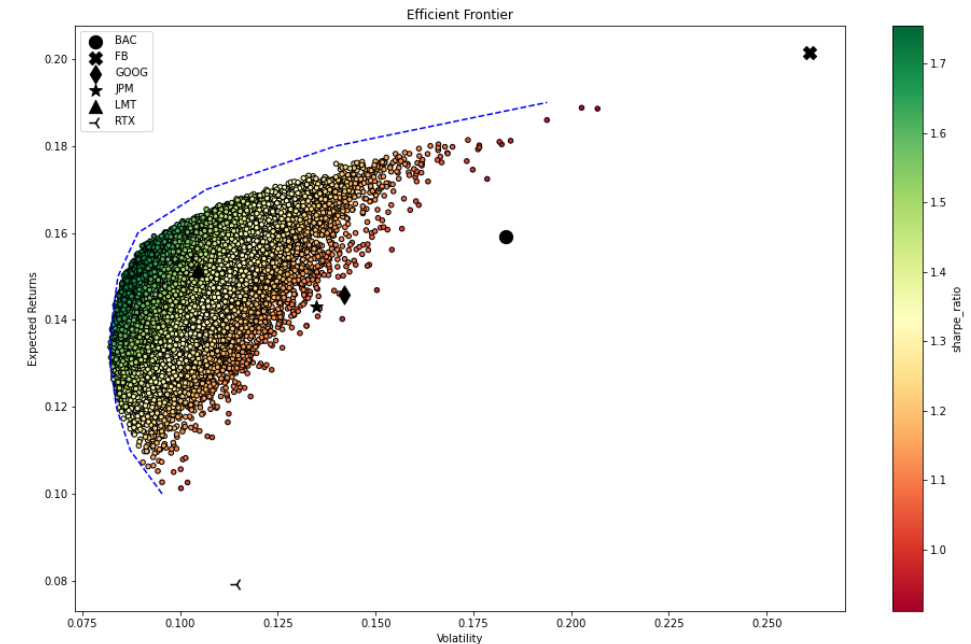
Portafoglio ottimale con monte carlo

Portafoglio con dati storici



Maximum Sharpe ratio portfolio ----
Performance
returns: 24.54% volatility: 19.48% sharpe_ratio: 125.94%
Weights
BAC: 1.55% FB: 15.66% GOOG: 31.05% JPM: 0.10% LMT: 51.17% RTX: 0.48%

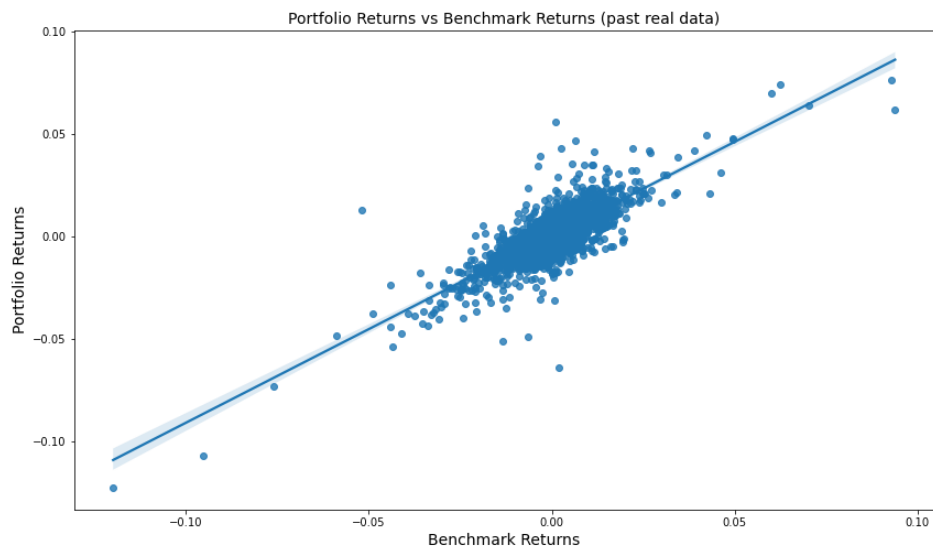
Portafoglio con dati di previsione (ARIMA)



Maximum Sharpe ratio portfolio ----
Performance
returns: 15.02% volatility: 8.56% sharpe_ratio: 175.42%
Weights
BAC: 0.50% FB: 10.80% GOOG: 17.47% JPM: 28.70% LMT: 38.01% RTX: 4.52%

Beta dei portafogli ottimali

Portfolio con dati passati



Portfolio con dati di previsione (ARIMA)

