3_Data_testing

June 21, 2022

1 TFG

1.1 In this notebook, the data is used to perform several tests

[1]:
```
import bt
from scipy.stats import norm
import yfinance as yf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.api as sm
import datetime
%matplotlib inline
plt.style.use("default")
import warnings
warnings.filterwarnings("ignore")
```

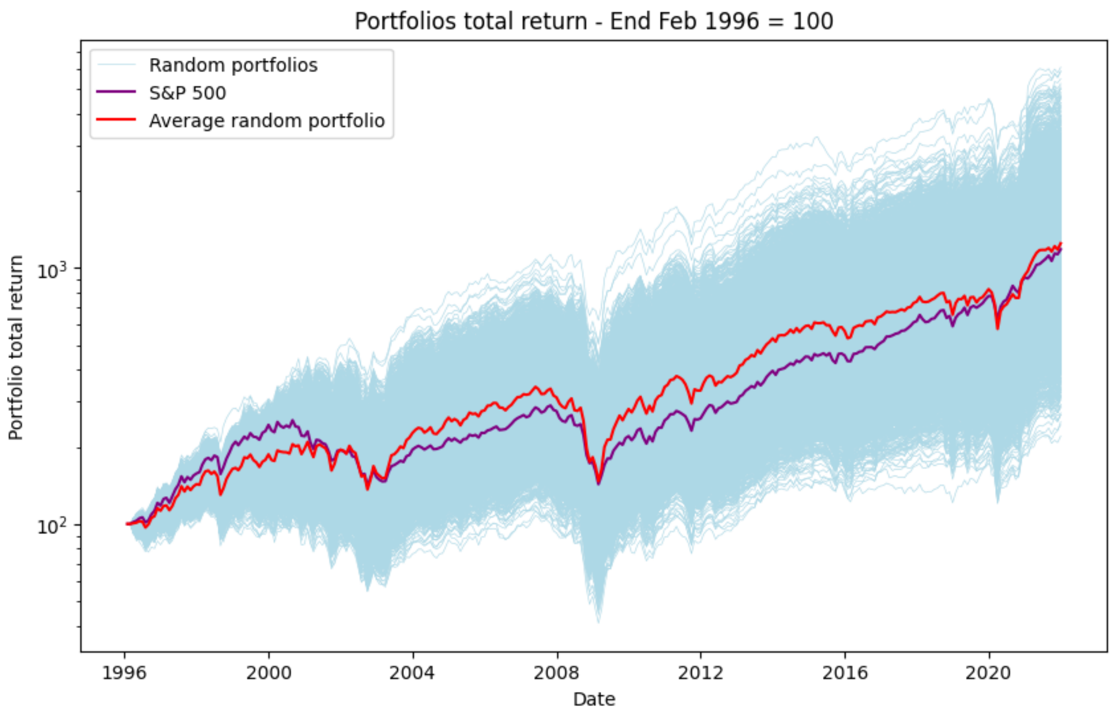
1.1.1 Data processed in the previous notebooks is loaded

[2]:
```
prices = pd.read_excel("price_index.xlsx",index_col=0)
company_returns = pd.read_excel("company_returns.xlsx",index_col=0)

index_portfolios = pd.read_excel("Simulations.xlsx",index_col=0)
index_portfolios["AVERAGE"] = index_portfolios.mean(axis=1)

returns = index_portfolios.pct_change()
```

1.1.2 Below we can see a graph with the evolution of every random portfolio, as well as the average and the S&P 500 index for reference

[13]:
```
fig,ax1 = plt.subplots(1,figsize=(10,6))
ax1.plot(index_portfolios.iloc[:,0],linewidth=0.
 ↪45,color="lightblue",label="Random portfolios");
ax1.plot(index_portfolios.iloc[:,1:-2],linewidth=0.45,color="lightblue");
ax1.plot(index_portfolios["SPX"],linewidth=1.5,color="purple",label="S&P 500");
ax1.plot(index_portfolios["AVERAGE"],linewidth=1.5,color="red", label="Average␣
 ↪random portfolio");
```

```
ax1.set_yscale('log')
ax1.set_title("Portfolios total return - End Feb 1996 = 100");
ax1.legend()

ax1.set_xlabel("Date");
ax1.set_ylabel("Portfolio total return");

plt.savefig("Graphs/Portfolios_total_return.png",dpi=300);
```



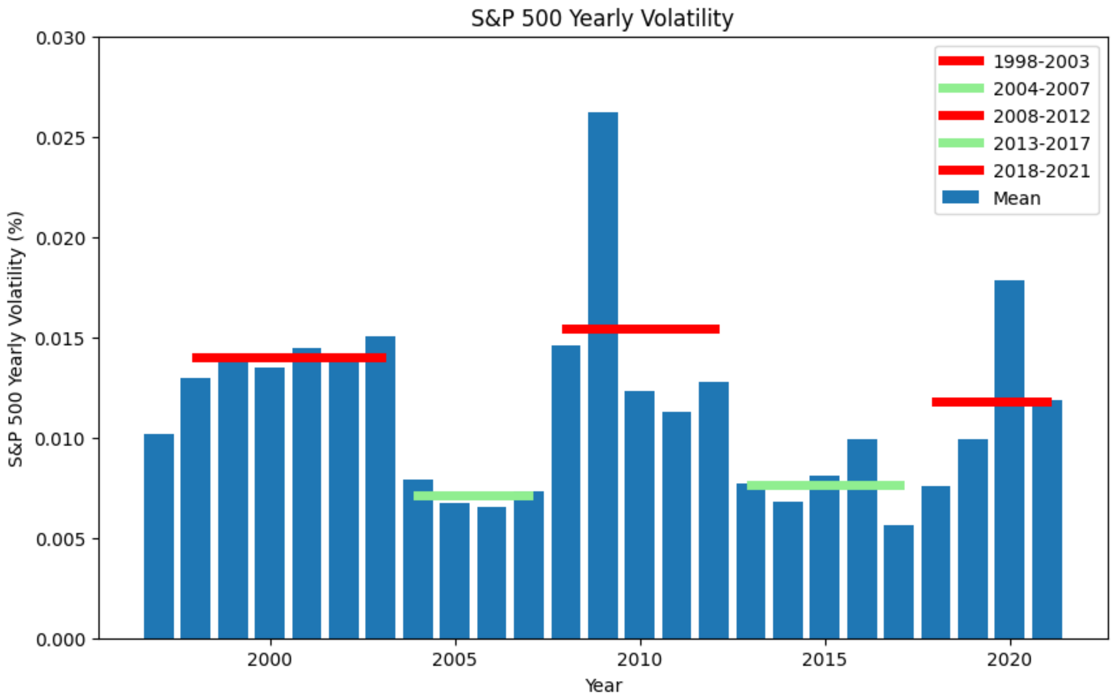
1.1.3 To divide the period into subperiods, yearly volatility is computed to identify regimes

[3]:
```
spxdata = yf.
↪download("SPY",start="1996-03-01",end="2021-12-31",progress=False)["Adj␣
↪Close"].pct_change().dropna()

spxvol = pd.DataFrame(spxdata.rolling(252).std())
spxyearvol = spxvol.groupby(lambda x: x.year)['Adj Close'].agg(['mean'])

spxyearvol["P1"] = np.nan
spxyearvol["P1"].loc[1998:2003]= spxyearvol.loc[1998:2003].mean().values[0]
spxyearvol["P2"] = np.nan
spxyearvol["P2"].loc[2004:2007]= spxyearvol.loc[2004:2007].mean().values[0]
```

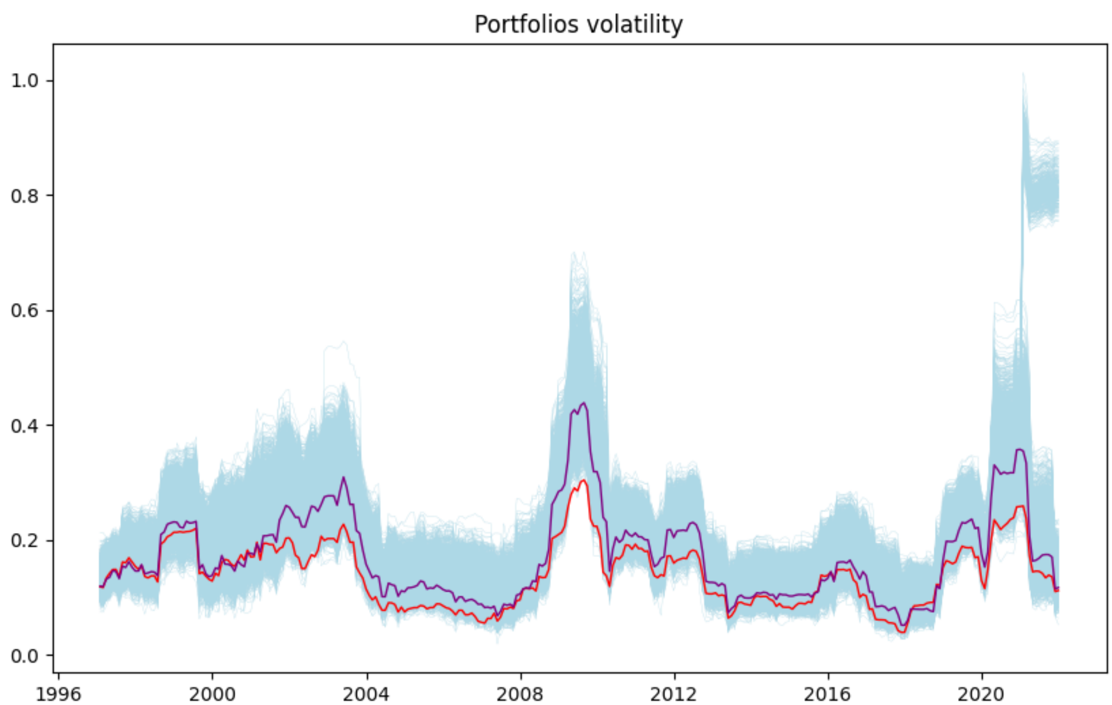
```
spxyearvol["P3"] = np.nan
spxyearvol["P3"].loc[2008:2012]= spxyearvol.loc[2008:2012].mean().values[0]
spxyearvol["P4"] = np.nan
spxyearvol["P4"].loc[2013:2017]= spxyearvol.loc[2013:2017].mean().values[0]
spxyearvol["P5"] = np.nan
spxyearvol["P5"].loc[2018:2021]= spxyearvol.loc[2018:2021].mean().values[0]
```

[4]:

```
fig,ax1 = plt.subplots(1,figsize=(10,6))
ax1.bar(list(spxyearvol.index),spxyearvol["mean"].values,label="Mean");
ax1.plot(spxyearvol.index,spxyearvol["P1"].
 ↪values,label="1998-2003",linewidth=5,color="red");
ax1.plot(spxyearvol.index,spxyearvol["P2"].
 ↪values,label="2004-2007",linewidth=5,color="lightgreen");
ax1.plot(spxyearvol.index,spxyearvol["P3"].
 ↪values,label="2008-2012",linewidth=5,color="red");
ax1.plot(spxyearvol.index,spxyearvol["P4"].
 ↪values,label="2013-2017",linewidth=5,color="lightgreen");
ax1.plot(spxyearvol.index,spxyearvol["P5"].
 ↪values,label="2018-2021",linewidth=5,color="red");
ax1.set_title("S&P 500 Yearly Volatility");
ax1.legend()

ax1.set_ylim(0,0.03)
ax1.set_xlabel("Year");
ax1.set_ylabel("S&P 500 Yearly Volatility (%)");

plt.savefig("Graphs/S&P_yearly_volatility.png",dpi=300);
```



[5]:
```
fig,ax1 = plt.subplots(1,figsize=(10,6))
ax1.plot(((returns.rolling(12).std() * np.sqrt(12)).iloc[:,:-2]),linewidth=0.
 ↪2,color="lightblue");
ax1.plot(((returns.rolling(12).std() * np.
 ↪sqrt(12))["SPX"]),linewidth=1,color="red");
ax1.plot(((returns.rolling(12).std() * np.
 ↪sqrt(12))["AVERAGE"]),linewidth=1,color="purple");
plt.title("Portfolios volatility");
```

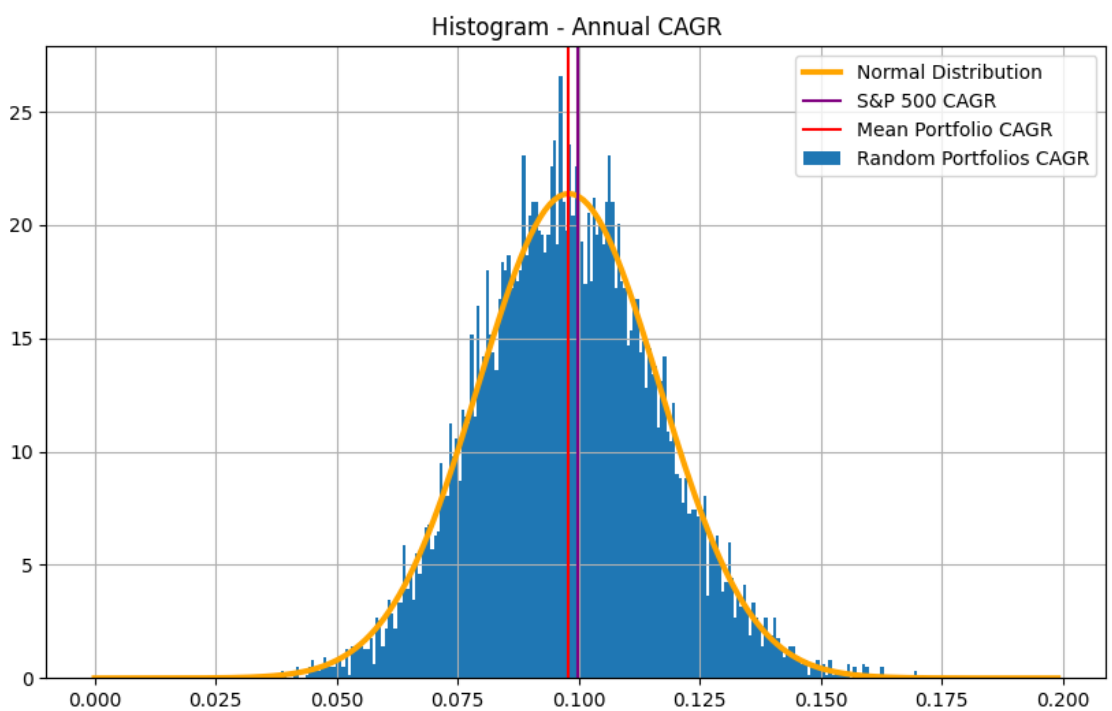


Several metrics like the volatility and CAGR

[6]:
```
ann_rets = (index_portfolios.iloc[-1] /  index_portfolios.iloc[0])**(12/
 ↪(12*26)) - 1

metrics = pd.DataFrame(ann_rets,columns=["Annual Return"])

metrics["Annual Volatility"] = index_portfolios.pct_change().dropna().std() *␣
 ↪np.sqrt(12)

metrics["Return / Volatility"] = metrics["Annual Return"] / metrics["Annual␣
 ↪Volatility"]

return_position_spx = metrics["Annual Return"].sort_values(ascending=False).
 ↪index.get_loc("SPX")

volatility_position_spx = metrics["Annual Volatility"].
 ↪sort_values(ascending=False).index.get_loc("SPX")

return_vol_position_spx = metrics["Return / Volatility"].
 ↪sort_values(ascending=False).index.get_loc("SPX")
```

1.1.4 Histogram of the portfolios' CAGR

[19]:
```
fig,ax1 = plt.subplots(1,figsize=(10,6))

x = np.arange(0, 0.2, 0.001)

mu, std = norm.fit(metrics["Annual Return"])

ax1.plot(x, norm.pdf(x, mu, std),color="orange",linewidth=3,label="Normal␣
↪Distribution")

ax1.hist(metrics["Annual␣
↪Return"],bins=222,cumulative=False,density=True,label="Random Portfolios␣
↪CAGR");
ax1.grid(True)
ax1.axvline(metrics["Annual Return"]["SPX"],color="purple",linewidth=1.
↪5,label="S&P 500 CAGR");
ax1.axvline(metrics["Annual Return"][0:10000].mean(),color="red",linewidth=1.
↪5,label="Mean Portfolio CAGR");
ax1.set_title("Histogram - Annual CAGR");
ax1.legend();

plt.savefig("Graphs/Histogram_CAGR.png")
```



1.1.5 Now, Fama-French data is loaded and processed

[3]:
```
ff = pd.read_csv("F-F_Research_Data_5_Factors_2x3.
↪CSV",skiprows=3,index_col=0,skipfooter=63,engine="python",parse_dates=True,infer_datetime_f

ff.index = pd.to_datetime(ff.index, format= '%Y%m')
ff.index = ff.index + pd.offsets.MonthEnd()
ff = ff["1996-03":"2021"]
ff = ff/100

ff.rename(columns={"Mkt-RF":"mkt_excess"}, inplace=True)
```

1.1.6 Regressions are performed for every random portfolio, for every period to compute every factor

[ ]:
```
from statsmodels.regression.rolling import RollingOLS

factorsp1 = pd.DataFrame(columns=returns[range(0,10000)].
↪columns,index=["Alpha","Beta","SMB","HML","RMW","CMA","R2","P-value Alpha"])


for i in returns[range(0,10000)].columns:

        endog = returns[i]["1998":"2003"].dropna() - ff["RF"]["1998":"2003"]
        exog = ff[["mkt_excess","SMB","HML","RMW","CMA"]]["1998":"2003"]
        exog = sm.add_constant(exog)

        mod = sm.regression.linear_model.OLS(endog,exog)
        rres = mod.fit()

        factorsp1.loc["Alpha"][i] = rres.params["const"]
        factorsp1.loc["Beta"][i] = rres.params["mkt_excess"]
        factorsp1.loc["SMB"][i] = rres.params["SMB"]
        factorsp1.loc["HML"][i] = rres.params["HML"]
        factorsp1.loc["RMW"][i] = rres.params["RMW"]
        factorsp1.loc["CMA"][i] = rres.params["CMA"]
        factorsp1.loc["R2"][i] = rres.rsquared
        factorsp1.loc["P-value Alpha"][i] = rres.pvalues["const"]

factorsp2 = pd.DataFrame(columns=returns[range(0,10000)].
↪columns,index=["Alpha","Beta","SMB","HML","RMW","CMA","R2","P-value Alpha"])


for i in returns[range(0,10000)].columns:

        endog = returns[i]["2004":"2007"].dropna() - ff["RF"]["2004":"2007"]
        exog = ff[["mkt_excess","SMB","HML","RMW","CMA"]]["2004":"2007"]
```

```
        exog = sm.add_constant(exog)

        mod = sm.regression.linear_model.OLS(endog,exog)
        rres = mod.fit()

        factorsp2.loc["Alpha"][i] = rres.params["const"]
        factorsp2.loc["Beta"][i] = rres.params["mkt_excess"]
        factorsp2.loc["SMB"][i] = rres.params["SMB"]
        factorsp2.loc["HML"][i] = rres.params["HML"]
        factorsp2.loc["RMW"][i] = rres.params["RMW"]
        factorsp2.loc["CMA"][i] = rres.params["CMA"]
        factorsp2.loc["R2"][i] = rres.rsquared
        factorsp2.loc["P-value Alpha"][i] = rres.pvalues["const"]


factorsp3 = pd.DataFrame(columns=returns[range(0,10000)].
 ↪columns,index=["Alpha","Beta","SMB","HML","RMW","CMA","R2","P-value Alpha"])


for i in returns[range(0,10000)].columns:

        endog = returns[i]["2008":"2012"].dropna() - ff["RF"]["2008":"2012"]
        exog = ff[["mkt_excess","SMB","HML","RMW","CMA"]]["2008":"2012"]
        exog = sm.add_constant(exog)

        mod = sm.regression.linear_model.OLS(endog,exog)
        rres = mod.fit()

        factorsp3.loc["Alpha"][i] = rres.params["const"]
        factorsp3.loc["Beta"][i] = rres.params["mkt_excess"]
        factorsp3.loc["SMB"][i] = rres.params["SMB"]
        factorsp3.loc["HML"][i] = rres.params["HML"]
        factorsp3.loc["RMW"][i] = rres.params["RMW"]
        factorsp3.loc["CMA"][i] = rres.params["CMA"]
        factorsp3.loc["R2"][i] = rres.rsquared
        factorsp3.loc["P-value Alpha"][i] = rres.pvalues["const"]


factorsp4 = pd.DataFrame(columns=returns[range(0,10000)].
 ↪columns,index=["Alpha","Beta","SMB","HML","RMW","CMA","R2","P-value Alpha"])


for i in returns[range(0,10000)].columns:

        endog = returns[i]["2013":"2017"].dropna() - ff["RF"]["2013":"2017"]
        exog = ff[["mkt_excess","SMB","HML","RMW","CMA"]]["2013":"2017"]
        exog = sm.add_constant(exog)
```

```
        mod = sm.regression.linear_model.OLS(endog,exog)
        rres = mod.fit()

        factorsp4.loc["Alpha"][i] = rres.params["const"]
        factorsp4.loc["Beta"][i] = rres.params["mkt_excess"]
        factorsp4.loc["SMB"][i] = rres.params["SMB"]
        factorsp4.loc["HML"][i] = rres.params["HML"]
        factorsp4.loc["RMW"][i] = rres.params["RMW"]
        factorsp4.loc["CMA"][i] = rres.params["CMA"]
        factorsp4.loc["R2"][i] = rres.rsquared
        factorsp4.loc["P-value Alpha"][i] = rres.pvalues["const"]


factorsp5 = pd.DataFrame(columns=returns[range(0,10000)].
 ↪columns,index=["Alpha","Beta","SMB","HML","RMW","CMA","R2","P-value Alpha"])


for i in returns[range(0,10000)].columns:

        endog = returns[i]["2018":"2021"].dropna() - ff["RF"]["2018":"2021"]
        exog = ff[["mkt_excess","SMB","HML","RMW","CMA"]]["2018":"2021"]
        exog = sm.add_constant(exog)

        mod = sm.regression.linear_model.OLS(endog,exog)
        rres = mod.fit()

        factorsp5.loc["Alpha"][i] = rres.params["const"]
        factorsp5.loc["Beta"][i] = rres.params["mkt_excess"]
        factorsp5.loc["SMB"][i] = rres.params["SMB"]
        factorsp5.loc["HML"][i] = rres.params["HML"]
        factorsp5.loc["RMW"][i] = rres.params["RMW"]
        factorsp5.loc["CMA"][i] = rres.params["CMA"]
        factorsp5.loc["R2"][i] = rres.rsquared
        factorsp5.loc["P-value Alpha"][i] = rres.pvalues["const"]

factorsp1.to_csv("Computations/factorsp1.csv")
factorsp2.to_csv("Computations/factorsp2.csv")
factorsp3.to_csv("Computations/factorsp3.csv")
factorsp4.to_csv("Computations/factorsp4.csv")
factorsp5.to_csv("Computations/factorsp5.csv")
```

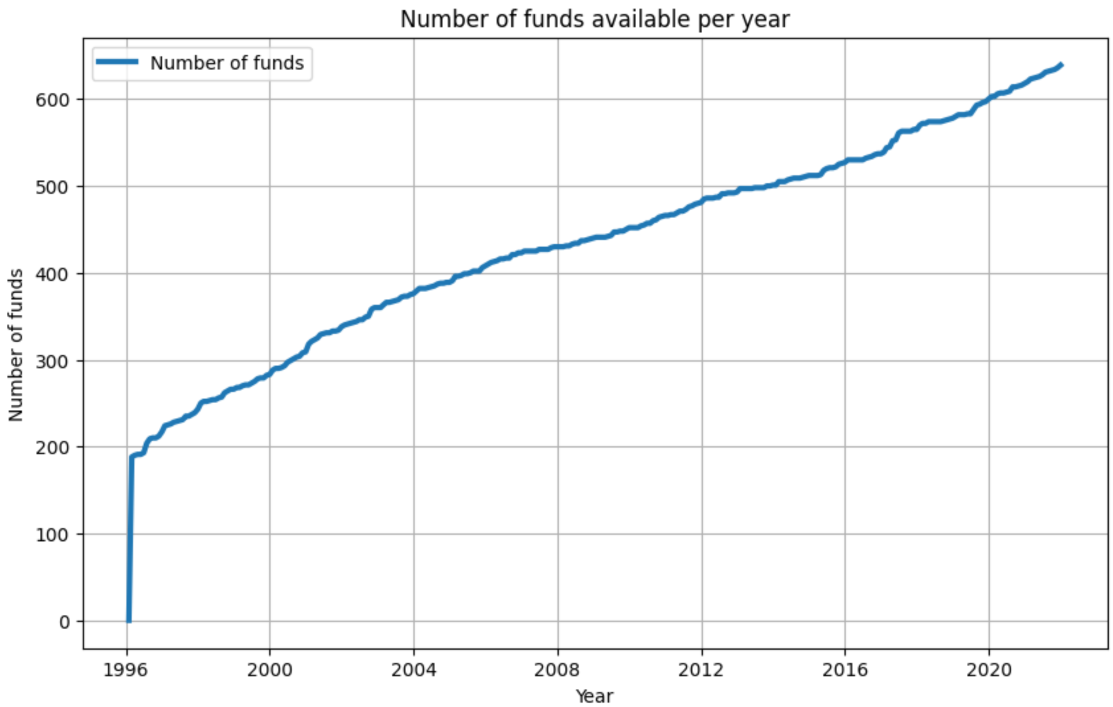
1.1.7 Mutual fund data is loaded

[7]:
```
funds = pd.read_excel("Reuters Mutual Fund Data.xlsx")

tickers = list(funds[funds["Index Based Fund"]!=1]["NASDAQ Ticker"].dropna())

data_f = yf.
 ↪download(tickers,start="1995-12-31",end="2022-01-01",progress=False,threads=4,periods="1mo"
 ↪Close"]
data_f = data_f.resample("M").pad().pct_change()
```

```
8 Failed downloads:
- DRFAX: No data found for this date range, symbol may be delisted
- CVRDX: Data doesn't exist for startDate = 820364400, endDate = 1640991600
- APDWX: Data doesn't exist for startDate = 820364400, endDate = 1640991600
- WVMIX: Data doesn't exist for startDate = 820364400, endDate = 1640991600
- MFSIX: Data doesn't exist for startDate = 820364400, endDate = 1640991600
- FIDJX: No data found for this date range, symbol may be delisted
- FIDEX: No data found for this date range, symbol may be delisted
- FIDHX: No data found for this date range, symbol may be delisted
```

1.1.8 To inspect the data, the number of funds available is computed

[81]:
```
fig,ax1 = plt.subplots(1,figsize=(10,6))

ax1.plot(data_f.count(axis=1),label="Number of funds",linewidth=3)
ax1.set_xlabel("Year");
ax1.set_ylabel("Number of funds");
ax1.grid(True);
ax1.legend();
ax1.set_title("Number of funds available per year");
plt.savefig("Graphs/numfunds.png",dpi=300);
```



1.1.9 As done before, regressions are performed

[ ]:
```
factorsfp1 = pd.DataFrame(columns=data_f.
 ↪columns,index=["Alpha","Beta","SMB","HML","RMW","CMA","R2","P-value Alpha"])


for i in data_f.columns:

        endog = data_f[i]["1998":"2003"].dropna() - ff["RF"]["1998":"2003"]
        exog = ff[["mkt_excess","SMB","HML","RMW","CMA"]]["1998":"2003"]
        exog = sm.add_constant(exog)

        mod = sm.regression.linear_model.OLS(endog,exog)
        rres = mod.fit()

        factorsfp1.loc["Alpha"][i] = rres.params["const"]
        factorsfp1.loc["Beta"][i] = rres.params["mkt_excess"]
        factorsfp1.loc["SMB"][i] = rres.params["SMB"]
        factorsfp1.loc["HML"][i] = rres.params["HML"]
        factorsfp1.loc["RMW"][i] = rres.params["RMW"]
        factorsfp1.loc["CMA"][i] = rres.params["CMA"]
        factorsfp1.loc["R2"][i] = rres.rsquared
        factorsfp1.loc["P-value Alpha"][i] = rres.pvalues["const"]
```

```python
factorsfp2 = pd.DataFrame(columns=data_f.
 ↪columns,index=["Alpha","Beta","SMB","HML","RMW","CMA","R2","P-value Alpha"])


for i in data_f.columns:

        endog = data_f[i]["2004":"2007"].dropna() - ff["RF"]["2004":"2007"]
        exog = ff[["mkt_excess","SMB","HML","RMW","CMA"]]["2004":"2007"]
        exog = sm.add_constant(exog)

        mod = sm.regression.linear_model.OLS(endog,exog)
        rres = mod.fit()

        factorsfp2.loc["Alpha"][i] = rres.params["const"]
        factorsfp2.loc["Beta"][i] = rres.params["mkt_excess"]
        factorsfp2.loc["SMB"][i] = rres.params["SMB"]
        factorsfp2.loc["HML"][i] = rres.params["HML"]
        factorsfp2.loc["RMW"][i] = rres.params["RMW"]
        factorsfp2.loc["CMA"][i] = rres.params["CMA"]
        factorsfp2.loc["R2"][i] = rres.rsquared
        factorsfp2.loc["P-value Alpha"][i] = rres.pvalues["const"]

factorsfp3 = pd.DataFrame(columns=data_f.
 ↪columns,index=["Alpha","Beta","SMB","HML","RMW","CMA","R2","P-value Alpha"])


for i in data_f.columns:

        endog = data_f[i]["2008":"2012"].dropna() - ff["RF"]["2008":"2012"]
        exog = ff[["mkt_excess","SMB","HML","RMW","CMA"]]["2008":"2012"]
        exog = sm.add_constant(exog)

        mod = sm.regression.linear_model.OLS(endog,exog)
        rres = mod.fit()

        factorsfp3.loc["Alpha"][i] = rres.params["const"]
        factorsfp3.loc["Beta"][i] = rres.params["mkt_excess"]
        factorsfp3.loc["SMB"][i] = rres.params["SMB"]
        factorsfp3.loc["HML"][i] = rres.params["HML"]
        factorsfp3.loc["RMW"][i] = rres.params["RMW"]
        factorsfp3.loc["CMA"][i] = rres.params["CMA"]
        factorsfp3.loc["R2"][i] = rres.rsquared
        factorsfp3.loc["P-value Alpha"][i] = rres.pvalues["const"]


factorsfp4 = pd.DataFrame(columns=data_f.
 ↪columns,index=["Alpha","Beta","SMB","HML","RMW","CMA","R2","P-value Alpha"])
```

```
for i in data_f.columns:

        endog = data_f[i]["2013":"2017"].dropna() - ff["RF"]["2013":"2017"]
        exog = ff[["mkt_excess","SMB","HML","RMW","CMA"]]["2013":"2017"]
        exog = sm.add_constant(exog)

        mod = sm.regression.linear_model.OLS(endog,exog)
        rres = mod.fit()

        factorsfp4.loc["Alpha"][i] = rres.params["const"]
        factorsfp4.loc["Beta"][i] = rres.params["mkt_excess"]
        factorsfp4.loc["SMB"][i] = rres.params["SMB"]
        factorsfp4.loc["HML"][i] = rres.params["HML"]
        factorsfp4.loc["RMW"][i] = rres.params["RMW"]
        factorsfp4.loc["CMA"][i] = rres.params["CMA"]
        factorsfp4.loc["R2"][i] = rres.rsquared
        factorsfp4.loc["P-value Alpha"][i] = rres.pvalues["const"]


factorsfp5 = pd.DataFrame(columns=data_f.
 ↪columns,index=["Alpha","Beta","SMB","HML","RMW","CMA","R2","P-value Alpha"])


for i in data_f.columns:

        endog = data_f[i]["2018":"2021"].dropna() - ff["RF"]["2018":"2021"]
        exog = ff[["mkt_excess","SMB","HML","RMW","CMA"]]["2018":"2021"]
        exog = sm.add_constant(exog)

        mod = sm.regression.linear_model.OLS(endog,exog)
        rres = mod.fit()

        factorsfp5.loc["Alpha"][i] = rres.params["const"]
        factorsfp5.loc["Beta"][i] = rres.params["mkt_excess"]
        factorsfp5.loc["SMB"][i] = rres.params["SMB"]
        factorsfp5.loc["HML"][i] = rres.params["HML"]
        factorsfp5.loc["RMW"][i] = rres.params["RMW"]
        factorsfp5.loc["CMA"][i] = rres.params["CMA"]
        factorsfp5.loc["R2"][i] = rres.rsquared
        factorsfp5.loc["P-value Alpha"][i] = rres.pvalues["const"]


factorsfp1.to_csv("Computations/factorsfp1.csv")
factorsfp2.to_csv("Computations/factorsfp2.csv")
factorsfp3.to_csv("Computations/factorsfp3.csv")
```

```
factorsfp4.to_csv("Computations/factorsfp4.csv")
factorsfp5.to_csv("Computations/factorsfp5.csv")
```

1.1.10 To avoid repeting this computationally expensive regressions, we can just load the previously processed data

[8]:
```
factorsfp1 = pd.read_csv("Computations/factorsfp1.
 ↪csv",index_col=0,parse_dates=True)
factorsfp2 = pd.read_csv("Computations/factorsfp2.
 ↪csv",index_col=0,parse_dates=True)
factorsfp3 = pd.read_csv("Computations/factorsfp3.
 ↪csv",index_col=0,parse_dates=True)
factorsfp4 = pd.read_csv("Computations/factorsfp4.
 ↪csv",index_col=0,parse_dates=True)
factorsfp5 = pd.read_csv("Computations/factorsfp5.
 ↪csv",index_col=0,parse_dates=True)



factorsp1 = pd.read_csv("Computations/factorsp1.csv",index_col=0)
factorsp2 = pd.read_csv("Computations/factorsp2.csv",index_col=0)
factorsp3 = pd.read_csv("Computations/factorsp3.csv",index_col=0)
factorsp4 = pd.read_csv("Computations/factorsp4.csv",index_col=0)
factorsp5 = pd.read_csv("Computations/factorsp5.csv",index_col=0)
```

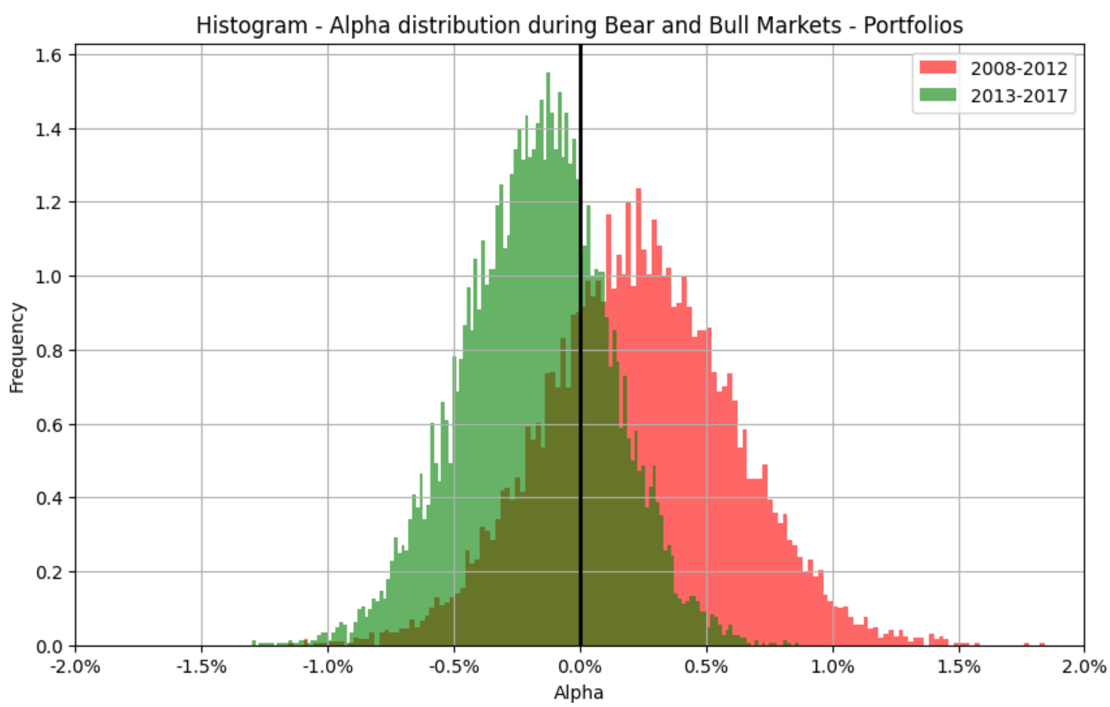
1.2 Now, we can start with the tests

1.2.1 First we plot the alphas depending of the market regime, for portfolios and funds

After looking at the data, we decide to focus on the bear market caused by the Great Financial Crisis, and the bull market of its subsequent recovery, so from now on those are going to be the periods studied.

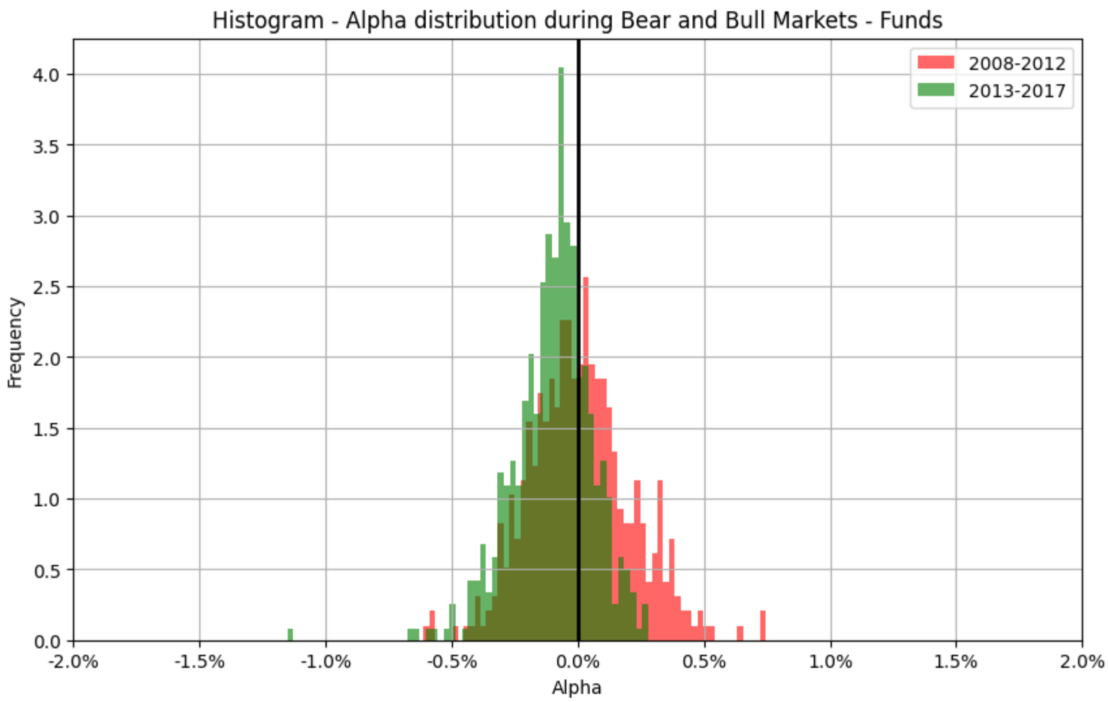
[9]:
```
import matplotlib.ticker as mtick

fig,ax1 = plt.subplots(1,figsize=(10,6))

plt.hist(factorsp3.loc["Alpha"]*100,bins=150,alpha=0.
 ↪6,label="2008-2012",color="red",density=True);
plt.hist(factorsp4.loc["Alpha"]*100,bins=150,alpha=0.
 ↪6,label="2013-2017",color="green",density=True);
plt.grid(True);
plt.legend();
plt.xlim((-2,2))
plt.axvline(0,color="black",linewidth=2);
plt.title("Histogram - Alpha distribution during Bear and Bull Markets -␣
 ↪Portfolios");
```

```
plt.xlabel("Alpha");
plt.ylabel("Frequency");

fmt = '%.1f%%' # Format you want the ticks, e.g. '40%'
xticks = mtick.FormatStrFormatter(fmt)
ax1.xaxis.set_major_formatter(xticks)

plt.savefig("Graphs/hist_alpha_portfolios.png",dpi=300);
```



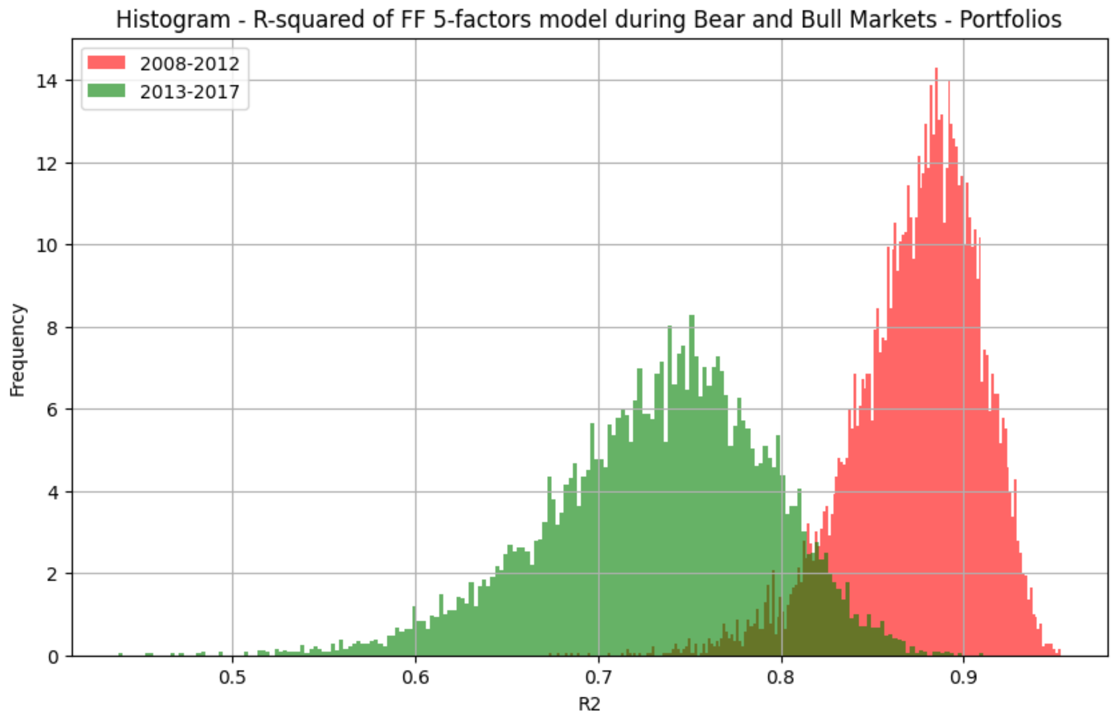
[10]:
```
fig,ax1 = plt.subplots(1,figsize=(10,6))

plt.hist(factorsfp3.loc["Alpha"]*100,bins=60,alpha=0.
 ↪6,label="2008-2012",color="red",density=True);
plt.hist(factorsfp4.loc["Alpha"]*100,bins=60,alpha=0.
 ↪6,label="2013-2017",color="green",density=True);
plt.grid(True);
plt.legend();
plt.xlim((-2,2))
plt.axvline(0,color="black",linewidth=2);
plt.title("Histogram - Alpha distribution during Bear and Bull Markets -␣
 ↪Funds");
plt.xlabel("Alpha");
plt.ylabel("Frequency");
```

```
fmt = '%.1f%%'
xticks = mtick.FormatStrFormatter(fmt)
ax1.xaxis.set_major_formatter(xticks)

plt.savefig("Graphs/hist_alpha_funds.png",dpi=300);
```



1.2.2 To try to explain the differences, the R-Squared is also plotted

[67]:
```
fig,ax1 = plt.subplots(1,figsize=(10,6))

plt.hist(factorsp3.loc["R2"],bins=200,alpha=0.
 ↪6,label="2008-2012",color="red",density=True);
plt.hist(factorsp4.loc["R2"],bins=200,alpha=0.
 ↪6,label="2013-2017",color="green",density=True);
plt.grid(True);
plt.legend();
ax1.set_ylabel("Frequency");
ax1.set_xlabel("R2");
plt.title("Histogram - R-squared of FF 5-factors model during Bear and Bull␣
 ↪Markets - Portfolios");
plt.savefig("Graphs/hist_r2_ff_portfolios.png",dpi=300);
```



Descriptive table of mean and std of the previous graph

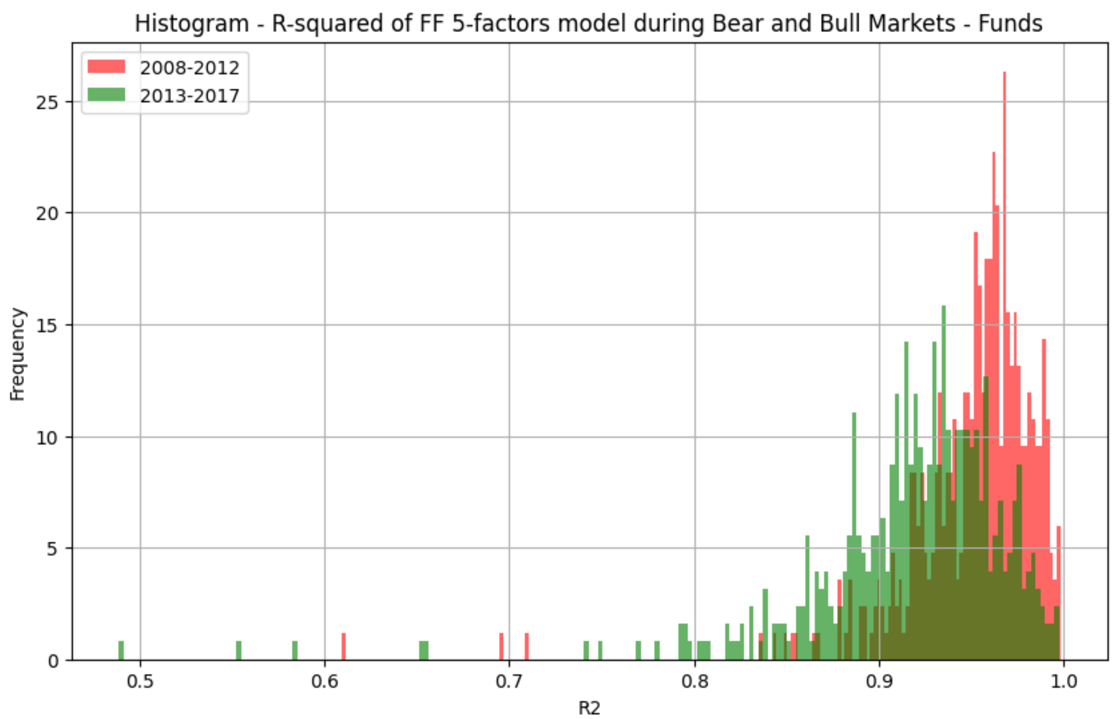
[28]:
```
describe_histogram_r2 = pd.
 ↪DataFrame(index=["mean","std"],columns=["2008-2012","2013-2017"])
describe_histogram_r2["2008-2012"] = factorsp3.loc["R2"].
 ↪describe()[["mean","std"]]
describe_histogram_r2["2013-2017"] = factorsp4.loc["R2"].
 ↪describe()[["mean","std"]]
describe_histogram_r2 = describe_histogram_r2.round(4)
describe_histogram_r2
```

[28]:

	2008-2012	2013-2017
mean	0.8740	0.7330
std	0.0349	0.0605

[68]:
```
fig,ax1 = plt.subplots(1,figsize=(10,6))

plt.hist(factorsfp3.loc["R2"],bins=200,alpha=0.
 ↪6,label="2008-2012",color="red",density=True);
plt.hist(factorsfp4.loc["R2"],bins=200,alpha=0.
 ↪6,label="2013-2017",color="green",density=True);
plt.grid(True);
plt.legend();
ax1.set_ylabel("Frequency");
```

```
ax1.set_xlabel("R2");
#plt.xlim((-0.02,0.02))
#plt.axvline(0,color="black",linewidth=2);
plt.title("Histogram - R-squared of FF 5-factors model during Bear and Bull␣
↪Markets - Funds");
plt.savefig("Graphs/hist_r2_ff_funds.png",dpi=300);
```



[29]:
```
describe_histogram_r2 = pd.
↪DataFrame(index=["mean","std"],columns=["2008-2012","2013-2017"])
describe_histogram_r2["2008-2012"] = factorsfp3.loc["R2"].
↪describe()[["mean","std"]]
describe_histogram_r2["2013-2017"] = factorsfp4.loc["R2"].
↪describe()[["mean","std"]]
describe_histogram_r2 = describe_histogram_r2.round(4)
describe_histogram_r2
```

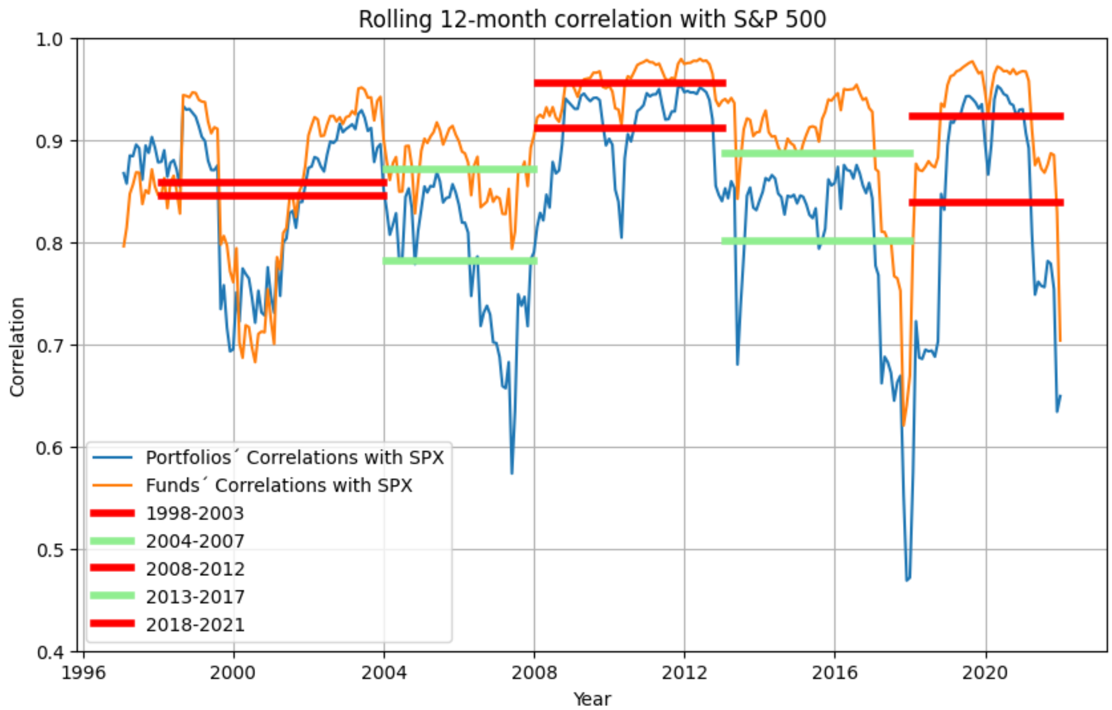
[29]:

	2008-2012	2013-2017
mean	0.9514	0.9179
std	0.0372	0.0543

[13]:
```
#### calculo correlaciones de carteras simuladas y fondos con sp500

correlations_with_spx = returns.iloc[:,:-2].rolling(12).corr(returns.iloc[:,-2])
```

```
correlations_with_spx["P1"] = np.nan
correlations_with_spx["P1"]["1998":"2003"]= correlations_with_spx["1998":
 ↪"2003"].mean(axis=1).mean()
correlations_with_spx["P2"] = np.nan
correlations_with_spx["P2"]["2004":"2007"]= correlations_with_spx["2004":
 ↪"2007"].mean(axis=1).mean()
correlations_with_spx["P3"] = np.nan
correlations_with_spx["P3"]["2008":"2012"]= correlations_with_spx["2008":
 ↪"2012"].mean(axis=1).mean()
correlations_with_spx["P4"] = np.nan
correlations_with_spx["P4"]["2013":"2017"]= correlations_with_spx["2013":
 ↪"2017"].mean(axis=1).mean()
correlations_with_spx["P5"] = np.nan
correlations_with_spx["P5"]["2018":"2021"]= correlations_with_spx["2018":
 ↪"2021"].mean(axis=1).mean()

correlations_with_spx = correlations_with_spx.dropna(axis=1,how="all")


data_f_corr = data_f
data_f_corr["SPX"] = returns["SPX"]
data_f_corr


correlations_with_spx_funds = data_f_corr.iloc[:,:-1].rolling(12).
 ↪corr(data_f_corr.iloc[:,-1])


correlations_with_spx_funds["P1"] = np.nan
correlations_with_spx_funds["P1"]["1998":"2003"]=␣
 ↪correlations_with_spx_funds["1998":"2003"].mean(axis=1).mean()
correlations_with_spx_funds["P2"] = np.nan
correlations_with_spx_funds["P2"]["2004":"2007"]=␣
 ↪correlations_with_spx_funds["2004":"2007"].mean(axis=1).mean()
correlations_with_spx_funds["P3"] = np.nan
correlations_with_spx_funds["P3"]["2008":"2012"]=␣
 ↪correlations_with_spx_funds["2008":"2012"].mean(axis=1).mean()
correlations_with_spx_funds["P4"] = np.nan
correlations_with_spx_funds["P4"]["2013":"2017"]=␣
 ↪correlations_with_spx_funds["2013":"2017"].mean(axis=1).mean()
correlations_with_spx_funds["P5"] = np.nan
correlations_with_spx_funds["P5"]["2018":"2021"]=␣
 ↪correlations_with_spx_funds["2018":"2021"].mean(axis=1).mean()
```

```
correlations_with_spx_funds = correlations_with_spx_funds.
 ↪dropna(axis=1,how="all")


fig,ax1 = plt.subplots(1,figsize=(10,6))
ax1.plot(correlations_with_spx.mean(axis=1),label="Portfolios´ Correlations␣
 ↪with SPX");
ax1.plot(correlations_with_spx_funds.mean(axis=1),label="Funds´ Correlations␣
 ↪with SPX");
ax1.set_title("Rolling 12-month correlation with S&P 500")


ax1.plot(correlations_with_spx.index,correlations_with_spx["P1"].
 ↪values,linewidth=4,color="red");
ax1.plot(correlations_with_spx.index,correlations_with_spx["P2"].
 ↪values,linewidth=4,color="lightgreen");
ax1.plot(correlations_with_spx.index,correlations_with_spx["P3"].
 ↪values,linewidth=4,color="red");
ax1.plot(correlations_with_spx.index,correlations_with_spx["P4"].
 ↪values,linewidth=4,color="lightgreen");
ax1.plot(correlations_with_spx.index,correlations_with_spx["P5"].
 ↪values,linewidth=4,color="red");

ax1.plot(correlations_with_spx_funds.index,correlations_with_spx_funds["P1"].
 ↪values,label="1998-2003",linewidth=4,color="red");
ax1.plot(correlations_with_spx_funds.index,correlations_with_spx_funds["P2"].
 ↪values,label="2004-2007",linewidth=4,color="lightgreen");
ax1.plot(correlations_with_spx_funds.index,correlations_with_spx_funds["P3"].
 ↪values,label="2008-2012",linewidth=4,color="red");
ax1.plot(correlations_with_spx_funds.index,correlations_with_spx_funds["P4"].
 ↪values,label="2013-2017",linewidth=4,color="lightgreen");
ax1.plot(correlations_with_spx_funds.index,correlations_with_spx_funds["P5"].
 ↪values,label="2018-2021",linewidth=4,color="red");

ax1.legend();
ax1.set_ylim((0.4,1))

ax1.set_xlabel("Year")
ax1.set_ylabel("Correlation")
ax1.grid(True)
plt.savefig("Graphs/correlation_with_spx.png",dpi=300)
```



1.2.3 Now, regressions are again computed, but in this case split by periods, for funds and portfolios

[ ]:
```
alpha5f_portfoliosp1 = pd.DataFrame(columns=returns["1998":"2003"].
 ↪dropna(axis=1).columns,index=returns.index)["1998":"2003"]
beta5f_portfoliosp1 = pd.DataFrame(columns=returns["1998":"2003"].
 ↪dropna(axis=1).columns,index=returns.index)["1998":"2003"]

for i in alpha5f_portfoliosp1.columns:
        ff_ = ff.copy()["1998":"2003"]
        ff_[i] = returns[i]["1998":"2003"]
        ff_["Excess"] = ff_[i] - ff_["RF"]
        mod = RollingOLS.from_formula("Excess ~ mkt_excess + SMB + HML + RMW +␣
 ↪CMA",window=12,data=ff_)
        rres = mod.fit()
        alpha5f_portfoliosp1[i] = rres.params["Intercept"]
        beta5f_portfoliosp1[i] = rres.params["mkt_excess"]


alpha5f_portfoliosp2 = pd.DataFrame(columns=returns["2004":"2007"].
 ↪dropna(axis=1).columns,index=returns.index)["2004":"2007"]
beta5f_portfoliosp2 = pd.DataFrame(columns=returns["2004":"2007"].
 ↪dropna(axis=1).columns,index=returns.index)["2004":"2007"]
```

```
for i in alpha5f_portfoliosp2.columns:
        ff_ = ff.copy()["2004":"2007"]
        ff_[i] = returns[i]["2004":"2007"]
        ff_["Excess"] = ff_[i] - ff_["RF"]
        mod = RollingOLS.from_formula("Excess ~ mkt_excess + SMB + HML + RMW +␣
 ↪CMA",window=12,data=ff_)
        rres = mod.fit()
        alpha5f_portfoliosp2[i] = rres.params["Intercept"]
        beta5f_portfoliosp2[i] = rres.params["mkt_excess"]

alpha5f_portfoliosp3 = pd.DataFrame(columns=returns["2008":"2012"].
 ↪dropna(axis=1).columns,index=returns.index)["2008":"2012"]
beta5f_portfoliosp3 = pd.DataFrame(columns=returns["2008":"2012"].
 ↪dropna(axis=1).columns,index=returns.index)["2008":"2012"]

for i in alpha5f_portfoliosp3.columns:
        ff_ = ff.copy()["2008":"2012"]
        ff_[i] = returns[i]["2008":"2012"]
        ff_["Excess"] = ff_[i] - ff_["RF"]
        mod = RollingOLS.from_formula("Excess ~ mkt_excess + SMB + HML + RMW +␣
 ↪CMA",window=12,data=ff_)
        rres = mod.fit()
        alpha5f_portfoliosp3[i] = rres.params["Intercept"]
        beta5f_portfoliosp3[i] = rres.params["mkt_excess"]

alpha5f_portfoliosp4 = pd.DataFrame(columns=returns["2013":"2017"].
 ↪dropna(axis=1).columns,index=returns.index)["2013":"2017"]
beta5f_portfoliosp4 = pd.DataFrame(columns=returns["2013":"2017"].
 ↪dropna(axis=1).columns,index=returns.index)["2013":"2017"]

for i in alpha5f_portfoliosp4.columns:
        ff_ = ff.copy()["2013":"2017"]
        ff_[i] = returns[i]["2013":"2017"]
        ff_["Excess"] = ff_[i] - ff_["RF"]
        mod = RollingOLS.from_formula("Excess ~ mkt_excess + SMB + HML + RMW +␣
 ↪CMA",window=12,data=ff_)
        rres = mod.fit()
        alpha5f_portfoliosp4[i] = rres.params["Intercept"]
        beta5f_portfoliosp4[i] = rres.params["mkt_excess"]

alpha5f_portfoliosp5 = pd.DataFrame(columns=returns["2018":"2021"].
 ↪dropna(axis=1).columns,index=returns.index)["2018":"2021"]
beta5f_portfoliosp5 = pd.DataFrame(columns=returns["2018":"2021"].
 ↪dropna(axis=1).columns,index=returns.index)["2018":"2021"]
```

```
for i in alpha5f_portfoliosp5.columns:
        ff_ = ff.copy()["2018":"2021"]
        ff_[i] = returns[i]["2018":"2021"]
        ff_["Excess"] = ff_[i] - ff_["RF"]
        mod = RollingOLS.from_formula("Excess ~ mkt_excess + SMB + HML + RMW +␣
 ↪CMA",window=12,data=ff_)
        rres = mod.fit()
        alpha5f_portfoliosp5[i] = rres.params["Intercept"]
        beta5f_portfoliosp5[i] = rres.params["mkt_excess"]


alpha5f_portfoliosp1.to_csv("Computations/alpha5f_portfoliosp1.csv")
alpha5f_portfoliosp2.to_csv("Computations/alpha5f_portfoliosp2.csv")
alpha5f_portfoliosp3.to_csv("Computations/alpha5f_portfoliosp3.csv")
alpha5f_portfoliosp4.to_csv("Computations/alpha5f_portfoliosp4.csv")
alpha5f_portfoliosp5.to_csv("Computations/alpha5f_portfoliosp5.csv")

beta5f_portfoliosp1.to_csv("Computations/beta5f_portfoliosp1.csv")
beta5f_portfoliosp2.to_csv("Computations/beta5f_portfoliosp2.csv")
beta5f_portfoliosp3.to_csv("Computations/beta5f_portfoliosp3.csv")
beta5f_portfoliosp4.to_csv("Computations/beta5f_portfoliosp4.csv")
beta5f_portfoliosp5.to_csv("Computations/beta5f_portfoliosp5.csv")
```

[ ]:
```
alpha5f_fundsp1 = pd.DataFrame(columns=data_f["1998":"2003"].dropna(axis=1).
 ↪columns,index=data_f.index)["1998":"2003"]
beta5f_fundsp1 = pd.DataFrame(columns=data_f["1998":"2003"].dropna(axis=1).
 ↪columns,index=data_f.index)["1998":"2003"]

for i in alpha5f_fundsp1.columns:
        ff_ = ff.copy()["1998":"2003"]
        ff_[i] = data_f[i]["1998":"2003"]
        ff_["Excess"] = ff_[i] - ff_["RF"]
        mod = RollingOLS.from_formula("Excess ~ mkt_excess + SMB + HML + RMW +␣
 ↪CMA",window=12,data=ff_)
        rres = mod.fit()
        alpha5f_fundsp1[i] = rres.params["Intercept"]
        beta5f_fundsp1[i] = rres.params["mkt_excess"]

alpha5f_fundsp2 = pd.DataFrame(columns=data_f["2004":"2007"].dropna(axis=1).
 ↪columns,index=data_f.index)["2004":"2007"]
beta5f_fundsp2 = pd.DataFrame(columns=data_f["2004":"2007"].dropna(axis=1).
 ↪columns,index=data_f.index)["2004":"2007"]

for i in alpha5f_fundsp2.columns:
        ff_ = ff.copy()["2004":"2007"]
        ff_[i] = data_f[i]["2004":"2007"]
```

```
        ff_["Excess"] = ff_[i] - ff_["RF"]
        mod = RollingOLS.from_formula("Excess ~ mkt_excess + SMB + HML + RMW +␣
↪CMA",window=12,data=ff_)
        rres = mod.fit()
        alpha5f_fundsp2[i] = rres.params["Intercept"]
        beta5f_fundsp2[i] = rres.params["mkt_excess"]

alpha5f_fundsp3 = pd.DataFrame(columns=data_f["2008":"2012"].dropna(axis=1).
↪columns,index=data_f.index)["2008":"2012"]
beta5f_fundsp3 = pd.DataFrame(columns=data_f["2008":"2012"].dropna(axis=1).
↪columns,index=data_f.index)["2008":"2012"]


for i in alpha5f_fundsp3.columns:
        ff_ = ff.copy()["2008":"2012"]
        ff_[i] = data_f[i]["2008":"2012"]
        ff_["Excess"] = ff_[i] - ff_["RF"]
        mod = RollingOLS.from_formula("Excess ~ mkt_excess + SMB + HML + RMW +␣
↪CMA",window=12,data=ff_)
        rres = mod.fit()
        alpha5f_fundsp3[i] = rres.params["Intercept"]
        beta5f_fundsp3[i] = rres.params["mkt_excess"]

alpha5f_fundsp4 = pd.DataFrame(columns=data_f["2013":"2017"].dropna(axis=1).
↪columns,index=data_f.index)["2013":"2017"]
beta5f_fundsp4 = pd.DataFrame(columns=data_f["2013":"2017"].dropna(axis=1).
↪columns,index=data_f.index)["2013":"2017"]

for i in alpha5f_fundsp4.columns:
        ff_ = ff.copy()["2013":"2017"]
        ff_[i] = data_f[i]["2013":"2017"]
        ff_["Excess"] = ff_[i] - ff_["RF"]
        mod = RollingOLS.from_formula("Excess ~ mkt_excess + SMB + HML + RMW +␣
↪CMA",window=12,data=ff_)
        rres = mod.fit()
        alpha5f_fundsp4[i] = rres.params["Intercept"]
        beta5f_fundsp4[i] = rres.params["mkt_excess"]


alpha5f_fundsp5 = pd.DataFrame(columns=data_f["2018":"2021"].dropna(axis=1).
↪columns,index=data_f.index)["2018":"2021"]
beta5f_fundsp5 = pd.DataFrame(columns=data_f["2018":"2021"].dropna(axis=1).
↪columns,index=data_f.index)["2018":"2021"]

for i in alpha5f_fundsp5.columns:
        ff_ = ff.copy()["2018":"2021"]
```

```
        ff_[i] = data_f[i]["2018":"2021"]
        ff_["Excess"] = ff_[i] - ff_["RF"]
        mod = RollingOLS.from_formula("Excess ~ mkt_excess + SMB + HML + RMW +␣
↪CMA",window=12,data=ff_)
        rres = mod.fit()
        alpha5f_fundsp5[i] = rres.params["Intercept"]
        beta5f_fundsp5[i] = rres.params["mkt_excess"]

alpha5f_fundsp1.to_csv("Computations/alpha5f_fundsp1.csv")
alpha5f_fundsp2.to_csv("Computations/alpha5f_fundsp2.csv")
alpha5f_fundsp3.to_csv("Computations/alpha5f_fundsp3.csv")
alpha5f_fundsp4.to_csv("Computations/alpha5f_fundsp4.csv")
alpha5f_fundsp5.to_csv("Computations/alpha5f_fundsp5.csv")

beta5f_fundsp1.to_csv("Computations/beta5f_fundsp1.csv")
beta5f_fundsp2.to_csv("Computations/beta5f_fundsp2.csv")
beta5f_fundsp3.to_csv("Computations/beta5f_fundsp3.csv")
beta5f_fundsp4.to_csv("Computations/beta5f_fundsp4.csv")
beta5f_fundsp5.to_csv("Computations/beta5f_fundsp5.csv")
```

1.3 To save time, we can load the data

[14]:
```
alpha5f_fundsp1 = pd.read_csv("Computations/alpha5f_fundsp1.
↪csv",index_col=0,parse_dates=True)
alpha5f_fundsp2 = pd.read_csv("Computations/alpha5f_fundsp2.
↪csv",index_col=0,parse_dates=True)
alpha5f_fundsp3 = pd.read_csv("Computations/alpha5f_fundsp3.
↪csv",index_col=0,parse_dates=True)
alpha5f_fundsp4 = pd.read_csv("Computations/alpha5f_fundsp4.
↪csv",index_col=0,parse_dates=True)
alpha5f_fundsp5 = pd.read_csv("Computations/alpha5f_fundsp5.
↪csv",index_col=0,parse_dates=True)

beta5f_fundsp1 = pd.read_csv("Computations/beta5f_fundsp1.
↪csv",index_col=0,parse_dates=True)
beta5f_fundsp2 = pd.read_csv("Computations/beta5f_fundsp2.
↪csv",index_col=0,parse_dates=True)
beta5f_fundsp3 = pd.read_csv("Computations/beta5f_fundsp3.
↪csv",index_col=0,parse_dates=True)
beta5f_fundsp4 = pd.read_csv("Computations/beta5f_fundsp4.
↪csv",index_col=0,parse_dates=True)
beta5f_fundsp5 = pd.read_csv("Computations/beta5f_fundsp5.
↪csv",index_col=0,parse_dates=True)

alpha5f_portfoliosp1 = pd.read_csv("Computations/alpha5f_portfoliosp1.
↪csv",index_col=0,parse_dates=True)
```

```
alpha5f_portfoliosp2 = pd.read_csv("Computations/alpha5f_portfoliosp2.
↪csv",index_col=0,parse_dates=True)
alpha5f_portfoliosp3 = pd.read_csv("Computations/alpha5f_portfoliosp3.
↪csv",index_col=0,parse_dates=True)
alpha5f_portfoliosp4 = pd.read_csv("Computations/alpha5f_portfoliosp4.
↪csv",index_col=0,parse_dates=True)
alpha5f_portfoliosp5 = pd.read_csv("Computations/alpha5f_portfoliosp5.
↪csv",index_col=0,parse_dates=True)

beta5f_portfoliosp1 = pd.read_csv("Computations/beta5f_portfoliosp1.
↪csv",index_col=0,parse_dates=True)
beta5f_portfoliosp2 = pd.read_csv("Computations/beta5f_portfoliosp2.
↪csv",index_col=0,parse_dates=True)
beta5f_portfoliosp3 = pd.read_csv("Computations/beta5f_portfoliosp3.
↪csv",index_col=0,parse_dates=True)
beta5f_portfoliosp4 = pd.read_csv("Computations/beta5f_portfoliosp4.
↪csv",index_col=0,parse_dates=True)
beta5f_portfoliosp5 = pd.read_csv("Computations/beta5f_portfoliosp5.
↪csv",index_col=0,parse_dates=True)
```

1.3.1 Now, we group the funds or portfolios with alpha in terms of their beta

[ ]:
```
alpha5f_bybetas_fundsp1 = pd.DataFrame(index=alpha5f_fundsp1.
↪index,columns=["low","mid","high"])

for i in alpha5f_fundsp1[alpha5f_fundsp1>0].index:

    lista_alpha = alpha5f_fundsp1.loc[i][alpha5f_fundsp1.loc[i]> 0].index.
↪to_list()

    alpha5f_bybetas_fundsp1.loc[i]["low"] = len(beta5f_fundsp1.
↪loc[i][lista_alpha][beta5f_fundsp1.loc[i][lista_alpha] < 0.9])

    alpha5f_bybetas_fundsp1.loc[i]["high"] = len(beta5f_fundsp1.
↪loc[i][lista_alpha][beta5f_fundsp1.loc[i][lista_alpha] > 1.1])

    alpha5f_bybetas_fundsp1.loc[i]["mid"] = len(beta5f_fundsp1.
↪loc[i][lista_alpha][  (beta5f_fundsp1.loc[i][lista_alpha] < 1.1) &␣
↪(beta5f_fundsp1.loc[i][lista_alpha] > 0.9)])


alpha5f_bybetas_fundsp2 = pd.DataFrame(index=alpha5f_fundsp2.
↪index,columns=["low","mid","high"])

for i in alpha5f_fundsp2[alpha5f_fundsp2>0].index:
```

```
    lista_alpha = alpha5f_fundsp2.loc[i][alpha5f_fundsp2.loc[i]> 0].index.
↪to_list()

    alpha5f_bybetas_fundsp2.loc[i]["low"] = len(beta5f_fundsp2.
↪loc[i][lista_alpha][beta5f_fundsp2.loc[i][lista_alpha] < 0.9])

    alpha5f_bybetas_fundsp2.loc[i]["high"] = len(beta5f_fundsp2.
↪loc[i][lista_alpha][beta5f_fundsp2.loc[i][lista_alpha] > 1.1])

    alpha5f_bybetas_fundsp2.loc[i]["mid"] = len(beta5f_fundsp2.
↪loc[i][lista_alpha][  (beta5f_fundsp2.loc[i][lista_alpha] < 1.1) &␣
↪(beta5f_fundsp2.loc[i][lista_alpha] > 0.9)])


alpha5f_bybetas_fundsp3 = pd.DataFrame(index=alpha5f_fundsp3.
↪index,columns=["low","mid","high"])

for i in alpha5f_fundsp3[alpha5f_fundsp3>0].index:

    lista_alpha = alpha5f_fundsp3.loc[i][alpha5f_fundsp3.loc[i]> 0].index.
↪to_list()

    alpha5f_bybetas_fundsp3.loc[i]["low"] = len(beta5f_fundsp3.
↪loc[i][lista_alpha][beta5f_fundsp3.loc[i][lista_alpha] < 0.9])

    alpha5f_bybetas_fundsp3.loc[i]["high"] = len(beta5f_fundsp3.
↪loc[i][lista_alpha][beta5f_fundsp3.loc[i][lista_alpha] > 1.1])

    alpha5f_bybetas_fundsp3.loc[i]["mid"] = len(beta5f_fundsp3.
↪loc[i][lista_alpha][  (beta5f_fundsp3.loc[i][lista_alpha] < 1.1) &␣
↪(beta5f_fundsp3.loc[i][lista_alpha] > 0.9)])

alpha5f_bybetas_fundsp4 = pd.DataFrame(index=alpha5f_fundsp4.
↪index,columns=["low","mid","high"])

for i in alpha5f_fundsp4[alpha5f_fundsp4>0].index:

    lista_alpha = alpha5f_fundsp4.loc[i][alpha5f_fundsp4.loc[i]> 0].index.
↪to_list()

    alpha5f_bybetas_fundsp4.loc[i]["low"] = len(beta5f_fundsp4.
↪loc[i][lista_alpha][beta5f_fundsp4.loc[i][lista_alpha] < 0.9])

    alpha5f_bybetas_fundsp4.loc[i]["high"] = len(beta5f_fundsp4.
↪loc[i][lista_alpha][beta5f_fundsp4.loc[i][lista_alpha] > 1.1])
```

```
    alpha5f_bybetas_fundsp4.loc[i]["mid"] = len(beta5f_fundsp4.
↪loc[i][lista_alpha][  (beta5f_fundsp4.loc[i][lista_alpha] < 1.1) &␣
↪(beta5f_fundsp4.loc[i][lista_alpha] > 0.9)])


alpha5f_bybetas_fundsp5 = pd.DataFrame(index=alpha5f_fundsp5.
↪index,columns=["low","mid","high"])

for i in alpha5f_fundsp5[alpha5f_fundsp5>0].index:

    lista_alpha = alpha5f_fundsp5.loc[i][alpha5f_fundsp5.loc[i]> 0].index.
↪to_list()

    alpha5f_bybetas_fundsp5.loc[i]["low"] = len(beta5f_fundsp5.
↪loc[i][lista_alpha][beta5f_fundsp5.loc[i][lista_alpha] < 0.9])

    alpha5f_bybetas_fundsp5.loc[i]["high"] = len(beta5f_fundsp5.
↪loc[i][lista_alpha][beta5f_fundsp5.loc[i][lista_alpha] > 1.1])

    alpha5f_bybetas_fundsp5.loc[i]["mid"] = len(beta5f_fundsp5.
↪loc[i][lista_alpha][  (beta5f_fundsp5.loc[i][lista_alpha] < 1.1) &␣
↪(beta5f_fundsp5.loc[i][lista_alpha] > 0.9)])


alpha5f_bybetas_fundsp1.to_csv("Computations/alpha5f_bybetas_fundsp1.csv")
alpha5f_bybetas_fundsp2.to_csv("Computations/alpha5f_bybetas_fundsp2.csv")
alpha5f_bybetas_fundsp3.to_csv("Computations/alpha5f_bybetas_fundsp3.csv")
alpha5f_bybetas_fundsp4.to_csv("Computations/alpha5f_bybetas_fundsp4.csv")
alpha5f_bybetas_fundsp5.to_csv("Computations/alpha5f_bybetas_fundsp5.csv")
```

[ ]:

```
alpha5f_bybetas_portfoliosp1 = pd.DataFrame(index=alpha5f_portfoliosp1.
↪index,columns=["low","mid","high"])

for i in alpha5f_portfoliosp1[alpha5f_portfoliosp1>0].index:

    lista_alpha = alpha5f_portfoliosp1.loc[i][:-2][alpha5f_portfoliosp1.loc[i][:
↪-2]> 0].index.to_list()

    alpha5f_bybetas_portfoliosp1.loc[i]["low"] = len(beta5f_portfoliosp1.
↪loc[i][:-2][lista_alpha][beta5f_portfoliosp1.loc[i][:-2][lista_alpha] < 0.9])

    alpha5f_bybetas_portfoliosp1.loc[i]["high"] = len(beta5f_portfoliosp1.
↪loc[i][:-2][lista_alpha][beta5f_portfoliosp1.loc[i][:-2][lista_alpha] > 1.1])
```

```
    alpha5f_bybetas_portfoliosp1.loc[i]["mid"] = len(beta5f_portfoliosp1.
↪loc[i][:-2][lista_alpha][  (beta5f_portfoliosp1.loc[i][:-2][lista_alpha] < 1.
↪1) &
                                                    (beta5f_portfoliosp1.loc[i][:
↪-2][lista_alpha] > 0.9)])


alpha5f_bybetas_portfoliosp2 = pd.DataFrame(index=alpha5f_portfoliosp2.
↪index,columns=["low","mid","high"])

for i in alpha5f_portfoliosp2[alpha5f_portfoliosp2>0].index:

    lista_alpha = alpha5f_portfoliosp2.loc[i][:-2][alpha5f_portfoliosp2.loc[i][:
↪-2]> 0].index.to_list()

    alpha5f_bybetas_portfoliosp2.loc[i]["low"] = len(beta5f_portfoliosp2.
↪loc[i][:-2][lista_alpha][beta5f_portfoliosp2.loc[i][:-2][lista_alpha] < 0.9])

    alpha5f_bybetas_portfoliosp2.loc[i]["high"] = len(beta5f_portfoliosp2.
↪loc[i][:-2][lista_alpha][beta5f_portfoliosp2.loc[i][:-2][lista_alpha] > 1.1])

    alpha5f_bybetas_portfoliosp2.loc[i]["mid"] = len(beta5f_portfoliosp2.
↪loc[i][:-2][lista_alpha][  (beta5f_portfoliosp2.loc[i][:-2][lista_alpha] < 1.
↪1) &
                                                    (beta5f_portfoliosp2.loc[i][:
↪-2][lista_alpha] > 0.9)])


alpha5f_bybetas_portfoliosp3 = pd.DataFrame(index=alpha5f_portfoliosp3.
↪index,columns=["low","mid","high"])

for i in alpha5f_portfoliosp3[alpha5f_portfoliosp3>0].index:

    lista_alpha = alpha5f_portfoliosp3.loc[i][:-2][alpha5f_portfoliosp3.loc[i][:
↪-2]> 0].index.to_list()

    alpha5f_bybetas_portfoliosp3.loc[i]["low"] = len(beta5f_portfoliosp3.
↪loc[i][:-2][lista_alpha][beta5f_portfoliosp3.loc[i][:-2][lista_alpha] < 0.9])

    alpha5f_bybetas_portfoliosp3.loc[i]["high"] = len(beta5f_portfoliosp3.
↪loc[i][:-2][lista_alpha][beta5f_portfoliosp3.loc[i][:-2][lista_alpha] > 1.1])

    alpha5f_bybetas_portfoliosp3.loc[i]["mid"] = len(beta5f_portfoliosp3.
↪loc[i][:-2][lista_alpha][  (beta5f_portfoliosp3.loc[i][:-2][lista_alpha] < 1.
↪1) &
```

```
                                                (beta5f_portfoliosp3.loc[i][:
↪-2][lista_alpha] > 0.9)])


alpha5f_bybetas_portfoliosp4 = pd.DataFrame(index=alpha5f_portfoliosp4.
↪index,columns=["low","mid","high"])

for i in alpha5f_portfoliosp4[alpha5f_portfoliosp4>0].index:

    lista_alpha = alpha5f_portfoliosp4.loc[i][:-2][alpha5f_portfoliosp4.loc[i][:
↪-2]> 0].index.to_list()

    alpha5f_bybetas_portfoliosp4.loc[i]["low"] = len(beta5f_portfoliosp4.
↪loc[i][:-2][lista_alpha][beta5f_portfoliosp4.loc[i][:-2][lista_alpha] < 0.9])

    alpha5f_bybetas_portfoliosp4.loc[i]["high"] = len(beta5f_portfoliosp4.
↪loc[i][:-2][lista_alpha][beta5f_portfoliosp4.loc[i][:-2][lista_alpha] > 1.1])

    alpha5f_bybetas_portfoliosp4.loc[i]["mid"] = len(beta5f_portfoliosp4.
↪loc[i][:-2][lista_alpha][  (beta5f_portfoliosp4.loc[i][:-2][lista_alpha] < 1.
↪1) &
                                                (beta5f_portfoliosp4.loc[i][:
↪-2][lista_alpha] > 0.9)])


alpha5f_bybetas_portfoliosp5 = pd.DataFrame(index=alpha5f_portfoliosp5.
↪index,columns=["low","mid","high"])

for i in alpha5f_portfoliosp5[alpha5f_portfoliosp5>0].index:

    lista_alpha = alpha5f_portfoliosp5.loc[i][:-2][alpha5f_portfoliosp5.loc[i][:
↪-2]> 0].index.to_list()

    alpha5f_bybetas_portfoliosp5.loc[i]["low"] = len(beta5f_portfoliosp5.
↪loc[i][:-2][lista_alpha][beta5f_portfoliosp5.loc[i][:-2][lista_alpha] < 0.9])

    alpha5f_bybetas_portfoliosp5.loc[i]["high"] = len(beta5f_portfoliosp5.
↪loc[i][:-2][lista_alpha][beta5f_portfoliosp5.loc[i][:-2][lista_alpha] > 1.1])

    alpha5f_bybetas_portfoliosp5.loc[i]["mid"] = len(beta5f_portfoliosp5.
↪loc[i][:-2][lista_alpha][  (beta5f_portfoliosp5.loc[i][:-2][lista_alpha] < 1.
↪1) &
                                                (beta5f_portfoliosp5.loc[i][:
↪-2][lista_alpha] > 0.9)])
```

```
alpha5f_bybetas_portfoliosp1.to_csv("Computations/alpha5f_bybetas_portfoliosp1.
 ↪csv")
alpha5f_bybetas_portfoliosp2.to_csv("Computations/alpha5f_bybetas_portfoliosp2.
 ↪csv")
alpha5f_bybetas_portfoliosp3.to_csv("Computations/alpha5f_bybetas_portfoliosp3.
 ↪csv")
alpha5f_bybetas_portfoliosp4.to_csv("Computations/alpha5f_bybetas_portfoliosp4.
 ↪csv")
alpha5f_bybetas_portfoliosp5.to_csv("Computations/alpha5f_bybetas_portfoliosp5.
 ↪csv")
```

1.3.2 Or load the data

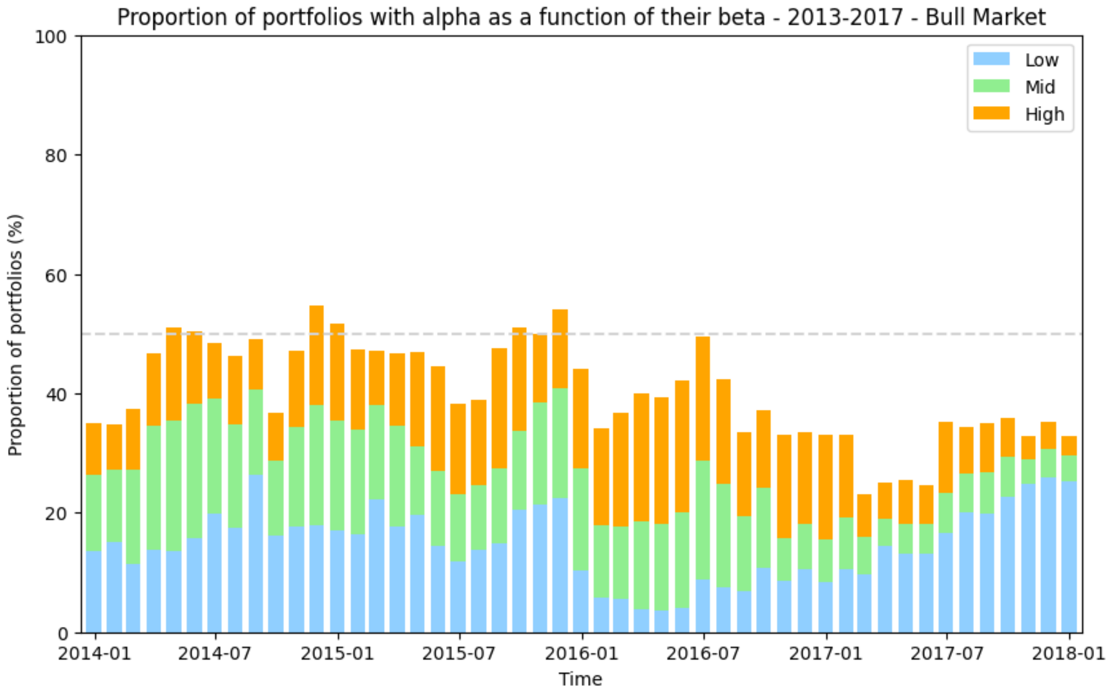
[15]:
```
alpha5f_bybetas_portfoliosp1 = pd.read_csv("Computations/
 ↪alpha5f_bybetas_portfoliosp1.csv",index_col=0,parse_dates=True)
alpha5f_bybetas_portfoliosp2 = pd.read_csv("Computations/
 ↪alpha5f_bybetas_portfoliosp2.csv",index_col=0,parse_dates=True)
alpha5f_bybetas_portfoliosp3 = pd.read_csv("Computations/
 ↪alpha5f_bybetas_portfoliosp3.csv",index_col=0,parse_dates=True)
alpha5f_bybetas_portfoliosp4 = pd.read_csv("Computations/
 ↪alpha5f_bybetas_portfoliosp4.csv",index_col=0,parse_dates=True)
alpha5f_bybetas_portfoliosp5 = pd.read_csv("Computations/
 ↪alpha5f_bybetas_portfoliosp5.csv",index_col=0,parse_dates=True)

alpha5f_bybetas_fundsp1 = pd.read_csv("Computations/alpha5f_bybetas_fundsp1.
 ↪csv",index_col=0,parse_dates=True)
alpha5f_bybetas_fundsp2 = pd.read_csv("Computations/alpha5f_bybetas_fundsp2.
 ↪csv",index_col=0,parse_dates=True)
alpha5f_bybetas_fundsp3 = pd.read_csv("Computations/alpha5f_bybetas_fundsp3.
 ↪csv",index_col=0,parse_dates=True)
alpha5f_bybetas_fundsp4 = pd.read_csv("Computations/alpha5f_bybetas_fundsp4.
 ↪csv",index_col=0,parse_dates=True)
alpha5f_bybetas_fundsp5 = pd.read_csv("Computations/alpha5f_bybetas_fundsp5.
 ↪csv",index_col=0,parse_dates=True)
```

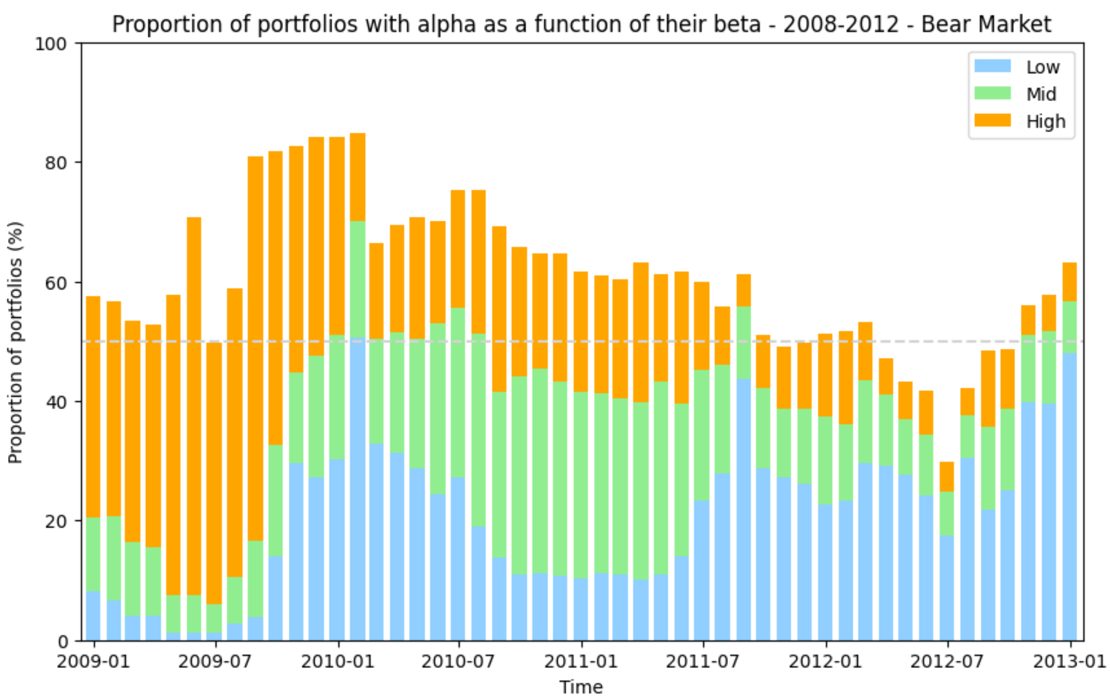
1.3.3 Now, we can visualize the proportion of portfolios and funds with alpha

[70]:
```
fig,ax1 = plt.subplots(1,figsize=(10,6))

ax1.bar(alpha5f_bybetas_portfoliosp4.
 ↪index,height=alpha5f_bybetas_portfoliosp4["low"]/
 ↪100,width=22,color="#90cfff",label="Low");
```

```
ax1.bar(alpha5f_bybetas_portfoliosp4.
 ↪index,height=alpha5f_bybetas_portfoliosp4["mid"]/
 ↪100,width=22,color="lightgreen",bottom=alpha5f_bybetas_portfoliosp4["low"]/
 ↪100,label="Mid");
ax1.bar(alpha5f_bybetas_portfoliosp4.
 ↪index,height=alpha5f_bybetas_portfoliosp4["high"]/
 ↪100,width=22,color="orange",
        bottom=alpha5f_bybetas_portfoliosp4["low"]/100 +␣
 ↪alpha5f_bybetas_portfoliosp4["mid"]/100,label="High");
plt.title("Proportion of portfolios with alpha as a function of their beta -␣
 ↪2013-2017 - Bull Market");
plt.legend()
ax1.set_ylabel("Proportion of portfolios (%)")
ax1.set_xlabel("Time")
ax1.set_xlim(16050,17550)
ax1.set_ylim(0,100)
ax1.axhline(y=50,color="lightgrey",linestyle="--")
ax1.get_xlim()

plt.savefig("Graphs/Proportion_portfolios_alpha_by_beta_carteras_p4.png")


fig,ax1 = plt.subplots(1,figsize=(10,6))

ax1.bar(alpha5f_bybetas_portfoliosp3.
 ↪index,height=alpha5f_bybetas_portfoliosp3["low"]/
 ↪100,width=22,color="#90cfff",label="Low");
ax1.bar(alpha5f_bybetas_portfoliosp3.
 ↪index,height=alpha5f_bybetas_portfoliosp3["mid"]/
 ↪100,width=22,color="lightgreen",bottom=alpha5f_bybetas_portfoliosp3["low"]/
 ↪100,label="Mid");
ax1.bar(alpha5f_bybetas_portfoliosp3.
 ↪index,height=alpha5f_bybetas_portfoliosp3["high"]/
 ↪100,width=22,color="orange",
        bottom=alpha5f_bybetas_portfoliosp3["low"]/100 +␣
 ↪alpha5f_bybetas_portfoliosp3["mid"]/100,label="High");
plt.title("Proportion of portfolios with alpha as a function of their beta -␣
 ↪2008-2012 - Bear Market");
plt.legend()
ax1.set_ylabel("Proportion of portfolios (%)")
ax1.set_xlabel("Time")
ax1.set_xlim(14225,15725)
ax1.set_ylim(0,100)
ax1.axhline(y=50,color="lightgrey",linestyle="--")
ax1.get_xlim()
```

```
plt.savefig("Graphs/Proportion_portfolios_alpha_by_beta_carteras_p3.png")
```

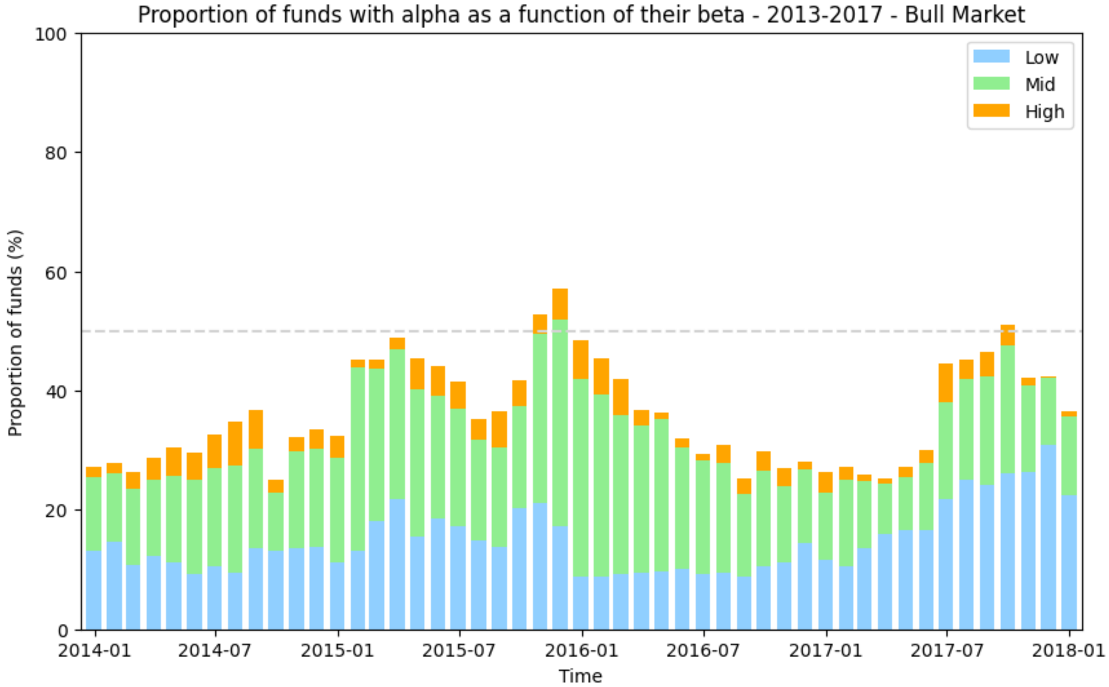


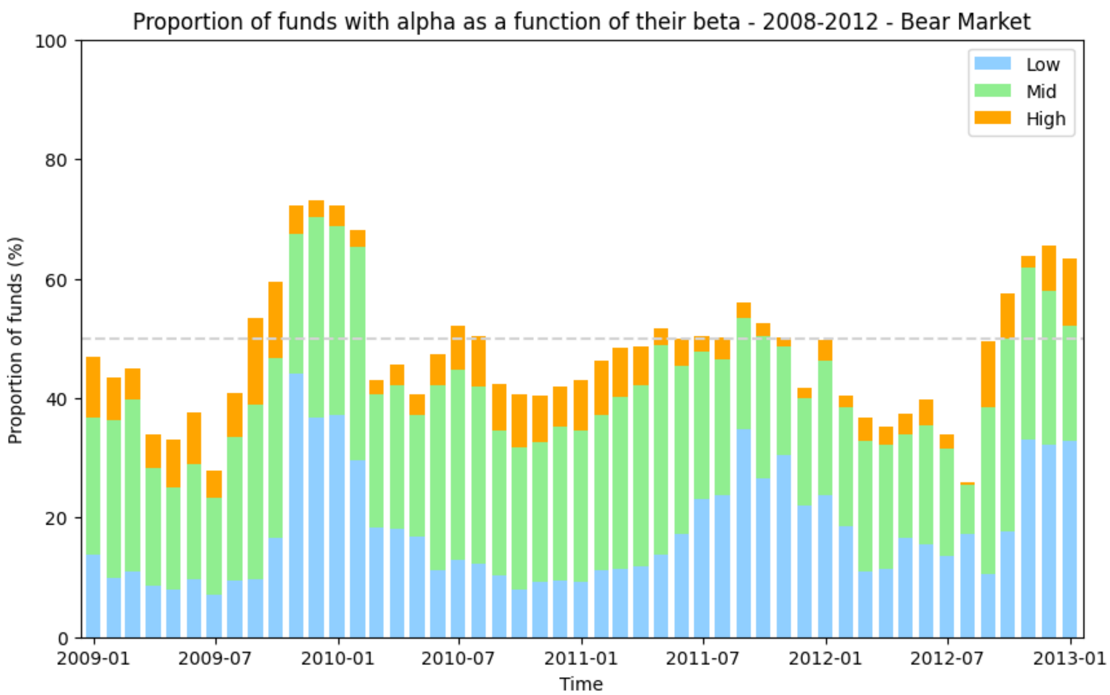


[40]:

```
fig,ax1 = plt.subplots(1,figsize=(10,6))

ax1.bar(alpha5f_bybetas_fundsp4.index,height=alpha5f_bybetas_fundsp4["low"]/
 ↪497*100,width=22,color="#90cfff",label="Low");
ax1.bar(alpha5f_bybetas_fundsp4.index,height=alpha5f_bybetas_fundsp4["mid"]/
 ↪497*100,width=22,color="lightgreen",bottom=alpha5f_bybetas_fundsp4["low"]/
 ↪497*100,label="Mid");
ax1.bar(alpha5f_bybetas_fundsp4.index,height=alpha5f_bybetas_fundsp4["high"]/
 ↪497*100,width=22,color="orange",
        bottom=alpha5f_bybetas_fundsp4["low"]/497*100 +␣
 ↪alpha5f_bybetas_fundsp4["mid"]/497*100,label="High");

plt.title("Proportion of funds with alpha as a function of their beta -␣
 ↪2013-2017 - Bull Market");
plt.legend()
ax1.set_ylabel("Proportion of funds (%)")
ax1.set_xlabel("Time")
ax1.set_xlim(16050,17550)
ax1.set_ylim(0,100)
ax1.axhline(y=50,color="lightgrey",linestyle="--")
ax1.get_xlim()

plt.savefig("Graphs/Proportion_funds_alpha_by_beta_fondos_p4.png")


fig,ax1 = plt.subplots(1,figsize=(10,6))

ax1.bar(alpha5f_bybetas_fundsp3.index,height=alpha5f_bybetas_fundsp3["low"]/
 ↪430*100,width=22,color="#90cfff",label="Low");
ax1.bar(alpha5f_bybetas_fundsp3.index,height=alpha5f_bybetas_fundsp3["mid"]/
 ↪430*100,width=22,color="lightgreen",bottom=alpha5f_bybetas_fundsp3["low"]/
 ↪430*100,label="Mid");
ax1.bar(alpha5f_bybetas_fundsp3.index,height=alpha5f_bybetas_fundsp3["high"]/
 ↪430*100,width=22,color="orange",
        bottom=alpha5f_bybetas_fundsp3["low"]/430*100 +␣
 ↪alpha5f_bybetas_fundsp3["mid"]/430*100,label="High");

plt.title("Proportion of funds with alpha as a function of their beta -␣
 ↪2008-2012 - Bear Market");
plt.legend()
ax1.set_ylabel("Proportion of funds (%)")
ax1.set_xlabel("Time")
ax1.set_xlim(14225,15725)
ax1.set_ylim(0,100)
ax1.axhline(y=50,color="lightgrey",linestyle="--")
ax1.get_xlim()
```

```python
plt.savefig("Graphs/Proportion_funds_alpha_by_beta_fondos_p3.png")
```





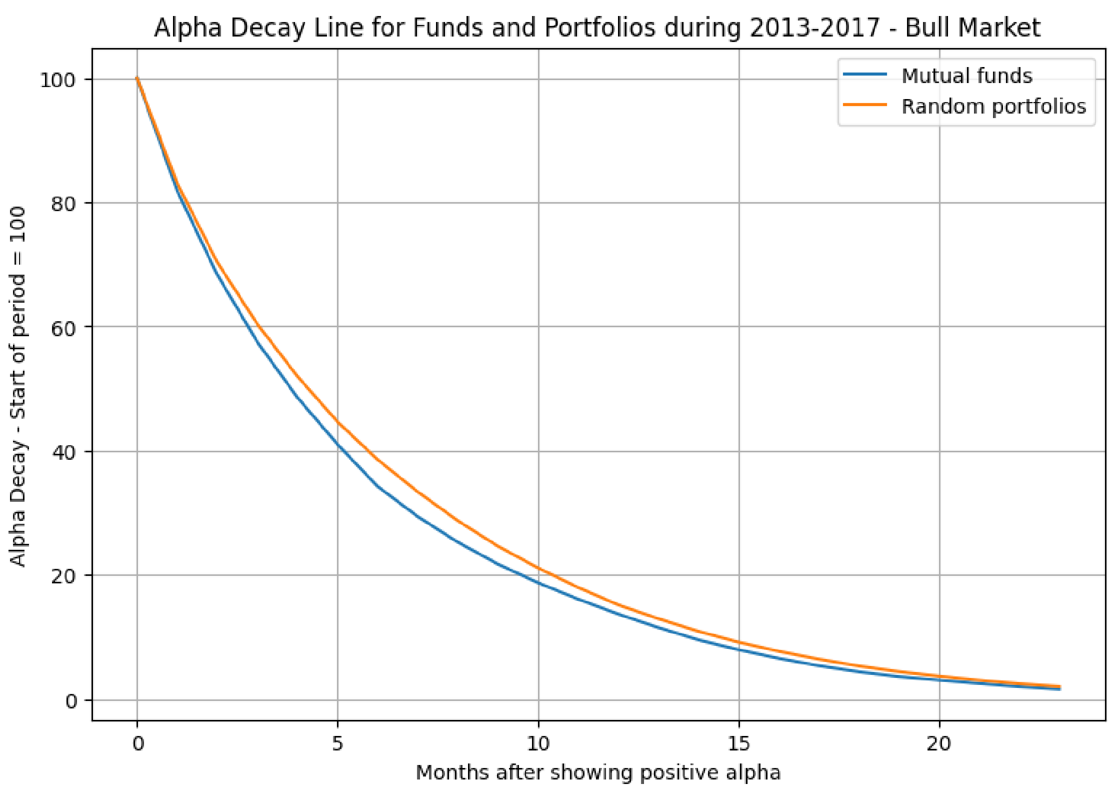
1.4 As an additional test, we introduce the "Alpha Decay Line" (ADL), where we can compute the proportion of portfolios/funds that conserve alpha following the month they achived it.

[16]:
```
def filter_positive_values_first_row(dataframe,column):
    return (dataframe.iloc[column][dataframe.iloc[column] >0]).index.to_list()


def filter_list_components(lista1,lista2):
    return list(set(lista1).intersection(lista2))


def alpha_decay(dataframe,months):

    selection = dataframe

    number_months = months
    number_periods = len(selection.dropna())-number_months

    dataframe_number = pd.
 ↪DataFrame(columns=range(1,number_periods),index=range(0,number_months))


    for period in range(1,number_periods):

        selection_ = selection.dropna().iloc[period:,]

        temp_list_0 = filter_positive_values_first_row(selection_.dropna(),0)

        temp_list_1 = filter_list_components(temp_list_0,selection_.dropna().
 ↪iloc[1][selection_.dropna().iloc[1] >0].index.to_list())

        temp_list_filtered = temp_list_1

        lista_numbers = [len(temp_list_0)]

        for month in range(1,(number_months)):

            temp_list_filtered = filter_list_components(temp_list_filtered,␣
 ↪selection_.dropna().iloc[month][selection_.dropna().iloc[month] >0].index.
 ↪to_list())

            lista_numbers.append(len(temp_list_filtered))

        dataframe_number[period] = lista_numbers

    return dataframe_number
```

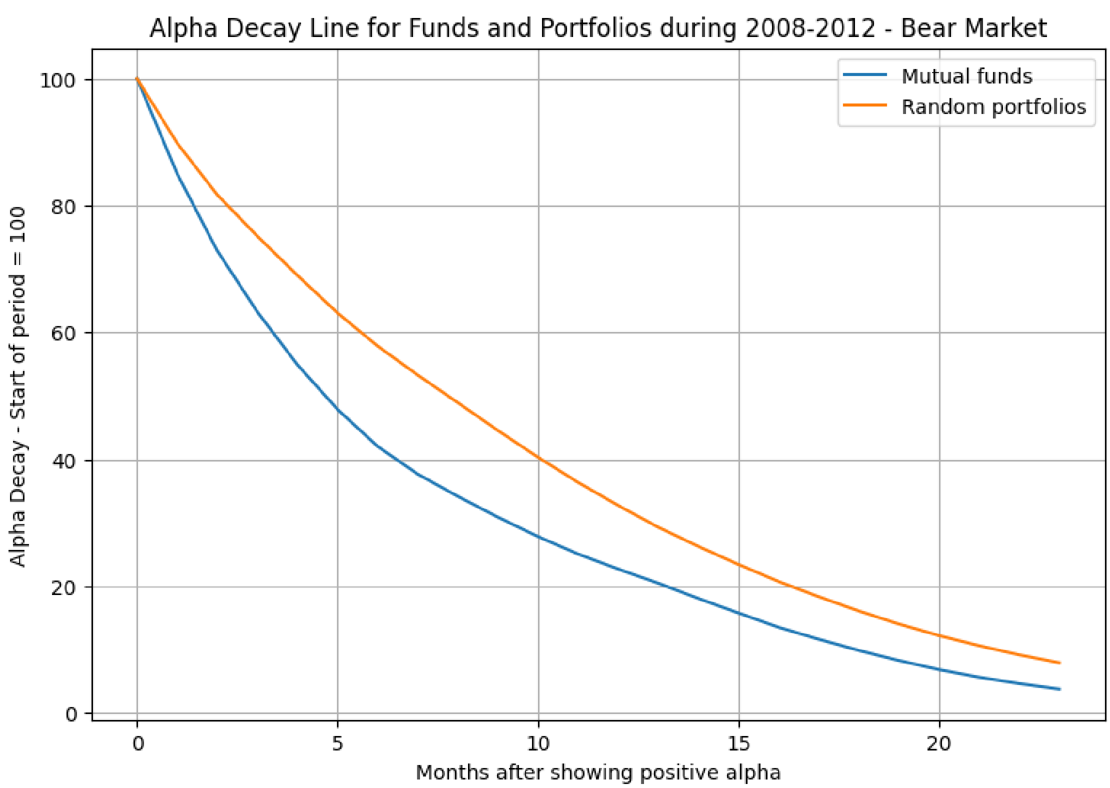
```
[17]: alpha_decayf3 = alpha_decay(alpha5f_fundsp3,24)
      alpha_decayf4 = alpha_decay(alpha5f_fundsp4,24)

      alpha_decayp3 = alpha_decay(alpha5f_portfoliosp3,24)
      alpha_decayp4 = alpha_decay(alpha5f_portfoliosp4,24)
```

1.4.1 We plot the ADL

```
[25]: fig,ax1 = plt.subplots(1,figsize=(9,6))

      ax1.plot((alpha_decayf4.mean(axis=1)/alpha_decayf4.mean(axis=1).
       ↪iloc[0])*100,label="Mutual funds");
      ax1.plot((alpha_decayp4.mean(axis=1)/alpha_decayp4.mean(axis=1).
       ↪iloc[0])*100,label="Random portfolios");
      ax1.set_title("Alpha Decay Line for Funds and Portfolios during 2013-2017 -␣
       ↪Bull Market");
      ax1.set_xlabel("Months after showing positive alpha");
      ax1.set_ylabel("Alpha Decay - Start of period = 100");
      plt.grid(True);
      ax1.legend();

      plt.savefig("Graphs/alpha_decay_bull.png",dpi=300);
```

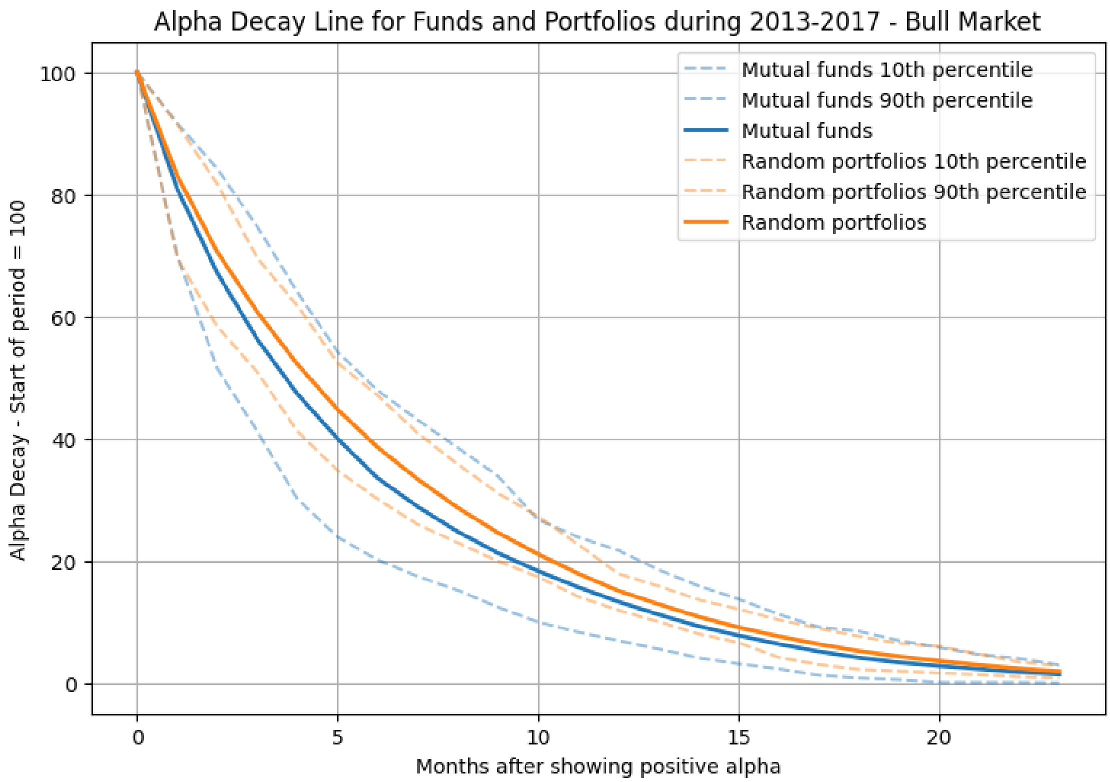


[26]:
```
fig,ax1 = plt.subplots(1,figsize=(9,6))

ax1.plot((alpha_decayf3.mean(axis=1)/alpha_decayf3.mean(axis=1).
 ↪iloc[0])*100,label="Mutual funds");
ax1.plot((alpha_decayp3.mean(axis=1)/alpha_decayp3.mean(axis=1).
 ↪iloc[0])*100,label="Random portfolios");
ax1.set_title("Alpha Decay Line for Funds and Portfolios during 2008-2012 -␣
 ↪Bear Market");
ax1.set_xlabel("Months after showing positive alpha");
ax1.set_ylabel("Alpha Decay - Start of period = 100");
plt.grid(True);
ax1.legend();

plt.savefig("Graphs/alpha_decay_bear.png",dpi=300);
```



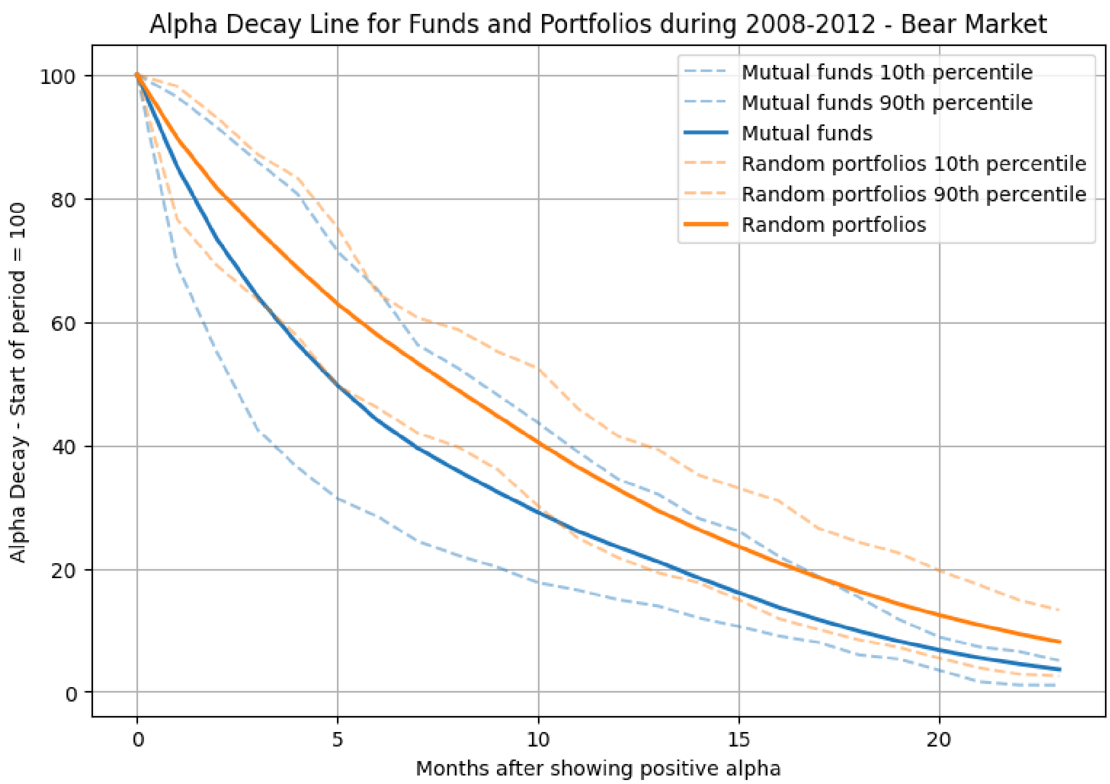
1.4.2 To visualize the dispersion, we plot as well the 10th and 90th percentile

[29]:
```
fig,ax1 = plt.subplots(1,figsize=(9,6))

ax1.plot((alpha_decayf4/alpha_decayf4.iloc[0]).quantile(0.
↪1,axis=1)*100,label="Mutual funds 10th percentile",color="#1f77ba",alpha=0.
↪45,linestyle="dashed");
ax1.plot((alpha_decayf4/alpha_decayf4.iloc[0]).quantile(0.
↪9,axis=1)*100,label="Mutual funds 90th percentile",color="#1f77ba",alpha=0.
↪45,linestyle="dashed");
ax1.plot((alpha_decayf4/alpha_decayf4.iloc[0]).mean(axis=1)*100,label="Mutual␣
↪funds",color="#1f77ba",alpha=1,linewidth=2);

ax1.plot((alpha_decayp4/alpha_decayp4.iloc[0]).quantile(0.
↪1,axis=1)*100,label="Random portfolios 10th␣
↪percentile",color="#ff7f0e",alpha=0.45,linestyle="dashed");
ax1.plot((alpha_decayp4/alpha_decayp4.iloc[0]).quantile(0.
↪9,axis=1)*100,label="Random portfolios 90th␣
↪percentile",color="#ff7f0e",alpha=0.45,linestyle="dashed");
ax1.plot((alpha_decayp4/alpha_decayp4.iloc[0]).mean(axis=1)*100,label="Random␣
↪portfolios",color="#ff7f0e",alpha=1,linewidth=2);

ax1.set_title("Alpha Decay Line for Funds and Portfolios during 2013-2017 -␣
↪Bull Market");
ax1.set_xlabel("Months after showing positive alpha");
ax1.set_ylabel("Alpha Decay - Start of period = 100");
plt.grid(True);
ax1.legend();

plt.savefig("Graphs/alpha_decay_bull_v2.png",dpi=300);
```



[30]:
```
fig,ax1 = plt.subplots(1,figsize=(9,6))

ax1.plot((alpha_decayf3/alpha_decayf3.iloc[0]).quantile(0.
↪1,axis=1)*100,label="Mutual funds 10th percentile",color="#1f77ba",alpha=0.
↪45,linestyle="dashed");
ax1.plot((alpha_decayf3/alpha_decayf3.iloc[0]).quantile(0.
↪9,axis=1)*100,label="Mutual funds 90th percentile",color="#1f77ba",alpha=0.
↪45,linestyle="dashed");
ax1.plot((alpha_decayf3/alpha_decayf3.iloc[0]).mean(axis=1)*100,label="Mutual␣
↪funds",color="#1f77ba",alpha=1,linewidth=2);

ax1.plot((alpha_decayp3/alpha_decayp3.iloc[0]).quantile(0.
↪1,axis=1)*100,label="Random portfolios 10th␣
↪percentile",color="#ff7f0e",alpha=0.45,linestyle="dashed");
ax1.plot((alpha_decayp3/alpha_decayp3.iloc[0]).quantile(0.
↪9,axis=1)*100,label="Random portfolios 90th␣
↪percentile",color="#ff7f0e",alpha=0.45,linestyle="dashed");
ax1.plot((alpha_decayp3/alpha_decayp3.iloc[0]).mean(axis=1)*100,label="Random␣
↪portfolios",color="#ff7f0e",alpha=1,linewidth=2);
```

```
ax1.set_title("Alpha Decay Line for Funds and Portfolios during 2008-2012 -␣
↪Bear Market");
ax1.set_xlabel("Months after showing positive alpha");
ax1.set_ylabel("Alpha Decay - Start of period = 100");
plt.grid(True);
ax1.legend();

plt.savefig("Graphs/alpha_decay_bear_v2.png",dpi=300);
```



1.5 As the last round of tests, we perform classification with k-means and Support Vector Machine algorithms

1.5.1 First, we label the data that will be used for SVM and other tests performed in Rapid Miner

[49]:
```
label_funds = pd.DataFrame(index=["Label"],columns=factorsfp3.dropna(axis=1).
↪columns,data="Mutual fund")
factorsfp3.dropna(axis=1).append(label_funds)

label_portfolios = pd.DataFrame(index=["Label"],columns=factorsp3[:-2].
↪columns,data="Random Portfolio")
```

```
factorsp3.append(label_portfolios)

test_labelled_p3 = factorsfp3.dropna(axis=1).append(label_funds).join(factorsp3.
 ↪append(label_portfolios))

test_labelled_p3.T.to_csv("Computations/ClassificationP3.csv")


label_funds = pd.DataFrame(index=["Label"],columns=factorsfp4.dropna(axis=1).
 ↪columns,data="Mutual fund")
factorsfp4.dropna(axis=1).append(label_funds)

label_cartera = pd.DataFrame(index=["Label"],columns=factorsp4[:-2].
 ↪columns,data="Random Portfolio")
factorsp4.append(label_cartera)

test_labelled_p4 = factorsfp4.dropna(axis=1).append(label_funds).join(factorsp4.
 ↪append(label_portfolios))

test_labelled_p4.T.to_csv("Computations/ClassificationP4.csv")
```

1.5.2 We build a SVM model and compute its accuracy and confusion matrix, for both periods

[51]:
```
from sklearn.model_selection import train_test_split

from sklearn.metrics import accuracy_score, confusion_matrix

target = test_labelled_p3.T["Label"]
features = test_labelled_p3.T.drop(["R2","Label","P-value Alpha"], axis=1)
X_train, X_test, y_train, y_test = train_test_split(features,target, test_size␣
 ↪= 0.5, random_state = 668410)
from sklearn.svm import SVC

# Building a Support Vector Machine on train data
svc_model = SVC(C= .1, kernel='linear', gamma= 1)
svc_model.fit(X_train, y_train)

prediction = svc_model .predict(X_test)
# check the accuracy on the training set
print(svc_model.score(X_train, y_train))
print(svc_model.score(X_test, y_test))

print("Confusion Matrix:\n",confusion_matrix(y_test,prediction))
```

```
0.9581975071907958
0.959731543624161
```

```
Confusion Matrix:
 [[   2  210]
 [   0 5003]]
```

[52]:
```python
from sklearn.model_selection import train_test_split

from sklearn.metrics import accuracy_score, confusion_matrix

target = test_labelled_p4.T["Label"]
features = test_labelled_p4.T.drop(["R2","Label","P-value Alpha"], axis=1)
X_train, X_test, y_train, y_test = train_test_split(features,target, test_size␣
↪= 0.5, random_state = 668410)
from sklearn.svm import SVC

# Building a Support Vector Machine on train data
svc_model = SVC(C= .1, kernel='linear', gamma= 1)
svc_model.fit(X_train, y_train)

prediction = svc_model.predict(X_test)
# check the accuracy on the training set
print(svc_model.score(X_train, y_train))
print(svc_model.score(X_test, y_test))

print("Confusion Matrix:\n",confusion_matrix(y_test,prediction))
```

```
0.9523628048780488
0.9529434177938655
Confusion Matrix:
 [[   0  247]
 [   0 5002]]
```

1.5.3 Now, we do the same for k-means

[59]:
```python
############## k means

from sklearn.cluster import KMeans
from sklearn.metrics import accuracy_score, confusion_matrix
kmeans = KMeans(n_clusters=2)
kmeans.fit(test_labelled_p3.T.drop(["R2","Label","P-value Alpha"], axis=1))


y_kmeans = kmeans.predict(test_labelled_p3.T.drop(["R2","Label","P-value␣
↪Alpha"], axis=1))


print(accuracy_score(test_labelled_p3.T["Label"].factorize()[0], y_kmeans))
confusion_matrix(test_labelled_p3.T["Label"].factorize()[0], y_kmeans)
```

```
0.5179290508149569
```

[59]:
```
array([[ 407,   23],
       [5005, 4995]], dtype=int64)
```

[58]:
```python
kmeans = KMeans(n_clusters=2)
kmeans.fit(test_labelled_p4.T.drop(["R2","Label","P-value Alpha"], axis=1))


y_kmeans = kmeans.predict(test_labelled_p4.T.drop(["R2","Label","P-value␣
↪Alpha"], axis=1))


print(accuracy_score(test_labelled_p4.T["Label"].factorize()[0], y_kmeans))
confusion_matrix(test_labelled_p4.T["Label"].factorize()[0], y_kmeans)
```

```
0.527102981804325
```

[58]:
```
array([[ 460,   37],
       [4927, 5073]], dtype=int64)
```