ChatGPT's svar på caset:

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# --- Setup ---
import numpy as np, pandas as pd
import yfinance as yf
import matplotlib.pyplot as plt
from scipy import stats
from datetime import datetime
from itertools import product
# Optional: from arch import arch model
# ===== User inputs =====
TICKERS = ["AAPL", "MSFT", "NVDA"] # BYTT til dine 3 aksjer
MARKET TICKER = "^GSPC"
                                  # BYTT til marked (OSEBX: "^OSEA
FACTOR PROXIES = {
    "MKT": MARKET TICKER,
    # legg til andre faktorer om ønskelig, f.eks. "ENERGY": "^SP500-
risk free annual = 0.03 # BYTT til din risikofrie rente (annualiser
INSAMPLE END = "2024-12-31"
START DATE = "2015-01-01" # eller tidligere om tilgjengelig
OOS START = "2025-01-01"
TODAY = datetime.today().strftime("%Y-%m-%d")
# ===== Download data =====
tickers all = list(set(TICKERS + list(FACTOR_PROXIES.values())))
px = yf.download(tickers all, start=START DATE, end=TODAY, auto adju
```

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px = px.dropna()
ret = np.log(px).diff().dropna()
# Align assets & factors
assets = ret[TICKERS].dropna()
factors = pd.concat({k: ret[v] for k, v in FACTOR PROXIES.items()}, ax
common = assets.index.intersection(factors.index)
assets = assets.loc[common]
factors = factors.loc[common]
# Split in-sample / out-of-sample
ins = slice(assets.index.min(), INSAMPLE END)
oos = slice(OOS START, assets.index.max())
assets in = assets.loc[ins].dropna()
assets oos = assets.loc[oos].dropna()
factors in = factors.loc[ins].dropna()
factors oos = factors.loc[oos].dropna()
# Risk-free daily
trading days = 252
rf daily = (1 + risk free annual)**(1/trading days) - 1
# ===== 1) Histograms + normal overlay =====
def plot hist norm(series, name):
    mu, sigma = series.mean(), series.std(ddof=1)
    jb = stats.jarque bera(series)
    fig = plt.figure()
    series.hist(bins=50, density=True, alpha=0.6)
    xs = np.linspace(series.min()*1.1, series.max()*1.1, 400)
    plt.plot(xs, stats.norm.pdf(xs, mu, sigma), lw=2)
    plt.title(f"{name} daily log-returns\n\mu={mu:.5f}, \sigma={sigma:.5f},
    plt.xlabel("Return")
    plt.ylabel("Density")
    plt.show()
for col in assets in:
```

```
plot hist norm(assets in[col], col)
# ===== 2) Efficient frontier =====
mu = assets in.mean()*trading days
                                          # annualized mean
Sigma = assets in.cov()*trading days
                                      # annualized covariance
ones = np.ones(len(TICKERS))
# Global Minimum Variance (GMV)
Sigma inv = np.linalq.pinv(Sigma.values)
w gmv = (Sigma inv @ ones) / (ones @ Sigma inv @ ones)
# Tangency (MVE) with rf
excess = mu.values - risk free annual*ones
w tan unscaled = Sigma inv @ excess
w tan = w tan unscaled / (ones @ w tan unscaled) # sum to 1 within
mu tan = float(w tan @ mu.values)
sig tan = float(np.sqrt(w tan @ Sigma.values @ w tan))
# Frontier (long-only or allow shorts)
def efficient frontier (mu, Sigma, n=200, allow shorts=False):
    mu = mu.values; S = Sigma.values
    if allow shorts:
        # grid target returns across [min, max]
        r targets = np.linspace(mu.min(), mu.max(), n)
        M = []
        for r in r targets:
            # solve min w'Sw s.t. w'1=1, w'\mu=r
            A = np.block([[2*S, ones[:,None], mu[:,None]],
                          [ones[None,:], np.zeros((1,2))],
                          [mu[None,:], np.zeros((1,2))])
            b = np.r [np.zeros(len(mu)), 1, r]
            sol = np.linalg.lstsq(A, b, rcond=None)[0]
            w = sol[:len(mu)]
            W.append((r, np.sqrt(w@S@w), w))
        return pd.DataFrame([(r, s) for r,s, in W], columns=["ret","
    else:
        # grid weights on simplex
        from itertools import product
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```
m = len(mu); grid = np.linspace(0,1,101)
        M = []
        for w in product(grid, repeat=m):
            w = np.array(w)
            if abs(w.sum()-1)<1e-9:
                r = w@mu; s = np.sqrt(w@Sigma.values@w)
                W.append((r,s,w))
        df = pd.DataFrame(W, columns=["ret", "risk", "w"])
        # keep lower envelope
        df = df.sort values("risk")
        hull = df[df["ret"] == df.groupby("risk")["ret"].transform("ma
        return hull[["ret", "risk"]], [(r,s,w) for r,s,w in zip(hull["
front df, Wlist = efficient frontier(mu, Sigma, allow shorts=False)
# Plot assets, factors, frontier, GMV, Tangency
plt.figure()
plt.plot(front df["risk"], front df["ret"], lw=2, label="Efficient F
for a in mu.index:
    plt.scatter(np.sqrt(Sigma.loc[a,a]), mu[a], s=60, label=a)
# Factors (annualized)
f mu = factors in.mean()*trading days
f sig = (factors in.std()*np.sqrt(trading days))
for f in f mu.index:
    plt.scatter(f sig[f], f mu[f], marker="x", s=80, label=f"Factor:
plt.scatter(np.sqrt(w gmv @ Sigma.values @ w gmv), w gmv @ mu.values
plt.scatter(sig tan, mu tan, marker="*", s=120, label="Tangency (MVE
plt.xlabel("Annualized Volatility")
plt.ylabel("Annualized Return")
plt.legend()
plt.title("Assets, Factors, and Efficient Frontier (in-sample)")
plt.show()
# ===== 3) Optimal portfolios for two investor-typer =====
# Risikoavers (mål: lav sigma, på CML mellom rf og tangens)
target sigma risk averse = 0.10 # BYTT terskel
weight risky = min(1.0, target sigma risk averse / sig tan)
w ra = weight risky * w tan # resten i risikofri
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mu ra = risk free annual*(1-weight risky) + weight risky*mu tan
sig ra = weight risky*sig tan
# Risikosøkende (tillat gearing opp langs CML)
target sigma risk seeking = 0.30 # BYTT terskel
weight risky rs = target sigma risk seeking / sig tan
w rs = weight risky rs * w tan # kan være >1 (låne risikofri)
mu rs = risk free annual*(1-weight risky rs) + weight risky rs*mu ta
sig rs = weight risky rs*sig tan
print("Risk-averse mix: risky weight =", weight risky, "Return=", mu
print("Risk-seeking mix: risky weight =", weight risky rs, "Return="
\# ===== 4) VaR models (1-day, 95%/99%) on in-sample portfolio (use t
def portfolio returns (w, R):
    return (R @ w).rename("p")
p in = portfolio returns(w tan, assets in)
def var historical(x, alpha=0.99):
    return -np.quantile(x, 1-alpha)
def var normal(x, alpha=0.99):
    mu, sigma = x.mean(), x.std(ddof=1)
    z = stats.norm.ppf(alpha)
    return - (mu + z*sigma)
def var student t(x, alpha=0.99):
   params = stats.t.fit(x) # df, loc, scale
    df, loc, scale = params
    q = stats.t.ppf(alpha, df, loc=loc, scale=scale)
    return -q
def var ewma(x, alpha=0.99, lam=0.94):
    x = x.values
    var = np.zeros like(x)
   var[0] = np.var(x[:50])
    for t in range (1, len(x)):
```

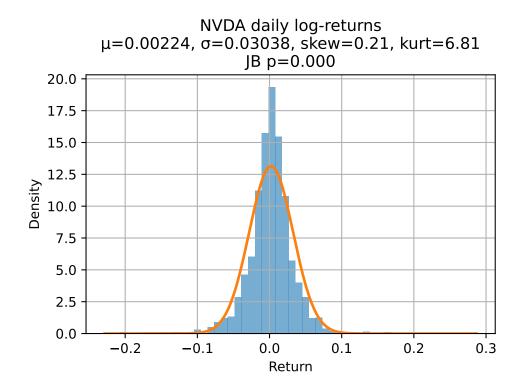
```
var[t] = lam*var[t-1] + (1-lam)*x[t-1]**2
    z = stats.norm.ppf(alpha)
    # last variance as forecast
    return -(x.mean() + z*np.sqrt(var[-1]))
VaR models = {
    "Hist 99": lambda s: var historical(s, 0.99),
    "Norm 99": lambda s: var normal(s, 0.99),
    "StudT 99": lambda s: var student t(s, 0.99),
    "EWMA 99": lambda s: var ewma(s, 0.99),
    "Hist 95": lambda s: var historical(s, 0.95),
    "Norm 95": lambda s: var normal(s, 0.95),
in sample VaR = {k: f(p in) for k,f in VaR models.items()}
pd.Series(in sample VaR).to frame("1d VaR (in-sample)").style.format
# ===== 5) Backtesting (Kupiec & Christoffersen) on out-of-sample ==
p oos = portfolio returns(w tan, assets oos)
def hit series(x, VaR):
    # exceedance when loss > VaR (x negative)
    return (x < -VaR).astype(int)</pre>
def kupiec pof(h, alpha):
    n = len(h); x = h.sum()
    pi hat = x/n
    # Likelihood ratio
    L0 = (1-alpha)**(n-x) * alpha**x
    L1 = (1-pi hat)**(n-x) * (pi hat**x if pi hat>0 else 1)
    LR = -2*np.log(L0/L1) if L0>0 and L1>0 else np.inf
    pval = 1 - stats.chi2.cdf(LR, df=1)
    return x, n, pi hat, LR, pval
def christoffersen independence(h):
    # counts of transitions
    h = h.astype(int)
    n00=n01=n10=n11=0
    for i in range (1, len(h)):
```

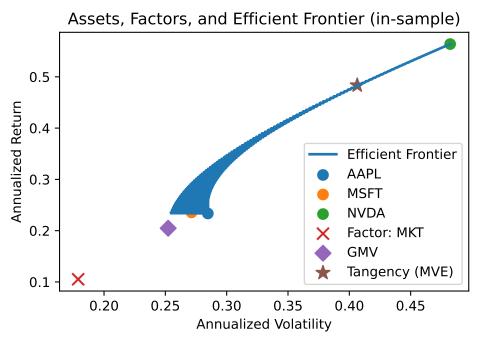
```
a,b = h[i-1], h[i]
        if a==0 and b==0: n00+=1
        if a==0 and b==1: n01+=1
        if a==1 and b==0: n10+=1
        if a==1 and b==1: n11+=1
    pi0 = n01/max(n00+n01, 1)
    pi1 = n11/max(n10+n11, 1)
    pi = (n01+n11) / max (n00+n01+n10+n11, 1)
    # LR ind
    L0 = ((1-pi)**(n00+n10))*(pi**(n01+n11))
    L1 = ((1-pi0)**n00)*(pi0**n01)*((1-pi1)**n10)*(pi1**n11)
    LR = -2*np.log(L0/L1) if L0>0 and L1>0 else np.inf
    pval = 1 - stats.chi2.cdf(LR, df=1)
    return {"n00":n00,"n01":n01,"n10":n10,"n11":n11,"LR":LR,"pval":pv
def backtest table (p oos, alpha list=(0.95, 0.99)):
    rows=[]
    for name, f in VaR models.items():
        # infer alpha from name
        alpha = 0.99 if "99" in name else 0.95
        VaR hat = f(p in) # fixed from in-sample (one-step naive)
        h = hit series(p oos, VaR hat)
        x,n,pi hat,LR,pval = kupiec pof(h, alpha)
        indep = christoffersen independence(h)
        rows.append([name, alpha, VaR hat, x, n, x/n, pval, indep["p
    return pd.DataFrame(rows, columns=["Model", "Alpha", "VaR", "Exceed"
bt = backtest table(p oos)
print(bt.to string(index=False))
# (Valgfritt) rullerende re-estimering kan implementeres for strenge
                                                  ] [**********
                        0%
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[

AAPL daily log-returns μ =0.00093, σ =0.01793, skew=-0.20, kurt=5.45 JB p=0.000

MSFT daily log-returns $\mu{=}0.00093,\,\sigma{=}0.01709,\,skew{=}{-}0.18,\,kurt{=}8.07$ JB p=0.000 35 30 25 Density 15 10 5 0 -0.05 0.00 0.05 -0.15 -0.10 0.10 0.15 Return





Risk-averse mix: risky weight = 0.24604169696655698 Return= 0.141564

```
Risk-seeking mix: risky weight = 0.7381250908996709 Return= 0.364694
                                         Rate Kupiec p
   Model Alpha
                     VaR Exceed
                                  N
                                                        Christoffe
Hist 99 0.99 0.066875
                                5 181 0.027624 0.000000
                                                                 0.
Norm 99 0.99 -0.061480
                             179 181 0.988950 0.888991
                                                                 0.
StudT 99 0.99 -0.073337
                             180 181 0.994475 0.508573
                                                                 0.
 EWMA 99 0.99 -0.041723
                             175 181 0.966851 0.013519
                                                                 0.
 Hist 95
           0.95 0.038785
                              12 181 0.066298 0.000000
                                                                 0.
                             177 181 0.977901 0.053922
 Norm 95
           0.95 - 0.044032
                                                                 0.
/var/folders/q2/8w2n22tj35v95srlf90nqd440000qp/T/ipykernel 22136/267
  a,b = h[i-1], h[i]
/var/folders/q2/8w2n22tj35v95srlf90nqd440000gp/T/ipykernel 22136/267
  a,b = h[i-1], h[i]
/var/folders/q2/8w2n22tj35v95srlf90nqd440000gp/T/ipykernel 22136/267
  a,b = h[i-1], h[i]
/var/folders/q2/8w2n22tj35v95srlf90nqd440000qp/T/ipykernel 22136/267
  a,b = h[i-1], h[i]
/var/folders/q2/8w2n22tj35v95srlf90nqd440000gp/T/ipykernel 22136/267
  a,b = h[i-1], h[i]
/var/folders/q2/8w2n22tj35v95srlf90nqd440000gp/T/ipykernel 22136/267
  a,b = h[i-1], h[i]
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