Construction et Optimisation de portfeuille

Import des bibliothèques et définition des paramètres globaux

In [1]:
```
import numpy as np
import pandas as pd
import yfinance as yf
import matplotlib.pyplot as plt
import seaborn as sns
import pandas_datareader.data as web
from scipy.optimize import minimize
plt.style.use("seaborn-v0_8")

# -----------------------------
# Paramètres globaux
# -----------------------------
start_date = "2022-10-25"
end_date   = "2025-11-25"

stocks = ["MSFT", "NVDA", "GOOGL", "AMZN", "META",
          "JNJ", "JPM", "COST", "PG", "XOM"]
cryptos = ["BTC-USD", "ETH-USD"]

tickers = stocks + cryptos

# Indices des cryptos dans le vecteur de poids
crypto_idx = [tickers.index(c) for c in cryptos]

# Taux sans risque annualisé (moyenne) : T-Bill 3 mois (daily)
rf_daily = web.DataReader("DTB3", "fred", start_date, end_date)
rf_daily = rf_daily.dropna()
rf = (rf_daily.mean().iloc[0] / 100).round(4)

trading_days = 252
```

Téléchargement des données de marché (actions et cryptomonnaies)

In [2]:
```
data = yf.download(
    tickers,
    start=start_date,
    end=end_date,
    auto_adjust=True,
    progress=False
)["Close"]
```

```python
data = data.dropna(how="any")  # garder uniquement les dates où tout cote
data.head()
```

Out[2]:

Ticker	AMZN	BTC-USD	COST	ETH-USD	GOOGL	JNJ	JI
Date							
2022-10-25	120.599998	20095.857422	478.121674	1461.665405	103.764328	154.828613	113.957
2022-10-26	115.660004	20770.441406	478.495270	1566.566650	94.279739	156.189072	115.266
2022-10-27	110.959999	20285.835938	476.566162	1514.374878	91.588310	156.279770	115.721
2022-10-28	103.410004	20595.351562	490.319702	1555.477905	95.630424	158.601593	117.096
2022-10-31	102.440002	20495.773438	481.326630	1572.714478	93.862625	157.785324	116.910

Calcul des rendements quotidiens et découpage in-sample / out-of-sample

In [3]:

```python
# Rendements log quotidiens
returns = np.log(data / data.shift(1)).dropna()

# Découpage in-sample / out-of-sample
split_date = "2024-10-25"
eval_date   = "2025-10-25"

returns_in   = returns.loc[:split_date]
returns_out = returns.loc[split_date:eval_date]

returns_in.tail()
```

Out[3]:

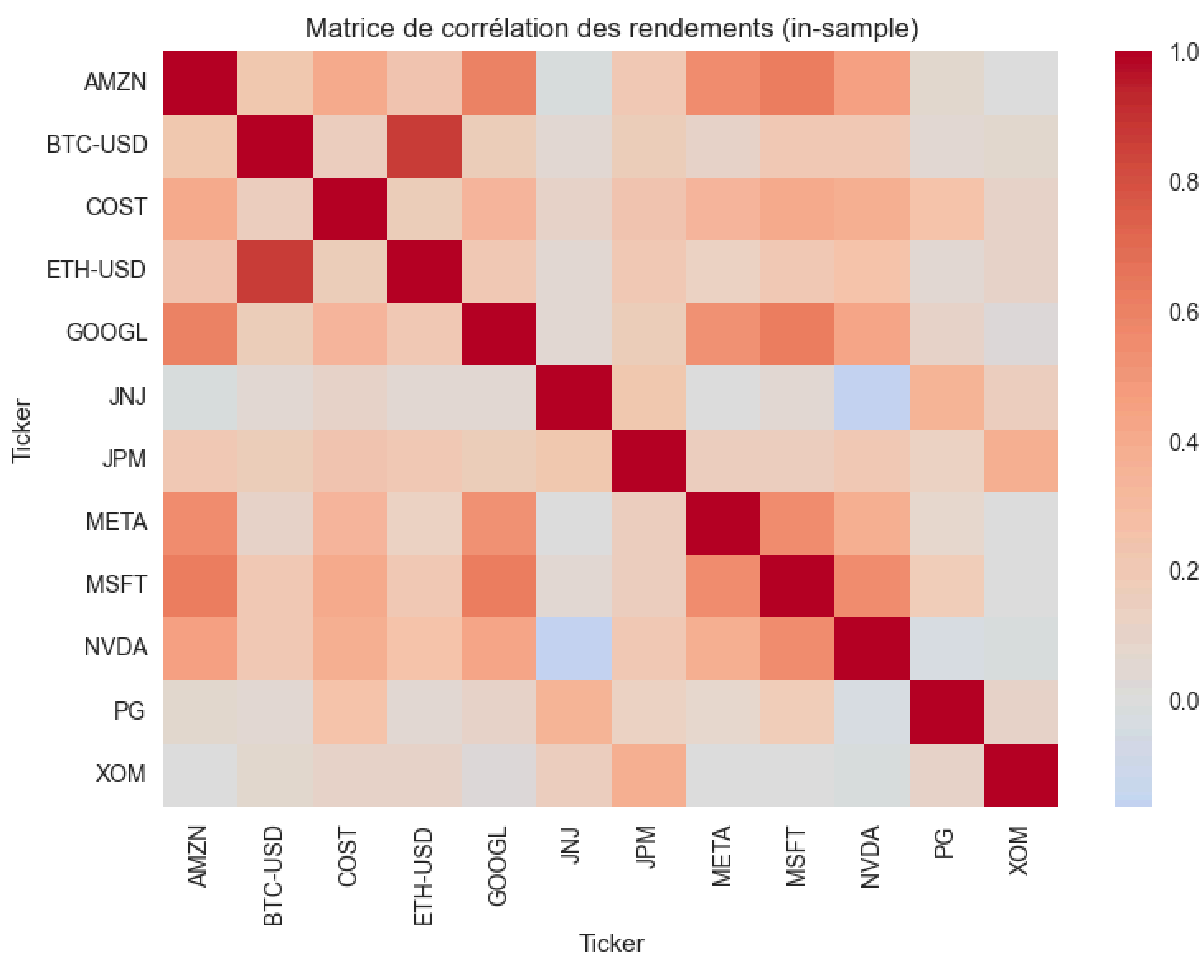
Ticker	AMZN	BTC-USD	COST	ETH-USD	GOOGL	JNJ	JPM	META
Date								
2024-10-21	0.000423	-0.015480	-0.003141	0.009105	0.003970	-0.013966	-0.010572	-0.00227
2024-10-22	0.003327	-0.000096	0.007549	-0.017222	0.006500	0.003800	0.005010	0.01183
2024-10-23	-0.026657	-0.013890	0.006337	-0.043326	-0.014394	0.014637	-0.003173	-0.03198
2024-10-24	0.009001	0.025692	-0.006415	0.010072	-0.000369	-0.013292	0.007003	0.00723
2024-10-25	0.007750	-0.022532	-0.002465	-0.039666	0.015550	-0.017193	-0.011939	0.00958

Statistiques descriptives et matrice de corrélation (plots pour le rapport)

In [4]:

```
# Statistiques annualisées (in-sample)
mu_in  = returns_in.mean() * trading_days        # rendement attendu annuel
vol_in = returns_in.std() * np.sqrt(trading_days)  # volatilité annuelle
cov_in = returns_in.cov() * trading_days         # matrice de covariance annuelle

stats_df = pd.DataFrame({
    "mu_annual": mu_in,
    "vol_annual": vol_in
})

display(stats_df)

# Heatmap des corrélations
corr_mat = returns_in.corr()

plt.figure(figsize=(8, 6))
sns.heatmap(corr_mat, annot=False, cmap="coolwarm", center=0)
plt.title("Matrice de corrélation des rendements (in-sample)")
plt.tight_layout()
plt.show()
```

	mu_annual	vol_annual
Ticker		
AMZN	0.221969	0.328644
BTC-USD	0.600605	0.514910
COST	0.308709	0.200903
ETH-USD	0.255885	0.606105
GOOGL	0.230987	0.307958
JNJ	0.000099	0.158095
JPM	0.324294	0.206812
META	0.716738	0.443256
MSFT	0.276783	0.247796
NVDA	1.186689	0.516435
PG	0.150701	0.149218
XOM	0.094124	0.230378



Fonctions utilitaires pour le portefeuille (rendement, risque, Sharpe...)

In [5]:
```
# === Fonctions de base portefeuilles ===

def portfolio_return(weights, mu):
    return float(np.dot(weights, mu))


def portfolio_volatility(weights, cov):
    cov_np = np.array(cov)
    return float(np.sqrt(np.dot(weights.T, np.dot(cov_np, weights))))


def portfolio_sharpe(weights, mu, cov, rf):
    rp = portfolio_return(weights, mu)
    sp = portfolio_volatility(weights, cov)
    return (rp - rf) / sp


def max_drawdown(series):
    """
    series : série de valeurs de portefeuille (index temps)
    """
    cummax = series.cummax()
    dd = 1 - series / cummax
    return dd.max()


# === Risk contribution (utile pour Risk Parity) ===

def risk_contributions(weights, cov):
    """
    Retourne (variance_portefeuille, contributions_au_risque)
    RC_i = w_i * (Sigma w)_i
    """
    cov_np = np.array(cov)
    port_var = np.dot(weights, np.dot(cov_np, weights))
    mrc = np.dot(cov_np, weights)        # marginal risk contribution
    rc = weights * mrc                   # risk contributions
    return port_var, rc
```

Fonction d'optimisation sous contraintes (somme=1, w_i<=30%, cryptos<=20%)

In [6]:
```
# === Contraintes & fonctions d'optimisation ===

n_assets = len(tickers)

# nouvelle définition des bornes, APRÈS avoir défini la liste tickers, stocks, cryp
bounds = []
```

```python
for t in tickers:
    if t in cryptos:
        bounds.append((0.00, 0.2))  # chaque crypto entre 0% et 15%
    else:
        bounds.append((0.00, 0.3))  # chaque action entre 0% et 25%

# contrainte somme des poids = 1
def weight_sum_constraint(weights):
    return np.sum(weights) - 1.0

# contrainte somme des cryptos <= 20%
def crypto_constraint(weights):
    return 0.20 - np.sum(weights[crypto_idx])


constraints = [
    {"type": "eq", "fun": weight_sum_constraint},
    {"type": "ineq", "fun": crypto_constraint},  # >= 0 -> w_crypto_total <= 0.20
]


def optimize_min_variance(mu, cov):
    x0 = np.array([1.0 / n_assets] * n_assets)

    def objective(weights):
        return portfolio_volatility(weights, cov) ** 2  # variance

    res = minimize(
        objective,
        x0,
        method="SLSQP",
        bounds=bounds,
        constraints=constraints,
        options={"disp": False}
    )
    return res.x


def optimize_max_sharpe(mu, cov, rf):
    x0 = np.array([1.0 / n_assets] * n_assets)

    def objective(weights):
        # on minimise le Sharpe négatif
        return -portfolio_sharpe(weights, mu, cov, rf)

    res = minimize(
        objective,
        x0,
        method="SLSQP",
        bounds=bounds,
        constraints=constraints,
        options={"disp": False}
    )
    return res.x
```

```python
def optimize_risk_parity(cov):
    """
    Portefeuille Risk Parity (Equal Risk Contribution)
    sous les mêmes contraintes (somme=1, bornes, crypto <= 20%)
    """
    cov_np = np.array(cov)
    x0 = np.array([1.0 / n_assets] * n_assets)

    def objective(weights):
        port_var = np.dot(weights, np.dot(cov_np, weights))
        mrc = np.dot(cov_np, weights)
        rc = weights * mrc
        target = port_var / n_assets
        return np.sum((rc - target) ** 2)

    res = minimize(
        objective,
        x0,
        method="SLSQP",
        bounds=bounds,
        constraints=constraints,
        options={"disp": False}
    )
    return res.x
```

Construction des portefeuilles : équipondéré, minimum variance, max Sharpe

In [7]:

```python
# === Construction des portefeuilles ===

# Portefeuille équipondéré (en respectant la contrainte crypto <= 20% si possible)
w_equal = np.array([1.0 / n_assets] * n_assets)

# Ajustement grossier si la contrainte crypto n'est pas respectée
crypto_weight_eq = w_equal[crypto_idx].sum()
if crypto_weight_eq > 0.20:
    # on réduit proportionnellement les poids crypto et on redistribue vers les act
    scale = 0.20 / crypto_weight_eq
    w_equal[crypto_idx] *= scale
    excess = (1.0 - w_equal.sum())  # ce qui manque pour sommer à 1
    # redistribuer l'excès sur les actions
    stock_idx = [i for i in range(n_assets) if i not in crypto_idx]
    w_equal[stock_idx] += excess / len(stock_idx)

# Portefeuille minimum variance (in-sample)
w_gmv = optimize_min_variance(mu_in.values, cov_in)

# Portefeuille max Sharpe
w_max_sharpe = optimize_max_sharpe(mu_in.values, cov_in, rf)

# Portefeuille Risk Parity
w_rp = optimize_risk_parity(cov_in)

# Portefeuille Mix (combinaison de GMV, Risk Parity et Max Sharpe)
```

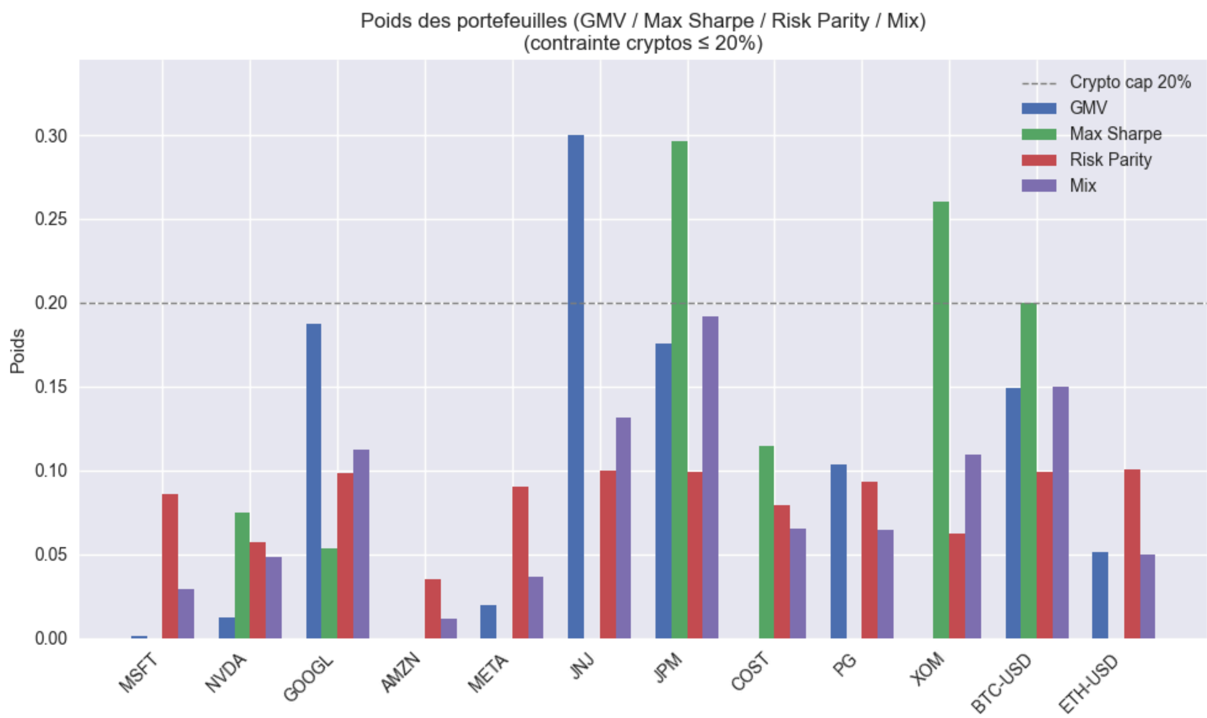
```python
w_mix = 0.33 * w_gmv + 0.33 * w_rp + 0.34 * w_max_sharpe

weights_df = pd.DataFrame({
    "Equal_Weight": w_equal,
    "GMV": w_gmv,
    "Max_Sharpe": w_max_sharpe,
    "Risk_Parity": w_rp,
    "Mix": w_mix
}, index=tickers)

display(weights_df)
```

	Equal_Weight	GMV	Max_Sharpe	Risk_Parity	Mix
MSFT	0.083333	1.343849e-03	0.000000e+00	0.086122	0.028864
NVDA	0.083333	1.240479e-02	7.481588e-02	0.056788	0.048271
GOOGL	0.083333	1.871965e-01	5.376717e-02	0.098238	0.112474
AMZN	0.083333	0.000000e+00	0.000000e+00	0.035078	0.011576
META	0.083333	1.954323e-02	0.000000e+00	0.090208	0.036218
JNJ	0.083333	3.000000e-01	1.580279e-16	0.099482	0.131829
JPM	0.083333	1.760066e-01	2.963148e-01	0.099445	0.191646
COST	0.083333	1.002887e-18	1.146580e-01	0.079233	0.065131
PG	0.083333	1.035050e-01	0.000000e+00	0.092851	0.064797
XOM	0.083333	0.000000e+00	2.604441e-01	0.062556	0.109194
BTC-USD	0.083333	1.490477e-01	2.000000e-01	0.099406	0.149990
ETH-USD	0.083333	5.095231e-02	1.515012e-15	0.100594	0.050010

Tracé des poids du portefeuille optimal (Graphique pour le rapport)

In [8]:
```python
# === Comparaison des poids Max Sharpe vs Risk Parity ===

idx = np.arange(len(weights_df))
width = 0.18

plt.figure(figsize=(10, 6))
plt.bar(idx - 1.5*width, weights_df["GMV"], width=width, label="GMV")
plt.bar(idx - 0.5*width, weights_df["Max_Sharpe"], width=width, label="Max Sharpe")
plt.bar(idx + 0.5*width, weights_df["Risk_Parity"], width=width, label="Risk Parity
plt.bar(idx + 1.5*width, weights_df["Mix"], width=width, label="Mix")

plt.xticks(idx, weights_df.index, rotation=45, ha="right")
plt.ylabel("Poids")
plt.title("Poids des portefeuilles (GMV / Max Sharpe / Risk Parity / Mix)\n(contrai
plt.axhline(0.20, color="gray", linestyle="--", linewidth=1, label="Crypto cap 20%"
```

```
top = max(weights_df.max().max(), 0.20) * 1.15
plt.ylim(0, top)
plt.legend()
plt.tight_layout()
plt.show()
```



Backtest des portefeuilles (in-sample et out-of-sample) + benchmarks

In [9]:

```
# === Fonction valeur de portefeuille + Benchmarks ===

def portfolio_value(returns, weights, initial_value=1.0):
    port_rets = (returns * weights).sum(axis=1)
    value = (1 + port_rets).cumprod() * initial_value
    return value, port_rets

# Benchmarks : S&P 500 (SPY) + Bitcoin seul
bench_tickers = ["SPY", "BTC-USD"]
bench_data = yf.download(
    bench_tickers,
    start=start_date,
    end=end_date,
    auto_adjust=True,
    progress=False
)["Close"].dropna(how="any")

bench_returns = np.log(bench_data / bench_data.shift(1)).dropna()

# Alignement des dates des portefeuilles avec celles des benchmarks
common_dates = returns.index.intersection(bench_returns.index)
rets_all = returns.loc[common_dates]
bench_returns = bench_returns.loc[common_dates]
```

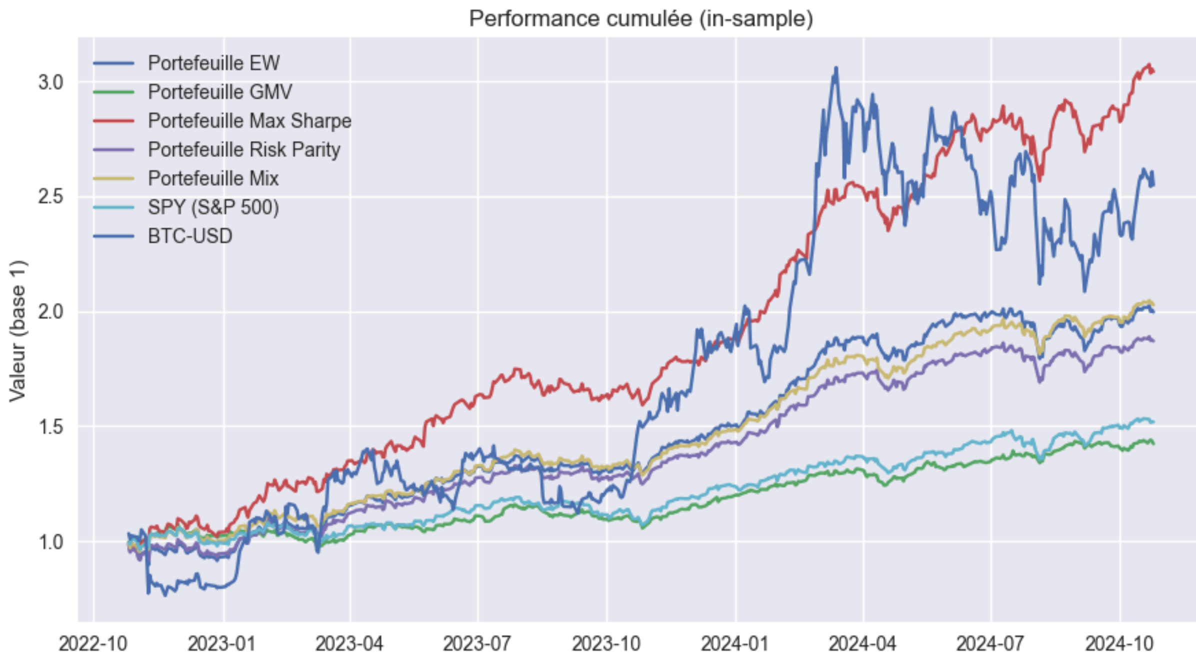
```python
rets_all_in  = rets_all.loc[:split_date]
rets_all_out = rets_all.loc[split_date:]
bench_in   = bench_returns.loc[:split_date]
bench_out = bench_returns.loc[split_date:]

# Valeurs in-sample
v_eq_in,  r_eq_in  = portfolio_value(rets_all_in, w_equal)
v_gmv_in, r_gmv_in = portfolio_value(rets_all_in, w_gmv)
v_ms_in,  r_ms_in  = portfolio_value(rets_all_in, w_max_sharpe)
v_rp_in,  r_rp_in  = portfolio_value(rets_all_in, w_rp)
v_mix_in, r_mix_in = portfolio_value(rets_all_in, w_mix)

# Valeurs out-of-sample
v_eq_out,  r_eq_out  = portfolio_value(rets_all_out, w_equal)
v_gmv_out, r_gmv_out = portfolio_value(rets_all_out, w_gmv)
v_ms_out,  r_ms_out  = portfolio_value(rets_all_out, w_max_sharpe)
v_rp_out,  r_rp_out  = portfolio_value(rets_all_out, w_rp)
v_mix_out, r_mix_out = portfolio_value(rets_all_out, w_mix)

# Benchmarks (S&P 500, BTC) in/out
v_spy_in,  r_spy_in  = portfolio_value(bench_in[["SPY"]], np.array([1.0]))
v_btc_in,  r_btc_in  = portfolio_value(bench_in[["BTC-USD"]], np.array([1.0]))

v_spy_out, r_spy_out = portfolio_value(bench_out[["SPY"]], np.array([1.0]))
v_btc_out, r_btc_out = portfolio_value(bench_out[["BTC-USD"]], np.array([1.0]))
```

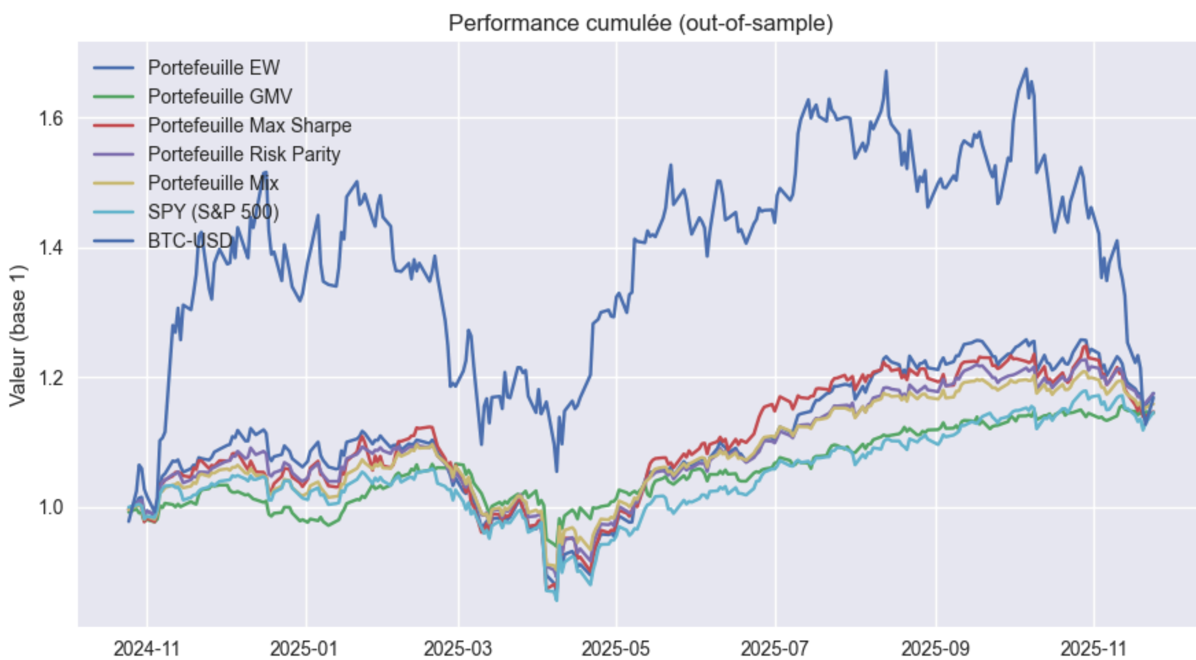
Graphiques de performance cumulée (in-sample et out-of-sample)

In [10]:

```python
# === Performance cumulée in-sample ===

plt.figure(figsize=(9, 5))
plt.plot(v_eq_in,  label="Portefeuille EW")
plt.plot(v_gmv_in, label="Portefeuille GMV")
plt.plot(v_ms_in,  label="Portefeuille Max Sharpe")
plt.plot(v_rp_in,  label="Portefeuille Risk Parity")
plt.plot(v_mix_in, label="Portefeuille Mix")
plt.plot(v_spy_in, label="SPY (S&P 500)")
plt.plot(v_btc_in, label="BTC-USD")
plt.legend()
plt.title("Performance cumulée (in-sample)")
plt.ylabel("Valeur (base 1)")
plt.tight_layout()
plt.show()

# === Performance cumulée out-of-sample ===

plt.figure(figsize=(9, 5))
plt.plot(v_eq_out,  label="Portefeuille EW")
plt.plot(v_gmv_out, label="Portefeuille GMV")
plt.plot(v_ms_out,  label="Portefeuille Max Sharpe")
plt.plot(v_rp_out,  label="Portefeuille Risk Parity")
plt.plot(v_mix_out, label="Portefeuille Mix")
```

```python
plt.plot(v_spy_out, label="SPY (S&P 500)")
plt.plot(v_btc_out, label="BTC-USD")
plt.legend()
plt.title("Performance cumulée (out-of-sample)")
plt.ylabel("Valeur (base 1)")
plt.tight_layout()
plt.show()
```





Calcul des metrics de performance (r, vol, Sharpe, drawdown)

In [11]:

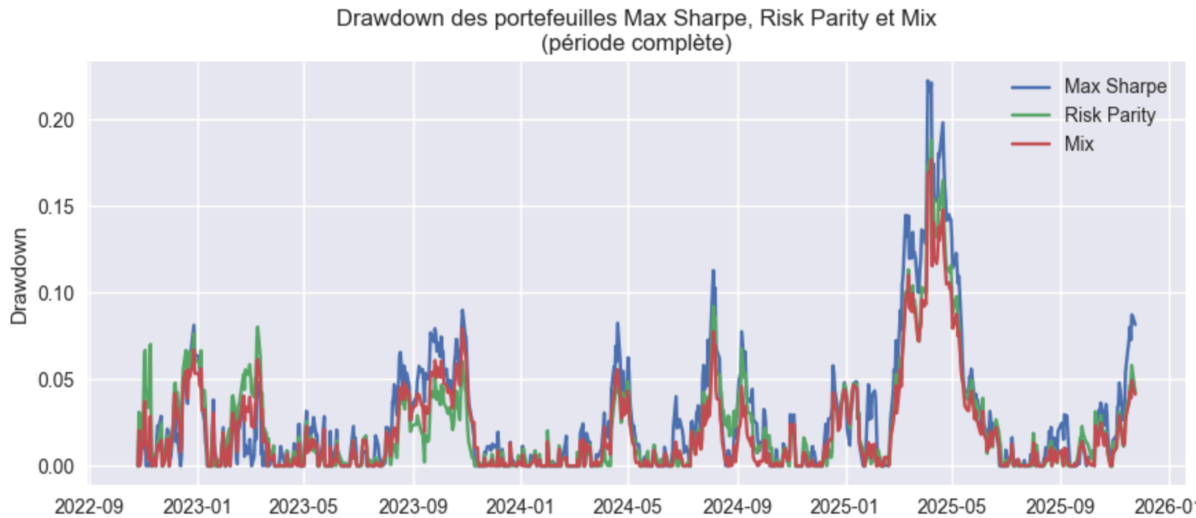
```python
# === Metrics de performance (in & out) ===

def performance_metrics(port_rets, rf, freq=252):
```

```python
    mu_annual = port_rets.mean() * freq
    vol_annual = port_rets.std() * np.sqrt(freq)
    sharpe = (mu_annual - rf) / vol_annual
    value = (1 + port_rets).cumprod()
    dd_max = max_drawdown(value)
    return mu_annual, vol_annual, sharpe, dd_max


rows = []
labels = [
    "EW_in", "GMV_in", "MaxSharpe_in", "RiskParity_in", "Mix_in",
    "SPY_in", "BTC_in",
    "EW_out", "GMV_out", "MaxSharpe_out", "RiskParity_out", "Mix_out",
    "SPY_out", "BTC_out"
]

rets_list = [
    r_eq_in, r_gmv_in, r_ms_in, r_rp_in, r_mix_in,
    r_spy_in, r_btc_in,
    r_eq_out, r_gmv_out, r_ms_out, r_rp_out, r_mix_out,
    r_spy_out, r_btc_out
]

for label, r in zip(labels, rets_list):
    mu_a, vol_a, s, dd = performance_metrics(r, rf)
    rows.append([label, mu_a, vol_a, s, dd])

perf_df = pd.DataFrame(
    rows,
    columns=["Portefeuille", "mu_annual", "vol_annual", "Sharpe", "Max_Drawdown"]
)
display(perf_df)
```

	Portefeuille	mu_annual	vol_annual	Sharpe	Max_Drawdown
0	EW_in	0.363965	0.186832	1.695994	0.108213
1	GMV_in	0.183066	0.111079	1.224049	0.089447
2	MaxSharpe_in	0.579013	0.206051	2.581465	0.112881
3	RiskParity_in	0.326795	0.161434	1.732558	0.092322
4	Mix_in	0.365118	0.147479	2.156369	0.079543
5	SPY_in	0.219129	0.139876	1.229862	0.101473
6	BTC_in	0.600605	0.514910	1.074955	0.318627
7	EW_out	0.170629	0.203417	0.607271	0.225660
8	GMV_out	0.133628	0.127730	0.677426	0.119498
9	MaxSharpe_out	0.151476	0.221857	0.470466	0.222457
10	RiskParity_out	0.164796	0.174459	0.674636	0.188281
11	Mix_out	0.149982	0.161390	0.637473	0.176643
12	SPY_out	0.144828	0.191867	0.509353	0.192090
13	BTC_out	0.240407	0.439579	0.439756	0.327090

Courbe de drawdown du portefeuille Max Sharpe

In [12]:
```
# === Drawdown sur la période complète : Max Sharpe vs Risk Parity vs Mix ===

v_ms_all, r_ms_all = portfolio_value(rets_all, w_max_sharpe)
v_rp_all, r_rp_all = portfolio_value(rets_all, w_rp)
v_mix_all, r_mix_all = portfolio_value(rets_all, w_mix)

cummax_ms  = v_ms_all.cummax()
cummax_rp  = v_rp_all.cummax()
cummax_mix = v_mix_all.cummax()

dd_ms  = 1 - v_ms_all / cummax_ms
dd_rp  = 1 - v_rp_all / cummax_rp
dd_mix = 1 - v_mix_all / cummax_mix

plt.figure(figsize=(9, 4))
plt.plot(dd_ms, label="Max Sharpe")
plt.plot(dd_rp, label="Risk Parity")
plt.plot(dd_mix, label="Mix")
plt.title("Drawdown des portefeuilles Max Sharpe, Risk Parity et Mix\n(période comp
plt.ylabel("Drawdown")
plt.legend()
plt.tight_layout()
plt.show()
```

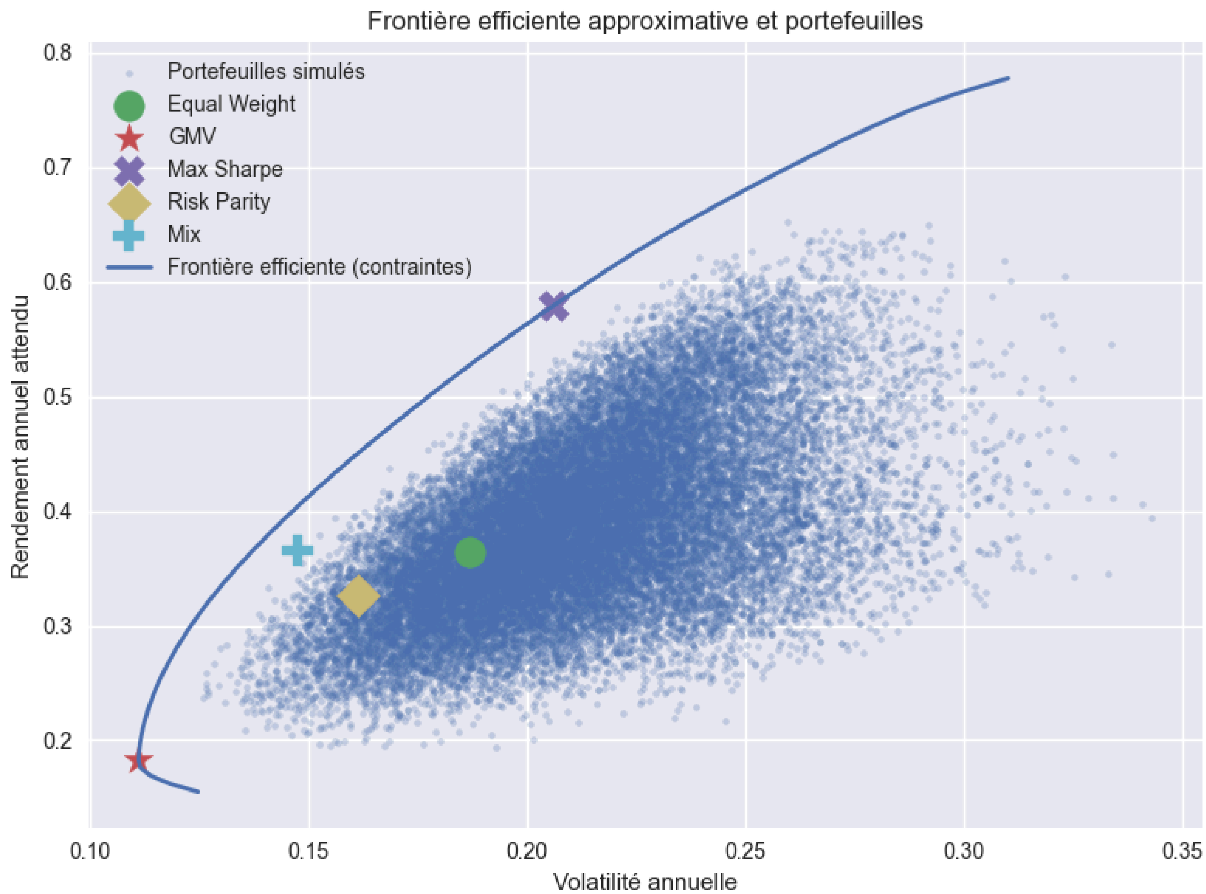


Simulation aléatoire de portefeuilles et frontière efficiente

In [13]:
```
# === Simulation aléatoire de portefeuilles + Frontière efficiente contraignante ==

n_sim = 100000
sim_returns = []
sim_vols = []
sim_sharpes = []

for _ in range(n_sim):
    # initialisation : dirichlet pour avoir somme=1
    w = np.random.dirichlet(np.ones(n_assets))

    # rejeter si contraintes non respectées
    if (w > 0.30).any():
        continue
    if (w < 0.002).any():  # minimum 0.2% pour diversification
        continue
    if w[crypto_idx].sum() > 0.15:  # limite crypto à 15% pour la simu
        continue

    mu_p = portfolio_return(w, mu_in.values)
    vol_p = portfolio_volatility(w, cov_in)
    s_p = (mu_p - rf) / vol_p

    sim_returns.append(mu_p)
    sim_vols.append(vol_p)
    sim_sharpes.append(s_p)

sim_returns = np.array(sim_returns)
sim_vols = np.array(sim_vols)
sim_sharpes = np.array(sim_sharpes)

# ----------------------------------------------------
# Calcul de la frontière efficiente sous contraintes
# ----------------------------------------------------
```

```
target_returns = np.linspace(sim_returns.min() * 0.8, sim_returns.max() * 1.3, 100)

frontier_vols = []
frontier_rets = []

for tr in target_returns:
    # contrainte supplémentaire : rendement cible = tr
    def target_return_constraint(weights, mu=mu_in.values, tr=tr):
        return np.dot(weights, mu) - tr

    constraints_frontier = [
        {"type": "eq",   "fun": weight_sum_constraint},   # somme des poids = 1
        {"type": "ineq", "fun": crypto_constraint},       # w_crypto_total <= 0.20
        {"type": "eq",   "fun": target_return_constraint} # rendement cible
    ]

    x0 = np.array([1.0 / n_assets] * n_assets)

    def objective_var(weights):
        return portfolio_volatility(weights, cov_in) ** 2

    res = minimize(
        objective_var,
        x0,
        method="SLSQP",
        bounds=bounds,
        constraints=constraints_frontier,
        options={"disp": False, "maxiter": 500}
    )

    if res.success:
        w_opt = res.x
        vol_opt = portfolio_volatility(w_opt, cov_in)
        mu_opt  = portfolio_return(w_opt, mu_in.values)
        frontier_vols.append(vol_opt)
        frontier_rets.append(mu_opt)

frontier_vols = np.array(frontier_vols)
frontier_rets = np.array(frontier_rets)

# ----------------------------------------------------
# Plot : nuage + EW + GMV + Max Sharpe + Risk Parity + Mix + Frontière
# ----------------------------------------------------
plt.figure(figsize=(8, 6))
plt.scatter(sim_vols, sim_returns, alpha=0.25, s=8, label="Portefeuilles simulés")

# Equal Weight
plt.scatter(
    portfolio_volatility(w_equal, cov_in),
    portfolio_return(w_equal, mu_in.values),
    marker="o",
    s=200,
    label="Equal Weight"
)

# GMV
```

```python
plt.scatter(
    portfolio_volatility(w_gmv, cov_in),
    portfolio_return(w_gmv, mu_in.values),
    marker="*",
    s=200,
    label="GMV"
)

# Max Sharpe
plt.scatter(
    portfolio_volatility(w_max_sharpe, cov_in),
    portfolio_return(w_max_sharpe, mu_in.values),
    marker="X",
    s=200,
    label="Max Sharpe"
)

# Risk Parity
plt.scatter(
    portfolio_volatility(w_rp, cov_in),
    portfolio_return(w_rp, mu_in.values),
    marker="D",
    s=200,
    label="Risk Parity"
)

# Mix
plt.scatter(
    portfolio_volatility(w_mix, cov_in),
    portfolio_return(w_mix, mu_in.values),
    marker="P",
    s=200,
    label="Mix"
)

# Frontière efficiente (ligne)
plt.plot(
    frontier_vols,
    frontier_rets,
    linewidth=2,
    label="Frontière efficiente (contraintes)"
)

plt.xlabel("Volatilité annuelle")
plt.ylabel("Rendement annuel attendu")
plt.title("Frontière efficiente approximative et portefeuilles")
plt.legend()
plt.tight_layout()
plt.show()
```



Performance des portefeuilles sur la période du challenge (25/10/2025–25/11/2025)

In [14]:

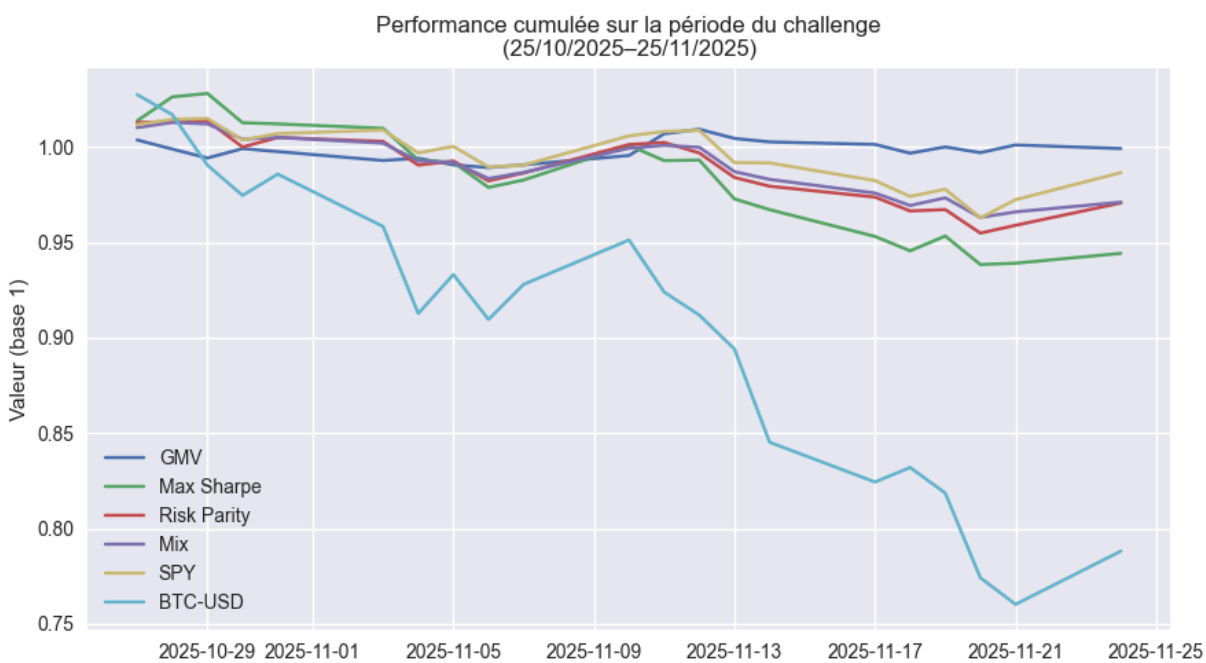
```
# === Performance sur la période du challenge : 25/10/2025–25/11/2025 ===

eval_start = "2025-10-25"
eval_end   = "2025-11-25"

eval_rets    = returns.loc[eval_start:eval_end]
eval_bench   = bench_returns.loc[eval_start:eval_end]   # SPY, BTC-USD

print("Nb de jours dans la période du challenge :", eval_rets.shape[0])

# Valeurs de portefeuille
v_gmv_eval,  r_gmv_eval   = portfolio_value(eval_rets, w_gmv)
v_ms_eval,   r_ms_eval    = portfolio_value(eval_rets, w_max_sharpe)
v_rp_eval,   r_rp_eval    = portfolio_value(eval_rets, w_rp)
v_mix_eval,  r_mix_eval   = portfolio_value(eval_rets, w_mix)

# Benchmarks
v_spy_eval,  r_spy_eval   = portfolio_value(eval_bench[["SPY"]], np.array([1.0]))
v_btc_eval,  r_btc_eval   = portfolio_value(eval_bench[["BTC-USD"]], np.array([1.0])

# Rendements mensuels (réels) pour la période du challenge
R_gmv = (1 + r_gmv_eval).prod() - 1
R_ms  = (1 + r_ms_eval).prod()  - 1
```

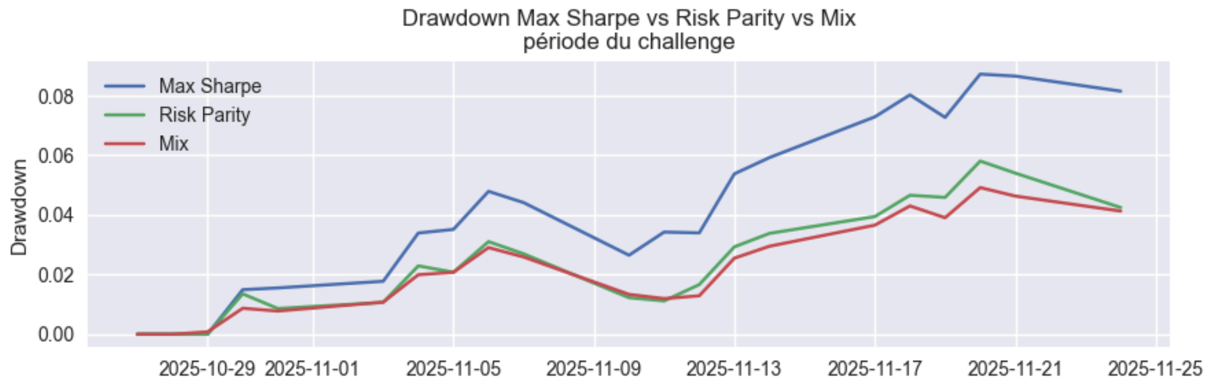
```
R_rp  = (1 + r_rp_eval).prod()  - 1
R_mix = (1 + r_mix_eval).prod() - 1
R_spy = (1 + r_spy_eval).prod() - 1
R_btc = (1 + r_btc_eval).prod() - 1

# Volatilités annuelles sur la période
vol_gmv = r_gmv_eval.std() * np.sqrt(trading_days)
vol_ms  = r_ms_eval.std()  * np.sqrt(trading_days)
vol_rp  = r_rp_eval.std()  * np.sqrt(trading_days)
vol_mix = r_mix_eval.std() * np.sqrt(trading_days)
vol_spy = r_spy_eval.std() * np.sqrt(trading_days)
vol_btc = r_btc_eval.std() * np.sqrt(trading_days)

# Max drawdown sur la période
dd_gmv = max_drawdown((1 + r_gmv_eval).cumprod())
dd_ms  = max_drawdown((1 + r_ms_eval).cumprod())
dd_rp  = max_drawdown((1 + r_rp_eval).cumprod())
dd_mix = max_drawdown((1 + r_mix_eval).cumprod())
dd_spy = max_drawdown((1 + r_spy_eval).cumprod())
dd_btc = max_drawdown((1 + r_btc_eval).cumprod())

# Tableau des performances sur la période du challenge
perf_df_eval = pd.DataFrame({
    "Portefeuille": [
         "GMV", "Max Sharpe", "Risk Parity", "Mix", "SPY", "BTC-USD"
    ],
    "Rendement Mensuel (%)": [
     R_gmv * 100, R_ms * 100, R_rp * 100, R_mix * 100, R_spy * 100, R_btc * 100
    ],
    "Volatilité Annuelle": [
        vol_gmv, vol_ms, vol_rp, vol_mix, vol_spy, vol_btc
    ],
    "Max Drawdown": [
        dd_gmv, dd_ms, dd_rp, dd_mix, dd_spy, dd_btc
    ]
})

display(perf_df_eval)

# Courbe de performance sur la période du challenge
plt.figure(figsize=(9, 5))
plt.plot(v_gmv_eval, label="GMV")
plt.plot(v_ms_eval,  label="Max Sharpe")
plt.plot(v_rp_eval,  label="Risk Parity")
plt.plot(v_mix_eval, label="Mix")
plt.plot(v_spy_eval, label="SPY")
plt.plot(v_btc_eval, label="BTC-USD")
plt.title("Performance cumulée sur la période du challenge\n(25/10/2025-25/11/2025)
plt.ylabel("Valeur (base 1)")
plt.legend()
plt.tight_layout()
plt.show()

# Drawdown du portefeuille Max Sharpe vs Risk Parity vs Mix sur la période du chall
cummax_ms_eval = v_ms_eval.cummax()
cummax_rp_eval = v_rp_eval.cummax()
```

```python
cummax_mix_eval = v_mix_eval.cummax()
dd_ms_eval = 1 - v_ms_eval / cummax_ms_eval
dd_rp_eval = 1 - v_rp_eval / cummax_rp_eval
dd_mix_eval = 1 - v_mix_eval / cummax_mix_eval

plt.figure(figsize=(9, 3))
plt.plot(dd_ms_eval, label="Max Sharpe")
plt.plot(dd_rp_eval, label="Risk Parity")
plt.plot(dd_mix_eval, label="Mix")
plt.title("Drawdown Max Sharpe vs Risk Parity vs Mix\npériode du challenge")
plt.ylabel("Drawdown")
plt.legend()
plt.tight_layout()
plt.show()
```

```
Nb de jours dans la période du challenge : 21
```

	Portefeuille	Rendement Mensuel (%)	Volatilité Annuelle	Max Drawdown
0	GMV	-0.088964	0.068718	0.014438
1	Max Sharpe	-5.579645	0.172477	0.087238
2	Risk Parity	-2.940446	0.137018	0.058068
3	Mix	-2.897431	0.107844	0.049183
4	SPY	-1.346985	0.150255	0.051354
5	BTC-USD	-21.189282	0.428431	0.260065




Drawdown Max Sharpe vs Risk Parity vs Mix
période du challenge
Max Sharpe
Risk Parity
Mix
Drawdown
0.08
0.06
0.04
0.02
0.00
2025-10-29
2025-11-01
2025-11-05
2025-11-09
2025-11-13
2025-11-17
2025-11-21
2025-11-25