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Momentum Strategy
in the FX Market

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1. Literature Review

1.1 The Origins of Momentum Investing

Amongst the very first experiences which contributed to the development of momentum investing, it is worth mentioning Levy's (1967) [1] rudimentary work on trend-following and relative strength. Although his early intuition suggested that past winners tend to outperform, his findings were largely overshadowed by the academic consensus surrounding Fama's (1970) Efficient Market Hypothesis [2], which posited that asset prices follow a random walk and therefore cannot be predicted using historical data.

This theoretical paradigm remained dominant until Lo and MacKinlay (1988) [3] provided robust empirical evidence of significant autocorrelation in stock returns, effectively challenging the random walk hypothesis and paving the way for the modern acceptance of price anomalies. Momentum-like strategies were first tested on the US stock market by traders Richard Donchian in the 1960s and Richard Driehaus in the 1980s.

1.2 More Rigorous Approaches

Jegadeesh and Titman (1993) [4] established the foundation of modern momentum literature by demonstrating that a formalized strategy of buying winners and selling losers generates robust excess returns unexplained by the CAPM. This anomaly was validated globally out-of-sample by Rouwenhorst (1998) [5], who showed that momentum persists across international markets and firm sizes, suggesting a common global driver rather than data snooping.

To explain these patterns, Hong and Stein (1999) [6] proposed a unified behavioral theory linking momentum to investor underreaction and subsequent overreaction. Finally, Moskowitz et al. (2012) [9] extended the framework with "time-series momentum", a trend-following strategy across diverse asset classes that offers diversification and hedging benefits against extreme market events.

1.3 Momentum Strategy in the FX Market

The Foreign Exchange (FX) market serves as an ideal laboratory for momentum strategies due to its massive liquidity and institutional dominance. Menkhoff et al. (2012) [8] provided seminal evidence that cross-sectional currency momentum generates significant excess returns, particularly at the 1-month horizon (Sharpe ratio $\simeq 0.95$). They attribute this to behavioral inefficiencies, specifically investor underreaction to news followed by overreaction. Burnside et al. (2011) [7] expanded this view by combining momentum with carry trade, arguing that these returns reflect a risk premium for rare disaster events and limits to arbitrage rather than simple behavioral biases.

However, recent studies document a distinct structural break following the Global Financial Crisis (GFC). Bartel et al. (2025) [15] reveal that whilst Dollar and Carry momentum were highly profitable pre-2009, "Dollar Momentum" has essentially vanished post-2010, and "Carry Momentum" now relies heavily on Emerging Market currencies rather than the G10. Consequently, Iwanaga and Sakemoto (2025) [16] argue that raw momentum strategies have deteriorated; they suggest that profitability in the modern era requires "conditional"

portfolios that adjust for market volatility and forward discounts to filter out unpromising signals.

1.4 Momentum Strategy during the Great Financial Crisis

The GFC highlighted a sharp dichotomy in momentum performance depending on the methodology applied. Barroso and Santa-Clara (2015) [12] focus on cross-sectional momentum (Winners Minus Losers, WML), documenting its structural vulnerability to "momentum crashes" characterized by severe negative skewness and excess kurtosis. They reveal that whilst WML is profitable long-term, it suffered a catastrophic drawdown (-73.42%) in 2009 during the market rebound, as past losers aggressively outperformed winners. However, they demonstrate that this risk is highly predictable; a risk-managed strategy that scales exposure based on realized volatility can virtually eliminate crash risk and nearly double the Sharpe ratio.

Conversely, Hutchinson and O'Brien (2014) [11] analyze trend following (time-series momentum), finding that these strategies performed exceptionally well *during* the 2008 crisis, effectively hedging equity drawdowns. However, they identify a distinct post-crisis deterioration, where trend following returns significantly underperform for approximately four years following financial turmoil. This decay is attributed not to sudden crashes, but to a fundamental breakdown in the serial correlation of futures markets.

1.5 Momentum Strategy after the Great Financial Crisis

In the aftermath of the GFC, the performance of standard momentum strategies deteriorated significantly compared to valuation strategies. Iwanaga and Sakemoto (2025) [16] attribute this relative underperformance to sudden spikes in market volatility, a view strongly supported by the theoretical framework of Daniel and Moskowitz (2016) [13]. They define these episodes as "momentum crashes," which occur in panic states characterized by high market volatility and subsequent market rebounds. During these reversals, the "loser" portfolio experiences strong positive returns, thereby generating large losses for the short leg of the momentum strategy.

Barroso and Santa-Clara (2015) [12] provide a critical structural analysis of this post-crisis behavior. They argue that the dismal performance of momentum in the decade following the crisis does not imply the anomaly is arbitraged away, but rather that the period was rich in high-risk episodes. Their empirical findings demonstrate that momentum risk is highly variable over time and distinctively predictable. While raw momentum offers a high Sharpe ratio over the long term, it suffers from severe crashes due to negative skewness. Consequently, the post-GFC landscape highlights the necessity of "risk-managed" approaches: by conditioning exposure on realized volatility, investors can mitigate crash risk and restore the strategy's profitability.

2. FX Momentum Strategy Analysis

2.1 Data Framework

The analysis focuses on daily spot exchange rate prices, converted into US Dollar (USD) terms using mid-rates. All rates are expressed as units of foreign currency per 1 USD (indirect quotation for the USD).

2.2 Methodology and Signal Generation

The strategy employs a standalone short-term momentum signal to determine the position for a one-month holding period.

A. Four-Day Momentum Calculation: The momentum is calculated as the log return of the spot rate over the last four trading days:

$$Ret_{mom} = \ln(S_{t-1}/S_{t-5}) \tag{1}$$

Where S_t represents the spot rate (Foreign/USD) at time t.

B. Signal and Position Allocation: Since the exchange rates are quoted indirectly (Foreign per USD), a positive return ($Ret_{mom} > 0$) implies a depreciation of the foreign currency against the USD. To capture the momentum of the foreign currency (i.e., buying the currency that is appreciating), we invert the signal:

$$Signal = -Ret_{mom} \tag{2}$$

Thus, a negative return in the spot rate (USD weakening) generates a positive signal to go long on the foreign currency.

C. Portfolio Construction For the purpose of this analysis, we generate five random portfolios using the available pool of currencies. The following table details the specific composition of the five portfolios we have constructed:

Portfolio	Currencies
Portfolio 1	JAPAYEN, SINGDOL, HUNFORT, NORKRON, CZECHCM
Portfolio 2	AUSTDOL, USEURSP, MEXPESO, THABAHT, SWEKRON
Portfolio 3	GBPOUND, INDRUPE, POLZLOT, COMRAND, NZDOLLR
Portfolio 4	CNDOLLR, PHILPES, SWISSFR, USEURSP, JAPAYEN
Portfolio 5	THABAHT, SINGDOL, MEXPESO, COMRAND, SWEKRON

Table 1: Portfolio Composition

2.3 Performance and Moments Analysis

To evaluate the effectiveness of the strategy, we analyze the distribution of monthly returns across each portfolio. This allows us to observe the variability of performance and identify key statistical moments such as the center of the distribution and the presence of extreme values.
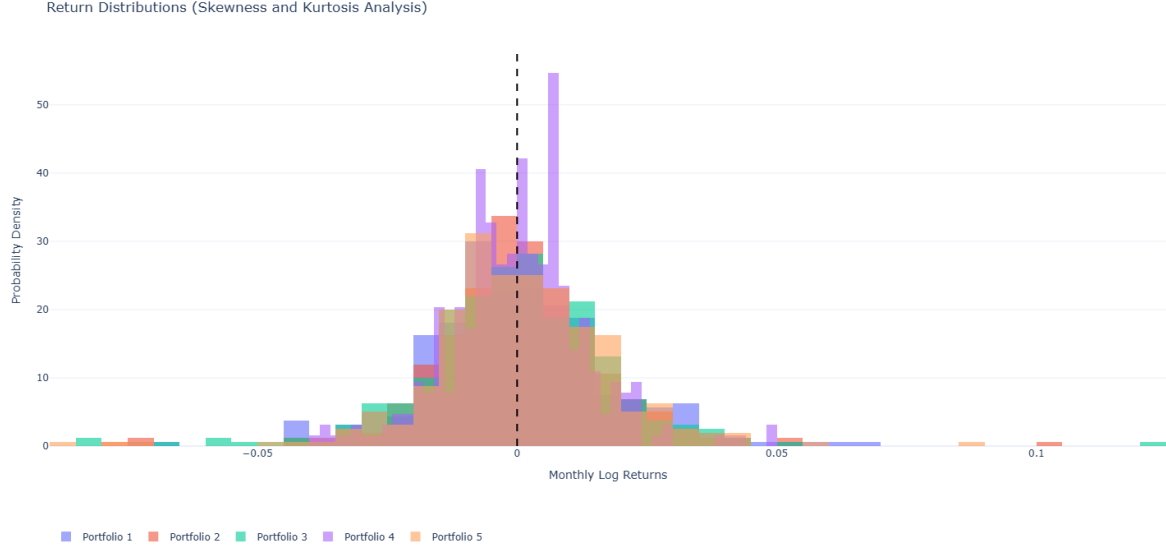
Figure 1: Return Distributions

Portfolio	Ret. Ann. (%)	Vol. Ann. (%)	Sharpe	Skewness	Kurtosis
Portfolio 1	0.01	6.40	0.001	0.092	1.705
Portfolio 2	0.60	6.03	0.100	0.025	5.994
Portfolio 3	-0.71	6.74	-0.105	0.059	6.292
Portfolio 4	0.34	4.54	0.074	0.198	1.597
Portfolio 5	0.75	6.13	0.123	-0.357	4.946

Table 2: Annualized Performance Metrics

Statistical Analysis:

- **Sharpe Ratio and Returns:** Portfolio 5 exhibits the highest risk-adjusted performance with a Sharpe ratio of 0.123 and an annualized return of 0.75%, closely followed by Portfolio 2 (0.100). Conversely, Portfolio 3 underperforms significantly with a negative return (-0.71%) and the lowest Sharpe ratio (-0.105). Overall, the risk-adjusted returns are modest across all baskets, reflecting the difficulty of a pure trend-following strategy over the full 26-year period.

- **Volatility:** Annualized volatility ranges from 4.54% to 6.74%. Portfolio 4 displays the lowest volatility (4.54%), which is consistent with its composition of "Safe Haven" currencies (JPY, CHF) alongside the USD. In contrast, Portfolio 3 shows the highest volatility (6.74%) combined with negative returns, indicating that this basket captured "bad volatility" or market noise rather than sustainable trends.

- **Skewness:** A key finding is the distinct behavior of the best-performing basket. While Portfolios 1, 2, 3, and 4 show **positive skewness** (typical of momentum strategies cutting losses), Portfolio 5 exhibits **negative skewness** (-0.357). This suggests that while Portfolio 5 generates the highest returns, it is exposed to sudden reversals, likely driven by the inclusion of emerging market currencies like the Mexican Peso and South African Rand.

- **Kurtosis:** The distribution profiles are heterogeneous. Portfolios 2 and 3 exhibit high kurtosis (5.99 and 6.29 respectively), indicating "fat tails" and frequent extreme observations. Conversely, Portfolios 1 and 4 show low kurtosis ($\approx$ 1.6–1.7), suggesting a more Gaussian distribution of returns with fewer outliers.

2.4 Sub-sample Analysis

We analyze the strategy across three distinct periods to check for consistency. The results reveal a significant time-variation in momentum profitability.
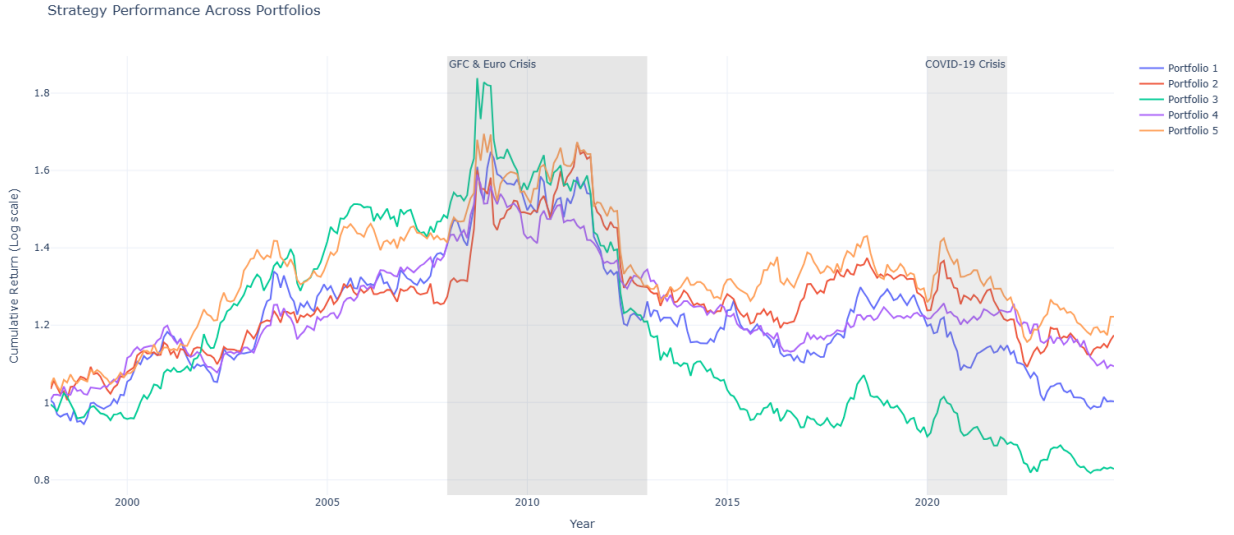

Figure 2: Return Distributions

Portfolio	Ret. Pre-2008	Ret. GFC & Euro Crisis	Ret. Post-2012
Portfolio 1	3.25	-2.45	-1.68
Portfolio 2	2.30	0.67	-0.86
Portfolio 3	3.98	-4.11	-3.22
Portfolio 4	3.24	-0.62	-1.71
Portfolio 5	3.56	-1.80	-0.54

Table 3: Sub-sample Annualized Returns (%)

Comments on Historical Performance:
- **Pre-2008 Period:** This was undeniably the "golden era" for the strategy. All five portfolios generated solid positive returns, ranging from 2.30% (Portfolio 2) to 3.98% (Portfolio 3). This consistency suggests that the pre-crisis macroeconomic environment provided clear, exploitable trends for short-term momentum signals.
- **GFC and Euro Crisis:** The strategy struggled significantly during this high-volatility regime. Only Portfolio 2 managed to remain positive (+0.67%), while Portfolio 3

suffered a severe drawdown (-4.11%). This divergence aligns with the literature on "momentum crashes" (Daniel & Moskowitz), where sudden market reversals punish trend-followers who are positioned on the wrong side of a recovery.

- **Post-2012 Period:** We observe a systemic deterioration. Every single portfolio posted negative annualized returns, ranging from -0.54% (Portfolio 5) to -3.22% (Portfolio 3). This confirms a major structural shift in FX markets. The massive liquidity injections and Central Bank interventions likely suppressed volatility and enforced mean-reversion, effectively erasing the traditional short-term momentum premium.

2.5 Discussion: Empirical Results vs. Literature

Our empirical findings provide a nuanced bridge to the academic consensus, highlighting both the historical validity of the momentum factor and its recent decay.

First, while the full-sample Sharpe ratios remain modest (peaking at 0.123 for Portfolio 5), the robust performance observed prior to 2008 supports the seminal work of Jegadeesh and Titman [4] and Menkhoff et al. [8]. Our results confirm that currency momentum historically captured a distinct risk premium. However, the low overall Sharpe ratios compared to earlier studies suggest that this premium is no longer easily harvestable via simple raw signals.

Second, our sub-sample analysis offers striking validation of Bartel et al. [15] and Iwanaga and Sakemoto [16] regarding the structural shift in the post-GFC era. The dramatic transition from universal positive returns pre-2008 (reaching 3.98% for Portfolio 3) to universal negative returns after 2012 perfectly illustrates the "deterioration" of momentum efficacy in the modern macro regime. This decline aligns with the theory that quantitative easing and suppressed volatility have eroded the directional trends that trend-followers rely upon.

Finally, the high Kurtosis values observed in specific baskets (reaching 6.292 for Portfolio 3) are consistent with the "momentum crash" theories of Barroso and Santa-Clara [12] and Daniel and Moskowitz [13]. Notably, the fact that our best-performing basket (Portfolio 5) is the only one exhibiting negative skewness (-0.357) reinforces the idea that generating alpha with momentum often comes at the cost of higher tail risk. This dichotomy underscores the necessity of moving from "static" to "conditional" risk-managed approaches to preserve profitability in the 21st century.

3. Strategic Implications: Integrating Value and Momentum

The deterioration of momentum returns observed in our post-2012 sub-sample analysis suggests that a single-factor approach may be insufficient in modern market regimes. To address this, the literature extensively explores the synergy between momentum and value strategies. Asness, Moskowitz, and Pedersen [10] provide a foundational analysis, demonstrating that in currency markets, Value strategies often yield higher long-term Sharpe ratios than raw momentum.

3.1 The Value Strategy Mechanism

The currency Value strategy is based on the principle of mean reversion to the Real Exchange Rate (Q). It assumes that exchange rates eventually converge toward their fundamental equilibrium. For a currency i in our basket, the RER is defined as:

$$Q_{i,t} = \frac{S_{i,t} \times P_{US,t}}{P_{i,t}} \tag{3}$$

Where $S_{i,t}$ is the nominal spot rate (units of foreign currency per USD), $P_{US,t}$ is the US price level, and $P_{i,t}$ is the foreign price level. The strategy evaluates the log RER ($q_{i,t} = \ln Q_{i,t}$) relative to its historical mean to determine portfolio allocation:

- **Buying Undervalued Currencies:** If the real exchange rate is high relative to its mean, the foreign currency is considered "cheap" in terms of purchasing power. The strategy goes long on these currencies.
- **Selling Overvalued Currencies:** Conversely, if the real exchange rate is low, the foreign currency is overvalued. The strategy shorts these currencies.

3.2 Complementarity and Risk Mitigation

The most critical advantage of this approach is the persistent negative correlation (approximately -0.40) between Value and Momentum factors [10]. This relationship exists because momentum exploits mid-term behavioral underreaction, while value profits from the eventual correction of price excesses.

As noted by Menkhoff et al. [14], while momentum captures the "trend" phase of a currency's movement, it remains vulnerable to "momentum crashes" when prices deviate too far from macroeconomic gravity. During such reversals, the gains from the Value component, which bets on the return to fundamentals, typically offset the losses in the Momentum leg [13].

By diversifying across these two negatively correlated risk premia, investors can achieve a much smoother equity curve. Our findings of post-crisis decay in raw momentum further support the necessity of such a multi-factor framework to transform a volatile single-factor strategy into a robust investment solution.

References

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Appendix: Python Code

```python
import numpy as np
import pandas as pd
import random
import plotly.graph_objects as go
import scipy.stats as stats

# --- DATA LOADING & CLEANING ---

spot_file = r"C:\Users\Vince\OneDrive\Desktop\Finance\Dauphine\↩
    International Finance\ASSIGNEMENT\spot_rates_clean.xls"
df_spot = pd.read_excel(spot_file, skiprows=1).set_index("Code")

fwd_file = r"C:\Users\Vince\OneDrive\Desktop\Finance\Dauphine\↩
    International Finance\ASSIGNEMENT\fwd_rates_clean.xlsx"
df_fwd = pd.read_excel(fwd_file, skiprows=1).set_index("Code")

mapping_spot_forward = {
    "AUSTDOL(ER)": "TDAUD1M(ER)", "CNDOLLR(ER)": "BBCAD1F(ER)",
    "USEURSP(ER)": "TDEUR1M(ER)", "HUNFORT(ER)": "USHUF1F(ER)",
    "INDRUPE(ER)": "USINR1F(ER)", "JAPAYEN(ER)": "TDJPY1M(ER)",
    "MEXPESO(ER)": "USMXN1F(ER)", "NZDOLLR(ER)": "TDNZD1M(ER)",
    "NORKRON(ER)": "TDNOK1M(ER)", "PHILPES(ER)": "USPHP1F(ER)",
    "POLZLOT(ER)": "TDPLN1M(ER)", "SINGDOL(ER)": "BBSGD1F(ER)",
    "COMRAND(ER)": "TDZAR1M(ER)", "SWEKRON(ER)": "TDSEK1M(ER)",
    "SWISSFR(ER)": "TDCHF1M(ER)", "THABAHT(ER)": "USTHB1F(ER)",
    "GBPOUND(ER)": "TDGBP1M(ER)", "CZECHCM(ER)": "TDCZK1M(ER)"
}

# Currency Conversion to USD Terms
gbp_cols = [col for col in df_spot.columns if (col != 'GBPOUND(ER)↩
    ' and col != 'USEURSP(ER)')]
for col in gbp_cols:
    df_spot[col] = df_spot[col] / df_spot['GBPOUND(ER)']
df_spot['USEURSP(ER)'] = 1 / df_spot['USEURSP(ER)']
df_spot['GBPOUND(ER)'] = 1 / df_spot['GBPOUND(ER)']

df_fwd['TDAUD1M(ER)'] = 1 / df_fwd['TDAUD1M(ER)']
df_fwd['TDEUR1M(ER)'] = 1 / df_fwd['TDEUR1M(ER)']
df_fwd['TDNZD1M(ER)'] = 1 / df_fwd['TDNZD1M(ER)']
df_fwd['TDGBP1M(ER)'] = 1 / df_fwd['TDGBP1M(ER)']

df_fwd.index = pd.to_datetime(df_fwd.index)
monthly_dates = df_fwd.index
df_spot_monthly = df_spot.reindex(monthly_dates, method='ffill')
```

```python
all_available = [k for k, v in mapping_spot_forward.items() if v ←
    is not None]

# BACKTEST FUNCTION

def backtest_portfolio(currencies):
    n = len(currencies)
    sig_list = []

    # 1. Monthly Rebalancing with 4-day looking back signal
    for i in range(1, len(monthly_dates)):
        current_date = monthly_dates[i]
        # Momentum: 4-day window strictly before the rebalancing ←
            date
        spot_history = df_spot[df_spot.index < current_date].tail←
            (5)
        if len(spot_history) < 5: continue

        row = {'Date': current_date}
        for c in currencies:
            fwd_code = mapping_spot_forward[c]
            # Signal: -Momentum + Carry (Forward Premia)
            mom = np.log(spot_history[c].iloc[-1] / spot_history[c←
                ].iloc[0])
            s_now = spot_history[c].iloc[-1]
            #f_now = df_fwd.loc[current_date, fwd_code]
            row[c] = -mom #+ (np.log(f_now) - np.log(s_now))
        sig_list.append(row)

    df_sig = pd.DataFrame(sig_list).set_index('Date')

    # 2. Performance Calculation (1-month holding period)
    pnl_list = []
    sig_dates = df_sig.index
    for i in range(len(sig_dates) - 1):
        d_start, d_end = sig_dates[i], sig_dates[i+1]
        month_ret = 0
        for c in currencies:
            pos = np.sign(df_sig.loc[d_start, c])
            s_0, s_1 = df_spot_monthly.loc[d_start, c], ←
                df_spot_monthly.loc[d_end, c]
            f_0 = df_fwd.loc[d_start, mapping_spot_forward[c]]

            # Total Return = Spot Return + Forward Premium (Carry)
            ret = pos * (-np.log(s_1 / s_0) + (np.log(f_0) - np.←
                log(s_0)))
```

```python
            month_ret += (ret / n)
        pnl_list.append(month_ret)

    returns = pd.Series(pnl_list, index=sig_dates[:-1])

    # 3. Annualized Metrics
    ann_return = returns.mean() * 12
    ann_vol = returns.std() * np.sqrt(12)
    sharpe = ann_return / ann_vol if ann_vol != 0 else 0
    skew = returns.skew()
    kurt = returns.kurtosis() # Excess Kurtosis

    # 4. Sub-samples Analysis
    def sub_perf(series):
        if len(series) < 6: return 0.0
        return round((series.mean() * 12) * 100, 2) # Annualized ↩
            Return %

    pre_08 = returns[returns.index < '2008-01-01']
    gfc = returns[(returns.index >= '2008-01-01') & (returns.index↩
        <= '2012-12-31')]
    post_12 = returns[returns.index > '2012-12-31']

    clean_names = [c.replace("(ER)", "") for c in currencies]

    return {
        "Return_Ann_%": round(ann_return * 100, 2),
        "Vol_Ann_%": round(ann_vol * 100, 2),
        "Sharpe": round(sharpe, 3),
        "Skewness": round(skew, 3),
        "Kurtosis": round(kurt, 3),
        "Ret_Pre08_%": sub_perf(pre_08),
        "Ret_GFC_%": sub_perf(gfc),
        "Ret_Post12_%": sub_perf(post_12),
        "History": np.exp(returns.cumsum()),
        "Monthly_Returns": returns,
        "Currencies": ", ".join(clean_names)
    }

# --- EXECUTION & PLOTTING ---

# Note: These portfolios were generated randomly as described in ↩
    the methodology.
# We explicitly define this specific draw here to ensure that ↩
    running this script
# reproduces the exact tables, figures, and statistical analysis ↩
    presented in the report.
```

```python
fixed_draw = [
    ['JAPAYEN(ER)', 'SINGDOL(ER)', 'HUNFORT(ER)', 'NORKRON(ER)', '
        CZECHCM(ER)'],
    ['AUSTDOL(ER)', 'USEURSP(ER)', 'MEXPESO(ER)', 'THABAHT(ER)', '
        SWEKRON(ER)'],
    ['GBPOUND(ER)', 'INDRUPE(ER)', 'POLZLOT(ER)', 'COMRAND(ER)', '
        NZDOLLR(ER)'],
    ['CNDOLLR(ER)', 'PHILPES(ER)', 'SWISSFR(ER)', 'USEURSP(ER)', '
        JAPAYEN(ER)'],
    ['THABAHT(ER)', 'SINGDOL(ER)', 'MEXPESO(ER)', 'COMRAND(ER)', '
        SWEKRON(ER)']
]

random.seed(None)
results_table = []
fig = go.Figure()

for i, currencies in enumerate(fixed_draw):
    p_name = f"Portfolio {i+1}"
    # Using the fixed draw for reproducibility
    res = backtest_portfolio(currencies)
    res["Portfolio"] = p_name
    results_table.append(res)
    fig.add_trace(go.Scatter(x=res["History"].index, y=res["
        History"].values, name=p_name))

# Shading GFC period
fig.add_vrect(x0="2008-01-01", x1="2012-12-31", fillcolor="gray",
    opacity=0.2, line_width=0,
            annotation_text="GFC & Euro Crisis",
                annotation_position="top left")

# Shading COVID period
fig.add_vrect(x0="2020-01-01", x1="2021-12-31", fillcolor="grey",
    opacity=0.15, line_width=0,
            annotation_text="COVID-19 Crisis",
                annotation_position="top right")

fig.update_layout(title="Strategy Performance Across Portfolios",
    template="plotly_white",
                xaxis_title="Year", yaxis_title="Cumulative
                    Return (Log scale)")
fig.show()

# --- DISTRIBUTION PLOT ---
```

```python
fig_dist = go.Figure()

for res in results_table:
    monthly_rets = res["Monthly_Returns"]

    fig_dist.add_trace(go.Histogram(
        x=monthly_rets,
        name=res["Portfolio"],
        opacity=0.6,
        nbinsx=50,
        histnorm='probability density'
    ))

fig_dist.update_layout(
    title="Return Distributions (Skewness and Kurtosis Analysis)",
    xaxis_title="Monthly Log Returns",
    yaxis_title="Probability Density",
    barmode='overlay',
    template="plotly_white",
    legend=dict(orientation="h", y=-0.2)
)

fig_dist.add_vline(x=0, line_dash="dash", line_color="black")
fig_dist.show()

# Final Dataframe
df_results = pd.DataFrame(results_table).sort_values(by="Sharpe", ←
    ascending=False)
cols = ["Portfolio", "Return_Ann_%", "Vol_Ann_%", "Sharpe", "←
    Skewness", "Kurtosis",
        "Ret_Pre08_%", "Ret_GFC_%", "Ret_Post12_%", "Currencies"]

print(df_results[cols].to_string(index=False))
```