FX Momentum Strategies Before and After the Global Financial Crisis: An Academic Review and Empirical Investigation

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Abstract

This paper examines the performance of FX momentum strategies before, during, and after the 2008 financial crisis. We analyze Forex momentum strategies in major currency portfolios and document their behavior across distinct market regimes. Our results show that momentum performed positively during periods of market stress, particularly in 2008–2009, while its profitability weakened during the calmer and less directional FX environment of the 2010s.

Note

You will find in this paper **[O]** annotations. These indicate that further details or clarifications are provided in the Appendix.

1 Introduction

Momentum strategies exploit the tendency of recent winners to keep outperforming and losers to keep underperforming over short to medium horizons. In FX markets short-selling is unconstrained and transaction costs are low, so momentum stands out as a robust style factor.

This project has two objectives: (i) to briefly review the FX momentum literature, with a focus on how performance behaved around the 2008 Global Financial Crisis (GFC), and (ii) to design and implement a short-horizon FX momentum strategy using a four-day lookback and a one-month holding period, then benchmark it against a PPP-based value strategy across several sub-samples, in line with the assignment guidelines.

Overall, our results are consistent with prior research. FX momentum generates positive excess returns and risk-adjusted performance, but its profitability depends on market conditions: returns are particularly strong in volatile periods with large cross-currency dispersion (especially around the GFC), and they fade materially in the low-volatility post-crisis environment. In contrast, the PPP value strategy produces small or negative monthly returns, highlighting its weak predictive power over short horizons.

2 Literature Review on FX Momentum Strategies

2.1 Momentum in finance and its extension to FX

In behavioural terms, momentum reflects a simple pattern: when a trend persists, agents tend to extrapolate it, producing the empirical fact that recent winners keep outperforming while losers keep underperforming over horizons of a few months to a year. Early empirical research extended the equity momentum anomaly to FX markets. Okunev and White (2003)[1] show that simple rules buying recent winners and selling recent losers among major exchange rates generate large, significant excess returns even with conservative transaction costs. Bianchi et al. (2005)[2] report similar evidence for G7 currencies, showing that momentum portfolios deliver consistently positive Sharpe ratios. Taken together, these findings suggest that FX momentum is a robust empirical pattern, not something driven by a particular sample or time period.

2.2 FX momentum as a distinct style factor

Menkhoff et al. (2012)[3] offer a benchmark analysis of currency momentum. Using up to 48 currencies from 1976–2010, they form long–short portfolios buying currencies with the highest past 3 to 12 month returns and shorting the lowest. The winner–loser spread delivers annualised excess returns of 8–10% with strong t-statistics, low correlations with standard FX factors (carry, dollar, value), and remains significant in multi-factor regressions, establishing momentum as an independent style factor. The literature distinguishes cross-sectional momentum (ranking currencies) from time-series momentum (trend-following each currency). Although both exist, cross-sectional strategies generally offer superior risk-adjusted performance in FX (Moskowitz et al., 2012[4]).

Recent research sharpens how we should think about this premium. Zhang (2022)[8] argues that a large part of currency momentum is really factor momentum: these strategies mainly pick up trends in broad FX factors especially carry and the dollar while truly idiosyncratic momentum is weak. This suggests the profits may reflect compensation for time-varying global FX risks rather than pure mispricing.

2.3 Performance during the Global Financial Crisis

A key literature strand examines momentum during crises. Burnside (2011)[5] shows that while carry trades earn high averages but bear crash risk, momentum performs well precisely in crash episodes, offering diversification[7]. Menkhoff et al. (2012) similarly find that momentum returns are strongly state-dependent and rise sharply in periods of high FX volatility, notably during 2007–2009.

During the GFC, FX momentum generated solid returns when many FX strategies incurred losses. Menkhoff et al. report that July 2007–June 2009 momentum returned about 0.8% per month, whereas carry trades slipped into negative territory and were strongly negatively correlated with momentum[7]. Unlike equity momentum, currency momentum displayed mild positive skewness and avoided crash behaviour (Daniel & Moskowitz, 2016[6]).

This robustness is explained by the simple fact that momentum strategies benefit from exposure to high-risk currencies that experience strong and persistent trends during deleveraging. Throughout the GFC, high-interest-rate investment currencies commonly used in carry trades such as the AUD, NZD, BRL, TRY, ZAR all experienced severe depreciations and benefited momentum strategies holding short positions. Also, Zhang (2022) shows that the poor performance of carry trades and dollar-related strategies in 2008 ended up reinforcing momentum returns via factor-momentum mechanisms.

2.4 Post-crisis developments and regime dependence

Post-2008 evidence shows a two-phase pattern: momentum remained profitable immediately after the crisis but weakened over the 2010s. Zhang (2022) documents a marked decline in rolling momentum returns, occasionally turning negative before partially recovering. This is not viewed as a disappearance of momentum but as a shift in FX conditions: exceptionally low rates, unconventional monetary policy, and muted, less directional exchange-rate movements reduced trend persistence, mechanically lowering momentum profits. Overall, FX momentum is robust yet state-dependent (strong in turbulent, high-dispersion regimes and weaker in calm markets) motivating our regime-based empirical analysis in the second part of the project.

3 Data and Methodology

3.1 Data, quotation basis and CIP assumption

The empirical analysis uses the FX spot and forward data provided in the assignment. We work under the standard assumption that Covered Interest Parity (CIP) holds throughout the sample and use mid-quotes both for spots and forwards, as required by the guidelines. The raw data quote currencies against either GBP or EUR, whereas our strategies require returns in a currency/USD format. We therefore reconstruct all series as X/USD using cross-exchange rate identities and enforcing triangular arbitrage consistency. This yields a consistent universe of 24 spot exchange rates expressed with USD as the base currency.

3.2 Log returns and momentum signal

From these spot series, we compute daily log returns for currency i at day t. Log returns are preferred because they are time-additive (a key property for multi-day momentum signals), naturally symmetric for appreciations and depreciations, and consistent with the theoretical treatment of deviations from parity conditions. The resulting dataset contains roughly 7,000 daily observations per currency.

The momentum signal is constructed using a four-day lookback window. For each currency i and day t, we define the cumulative four-day return M(i,t) = MOM= $r_{t-1} + r_{t-2} + r_{t-3} + r_{t-4}$. A positive value of $M_{i,t}$ identifies a recent "winner" (short-term appreciation), while a negative value indicates a recent "loser" (short-term depreciation). Although the signal is computed on a daily basis, portfolios are formed and rebalanced at a monthly frequency: we resample the momentum series at month-ends and use the last available $M_{i,t}$ in each month to rank currencies. Portfolios formed at month m are then held unchanged until month $m + 1$.

3.3 Portfolio construction and returns

At each month-end, we sort currencies into five equally-weighted portfolios $P1$ to $P5$ based on their four-day momentum signal. Portfolio $P1$ contains currencies with the highest momentum (strongest recent appreciation), while $P5$ groups those with the lowest momentum (strongest recent depreciation). Intermediate portfolios $P2$–$P4$ represent sorted middle groups that we mainly use for completeness; the focus of the analysis is on the winner and loser portfolios and on the long–short momentum factor.

Daily portfolio returns are computed as the simple average of constituent currency returns: $r_{Pj,t} = \sum r_{i,t}$ / N_j, where N_j is the number of currencies in portfolio j. Monthly portfolio returns are obtained by summing daily log returns within each month. The *gross* momentum factor is defined as the difference between the winner and loser portfolios: $r^{gross}_{MOM,t} = r_{P1,t} - r_{P5,t}$.

3.4 Transaction costs and net returns

FX trading costs are known to materially affect the profitability of short-horizon strategies. We therefore compute both gross and net returns for the momentum factor. In our setting, explicit trading costs are set at 5 basis points per transaction. Implicit trading costs are also taken into account and correspond to the effective cost of crossing the bid–ask spread. Specifically, they are measured as the difference between the mid-price and the execution price, where executions occur at the ask when the strategy buys a currency pair and at the bid when it sells. Given that the momentum trade is long the winner portfolio and short the loser portfolio, the strategy crosses the spread on both legs; we thus apply both explicit and implicit costs symmetrically. Denoting by $c_{i,t}$ the proportional total trading cost for currency i at time t, the effective daily net return contribution of currency i when portfolios are rebalanced is reduced by $c_{i,t}$. Aggregating across currencies and over the month yields a net monthly momentum factor $r^{net}_{MOM,t} = r^{gross}_{MOM,t} - TC_t$, where TC_t is the average transaction cost of the long and short legs at month t.

3.5 PPP Strategy Construction

Purchasing Power Parity (PPP) is a long-run equilibrium condition stating that exchange rates should adjust to offset inflation differentials across countries. In practice, measuring PPP deviations requires price indices such as CPI or PPI. Since these data are not available in our dataset, we cannot compute the theoretical PPP-implied value of each currency directly. Following the FX asset-pricing literature, we therefore use a financial proxy for PPP misalignment based on the forward discount. Under covered interest parity (CIP), the forward exchange rate is the unique no-arbitrage price consistent with interest-rate differentials. As a result, the forward rate can be interpreted as a frictionless fair-value anchor for the future spot rate, while the current spot rate may deviate temporarily due to risk premia, capital flows, liquidity effects, or market segmentation. The gap between the forward and the spot rate thus provides a practical measure of short-run mispricing when price-based PPP estimates are unavailable.

We define our PPP-proxy signal as the forward discount, computed as $PPP_{proxy}(i,t) = log(F_{i,t}/S_{i,t})$. Currencies with a high forward-to-spot ratio (i.e., $F \gg S$) appear relatively expensive, while those with low values ($F \ll S$) appear relatively cheap. This interpretation is consistent with the "FX value" factor of Lustig and Verdelhan (2011), where deviations from the forward-implied value capture cross-sectional variation in expected currency returns. Using this misalignment measure, we sort currencies each month into five equally-weighted portfolios, from the most undervalued to the most overvalued. Our PPP factor is then constructed as a long–short strategy that buys undervalued currencies and sells overvalued ones: $r_{PPP,t} = r_{P1,t} - r_{P5,t}$. This approach provides a tractable and empirically validated method for approximating PPP-based value signals in the absence of price-level data.

4 Empirical Results

4.1 Full-sample performance of the momentum strategy

Over the full sample (1998–2024), the four-day lookback FX momentum strategy delivers positive average returns gross of transaction costs, but becomes slightly unprofitable once realistic trading frictions are taken into account. The long–short factor earns an annualised gross return of about 4.1%, while net returns are close to zero and mildly negative ($\approx$ -0.4%), highlighting the sensitivity of short-horizon FX momentum strategies to transaction costs [**A**]. Annualised volatility is moderate ($\approx$ 8.6-8.8%), substantially lower than individual currency volatilities due to cross-currency diversification. As a result, gross Sharpe ratios remain positive but modest, whereas net risk-adjusted performance deteriorates after costs.

The return distribution deviates significantly from the normal distribution. The Momentum strategy exhibits pronounced fat tails, with an excess kurtosis of 4.3, reflecting a higher possibility of extreme outcomes comparatively to the Gaussian benchmark. Positive skewness across the full sample suggests that the likelihood of extreme positive outcomes dominates the extreme negative outcomes. The cumulative return profile showcases major regime shifts, including the post-GFC period, when abrupt reversals in exchange rate trends led to temporary losses.

However, the profitability of the strategy needs to be interpreted cautiously. The result from testing on past data depends on mid-quotes that were chosen initially and relies on simplified assumptions regarding execution and trading frictions, and does not explicitly model slippage, market impact, or timing constraints. Consequently, gross performance should be viewed as an upper bound, while near-zero net results underscore the practical challenges of implementing short-horizon FX momentum strategies.

4.2 Regime dependence of momentum returns

To assess regime dependence, we split the sample into five macro sub-periods. [**B**] Pre-crisis (1998–2006). In a context of high liquidity and low risk aversion, short-term continuation effects are present. The momentum factor delivers strong gross returns ($\approx$14% annualized) with moderate volatility ($\approx$10%), producing positive Sharpe ratios around 1.4. Once transaction costs are incorporated, performance remains positive but weaker, with net annualised returns of about 7.1% and a Sharpe ratio around 0.77, indicating that trading frictions reduce but do not eliminate profitability in this relatively calm environment.

Global Financial Crisis (2007–2009). Momentum performs moderately well in gross terms during the crisis. Elevated cross-currency dispersion during deleveraging episodes supports trend persistence, generating gross annualised returns of about 4.4% and positive Sharpe ratios ($\approx$0.5). Tail risk increases markedly, with higher kurtosis reflecting extreme outcomes. Net performance deteriorates substantially, with net annualised returns close to zero ($\approx$0.5%) and a Sharpe ratio near zero, as volatility and trading costs rise.

Post-crisis low-volatility period (2010–2019). Profitability declines substantially as FX volatility and cross-sectional dispersion compress. Momentum delivers negative gross annualised returns ($\approx$ -2.7%), while net returns fall further to around -6.1% per year. Sharpe ratios turn negative ($\approx$-1), indicating that short-term momentum loses predictive power in prolonged low-volatility regimes.

COVID-19 shock (2020–2021). Momentum benefits from large and rapid exchange rate movements during the Covid period. Gross performance improves, with annualised returns of about 10%, but volatility rises sharply ($\approx$10.6%) and tail risk becomes extreme, as reflected in very high kurtosis ($\approx$7.3). Despite favourable gross outcomes, increased spreads and turnover substantially reduce profitability, leaving net returns positive but modest ($\approx$6.5%).

Post-Covid period (2022–2024). The recent tightening cycle is characterised by renewed volatility and diverging monetary policies. However, momentum fails to translate these conditions into sustained profitability. Gross returns turn negative again ($\approx$-3.9% annualised), while net returns decline further to around -7.9%, with negative Sharpe ratios and pronounced downside skewness.

Summary. FX momentum is clearly regime-dependent. Gross performance is strongest during periods of heightened volatility and cross-currency dispersion, while prolonged calm environments are associated with weak or negative returns. Once transaction costs are accounted for, net profitability varies substantially across regimes and is particularly weak in low-volatility environments, highlighting the sensitivity of short-horizon momentum strategies to trading frictions and market conditions.

4.3 Performance of the PPP value strategy

On the full sample, the PPP factor delivers near-zero gross returns and around –10% net returns. Its volatility is lower than momentum (≈6.7%), reflecting slow-moving PPP mispricing signals. The return distribution shows strong positive skewness (≈0.85) and high excess kurtosis (>5), meaning many small losses punctuated by a few large gains when severe misalignments correct [**C**].

Cross-sectional PPP signals are smoother and smaller because inflation dynamics are similar across countries, especially advanced economies. This limited dispersion mechanically reduces PPP spreads and expected returns. The only major positive spike appears in 2020–2021, when COVID-related dislocations caused extreme PPP deviations (emerging-market depreciations, safe-haven inflows and slow forward-rate adjustment) temporarily making the strategy highly profitable. Such episodes, however, are rare and driven by exceptional shocks.

Across sub-samples, PPP returns vary little and profitability remains weak. Crises generate some gains due to temporary overshooting, but central-bank tightening and inflation dynamics quickly eliminate mispricing. Overall, the PPP factor exhibits low performance, high noise, fat tails and very low Sharpe ratios. This aligns with the literature: PPP offers poor short-horizon predictive power and lacks economic viability at monthly rebalancing frequencies, except in rare macro-shock episodes.

4.4 Comparison and interpretation

Comparing the two strategies, several conclusions emerge. First, gross of transaction costs, the four-day FX momentum strategy delivers higher average returns and Sharpe ratios than the PPP-based value strategy in the full sample and across most sub-periods. Once transaction costs are accounted for, however, both strategies exhibit negative average returns, with PPP being particularly affected, highlighting the importance of trading frictions at short horizons.

Second, momentum returns display pronounced fat tails, as reflected in elevated kurtosis, particularly during crisis periods, while PPP is characterized by very low average returns and weak risk-adjusted performance on a monthly horizon, with profitability concentrated in rare, macro-driven episodes. Outside these episodes, PPP returns are close to zero or negative and insufficient to compensate for trading costs.

Third, regime dependence is stronger and more economically meaningful for momentum : momentum premia expand in volatile, crisis-like environments with high cross-currency dispersion and compress or reverse in calmer periods. PPP, by contrast, remains weak on average and becomes temporarily profitable only when large macroeconomic shocks generate substantial and rapid PPP misalignments [**D**].

5 Conclusion

This project combined a review of FX momentum with an empirical implementation of a short-horizon strategy and its comparison to a PPP-based value approach. The literature documents FX momentum as a robust and distinct return factor, characterized by state dependence, with stronger performance in volatile crisis periods and weaker outcomes in calm markets.

Our four-day lookback, one-month holding momentum strategy delivers positive average returns gross of transaction costs, but becomes slightly unprofitable once realistic trading frictions are incorporated. The return distribution exhibits pronounced fat tails and strong regime dependence, with profitability increasing during periods of elevated cross-currency dispersion and compressing or reversing in low-volatility environments.

The PPP value strategy, built from forward–spot mispricing, produces very low and often negative monthly returns with weak risk-adjusted performance, becoming temporarily attractive only during rare macroeconomic shock episodes such as the COVID-19 period. Overall, FX momentum emerges as a regime-dependent premium whose economic relevance is highly sensitive to transaction costs, while PPP-based strategies appear to lack economic significance at monthly horizons. The comparison highlights the fundamental difference between exploiting short-run trends and trading slow mean reversion toward long-run PPP equilibria.

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Appendix

[A] : Detailed graphs of Momentum return strategy (monthly return and distribution)

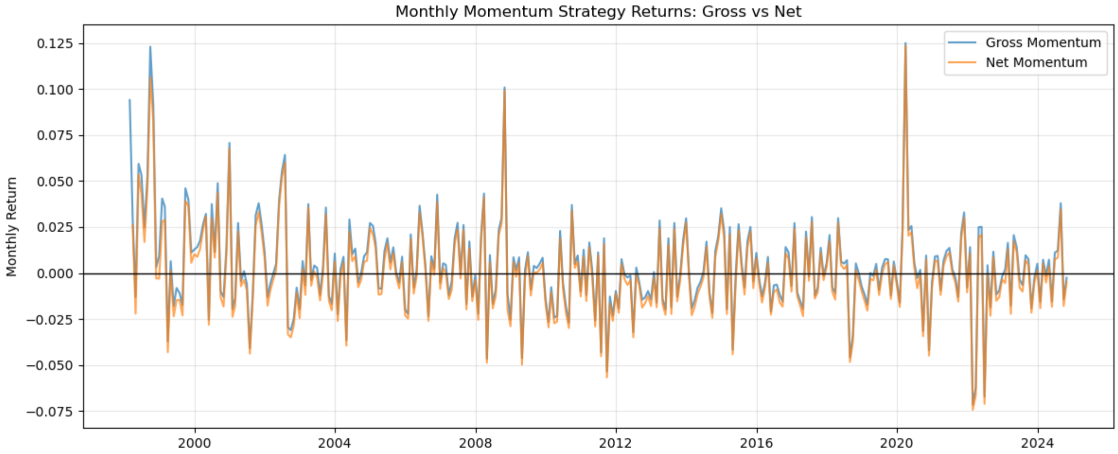

Figure 1: Monthly Momentum Returns

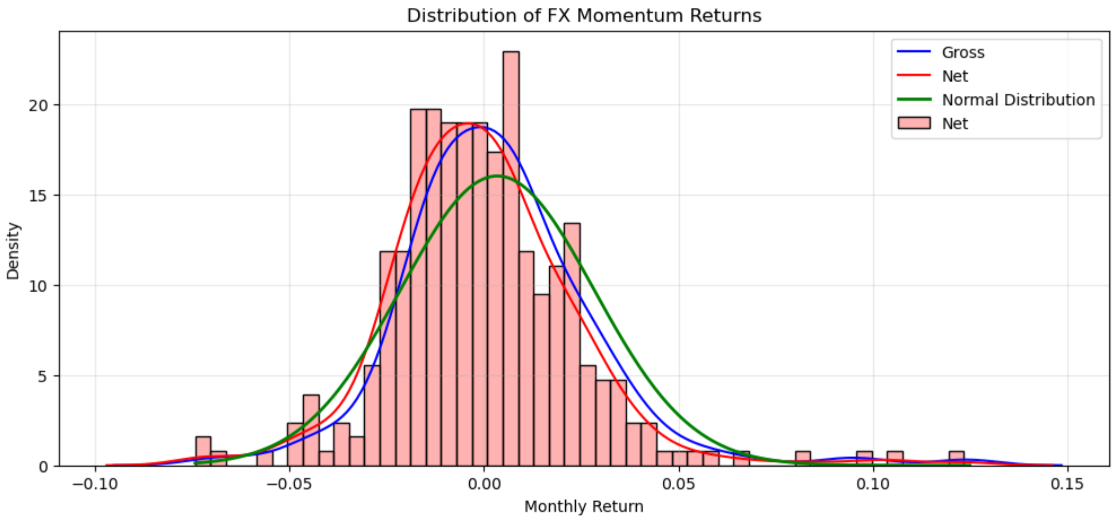

Figure 2: Momentum returns distribution

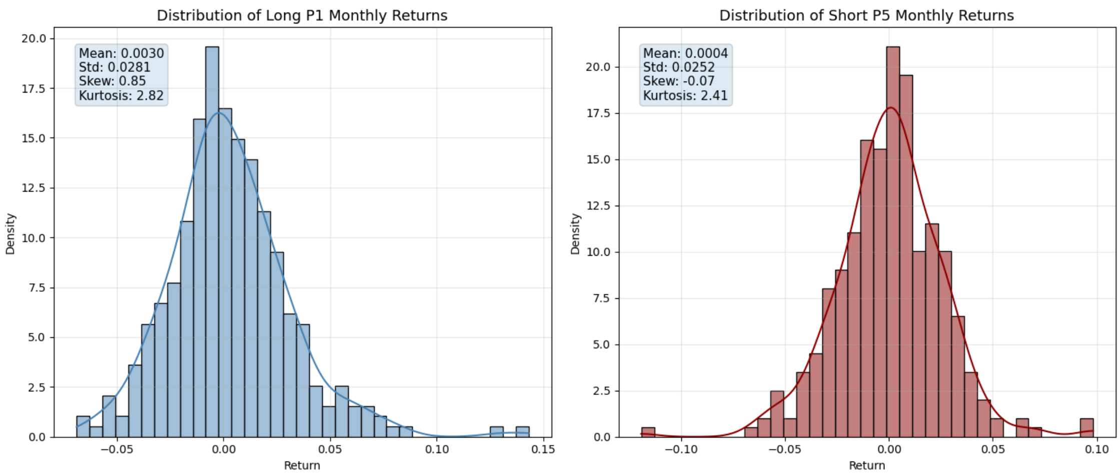

Figure 3: Detailed distribution of P5 long and P1 short Momentum strategy (monthly return and distribution)

[B] : Detailed returns of Momentum strategy (gross and net)

Gross Momentum Strategy (Sub-Samples)

	Mean (monthly)	Mean (annualized)	Std (monthly)	Std (annualized)	Skew	Kurtosis	Sharpe (annualized)
Pre-Crisis (1998–2006)	0.010827	0.137945	0.028375	0.098293	1.056464	1.894246	1.403404
Financial Crisis (2007–2009)	0.003572	0.043714	0.025561	0.088546	1.240127	4.417317	0.493685
Post-Crisis (2010–2019)	-0.002256	-0.026742	0.017764	0.061538	-0.074969	-0.001524	-0.434569
Covid Period (2020–2021)	0.008013	0.100513	0.030558	0.105855	2.189469	7.258310	0.949529
Post-Covid (2022–2024)	-0.003279	-0.038646	0.024407	0.084548	-1.352302	1.920958	-0.457090

Figure 4: Gross Momentum Returns

Net Momentum Strategy (Sub-Samples)

	Mean (monthly)	Mean (annualized)	Std (monthly)	Std (annualized)	Skew	Kurtosis	Sharpe (annualized)
Pre-Crisis (1998–2006)	0.005700	0.070587	0.026417	0.091511	0.856420	1.351689	0.771348
Financial Crisis (2007–2009)	0.000395	0.004752	0.025835	0.089496	1.285078	4.477323	0.053102
Post-Crisis (2010–2019)	-0.005224	-0.060913	0.017689	0.061276	-0.084743	-0.003921	-0.994080
Covid Period (2020–2021)	0.005264	0.065034	0.030774	0.106605	2.218560	7.385434	0.610044
Post-Covid (2022–2024)	-0.006861	-0.079300	0.024384	0.084469	-1.358983	1.910001	-0.938806

Figure 5: Net Momentum Returns

[C] : Detailed graphs of PPP return strategy (monthly return and distribution)

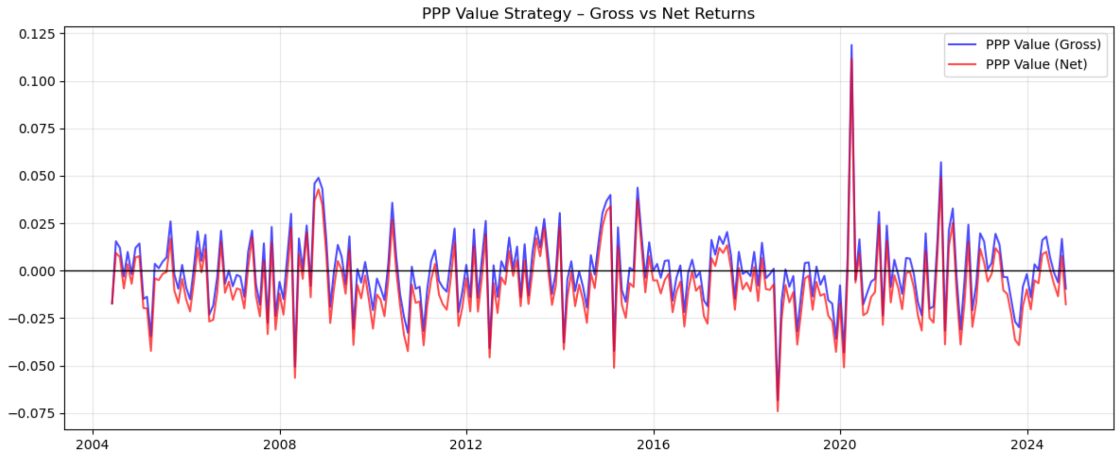

Figure 6: Monthly PPP Returns

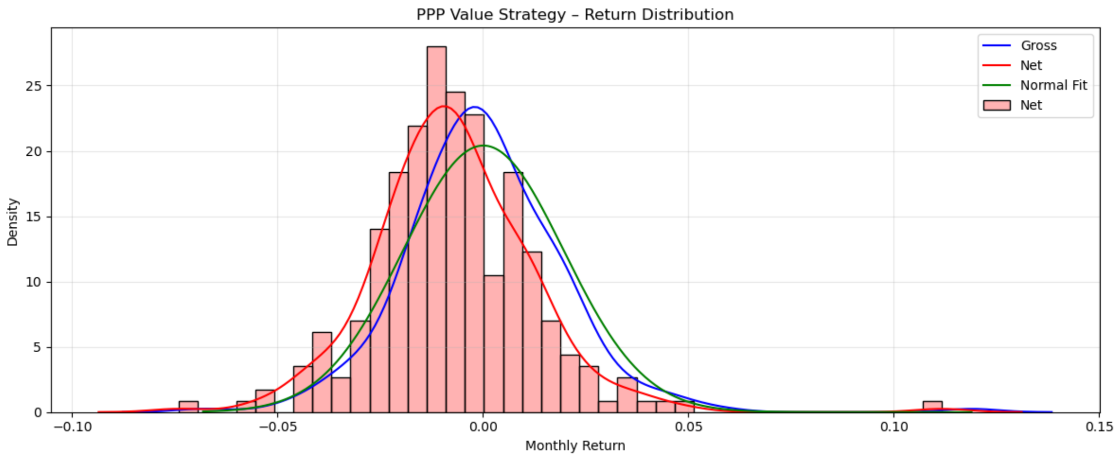

Figure 7: PPP returns distribution

[D] : Evolution of returns for each strategy through time

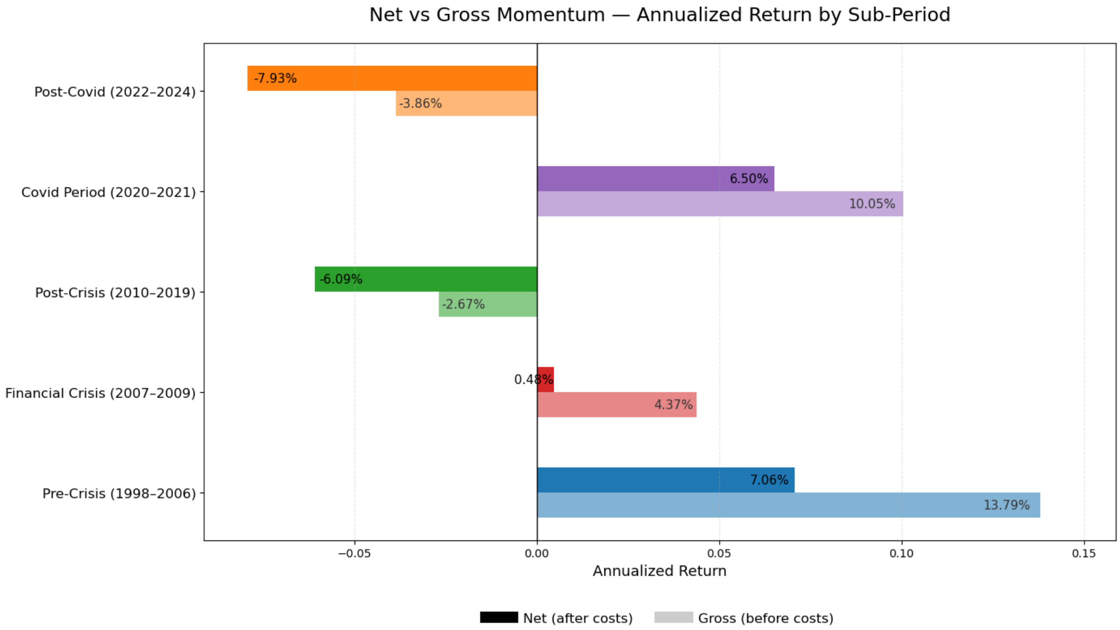

Figure 8: Momentum Returns

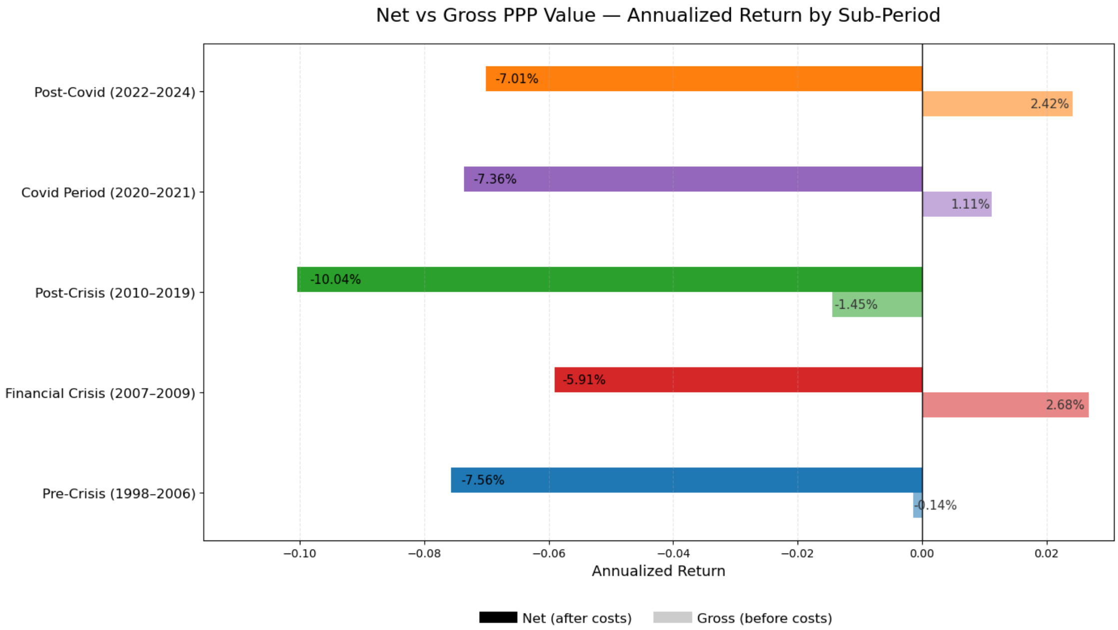

Figure 9: PPP returns

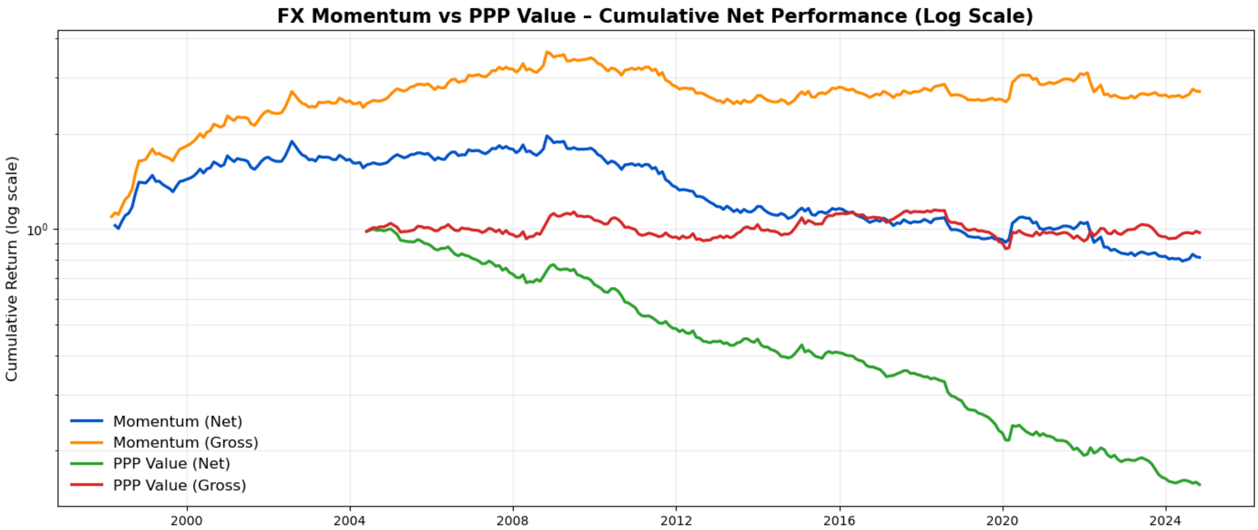

Figure 10: Cumulative returns for each strategy over time

Individual Contributions

Christian Abi Rizk: research and literature review.

Tristan Le Nest: integration of all sections and reduction of the report to the final five-page format.

Yassine Oueriemmi: coding, strategy implementation, and backtesting.

Younes Louafi: research and literature review.

Vuk David Stramput: analysis and interpretation of results.