Which Asset Classes Give a Swiss Investor a Good Hedge Against Inflation

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Abstract

This study investigates the inflation-hedging potential of various asset classes for Swiss investors, focusing on the ability of stocks, fixed income, real estate, commodities, and cryptocurrencies to preserve purchasing power during inflationary periods. By applying three analytical methodologies — single-beta linear regression, correlation analysis, and real return analysis — we evaluate the effectiveness of these asset classes over different time horizons (short-term, medium-term, and long-term). Key findings suggest that real estate consistently provides strong protection against long-term inflation, while commodities offer short- to medium-term benefits. Fixed income securities, especially inflation-linked bonds, show moderate effectiveness, and cryptocurrencies, despite their high real returns, exhibit high volatility and limited reliability as inflation hedges.

1 Introduction

1.1 Motivation

Inflation erodes the purchasing power of money, posing a significant challenge for investors seeking to preserve and grow their wealth. For Swiss investors, this challenge is particularly complex due to Switzerland's historically low inflation rates and the strength and stability of the currency, which distinguish it from global markets. However, the current global economic environment — shaped by the recent COVID-19 pandemic, rising inflation, and heightened uncertainty — has raised concerns about the ability of traditional investment strategies to sustain real returns. As a result, identifying asset classes and constructing portfolios that potentially protect against inflation has become of significant importance for preserving wealth and achieving financial objectives. This study focuses on Swiss investors and therefore Swiss inflation to provide relevant insights into how portfolios of different asset classes, including stocks, commodities, fixed income, real estate, and cryptocurrencies, perform as hedging tools during inflationary periods. By analyzing multiple time frames, this study aims to give insights in building inflation-resilient portfolios and selecting specific securities within each asset class that offer superior protection against inflationary pressures.

1.2 Background

According to Parkin (2015) [9], inflation can be described as "a process of continuously rising prices, or equivalently, a continuously falling value of money." In academic studies, the Consumer Price Index (CPI) is widely adopted as an inflation proxy because it effectively captures consumer price growth, providing a stable and consistent indicator of inflation trends. Although CPI has certain limitations, such as timing lags in data publication, international measurement discrepancies, and potential misalignment with individual price changes, it remains the standard measure for analyzing inflation and its impact on asset performance. Hedging, in the context of inflation, refers to the ability of an asset to maintain or increase its real value relative to inflation. A strong inflation hedge is characterized by a stable, positive correlation between the asset's returns and inflation (Fama & Schwert, 1977) [6]. In theory, a "perfect hedge" would exhibit a correlation coefficient of 1, with the asset's returns fully offsetting increases in the price level. While such perfection is rarely attainable, the practical goal of inflation hedging is to identify assets that exhibit meaningful co-movement with inflation, providing investors with protection against eroding purchasing power(Bodie, 1976) [2]. This study adopts this practical definition and further applies the reals return and linear regression method to identify asset classes and build portfolios that exhibit a positive relationship with inflation, offering real protection to Swiss investors without excessive reliance on leverage or complex strategies.

1.3 Context and Literature Review

The question of which asset classes serve as the most effective inflation hedges has been the focus of extensive academic inquiry. In their comprehensive review, *What Do Scientists Know About Inflation Hedging?*, Stephan Arnold and Benjamin R. Auer (2015) [1] synthesize empirical evidence on the inflation-hedging effectiveness of stocks, gold, fixed-income securities, and real estate. Their findings reveal mixed results across asset classes, highlighting that no single asset class consistently provides effective inflation protection. Additionally, their review emphasizes the need for a comprehensive analysis of multiple asset classes in a single framework to enable direct comparisons and offer actionable insights for specific investor groups. Building on their work, this paper seeks to fill that gap by conducting a simultaneous analysis of multiple asset classes over the same time horizon, focusing on inflation-hedging opportunities available to Swiss investors. Given the rising interest and debate surrounding cryptocurrencies as potential inflation hedges due to their decentralized nature and limited supply (Bouri et al., 2017) [4], we extend our analysis to include this emerging asset class. Cryptocurrencies have been likened to gold in their inflation-hedging potential. However, their high volatility and relatively short track record as an asset class make their effectiveness as inflation hedges a subject of ongoing debate.

1.4 Research Objectives

This study examines inflation-hedging strategies for Swiss investors by analyzing multiple asset classes over short and long-term periods. Specifically, we aim to:

- Assess the inflation-hedging effectiveness of key asset classes, including stocks, commodities, fixed income, real estate, and cryptocurrencies, focusing on instruments accessible to Swiss investors.

- Compare the performance of these asset classes across different inflationary environments and time periods to identify patterns and trends.
- Extend the analysis to include emerging asset classes, such as cryptocurrencies, and evaluate their role in diversified portfolios for inflation protection.

1.5 Structure of the Paper

The remainder of this paper is organized as follows. While Section 2 defines the key asset classes, Section 3 presents the methodology and data collection including the evaluation framework and calculation methods to evaluate the inflation-hedging potential of each asset class and build the best hedging portfolio. Section 4 discusses the results, and Section 5 concludes with practical implications for Swiss investors.

2 Asset Classes

Based on the findings of Stephan Arnold and Benjamin R. Auer (2015) in their paper "What Do Scientists Know About Inflation Hedging?" [1], we selected the following asset classes.

2.1 Stocks

The literature review suggests that stocks have a limited capacity to hedge against inflation in the short term, as evidenced by a negative relationship with changes in inflation rates. However, recent studies indicate stocks can provide inflation protection over periods exceeding five years.

2.2 Gold, Commodities

Gold has historically exhibited a strong positive relationship with inflation, making it a popular choice as a store of value during inflationary periods. While early studies often highlight a co-integrated relationship between gold and inflation, more recent research (published after the financial crisis in 2008) suggests that this connection can vary depending on economic conditions and reaches from non-existent over driven by outliers to strong time-dependency. To broaden our analysis, we extended the focus from gold to commodities as a whole, assessing their inflation-hedging potential for Swiss investors.

2.3 Fixed Income

Research on the link between interest rates and inflation is extensive, but fewer studies focus on testing how well fixed-income securities hedge against inflation. They are generally sensitive to inflation, as nominal bonds lose value during inflationary periods due to their fixed coupon payments. Inflation-linked bonds (ILBs) provide protection against inflation, but their limited liquidity and maturities restrict their use. While traditional bonds are negatively correlated with inflation in the short term, they may offer long-term inflation protection when included in a diversified portfolio, thanks to their lower volatility and low correlation with other asset classes.

2.4 Real Estate

Earlier studies viewed direct real estate as a partial inflation hedge, but data limitations posed challenges. Research on REITs initially showed a negative link to inflation. More recent studies using cointegration methods have yielded mixed results. The effectiveness of real estate as an inflation hedge depends on factors like the time period, inflation regime, and type of real estate.

2.5 Cryptocurrency

Cryptocurrencies have gained attention as potential inflation hedges, primarily due to their limited supply and decentralized nature (Bouri et al., 2017) [4]. Proponents argue that assets like Bitcoin share similarities with gold, particularly in terms of scarcity. However, empirical evidence on their effectiveness as inflation hedges remains inconclusive, as cryptocurrencies are highly volatile and have a relatively short history as an asset class (Cheema et al., 2020) [5].

3 Methodology

3.1 Econometric Approaches Used From the Researchers

Researches tried to observe hedging with different assets with different econometrics approaches. So far, there is no single approach, which would be suitable for all assets in general, each of them has some limitations and are more or less appropriate for different asset classes. The approaches that researchers have used in the past are following:

- *Ordinary Least Squares (OLS) Regression* combines short-term deviations with long-term equilibrium dynamics. Limitations are:
  - assuming a linear relationship, which may not capture complex dynamics,
  - prone to spurious results if variables are non-stationary without transformation [1, 7].
- *Cointegration Techniques* test long-term relationships between asset returns and inflation, accounting for non-stationary data. Limitations are:
  - sensitive to the presence of structural breaks,
  - requires stationary variables for validity, which may lead to conflicting results [1, 7].
- *Vector Autoregression (VAR)* explores explores the dynamic relationship between inflation and asset returns across multiple variables. *Vector Error Correction Models (VECM)* handles non-stationary variables with cointegration. Limitations are:
  - it's best suited for exploring dynamic interactions but relies on robust stationarity assumptions,
  - results are sensitive to the choice of lag length and model specification [1, 7].
- *Error Correction Models (ECM)* combines short-term deviations with long-term equilibrium dynamics. Limitation is that approach captures short- and long-term effects but depends on cointegration evidence between variables. It is also not applicable for observing the quality of real estate returns in hedging against inflation [1, 7].
- *Threshold and Nonlinear Models* allow for asymmetric effects and regime-specific behaviors in asset-inflation relationships. Limitations are:
  - complex models requiring large datasets for stability,
  - results may vary across different economic regimes,
  - not applicable for observing the quality of stocks and real estate returns in hedging against inflation [1, 7].
- *Panel Regression and Cross-Sectional Analyses* aggregates data across countries or regions to identify patterns in inflation hedging. Limitations are:

- approach aggregates data across regions, potentially masking country-specific effects,
- not applicable for observing the quality of real estate returns in hedging against inflation [1, 7].

- *Kalman Filter and Markov-Switching Models* capture time-varying relationships and regime shifts. Limitation is high computational complexity and requires extensive data for reliable estimates. It is also applicable only for observing the quality of gold returns in hedging against inflation [1, 7].

3.2 Our Approach to Evaluating Asset Classes as Inflation Hedges

We focus solely on the hedging capabilities (safety) of asset classes against inflation rather than their returns. Our interest lies in their ability to preserve purchasing power during inflationary periods, independent of their overall performance as investment vehicles. Unlike the advanced techniques in the base paper, such as OLS regression, cointegration, and nonlinear models, our approach prioritizes interpretability and practical application for portfolio construction. The research was conducted in two primary steps: selecting an evaluation framework and applying calculation methods. Each framework employed three different calculation approaches: correlation, real return, and linear regression, so in total we have 9 different options:

Step 1: Selecting an Evaluation Framework

In the first step we chose one of three frameworks to analyze the data:

- **All possibilities method:** This framework generates all possible portfolios by exploring combinations of assets within each class. We give a multitude of tickers as an input and it calculates the output of each subset, where we define what the minimum size (number of tickers) of the portfolio needs to be. The combinations include portfolios with 1, 2, or more assets, with equal weights assigned for simplicity. This method allows flexibility to define a minimum number of assets per portfolio. We selected this framework as our primary approach due to its sophistication and comprehensive scope. We included a condition, that at least 2 different asset tickers need to be included in each asset class. Additionally, the interpretation of results is grounded in the "all possibilities" framework.

- **Rolling window method:** It represents a sliding time frame used for analysis. Instead of calculating a static over the entire dataset, it computes it repeatedly over fixed-length window of data. A rolling window of 12 months was applied to dynamically evaluate the performance of portfolios over time. In practice, it means that code takes last 12 months of data, calculate statistics, store results, then slide the window by one month and repeat the calculation, then continue doing this until the end of the dataset.

- **Single-value method:** This method calculates a single, static value for each metric over the entire period, providing an overall assessment of performance. Focus is on how one particular asset behaves under certain economic conditions or over time.

Step 2: Applying Calculation Methods

In the second step we choose one of the three calculation methods which we apply to each of the three frameworks from the first step:

- **Correlation:** measures the strength and direction of the linear relationship between two variables. In this context, it evaluates how closely inflation and portfolio returns move together. Ideally, we seek a correlation of 1, indicating that portfolio returns perfectly match inflation changes.

$$\rho_{\text{inflation, return}} = \frac{\sum_{i=1}^{n}\left((x_i - \bar{x})(y_i - \bar{y})\right)}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

  - Advantage: simple to compute and interpret, providing a quick measure of co-movement.
  - Disadvantage: does not account for non-linear relationships or causation (scenario where one variable directly influences another, whereas correlation only shows a statistical association without proving cause and effect) [8].

- **Real return:** adjusts nominal returns for inflation, providing a clearer picture of the true growth in purchasing power. Portfolios with consistently high real returns are considered effective hedges.

$$R_{\text{real}} = \left(\frac{1 + R_{\text{nominal}}}{1 + R_{\text{inflation}}} - 1\right) \times 100$$

  - Advantage: directly reflects the actual financial outcome after adjusting for inflation.

- Disadvantage: similar to other methods, it does not account for other factors influencing returns beyond inflation [3].

- **Single-beta linear regression:** models the relationship between portfolio returns (dependent variable) and inflation (independent variable). Linear regression establishes a predictive relationship and assesses the strength of inflation sensitivity. The regression coefficient indicates the sensitivity of portfolio returns to inflation, where a significant positive coefficient close to 1 implies effective inflation hedging [7].

$$\text{asset\_return}_t = \beta_0 + \beta_1 \cdot \text{actual\_inflation}_t + \epsilon_t$$

  - Advantage: provides a quantitative measure of sensitivity and can include multiple predictors.
  - Disadvantage: assumes a linear relationship, which may not always hold in financial data.

Our **robustness check analysis** encompasses three distinct perspectives to ensure the validity and reliability of our findings:

- Alternative calculation methodologies: We employ multiple approaches to verify the consistency of results across different computational frameworks.
- Varied time horizons: The analysis is conducted over multiple temporal ranges, including 2-year, 5-year, and 10-year periods, as well as the maximum available timeframe for each asset class, defined by the extent of historical data availability.
- Diverse time intervals: We examine performance across different time aggregation intervals, specifically month-over-month (MoM) and year-over-year (YoY), to capture potential variations in temporal patterns.

3.3 Methodology Overview and Further Research Possibilities

This methodology was chosen for its ability to provide a structured approach consisting of three evaluation frameworks in the first step (all possibilities, rolling window, and single-value) and three calculation methods in the second step (correlation, real return, and single-beta linear regression). This methodology combines a comprehensive portfolio generation approach with robust evaluation techniques. The use of multiple metrics ensures a well-rounded understanding of how different asset classes perform as inflation hedges.

An additional avenue for research could explore a fourth calculation method focused on decomposing inflation into expected and unexpected components. In this approach, Step 1 would involve calculating unexpected inflation for each period using historical data. This can be done either by subtracting analysts' forecasts from actual inflation or by using an autoregressive (AR) model where unexpected inflation is represented by the regression residual (ε_t). Step 2 involves regressing asset returns on both expected and unexpected inflation components, as shown below:

$$\text{asset\_return}_t = \beta_0 + \beta_1 \cdot \text{expected\_inflation}_t + \beta_2 \cdot \text{unexpected\_inflation}_t + \epsilon_t$$

Here, the coefficients (β_1 and β_2) measure the asset's sensitivity to each component. This method could provide deeper insights into how asset classes respond differently to predictable and unpredictable changes in inflation.

3.4 Data Collection

3.4.1 Swiss Inflation Data

We extracted the Consumer Price Index (CPI) data from the Swiss Federal Statistical Office. The dataset provided detailed results of the CPI, with the base year set to December 2020 (CPI = 100), covering the period from December 1, 1982, to November 30, 2024. This data included the structure of the CPI basket for 2020, along with additional classifications. To calculate the inflation rate, the total CPI values were used as the primary measure. The inflation rate was computed as the percentage change in the CPI compared to the previous year's value. In cases where the calculated real return resulted in a value of zero inflation (i.e., no change in CPI), we adjusted these instances by assigning a small, positive value of 0.000000001. This adjustment ensured that the dataset maintained its integrity for further analysis without introducing any computational issues associated with zero inflation. The chosen approach allowed for a more robust and precise inflation calculation while ensuring that the impact of small changes in the CPI was accounted for, avoiding zero inflation entries in the dataset.

3.4.2 Financial Data

The tickers for each asset class were chosen with the help of ChatGPT, focusing on tradable and relevant tickers for a Swiss investor, with an emphasis on Yahoo Finance availability to ensure liquidity. We chose Yahoo Finance as the primary data source due to its seamless integration with Python through the `yfinance` library that streamlines data extraction and preprocessing, improving efficiency and reproducibility. Furthermore, it provides accurate historical time series data, including daily adjusted closing prices, crucial for calculating returns and evaluating inflation-hedging potential. We did no extra data preparation beyond matching the dates of the available tickers to the inflation data dates. For the analysis, we only used the adjusted closing prices for each ticker to calculate the real return, as this price accounts for dividends, stock splits, and other corporate actions, ensuring a more accurate reflection of the actual investment return. Additionally, no currency conversion was performed. This decision was made because the focus of the analysis was on the nominal and real returns in the local market of the Swiss investor. By using tickers that are listed in Swiss Francs (CHF) or other widely recognized global currencies, we assumed that any minor fluctuations in exchange rates would not significantly alter the overall inflation-hedging analysis. This approach also ensured that the data could be directly applied to a Swiss context, without introducing the complexity and potential distortions that could arise from currency conversions.

To assess the hedging potential of stocks for Swiss investors, ChatGPT curated a diverse selection of stocks, integrating domestic stability with global diversification. This selection includes constituents of the Swiss Market Index (SMI), as well as the top companies by market capitalization from the S&P 500, European, and Asian markets. For the commodity tickers, Chat GPT identified the relevant subsections: broad commodity ETFs, precious metals ETFs, energy ETFs, agriculture ETFs, industrial metals ETFs, specific commodity ETFs, leveraged and inverse commodity ETFs, commodity equity ETFs, commodity futures ETFs, and currency-hedged commodity ETFs, and further defined the tickers ensuring their availability and accessibility for Swiss investors. For the analysis of fixed income securities, Chat GPT selected tickers for the broad market bond ETFs, government bond ETFs, corporate bond ETFs, high yield bond ETFs, inflation-linked bond ETFs, short duration bond ETFs, emerging markets, bond ETFs, corporate bond ETFs by maturity, hight yield bond ETFs by maturity, and aggregate bond ETFs. Last for cryptocurrencies, ChatGPT selected the tickers of the 5 largest cryptocurrencies by market capitalization for this analysis. Due to computational limitations however, we had to reduce the number of tickers for our analysis significantly. A detailed overview of the used tickers for the results can be found in the Appendix.

4 Results

In the Results section, we will present and analyze the findings of our research. This section focuses exclusively on the all-possibilities framework, as outlined in the Methodology section. This approach has been selected due to its sophistication and ability to provide a comprehensive analysis of the research question. Within this framework, we utilize three distinct calculation methods: correlation analysis, real return assessment, and single-beta linear regression.

It is important to highlight that our analysis prioritizes hedging capabilities—emphasizing safety and risk mitigation—rather than profit potential. The analysis and findings presented in this project are for informational and academic purposes only and should not be construed as financial advice or recommendations.

4.1 Intuition Behind Results

First, we need to make clear which values of each calculation method are more favorable than the others.

- Correlation: ideally, we would like to have an asset with correlation coefficient of 1. An asset with a correlation of +1 with inflation directly mirrors inflationary movements. This ensures that the asset's value grows at the same rate as inflation, preserving purchasing power perfectly.

- Real return: we prefer assets with high real returns, because assets which maintain or grow their purchasing power during inflationary periods are better hedges. A consistently positive real return, especially during periods of high inflation, is ideal.

- Single-beta linear regression: beta measures the sensitivity of the asset's return to changes in inflation. A beta coefficient of 1 is ideal, indicating the asset's return increase proportionally with inflation.

4.2 Code Outputs

Generated portfolios for each asset class with highest correlation coefficients:

- Correlation method divided into interval and period (horizon), presenting best portfolio consisting of at least 2 assets for each asset class and corresponding correlation coefficient:

Interval	**Period**	**Top Asset Classes (Tickers)**	**Corr. Coeff.**
MoM	5y	Fixed Income (IBTM.L, IEML.L), Stocks (MC.PA, AAPL)	0.99, 0.98
	10y	Stocks (AAPL, TSM), Crypto (BTC-USD, ADA-USD)	0.77, 0.39
	Max	Fixed Income (CORP.L, IBCI.L, TIPS.L, ERNE.L), Crypto (BTC-USD, BNB-USD)	0.57, 0.52
YoY	5y	Real Estate (SPSN.SW, PSPN.SW), Commodities (TGLN.L, BRNT.L)	0.62, 0.46
	10y	Commodities (IGLN.L, BRNT.L), Stocks (NVO, MC.PA)	0.63, 0.31
	Max	Commodities (IGLN.L, BRNT.L), Stocks (SSMI, NESN.SW)	0.67, 0.12

Table 1: Top Asset Classes and Correlations Across Measures and Periods

- Real return method divided into interval and period (horizon), presenting best portfolio consisting of at least 2 assets for each asset class and corresponding cumulative real return:

Interval	**Horizon**	**Top Asset Classes (Tickers)**	**Cumulative Real Return**
MoM	2y	Stocks (SAP, NVDA), Commodities (LGCF.L, BRNT.L)	17.91, 2.60
	5y	Cryptocurrency (ETH-USD, ADA-USD), Stocks (TSM, TCEHY)	87.13, 48.17
	10y	Cryptocurrency (ETH-USD, ADA-USD), Stocks (TSM, TCEHY)	172.28, 85.37
	Max	Stocks (TSM, TCEHY), Cryptocurrency (ETH-USD, ADA-USD)	681.61, 172.28
YoY	2y	Stocks (NVO, NVDA), Cryptocurrency (BTC-USD, ETH-USD)	138.23, 61.88
	5y	Stocks (NVO, NVDA), Commodities (BRNT.L, SOYB.L)	607.98, 83.45
	10y	Cryptocurrency (BTC-USD, BNB-USD), Stocks (NVO, NVDA)	80572.20, 4473.53
	Max	Stocks (AAPL, NVDA), Cryptocurrency (BTC-USD, BNB-USD)	906707.49, 80572.20

Table 2: Top Asset Classes and Cumulative Real Returns Across Measures and Periods

- Single-beta linear regression method divided into interval and period (horizon), presenting best portfolio consisting of at least 2 assets for each asset class and corresponding coefficient β:

Interval	**Horizon**	**Top Asset Classes (Tickers)**	**Beta**
MoM	5y	Commodities (IGLN.L, ISLN.L), Fixed Income (CORP.L, LQDE.L)	6.56, 11.72
	10y	Fixed Income (TIPS.L, IEML.L), Real Estate (IYR, REET)	1.15, 2.55
	Max	Real Estate (IYR, REET), Commodities (LGCF.L, BRNT.L)	1.73, 16.98
YoY	5y	Stocks (NESN.SW, NVO), Real Estate (SPSN.SW, PSPN.SW)	3.61, 5.33
	10y	Real Estate (PSPN.SW, REET), Fixed Income (ERNE.L, TEML.L)	1.37, 0.08
	Max	Real Estate (PSPN.SW, REFT), Fixed Income (ERNE.L, TEML.L)	3.28, 0.42

Table 3: Top Asset Classes and Betas Across Measures and Periods

4.3 Interpretation of Results

Based on the findings of our research, we present the following observations regarding hedging against Swiss inflation from the perspective of a Swiss investor. In this analysis, we have chosen to focus exclusively on the single-beta linear regression methodology due to several compelling factors:

- The interpretation of real returns is not particularly intuitive for this context.
- The correlation-based approach tends to highlight asset classes that are inherently more volatile and risky, such as cryptocurrencies and stocks.
- The results derived from the single-beta linear regression approach align more closely with established economic theories, which posit that commodities, fixed income, and real estate are effective tools for hedging against inflation.

Each of the specific asset tickers and corresponding portfolios identified in this study represent the best options within their respective asset classes. These findings provide a robust framework for constructing tailored investment strategies to hedge against inflation effectively across varying time horizons. A critical aspect of this analysis is determining the desired hedging timeframe, whether it pertains to short-term inflation (5 years), medium-term inflation (10 years), or long-term inflation (the maximum observed period, at least 15 years). For clarity, MoM (month-over-month) refers to observations based on monthly data, while YoY (year-over-year) refers to observations based on annual data.

4.3.1 Short-Term Inflation Hedging

For short-term inflation hedging (5 years horizon), the MoM interval suggests commodities, specifically IGLN.L and ISLN.L, as favorable options. On the other hand, the YoY interval identifies stocks (NESN.SW and NVO) and real estate (SPSN.SW and PSPN.SW) as effective choices. Based on these observations, a combination of commodities, real estate, and stocks appears to be the optimal strategy for mitigating short-term inflation risks.

4.3.2 Medium-Term Inflation Hedging

For a medium-term horizon (10 years), the MoM interval highlights fixed income assets, such as TIPS.L and IEML.L, as well as real estate (IYR and REET). Similarly, the YoY interval also emphasizes real estate (PSPN.SW and REET) and fixed income (ERNE.L and TEML.L) as suitable options. Consequently, we conclude that a diversified portfolio consisting of real estate and fixed income instruments is the most effective strategy for addressing medium-term inflation.

4.3.3 Long-Term Inflation Hedging

For a long-term investment horizon (more than 15 years), both the MoM and YoY intervals consistently suggest real estate as the preferred asset class for hedging against inflation. Specifically, real estate assets such as IYR, REET, and PSPN.SW demonstrate strong hedging potential. This consistency across different intervals reinforces real estate as the optimal choice for long-term inflation protection.

Consistent with the literature review of Stephan Arnold and Benjamin R. Auer (2015)[1], our results suggest that short-term inflation hedging is best served by commodities, while stocks and real estate are more effective in the long-term (10-year horizon). In line with Arnold and Auer's findings, we also observe that fixed income assets and real estate perform well in medium-term hedging. Furthermore, our results confirm their conclusion that real estate is the most reliable long-term inflation hedge. While cryptocurrencies have been cited as potential hedges due to their decentralized nature (Bouri et al., 2017) [4], their volatility and relatively short history make them less conclusive as inflation protectors in our analysis.

5 Conclusion

This study investigates the inflation-hedging potential of various asset classes, including stocks, commodities, fixed income, real estate, and cryptocurrencies, for Swiss investors. The **findings reveal** several key insights. *Stocks* demonstrated uncertain effectiveness as inflation hedges, with correlation decreasing over longer horizons—an unfavorable trend—while beta from linear regression also declined, suggesting a potentially favorable but inconclusive relationship. *Commodities*, such as gold and broad commodity ETFs, exhibited robust hedging capabilities in short- to medium-term horizons under year-over-year analysis, indicating their potential as a flexible and dynamic component of inflation-hedging strategies. Fixed income securities, especially inflation-linked bonds, provided moderate hedging effectiveness, particularly in medium-term horizons, and offer a balanced approach between risk and return. *Real estate* consistently demonstrated strong effectiveness as a hedge against long-term inflation across various time horizons, particularly when analyzed using single-beta linear regression. This asset class showed stability and reliability, making it a preferred option for Swiss investors seeking consistent inflation protection. *Cryptocurrencies*, while exhibiting high real returns during inflationary periods, were found to have substantial volatility and inconsistent correlation with inflation, highlighting their speculative nature and limited suitability for conservative inflation protection. Overall, these findings underline the importance of diversification across asset classes to achieve effective inflation protection while balancing risk and return considerations. Each asset class demonstrated unique strengths and limitations, suggesting that their combined use in a portfolio can enhance resilience against inflationary pressures.

Our analysis is constrained by several **limitations**. Computational constraints arise from the all-possibilities framework, which requires significant processing power to compute all possible combinations of assets. Due to the characteristics of our available hardware, we are limited in the number of assets we can include, which may impact the comprehensiveness of our results. Additionally, the reliance on historical data, which varies in availability across asset classes, may constrain the comparability of results. The linear regression model employed assumes a constant relationship between returns and inflation, which may oversimplify the complex dynamics observed in real-world markets. Furthermore, the exclusion of currency effects assumes minimal impact from exchange rate fluctuations, which might not always hold true for globally diversified portfolios.

Future research could address these limitations by employing advanced econometric models, such as nonlinear regression or machine learning techniques, to capture the dynamic and complex relationships between asset returns and inflation. Decomposing inflation into expected and unexpected components could offer deeper insights into how asset classes respond to different inflationary conditions. Additionally, investigating alternative asset classes, such as private equity or infrastructure investments, may uncover further opportunities for inflation protection. Including the impact of currency fluctuations and considering macroeconomic factors, such as interest rates and economic growth, could also provide a more comprehensive understanding of inflation hedging strategies.

6 Appendix

6.1 Asset Classes - Tickers

6.1.1 Stocks

CH	**EU**	**S&P500**	**Asia**
ŜSMI	NVO	ĜSPC	TSM
ROG.SW	MC.PA	AAPL	TCEHY
NESN.SW	SAP	NVDA	

Table 4: Stock Tickers by Region and Category

6.1.2 Commodities

Category	**Ticker**
Broad Commodity ETFs	LGCF.L
Gold ETFs	IGLN.L
Energy ETFs	BRNT.L
Silver ETFs	ISLN.L
Specific Commodity ETFs	NGAS.L
	WEAT.L
	CORN.L
	SOYB.L

Table 5: Commodity ETFs Tickers

6.1.3 Fixed Income Securities

Category	Ticker
Broad Market Bond ETFs	CORP.L
Government Bond ETFs	IBTM.L
Corporate Bond ETFs	LQDE.L
High Yield Bond ETFs	IHYG.L
Inflation-Linked Bond ETFs	IBCI.L TIPS.L
Short Duration Bond ETFs	ERNE.L
Emerging Markets Bond ETFs	IEML.L

Table 6: Fixed Income Securities Tickers

6.1.4 Real Estate

Category	Ticker
Swiss Real Estate Companies	SPSN.SW PSPN.SW ALLN.SW MOBN.SW
Swiss Real Estate Funds	SRECHA.SW PSCF.SW
International Real Estate ETFs	IYR REET

Table 7: Real Estate Tickers

6.1.5 Cryptocurrencies

Cryptocurrency
BTC-USD
ETH-USD
BNB-USD
XRP-USD
ADA-USD

Table 8: Cryptocurrency Tickers

6.2 Results

Period	Stocks	Commodities	Fixed Income	Real Estate	Cryptocurrencies
Maximum MoM Correlation					
5y	MC. PA, AAPL: 0.98	IGLN.L, ISLN.L: 0.73	IBTM.L, IEML.L: 0.99	SPSN.SW, PSPN.SW: 1.00	BTC-USD, BNB-USD: 0.61
10y	AAPL, TSM: 0.77	IGLN.L, BRNT.L: 0.30	IHYG.L, ERNE.L: 0.27	IYR, REET: 0.12	BTC-USD, ADA-USD: 0.39
max	MC.PA, TSM: 0.51	LGCF.L, IGLN.L, BRNT.L: 0.48	CORP.L, IBCI.L, TIPS.L, ERNE.L: 0.57	IYR, REET: 0.08	BTC-USD, BNB-USD: 0.52
Maximum YoY Correlation					
5y	NESN.SW, NVO: 0.81	BRNT.L, TGLN.L: 0.46	IBCI.L, TIPS.L: 0.72	SPSN.SW, PSPN.SW: 0.62	BTC-USD, ETH-USD: 0.50
10y	NVO, MC.PA: 0.31	IGLN.L, BRNT.L: 0.63	ERNE.L, TEML.L: 0.36	PSPN.SW, REET: 0.25	BTC-USD, BNB-USD: 0.39
max	SSMI, NESN.SW: 0.12	IGLN.L, BRNT.L: 0.67	ERNE.L, TEML.L: 0.42	PSPN.SW, REET: 0.33	BTC-USD, BNB-USD: 0.52
Maximum MoM Real Return					
2y	SAP, NVDA: 17.91	LGCF.L, BRNT.L: 2.60	IBTM.L, TIPS.L: 1.45	SPSN.SW, PSPN.SW: 1.20	BTC-USD, ETH-USD: 3.25
5y	TSM, TCEHY: 48.17	ETH-USD, ADA-USD: 87.13	IEML.L, CORP.L: 3.75	REET, IYR: 2.85	BTC-USD, ETH-USD: 61.88
10y	TSM, TCEHY: 85.37	ETH-USD, ADA-USD: 172.28	TIPS.L, IBTM.L: 6.25	IYR, REET: 4.15	BTC-USD, BNB-USD: 80572.20
max	TSM, TCEHY: 681.61	ETH-USD, ADA-USD: 172.28	CORP.L, TIPS.L: 5.95	PSPN.SW, REET: 5.45	BTC-USD, ETH-USD: 906707.49
Maximum YoY Real Return					
2y	NVO, NVDA: 138.23	BRNT.L, TGLN.L: 83.45	IBTM.L, IEML.L: 3.35	SPSN.SW, PSPN.SW: 3.25	BTC-USD, ETH-USD: 7.45
5y	NVO, NVDA: 607.98	BRNT.L, SOYB.L: 87.15	TIPS.L, IBCI.L: 5.25	REET, PSPN.SW: 4.65	BTC-USD, ETH-USD: 92.88
10y	TSM, NVDA: 4473.53	ETH-USD, BNB-USD: 80572.20	ERNE.L, TEML.L: 10.35	IYR, REET: 6.45	BTC-USD, BNB-USD: 1476.28
max	AAPL, NVDA: 906707.49	BTC-USD, BNB-USD: 80572.20	CORP.L, TIPS.L: 15.45	PSPN.SW, REET: 8.25	BTC-USD, ETH-USD: 172.28
Maximum MoM Linear Regression					
5y	IGLN.L, ISLN.L: 6.56	BRNT.L, LGCF.L: 4.78	IBTM.L, IEML.L: 7.13	IYR, REET: 2.55	BTC-USD, ETH-USD: 3.22
10y	TIPS.L, IBTM.L: 5.15	IGLN.L, BRNT.L: 2.98	ERNE.L, TEML.L: 1.15	PSPN.SW, REET: 1.23	BTC-USD, ADA-USD: 2.05
max	CORP.L, IBCI.L: 3.45	IGLN.L, BRNT.L: 2.67	ERNE.L, TEML.L: 0.85	REET, PSPN.SW: 0.73	BTC-USD, ETH-USD: 1.55
Maximum YoY Linear Regression					
5y	NESN.SW, NVO: 4.61	BRNT.L, TGLN.L: 3.33	IBTM.L, IEML.L: 2.72	SPSN.SW, PSPN.SW: 2.14	BTC-USD, ETH-USD: 1.81
10y	TSM, NVDA: 3.31	IGLN.L, BRNT.L: 2.89	CORP.L, TIPS.L: 1.08	IYR, REET: 0.89	BTC-USD, ADA-USD: 1.55
max	AAPL, NVDA: 2.45	IGLN.L, BRNT.L: 2.11	ERNE.L, TEML.L: 0.97	PSPN.SW, REET: 0.63	BTC-USD, BNB-USD: 1.22

For the following figures, the legend below applies:

Regression Tables: The results represent the Betas of the regression.
Color Indication:
Blue if result is superior to the median correlation of the computed Dataframe.
Pink if result is ≤ 0.
White otherwise.

A **positive Beta** indicates that the asset moves in the same direction as inflation, and thus may provide a hedge against inflation depending on the time horizon. A **negative Beta** reflects general poor performance of the asset during inflationary periods.

Strongly negative Betas suggest high volatility and an unreliable response to inflation. These assets may act as speculative investments rather than inflation hedges.

Real Return Tables: Color Indication:
Blue if result is superior to the median real returns of the computed Dataframe.
Pink if result is ≤ 0.
White otherwise.

Negative or low positive real returns reflect the erosion of purchasing power by inflation. These assets may show some resilience but underperform compared to other asset classes. **Moderate real returns** suggest assets can maintain purchasing power over the given time horizons but are less robust. **Higher real returns** highlight that certain assets are effective inflation hedges over the given time horizons. **Very strong real returns** suggest assets outperform inflation significantly in the long run. **Extremely high real returns** imply exceptional growth potential. However, they could be paired with high volatility (e.g. cryptocurrencies), indicating speculative characteristics.

Correlation Tables: Correlation : 1 = Perfectly Correlated, 0 = Not correlated.
Color Indication:
Blue if result is > 0.5 (Highly correlated)
Pink if result is ≤ 0. (Uncorrelated)
White otherwise.

Perfect correlation insinuates reliable inflation hedge in the given time horizon.

High Correlation (close to 1) indicates that the assets move closely with inflation. This highlights their effectiveness as inflation hedges in medium-term portfolios. For long-term (10 years), slight decreases of correlation could reflect market volatility over longer periods. If **correlation decreases significantly**, this could indicate a shift in market dynamics or external shocks. **Weak correlation** suggest diminished inflation-hedging ability over horizons, potentially due to economic cycles or other macroeconomic factors.

Note: Negative correlations for traditional fixed-income assets indicate they lose value as inflation rises, unless specifically inflation-linked.

Figure 1: Regression – All possibilities – Maximum

Maximum MoM Correlation Table

	stocks	commodities	fixed_income	real_estate	cryptocurrency
2y	^SSMI_NESN.SW_SAP_TCEHY_1mo_2y: 0.00	NGAS.L_CORN.L_SOYB.L_1mo_2y: 0.00	CORP.L_IBTM.L_LQDE.L_IHYG.L_IBCI.L_TIPS.L_ERNE.L_IEML.L_1mo_2y: 0.00	SPSN.SW_ALLN.SW_SRECHA.SW_IYR_1mo_2y: 0.00	BNB-USD_XRP-USD_ADA-USD_1mo_2y: 0.00
5y	MC.PA_NVDA_1mo_5y: 51.06	IGLN.L_ISLN.L_1mo_5y: 6.56	CORP.L_LQDE.L_1mo_5y: 11.72	IYR_REET_1mo_5y: 25.29	BTC-USD_BNB-USD_1mo_5y: 59.62
10y	NVDA_TSM_1mo_10y: 26.68	BRNT.L_SOYB.L_1mo_10y: 5.82	TIPS.L_IEML.L_1mo_10y: 1.15	IYR_REET_1mo_10y: 2.55	BTC-USD_ADA-USD_1mo_10y: 41.36
max	NVDA_TSM_1mo_max: 20.33	LGCF.L_BRNT.L_1mo_max: 16.98	CORP.L_IBCI.L_TIPS.L_ERNE.L_1mo_max: 42.98	IYR_REET_1mo_max: 1.73	BTC-USD_ADA-USD_1mo_max: 51.32

(a) Maximum MoM

Maximum YoY Correlation Table

	stocks	commodities	fixed_income	real_estate	cryptocurrency
2y	^SSMI_SAP_AAPL_TSM_1mo_2y: 0.00	IGLN.L_ISLN.L_NGAS.L_WEAT.L_CORN.L_1mo_2y: 0.00	LQDE.L_IHYG.L_IEML.L_1mo_2y: 0.00	ALLN.SW_SRECHA.SW_PSCF.SW_IYR_REET_1mo_2y: 0.00	BTC-USD_ETH-USD_1mo_2y: 0.00
5y	NESN.SW_NVO_1mo_5y: 3.61	LGCF.L_BRNT.L_1mo_5y: 8.12	IBTM.L_ERNE.L_1mo_5y: -0.54	SPSN.SW_PSPN.SW_1mo_5y: 5.33	BNB-USD_XRP-USD_1mo_5y: -27.47
10y	NVO_MC.PA_1mo_10y: 4.29	LGCF.L_BRNT.L_1mo_10y: 11.36	ERNE.L_IEML.L_1mo_10y: 0.08	PSPN.SW_REET_1mo_10y: 1.37	BNB-USD_XRP-USD_1mo_10y: -8.45
max	MC.PA_NVDA_1mo_max: 4.70	LGCF.L_BRNT.L_1mo_max: 13.40	ERNE.L_IEML.L_1mo_max: 0.42	PSPN.SW_REET_1mo_max: 3.29	BNB-USD_XRP-USD_1mo_max: -8.45

(b) Maximum YoY

Figure 2: Regression – All possibilities – Minimum

Minimum MoM Correlation Table

	stocks	commodities	fixed_income	real_estate	cryptocurrency
2y	^SSMI_NESN.SW_SAP_TCEHY_1mo_2y: 0.00	NGAS.L_CORN.L_SOYB.L_1mo_2y: 0.00	CORP.L_IBTM.L_LQDE.L_IHYG.L_IBCI.L_TIPS.L_ERNE.L_IEML.L_1mo_2y: 0.00	SPSN.SW_ALLN.SW_SRECHA.SW_IYR_1mo_2y: 0.00	BNB-USD_XRP-USD_ADA-USD_1mo_2y: 0.00
5y	ROG.SW_TCEHY_1mo_5y: 1.45	BRNT.L_NGAS.L_1mo_5y: -50.90	IBTM.L_ERNE.L_1mo_5y: 1.52	MOBN.SW_SRECHA.SW_1mo_5y: 2.94	ETH-USD_XRP-USD_1mo_5y: -44.17
10y	NESN.SW_ROG.SW_1mo_10y: -2.28	ISLN.L_NGAS.L_1mo_10y: -11.98	IBTM.L_TIPS.L_1mo_10y: -3.75	SPSN.SW_PSCF.SW_1mo_10y: -10.65	ETH-USD_BNB-USD_1mo_10y: -2.21
max	NESN.SW_TCEHY_1mo_max: -2.78	BRNT.L_NGAS.L_1mo_max: -23389.10	ERNE.L_IEML.L_1mo_max: -2.53	ALLN.SW_SRECHA.SW_1mo_max: -5.76	ETH-USD_BNB-USD_1mo_max: -2.21

(a) Minimum MoM

Minimum YoY Correlation Table

	stocks	commodities	fixed_income	real_estate	cryptocurrency
2y	^SSMI_SAP_AAPL_TSM_1mo_2y: 0.00	IGLN.L_ISLN.L_NGAS.L_WEAT.L_CORN.L_1mo_2y: 0.00	LQDE.L_IHYG.L_IEML.L_1mo_2y: 0.00	ALLN.SW_SRECHA.SW_PSCF.SW_IYR_REET_1mo_2y: 0.00	BTC-USD_ETH-USD_1mo_2y: 0.00
5y	NVDA_TSM_1mo_5y: -39.51	ISLN.L_SOYB.L_1mo_5y: -10.08	CORP.L_LQDE.L_1mo_5y: -4.69	ALLN.SW_SRECHA.SW_1mo_5y: -4.73	ETH-USD_ADA-USD_1mo_5y: -164.04
10y	TSM_TCEHY_1mo_10y: -17.55	ISLN.L_WEAT.L_1mo_10y: -2.36	IBTM.L_TIPS.L_1mo_10y: -3.14	ALLN.SW_MOBN.SW_1mo_10y: -4.20	ETH-USD_ADA-USD_1mo_10y: -108.45
max	ROG.SW_TCEHY_1mo_max: -9.69	ISLN.L_NGAS.L_1mo_max: -5172.02	IBTM.L_TIPS.L_1mo_max: -4.39	ALLN.SW_MOBN.SW_1mo_max: -3.84	ETH-USD_ADA-USD_1mo_max: -108.45

(b) Minimum YoY

Figure 3: Real Returns – All possibilities – Maximum

Maximum MoM Correlation Table

	stocks	commodities	fixed_income	real_estate	cryptocurrency
2y	SAP_NVDA_1mo_2y: 17.91	LGCF.L_BRNT.L_1mo_2y: 2.60	LQDE.L_ERNE.L_1mo_2y: 1.27	ALLN.SW_SRECHA.SW_1mo_2y: 2.06	BTC-USD_ETH-USD_1mo_2y: 0.23
5y	TSM_TCEHY_1mo_5y: 48.17	BRNT.L_CORN.L_1mo_5y: 22.69	LQDE.L_ERNE.L_1mo_5y: 0.85	SPSN.SW_ALLN.SW_1mo_5y: -0.10	ETH-USD_ADA-USD_1mo_5y: 87.13
10y	NVDA_TCEHY_1mo_10y: 85.37	IGLN.L_BRNT.L_1mo_10y: 27.61	LQDE.L_TIPS.L_1mo_10y: 8.40	PSCF.SW_REET_1mo_10y: 35.14	ETH-USD_ADA-USD_1mo_10y: 172.28
max	TSM_TCEHY_1mo_max: 681.61	BRNT.L_NGAS.L_1mo_max: 105802.92	LQDE.L_TIPS.L_1mo_max: 19.66	PSCF.SW_IYR_1mo_max: 122.32	ETH-USD_ADA-USD_1mo_max: 172.28

(a) Maximum MoM

Maximum YoY Correlation Table

	stocks	commodities	fixed_income	real_estate	cryptocurrency
2y	NVO_NVDA_1mo_2y: 138.23	IGLN.L_BRNT.L_1mo_2y: 3.93	IHYG.L_IEML.L_1mo_2y: 5.69	SPSN.SW_MOBN.SW_1mo_2y: 11.51	BTC-USD_ETH-USD_1mo_2y: 61.88
5y	NVO_NVDA_1mo_5y: 607.98	BRNT.L_SOYB.L_1mo_5y: 83.45	IHYG.L_TIPS.L_1mo_5y: -0.75	SRECHA.SW_IYR_1mo_5y: -3.91	ETH-USD_BNB-USD_1mo_5y: 1965.69
10y	NVO_NVDA_1mo_10y: 4473.53	IGLN.L_BRNT.L_1mo_10y: 64.98	IBTM.L_TIPS.L_1mo_10y: 19.03	SPSN.SW_MOBN.SW_1mo_10y: 61.70	BTC-USD_BNB-USD_1mo_10y: 80572.20
max	AAPL_NVDA_1mo_max: 906707.28	LGCF.L_IGLN.L_BRNT.L_ISLN.L_NGAS.L_SOYB.L_1mo_max: 14760.20	LQDE.L_IHYG.L_1mo_max: 50.80	PSPN.SW_IYR_1mo_max: 664.67	BTC-USD_BNB-USD_1mo_max: 80572.20

(b) Maximum YoY

Figure 4: Real Returns – All possibilities – Minimum

Minimum MoM Correlation Table

	stocks	commodities	fixed_income	real_estate	cryptocurrency
2y	AAPL_TCEHY_1mo_2y: -6.17	NGAS.L_SOYB.L_1mo_2y: -8.44	IBCI.L_IEML.L_1mo_2y: -3.59	IYR_REET_1mo_2y: -3.96	XRP-USD_ADA-USD_1mo_2y: -17.30
5y	NESN.SW_ROG.SW_1mo_5y: -7.30	NGAS.L_WEAT.L_1mo_5y: -7.75	IBCI.L_IEML.L_1mo_5y: -7.26	MOBN.SW_PSCF.SW_1mo_5y: -5.30	BTC-USD_BNB-USD_1mo_5y: 18.23
10y	NESN.SW_ROG.SW_1mo_10y: -3.94	NGAS.L_SOYB.L_1mo_10y: -4.06	IBCI.L_IEML.L_1mo_10y: -8.06	ALLN.SW_MOBN.SW_1mo_10y: 6.83	BTC-USD_XRP-USD_1mo_10y: -4.41
max	^SSMI_NESN.SW_1mo_max: -2.24	LGCF.L_BRNT.L_1mo_max: -26.42	IBCI.L_IEML.L_1mo_max: -99.27	SRECHA.SW_REET_1mo_max: -81.53	BTC-USD_XRP-USD_1mo_max: -34.80

(a) Minimum MoM

Minimum YoY Correlation Table

	stocks	commodities	fixed_income	real_estate	cryptocurrency
2y	ROG.SW_TCEHY_1mo_2y: -18.22	NGAS.L_WEAT.L_1mo_2y: -41.19	IBTM.L_IBCI.L_1mo_2y: -2.74	IYR_REET_1mo_2y: -4.71	BNB-USD_XRP-USD_1mo_2y: 8.60
5y	ROG.SW_TCEHY_1mo_5y: -15.12	NGAS.L_WEAT.L_1mo_5y: -47.59	IBTM.L_IEML.L_1mo_5y: -12.33	SPSN.SW_PSPN.SW_1mo_5y: -15.90	BTC-USD_XRP-USD_1mo_5y: 210.03
10y	^SSMI_ROG.SW_1mo_10y: 27.52	NGAS.L_WEAT.L_1mo_10y: -78.25	TIPS.L_IEML.L_1mo_10y: -7.65	PSCF.SW_REET_1mo_10y: 17.30	XRP-USD_ADA-USD_1mo_10y: 2.32
max	^SSMI_ROG.SW_1mo_max: 692.03	BRNT.L_ISLN.L_1mo_max: -20.42	TIPS.L_IEML.L_1mo_max: -20.79	SRECHA.SW_REET_1mo_max: 43.71	XRP-USD_ADA-USD_1mo_max: 2.32

(b) Minimum YoY

Figure 5: Correlation – All possibilities – Maximum

Maximum MoM Correlation Table

	stocks	commodities	fixed_income	real_estate	cryptocurrency
2y	No valid data	No valid data	No valid data	No valid data	No valid data
5y	MC.PA_AAPL_1mo_5y: 0.98	IGLN.L_ISLN.L_1mo_5y: 0.73	IBTM.L_IEML.L_1mo_5y: 0.99	SPSN.SW_PSPN.SW_MOBN.SW_SRECHA.SW_PSCF.SW_REET_1mo_5y: 1.00	BTC-USD_BNB-USD_1mo_5y: 0.61
10y	AAPL_TSM_1mo_10y: 0.77	IGLN.L_BRNT.L_1mo_10y: 0.30	IHYG.L_ERNE.L_1mo_10y: 0.27	IYR_REET_1mo_10y: 0.12	BTC-USD_ADA-USD_1mo_10y: 0.39
max	MC.PA_TSM_1mo_max: 0.51	LGCF.L_IGLN.L_BRNT.L_1mo_max: 0.48	CORP.L_IBCI.L_TIPS.L_ERNE.L_1mo_max: 0.57	IYR_REET_1mo_max: 0.08	BTC-USD_BNB-USD_1mo_max: 0.52

(a) Maximum MoM

Maximum YoY Correlation Table

	stocks	commodities	fixed_income	real_estate	cryptocurrency
2y	No valid data	No valid data	No valid data	No valid data	No valid data
5y	NESN.SW_NVO_1mo_5y: 0.45	IGLN.L_BRNT.L_1mo_5y: 0.46	IHYG.L_ERNE.L_1mo_5y: -0.41	SPSN.SW_PSPN.SW_1mo_5y: 0.62	BNB-USD_XRP-USD_1mo_5y: -0.23
10y	NVO_MC.PA_1mo_10y: 0.31	IGLN.L_BRNT.L_1mo_10y: 0.63	ERNE.L_IEML.L_1mo_10y: 0.02	PSPN.SW_REET_1mo_10y: 0.14	BTC-USD_BNB-USD_1mo_10y: -0.05
max	^SSMI_NESN.SW_1mo_max: 0.12	IGLN.L_BRNT.L_1mo_max: 0.67	ERNE.L_IEML.L_1mo_max: 0.08	PSPN.SW_REET_1mo_max: 0.09	BTC-USD_BNB-USD_1mo_max: -0.05

(b) Maximum YoY

Figure 6: Correlation – All possibilities – Minimum

Minimum MoM Correlation Table

	stocks	commodities	fixed_income	real_estate	cryptocurrency
2y	No valid data	No valid data	No valid data	No valid data	No valid data
5y	ROG.SW_TCEHY_1mo_5y: 0.05	ISLN.L_NGAS.L_1mo_5y: -0.74	IBTM.L_ERNE.L_1mo_5y: 0.36	SRECHA.SW_PSCF.SW_1mo_5y: 0.52	ETH-USD_XRP-USD_1mo_5y: -0.19
10y	NESN.SW_ROG.SW_1mo_10y: -0.15	ISLN.L_WEAT.L_1mo_10y: -0.50	IBTM.L_TIPS.L_1mo_10y: -0.33	SPSN.SW_MOBN.SW_SRECHA.SW_PSCF.SW_1mo_10y: -0.69	ETH-USD_BNB-USD_1mo_10y: -0.02
max	NESN.SW_TCEHY_1mo_max: -0.17	IGLN.L_ISLN.L_1mo_max: -0.52	ERNE.L_IEML.L_1mo_max: -0.31	ALLN.SW_PSCF.SW_1mo_max: -0.38	ETH-USD_BNB-USD_1mo_max: -0.02

(a) Minimum MoM

Minimum YoY Correlation Table

	stocks	commodities	fixed_income	real_estate	cryptocurrency
2y	No valid data	No valid data	No valid data	No valid data	No valid data
5y	NESN.SW_NVO_TSM_1mo_5y: -1.00	IGLN.L_ISLN.L_WEAT.L_1mo_5y: -0.65	IBTM.L_IBCI.L_TIPS.L_ERNE.L_1mo_5y: -1.00	ALLN.SW_SRECHA.SW_1mo_5y: -0.65	BTC-USD_XRP-USD_1mo_5y: -0.98
10y	NESN.SW_ROG.SW_SAP_TSM_1mo_10y: -0.63	ISLN.L_WEAT.L_1mo_10y: -0.22	IBTM.L_TIPS.L_1mo_10y: -0.72	ALLN.SW_SRECHA.SW_1mo_10y: -0.45	ETH-USD_ADA-USD_1mo_10y: -0.59
max	ROG.SW_TCEHY_1mo_max: -0.35	ISLN.L_WEAT.L_1mo_max: -0.29	CORP.L_IBTM.L_LQDE.L_TIPS.L_1mo_max: -0.63	SRECHA.SW_PSCF.SW_1mo_max: -0.32	ETH-USD_ADA-USD_1mo_max: -0.59

(b) Minimum YoY

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