

Can Diversified Investment Portfolios Hedge Against Inflation and Market Volatility?

"Do Diversified Portfolios Effectively Hedge Inflation and Volatility Risks?”

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Dissertation written under the supervision of Professor Eva Schliephake

Dissertation submitted in partial fulfilment of requirements for the MSc in Finance, at the Universidade Católica Portuguesa, June 2nd 2025.

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Abstract

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Resumo

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1. **Introduction**

Inflation and Market Volatility are at the core of every investment manager’s decision-making process, capital allocation and in every retail investor’s concerns. Inflation will diminish the purchasing-power of your income and the real value of your portfolio’s returns, while market volatility will introduce uncertainty and a degree of risk that may not be adjusted to your risk aversion. Innovations in any of these macroeconomic variables are in the top tier of the concern scale of money managers and retail investors. Protection against these variables is often measured and named in the form of a hedge. Following [Bodie (1976)](#Bodie1), an effective hedge, against both inflation and market volatility, is defined to the extent that they can be used to diminish or eliminate the risk of the portfolio’s real return in what concerns the future levels of the consumer price index (CPI) and the future levels of market volatility. Over the past century, the world has experienced periods of high inflation, such as the German hyperinflation post-World War I, the “Great Inflation” of the 1970s and the post-COVID inflation surge. The periods on which high volatility was observed have not been less significative than those we have seen, most of these periods are and will be remembered for decades to come, namely, the Great Depression of 1929, the Black Monday on October 1987, the Dot-com crash, the Global Financial Crisis and the latest, the COVID-19 crash. However, there are multiple periods on which both phenomena were observed. The most remarkable have been the 1970s Stagflation and the post-COVID period. It is with the latest period of the aforementioned events still in mind, and with the latest market turmoil caused by the reciprocal tariffs that the relevance of the topic addressed in this thesis becomes increasingly relevant. Many studies have been conducted regarding the effectiveness of certain asset classes in hedging inflation, but this paper aims to include different asset classes, including alternative assets, with different geographies. Concerning the study of market volatility hedges, most of past literature focuses on the use of complex and structured derivative products primarily aimed at short-term hedging.

This paper focuses on addressing a topic that has not been addressed in past literature, creating a strategic asset allocation by buying and holding the same assets for the same investment horizon, fixing weights for the whole holding period and trying to hedge against inflation and market volatility risk, while building on geographical diversification. By trying to hedge both risks, the paper contributes to the vast literature on inflation hedging and the not so sizable literature on market risk hedging without complex financial products. Nonetheless, a natural answer may arise for the reader, one that aims to question the orthogonality of inflation and volatility and whether it is meaningful to study the hypotheses proposed in this paper. This will also be discussed further in the paper, but, in a nutshell, it seems that the orthogonality is existent, and it does make sense to do this split both variables and test the hypotheses proposed, even though causality results are somewhat ambiguous.

**What the paper finds**.

**Extensions/heterogeneity analyses/mechanisms (“extensions+”)**

**Paragraphs X+1/X+2: Literature contributions.**

**Structure of the Paper**

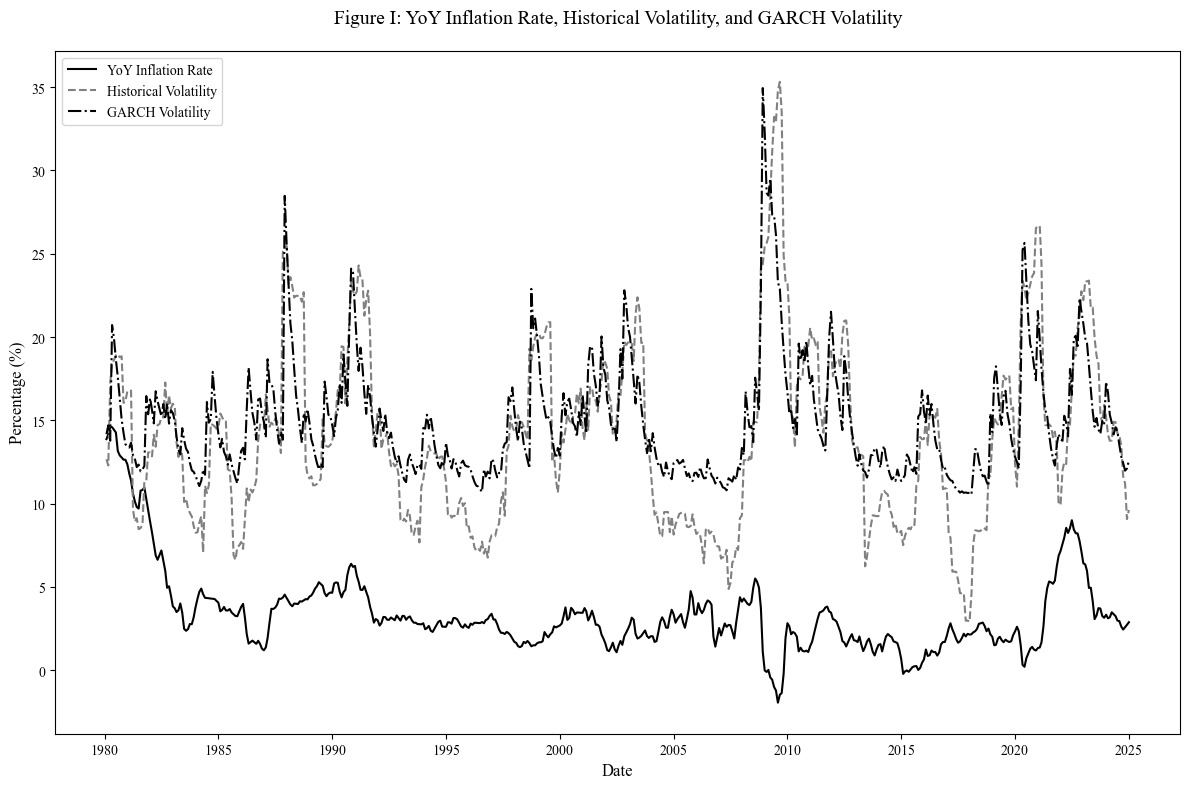
1. **Data**

**2.1 Data Description**

The data used in this paper is fetched from different sources and databases. The period that serves as input is the start of 1980 until the last trading day of December 2024, and data is . Wi Inflation rates are estimated using the log difference of monthly values, either in a one-month interval or a twelve-month interval, in the series US Consumer Price Index for All Urban Consumers from FRED. Inflation rate in the whole paper will be addressed at on a Year-over-Year basis mainly and its evolution throughout the studied period from 1980 until 2024 can be seen on Figure I.

Volatility data is calculated from the monthly returns on MSCI World Index, with data from Refinitiv Eikon/LSEG Workspace, the returns for this series are calculated as the log differential from the monthly closing prices of the index. From the previously mentioned data, two volatility estimates were calculated, an Historical (realized) Volatility Variable, computed from a rolling twelve-month standard deviation of the index continuously compounded monthly returns, and a GARCH (conditional) Volatility variable, using a GARCH (1,1) model, meaning, an order one autoregressive term and an order one moving average term. The GARCH (1,1) model is used to capture and forecast the volatility of the MSCI World Index returns, representing the model's estimate of the volatility at each month, to capture the volatility clustering we are expecting to find on this study. This variable will be mainly used for robustness. On Figure I, the reader can observe the small amplitude between both measurements of volatility.

To build the diversified investment portfolios several assets were selected. This selection was done to have as much diversification as possible, on the one hand to have as much exposure to different asset classes as possible, on the other hand, this diversification also happens geographically. For all assets, continuously compounded returns were calculated, allowing an easier computation of cumulative returns, through its additive properties, whilst its statistical properties allow greater symmetry and its approximation to normal distribution, catalysing a increasingly reliable regression analysis and hypothesis testing. The equity indexes chosen are the S&P 500 Index, the Russell 2000 Index, the tech heavy NASDAQ Composite Index, the FTSE 100 Index, the DAX 40 Index, the Euro Stoxx 50 Index, and the Nikkei 225 Index. These indices’ data was obtained mainly from LSEG Workspace, whilst the S&P 500 data was extracted from CRSP and the Nikkei 225 data was retrieved from Compustat in WRDS. For Real Estate Investment Trusts (REITs), the selection was the FTSE Nareit U.S. Real Estate Index Series, from National Association of Real Estate Investment Trusts database.

Gold, commonly regarded by the average investor as the obvious hedge against inflation risk, is one of the key assets in this paper, its spot price in US Dollars is also extracted from LSEG Workspace. For Oil, the most traded commodity worldwide, this paper will study the NYMEX Light Sweet Crude Oil (WTI) Electronic Energy Future Continuation 1 (CLc1). On Foreign Exchange pair territory, the EUR/USD, JPY/USD, CHF/USD spot rates were selected for the portfolios construction. The reader may argue that the EURO was only launched in 1999, that’s why Refinitiv uses a synthetic rate, following the European Central Bank’s approach, of a weighted average of the currencies of the eleven countries that originally constituted the Eurozone. Due to limited access to Treasury Inflation-Protected Securities data, as a proxy, for the total return index, the chosen asset was the iShares TIPS Bond ETF which tracks the results of an index composed by Treasury Inflation-Protected Securities bonds with different maturities. To conclude the disclosure of the sources for the universe of assets, for the 10-Year Treasury Bond, we selected the data from CRSP on the Total Return Index and the Risk-Free Rate is extracted from Kenneth French Data Library.

In order to complement the regressions enumerated on Section III: Data for Expected Inflation, Expected Volatility (rule of 16), further Factors Data from Kenneth French

* 1. **Summary Statistics**

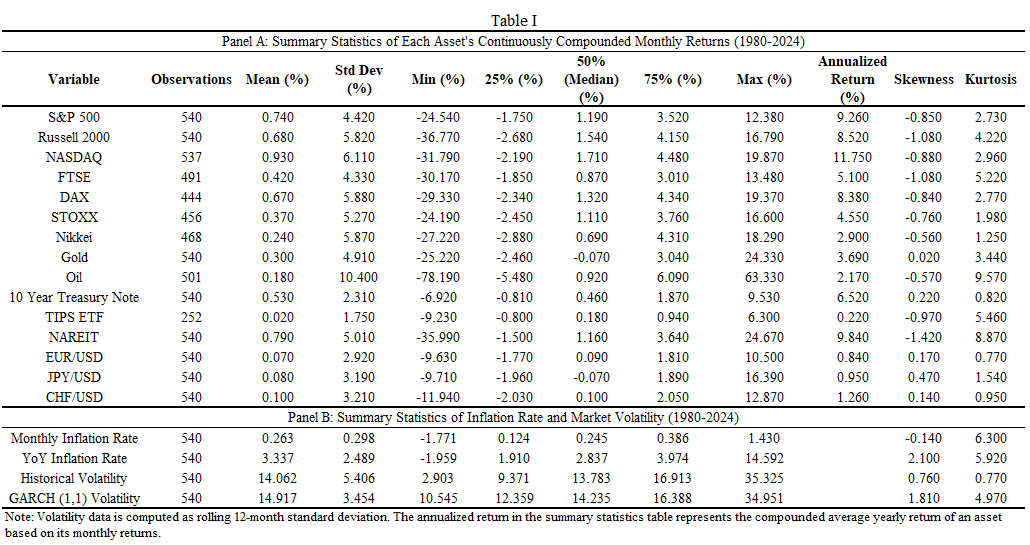


Table I presents the summary statistics for all the assets selected for portfolio construction and for the two macroeconomic variables this paper studies. The study is conducted on 540 months of data and most assets have observable data on all these months, in fact, 15 of the 16 assets have data on more than 82% of the period’s months.

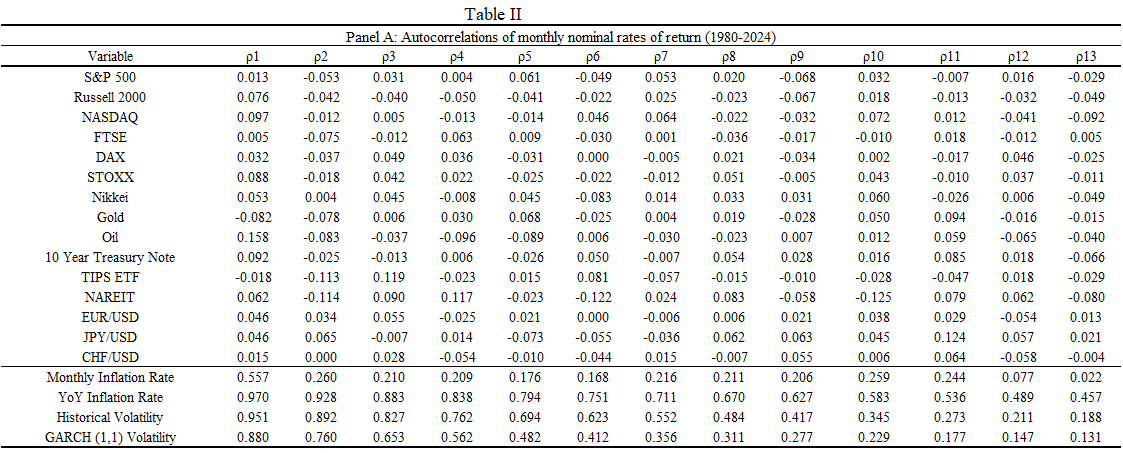
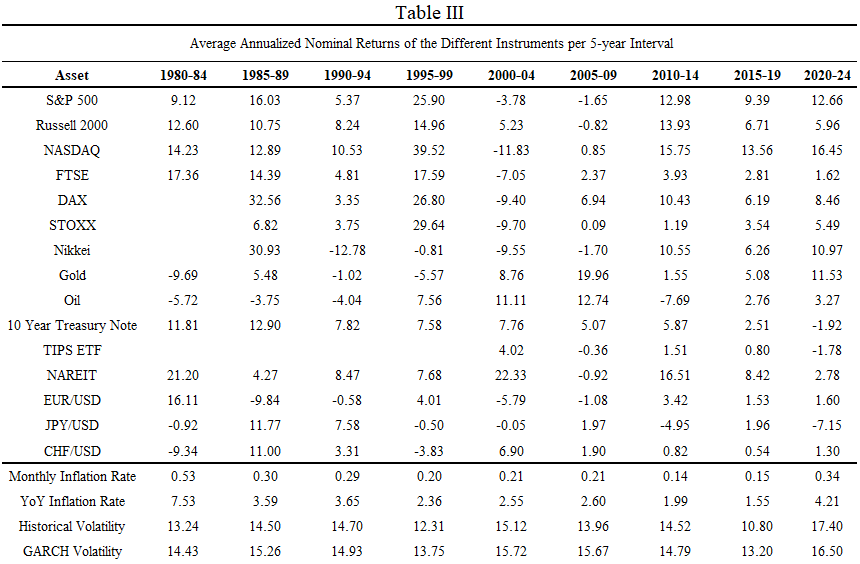
From this Table, the reader can infer that the best performing assets, in this universe, in the period from 1980 through 2024, based on the Annualized Return Data, were the Equity Indexes from the United States and Germany and the NAREIT Index. Whilst the ones that exhibited the lowest level of returns were the currencies and the iShares TIPS Bond ETF. In what concerns volatility of these assets, one can immediately observe that the instruments with lowest performance throughout this period are also the ones with the lowest volatility.

Table II displays the estimation of the first thirteen autocorrelations of the CPI Year-over-Year Inflation Rate, estimates of the rolling 12-month standard deviation of returns of the MSCI World Index and the monthly nominal rates of return of the different assets.

It is evident to the unaided eye that for all lags of the assets, except for Oil in the first lag, are low and very close to zero, indicating that most Equity Indexes confirm and are in line the efficient market hypothesis. Small-cap index Russell 2000 exhibits some short-term mean reversion, since its first order autocorrelation lags are mildly negative. Commodities on the other hand, vary slightly, whilst Oil, has positive and high (when compared to other asset classes) first order autocorrelation, which indicates that its returns gain from momentum from supply or demand shocks. Gold has negative autocorrelation, which may suggest a slight tendency towards mean-reversion over short horizons. The analysis for the 10-year treasury note demonstrates that there is a modest positive autocorrelation, which tends to decay over 1 or 2 lags, meaning that yields usually change gradually and its ability to reflect policy changes.

Currencies experience a random walk throughout the 13 order lags reflecting its random-walk behaviour. Finaly, the results for the NAREIT Index infer that it shows some cyclicality throughout the period under analysis. Anyhow, the results now discussed do not have much significance since they are all very close to 0. However, the results for Inflation and Volatility are much more interesting to analyse. Monthly Inflation Rate and YoY Inflation rate have very high and significantly different from zero sample autocorrelations, particularly in the short-term ones, suggesting that there is a very significant degree of persistence, with slow movements and small fluctuations, a clear argument that supports the idea that, in the short-term, current inflation influences next month’s inflation, and, in the longer-term and strong memory. The same can be inferred for Historical and GARCH Volatility, high or low levels of volatility tend to stay in that way for months.

Following [Fama and Schwert (1977)](#FamaSchwert) approach, we have created a table, Table III, that contrasts the average annualized continuously compounded nominal rates of return with the average inflation and volatility rates in different subperiods, which, as they suggest, can provide a general picture of the ability of some of these assets to hedge against inflation and market volatility.

From this table, we can immediately conclude that all Equity Indices fail to consistently hedge

inflation and/or volatility. The returns exhibited vary substantially in the different sub-periods and suffer when there are highly inflationary and volatile episodes (e.g. 2000-09, 2020-24), indicating that a somewhat inverse relationship between stocks and inflation and/or volatility is the base case for this sample, which meets our prior expectations for this particular asset class. Gold, however, provides protection against both macroeconomic shocks, performing remarkably in periods of high inflation, such as the period 2000-09. This reinforces its status as a safe-haven and hedge asset, as we had anticipated earlier in the paper. For Oil, though the relationships are not so straightforward, but it points to a positive correlation with inflation, and volatility, again aligned with our forecast of its poor status as an hedge against inflation and its characteristics as a commodity, so when there is a supply side driven increase in the prices, meaning that production costs are then passed on to the consumers, leading to further inflation. Additionally, as we saw in Table I, Oil is the most volatile asset in this universe. The Fixed-income securities on our universe, as we saw earlier, are expected to have different behaviors during inflationary times, due to the increase in interest rates, whilst Treasury Inflation-Protected Securities (TIPS) are designed to naturally hedge inflation. Furthermore, during volatile periods, fixed-income securities are considered natural safe-havens and hedges. Real Estate, commonly regarded as an inflation hedge, exhibits good and sustained returns in all sub-sample periods except for the turbulent period of the subprime crisis, as expected. Finally, currencies, display inconsistent behaviors during volatile and inflationary periods, albeit the Swiss Franc is commonly regarded also as a safe-haven asset during these periods. These inconsistencies may be related to some idiosyncratic and/or country specific risks that are beyond the scope of this paper.

In the subsequent sections of this paper, the reader will be better informed with enhanced tests and methodologies to better clarify the relationship between the assets in our universe and diversified investment portfolios of these same assets with inflation and market volatility.

* 1. **Inflation and Volatility: Independent Forces?**

Following the brief introduction of this topic in the beginning of the paper, a natural next step is to address the relationship of inflation and market volatility. To do so, we must question whether they evolve independently, and are orthogonal, or if they are correlated or exhibit some degree of causality. In this section we have performed two separate tests to check for correlation and causality between both variables: correlation analysis and Granger causality testing. These two approaches are, in a way, complimentary. For instance, two variables can have a significantly low correlation or even be totally uncorrelated, and causality can still detect the predictive relationship between the variables that correlation fail to capture.

The correlation analysis was done to assess the power and path of the linear relationship between inflation rate and volatility rate. This would test if changes in the rate of inflation are associated with simultaneous changes in the volatility rate. The assessment was done to the A graph of a graph

AI-generated content may be incorrect.variable YoY Inflation Rate with both measurements of volatility. For Historical Volatility the result was -0.0063, whilst for GARCH Volatility the result was -0.0287. Actually, the number of months that exhibit positive rolling 12-month correlation, on average for both volatility estimates, is 225, whilst the number of the ones with negative is 304. The pattern is quite clear, a negligible and very weak negative relationship between the inflation rate and volatility rates. Figure 2 helps us visualize this. It tells us that the correlation levels fluctuate significantly over time, oscillating between strong positive and negative values. Which may indicate some degree of influence from exogenous factors. Even though, there is not a perfect alignment between both measures of volatility, they tend to move in similar directions, capturing similar dynamics of correlation. Essentially, changes in the Inflation Rate do not have a meaningful impact on volatility, which highlights the fact that they are pretty much independent from each other on our data sample. We can therefore conclude that these variables are orthogonal.

It is now required to address the causality that can be exhibited by the variables, in other words, whether one of the variables leads or is able to predict the behaviour of the other. To achieve this, the Granger Causality test was used to assess the potential of past values of one of the time series to provide statistically significant information to predict future values of another time series. Before proceeding, it is worth noting that Granger-Causality tests are dependent on the fact that both Inflation and Volatility Data are stationary. This stationarity of our variables was verified through an Augmented Dickey-Fuller (ADF) test. The null hypotheses tested here is if any of the variables contains a unit root, i.e., is non-stationary. The p-values for all variables tests are all smaller than 0.05, meaning that we reject the null hypothesis, and confirms that all variables are, therefore, stationary. [Granger (1969)](#Granger_Causality) proposed a statistical framework to test whether a time series past values may be able to predict another time series’ future values. In this study, the test was conducted on both directions of our variables, that is, if inflation’s past values can predict future values of volatility and vice-versa. The application consisted of performing the Granger-causality test at four lags and through all of them, the p-values are high, and well above the 0.05 threshold, and confirm that we fail to reject the null hypotheses of “inflation does not Granger-cause volatility”. Meaning that there is no statistically significant evidence that sustains the null hypothesis. It is worth mentioning that the p-values decrease as the lags increase. More perplexing are the results for the other hypothesis tested. While we would expect some degree of forecasting in inflation data towards volatility, it is actually the other way around on our sample data, as can be seen on Table IV, which displays the results of the conducted tests. It does appear that on longer lags, historical volatility, is Granger-causing inflation, and with past volatility data, one may be able to predict future levels of inflation. However, the exact opposite is verified for GARCH Volatility, which indicates that on the short-term lag it rejects the null hypothesis but on the long-term lags it fails to reject it. It is because of this incongruence between both “Volatilities” that the further study of our hypotheses makes sense. Furthermore, portfolios that provide shelter for investors against both volatility estimates will underscore the robustness of our results.

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| --- | --- | --- | --- | --- | --- |
| Table IV | | | | | |
| Granger Causality Test Results for Different Lags | | | | | |
| Causality Direction | Null Hypothesis | Lag | F-Statistic | P-Value | Decision |
| Inflation -> Volatility (Hist) | Inflation does not Granger-cause Volatility | 1 | 0.9335 | 0.3344 | Fail to Reject |
| Inflation -> Volatility (Hist) | Inflation does not Granger-cause Volatility | 2 | 1.4190 | 0.2429 | Fail to Reject |
| Inflation -> Volatility (Hist) | Inflation does not Granger-cause Volatility | 3 | 1.5102 | 0.2109 | Fail to Reject |
| Inflation -> Volatility (Hist) | Inflation does not Granger-cause Volatility | 4 | 1.7926 | 0.1289 | Fail to Reject |
| Volatility (Hist) -> Inflation | Volatility does not Granger-cause Inflation | 1 | 3.3763 | 0.0667 | Fail to Reject |
| Volatility (Hist) -> Inflation | Volatility does not Granger-cause Inflation | 2 | 17.0269 | 0.0000 | Reject |
| Volatility (Hist) -> Inflation | Volatility does not Granger-cause Inflation | 3 | 11.8282 | 0.0000 | Reject |
| Volatility (Hist) -> Inflation | Volatility does not Granger-cause Inflation | 4 | 9.4804 | 0.0000 | Reject |
| Inflation -> Volatility (GARCH) | Inflation does not Granger-cause GARCH Volatility | 1 | 2.0662 | 0.1512 | Fail to Reject |
| Inflation -> Volatility (GARCH) | Inflation does not Granger-cause GARCH Volatility | 2 | 1.8816 | 0.1534 | Fail to Reject |
| Inflation -> Volatility (GARCH) | Inflation does not Granger-cause GARCH Volatility | 3 | 1.3434 | 0.2594 | Fail to Reject |
| Inflation -> Volatility (GARCH) | Inflation does not Granger-cause GARCH Volatility | 4 | 1.7756 | 0.1323 | Fail to Reject |
| Volatility (GARCH) -> Inflation | GARCH Volatility does not Granger-cause Inflation | 1 | 5.3869 | 0.0207 | Reject |
| Volatility (GARCH) -> Inflation | GARCH Volatility does not Granger-cause Inflation | 2 | 0.4426 | 0.6426 | Fail to Reject |
| Volatility (GARCH) -> Inflation | GARCH Volatility does not Granger-cause Inflation | 3 | 0.4614 | 0.7094 | Fail to Reject |
| Volatility (GARCH) -> Inflation | GARCH Volatility does not Granger-cause Inflation | 4 | 0.6086 | 0.6566 | Fail to Reject |

1. **Methodology**

**3.1 Measuring a Hedge**

As initially highlighted in the introduction of the paper, we followed [Bodie (1976)](#Bodie1) approach

to measure an effective hedge. Despite the reason that Bodie’s paper focus solely on inflation, in this paper the approach will be extended to measure the effectiveness of the diversified portfolio or asset against volatility. This definition indicates that for our portfolios or individual assets to hedge inflation and / or volatility risks their goal is to minimize the influence of the risk factors associated with these variables on the excess returns of the diversified portfolios or the individual assets used on our hypothesis.

Empirically, our methodology will be primarily based on the equation in (1) and will, upon the course of the analysis, evolve into different equations with additional independent variables or incorporate the lagged data around YoY Inflation Rate and both the realized and conditional estimates of volatility. These coefficients will be estimated through an OLS (Ordinary Least Squares) regression. On the left-hand side of equation (1), is the nominal rate of return of the portfolio or asset *i,* at time *t*, whereas represents the risk-free rate at time *t*. On the right-hand side of the equation, stands for the coefficient of the YoY Inflation Rate at time *t*, or, in other words, the sensitivity of the excess returns of the asset/portfolio *i* to changes in the inflation rate. Similarly, represents the coefficient of the Historical (realized) Volatility at time *t*, meaning, the sensitivity of the excess returns of asset/portfolio *i* to changes in the volatility. , the intercept, denotes the average excess returns of asset/portfolio *i* after accounting for the impact of inflation and volatility. Finally, , represents, the error term, which captures the variations of the excess returns of asset/portfolio *i* that are not captured by the model. This methodology will help in answering the main goal of the paper, to assess whether any of the diversified investment portfolios constructed effectively hedges inflation and volatility. It will also foster the answering of the remaining hypotheses proposed in the introduction, such as the one where we aim to question whether assets commonly regarded as inflation hedges, safe-haven assets, or volatility hedges exhibit these qualities better than any of the portfolios built; if these newly created portfolios overperform while hedging volatility and inflation, more traditional portfolios, such as the 60/40 portfolio.

The “hedge” will be measured, as seen, by the degree of sensitivity of the excess returns of portfolios, to either inflation and/or volatility. It is imperative that for the instrument to effectively hedge both variables, the coefficients of and need to be close 1 for inflation beta, meaning that the nominal return of the portfolio increases in line with inflation, hence preserving the purchasing-power of the investor; the volatility beta, however, must be close to 0, implying that return of the portfolio will be independent from stock market volatility shocks. The primary objective of this study is to identify portfolios that simultaneously hedge against both inflation and volatility, while delivering returns comparable to those of traditional inflation-hedging or safe-haven assets, but with reduced exposure to inflationary erosion and volatility-induced risk. Moreover, the presence of a statistically significant and positive 𝛼 in these portfolios would further validate the robustness and reliability of the results.

**3.2 Inflation and Volatility Decomposition**

1. Fisher hypothesis
2. On the Accuracy of Time-Series, Interest Rate, and Survey Forecasts of Inflation
3. Fama and Schwert
4. Importance of the decomposition
5. Finish data description part on expected inflation and volatility (rule of 16)
6. Create new section where the importance of each factor chosen to regress, also papers where they are highlighted
7. See statistical stuff like heterogeneity, heteroskedasticity and autocorrelation topics on the thesis structure
8. New section on methodology for portfolio construction, why static asset allocation instead of dynamic asset allocation

To more precisely evaluate how different assets and portfolios respond to macroeconomic uncertainty, this study decomposes both inflation and volatility into **expected** and **unexpected** components. This approach enables the analysis to distinguish between reactions to forecasted economic developments—often priced into markets—and those to unforeseen shocks, which pose greater risks to investors.

**Inflation decomposition** is carried out by separating observed year-over-year (YoY) inflation into two parts. The **expected component** is proxied using both survey-based and market-implied measures. First, the *University of Michigan Inflation Expectations* provides median consumer expectations for price changes over the next 12 months and reflects prevailing sentiment regarding future inflation. Second, the *10-Year Breakeven Inflation Rate*, sourced from the Federal Reserve Economic Data (FRED), captures market expectations by comparing yields on nominal Treasury bonds with those on Treasury Inflation-Protected Securities (TIPS). The **unexpected component** of inflation is then derived as the difference between the actual YoY inflation rate—measured using monthly Consumer Price Index (CPI) data—and the expected rate derived from the aforementioned indicators.

**Volatility decomposition** follows a similar methodology. The **expected component** is estimated using forward-looking indicators from financial markets. The *VIX Index*, often referred to as the “fear gauge,” captures market expectations of short-term equity market volatility and is obtained via FRED. In parallel, the *MOVE Index*, which measures implied volatility in the U.S. Treasury bond market, is sourced from Refinitiv Eikon. To calculate the **unexpected component** of volatility, these expected measures are compared with **realized volatility**, obtained through two methods: (1) the historical rolling 12-month standard deviation of asset returns, and (2) conditional volatility estimates derived from a GARCH(1,1) model. The residual difference between realized and expected volatility reflects the portion attributable to unforeseen market turbulence.

By incorporating both expected and unexpected components of inflation and volatility, the empirical model is better positioned to capture the differential impact of anticipated trends versus macroeconomic surprises. This layered analysis deepens the investigation into whether certain portfolios offer more robust protection against purchasing-power erosion and market instability.

**Model Framework**

The theoretical foundation of this paper is built on the dual-hedge hypothesis, which proposes that certain portfolios or assets can effectively hedge both inflation and volatility. Specifically, assets with an inflation beta (βπ,t\beta\_{\pi,t}βπ,t​) close to 1 are hypothesized to hedge inflation effectively by preserving the investor’s purchasing power through nominal returns that move in tandem with inflation. At the same time, assets with a volatility beta (βσ,t\beta\_{\sigma,t}βσ,t​) close to 0 are considered effective volatility hedges, as their returns are largely unaffected by market turbulence. The model also distinguishes between expected and unexpected components of both inflation and volatility, allowing for a more granular understanding of their respective impacts on asset performance.

**Hypotheses**

This framework gives rise to several testable hypotheses. First, assets traditionally considered inflation hedges, such as gold and Treasury Inflation-Protected Securities (TIPS), are expected to exhibit βπ,t≈1\beta\_{\pi,t} \approx 1βπ,t​≈1 (H1). Second, defensive portfolios are hypothesized to show βσ,t≈0\beta\_{\sigma,t} \approx 0βσ,t​≈0, indicating minimal sensitivity to volatility shocks (H2). Third, it is posited that portfolios constructed with alternative assets outperform conventional strategies like the 60/40 portfolio in hedging both inflation and volatility (H3). Finally, the analysis will test whether unexpected components of inflation and volatility exert a stronger influence on asset returns than their expected counterparts (H4).

**Portfolio Construction**

To empirically test these hypotheses, a variety of portfolio strategies will be constructed, including equal-weighted portfolios, the traditional 60/40 stock-bond mix, minimum variance portfolios, and mean-variance efficient (tangent) portfolios. These constructions will allow for comprehensive comparisons across different hedging profiles. Practical elements such as transaction costs and portfolio rebalancing frequency will be incorporated to ensure the analysis reflects realistic investment conditions.

**Econometric Techniques**

The empirical analysis will employ several regression-based models to evaluate the sensitivity of excess portfolio returns to inflation and volatility. The baseline model will regress excess returns on lagged measures of inflation and realized volatility, using both historical and GARCH-derived estimates. An extended model will further decompose inflation and volatility into their expected and unexpected components, enabling a deeper investigation into their respective effects. Additionally, multi-factor models such as the Fama-French three-factor model, the Carhart four-factor model, and extended versions will be used to control for systematic risk exposures.

To ensure statistical rigor, several econometric issues will be addressed. Endogeneity concerns will be mitigated by using lagged explanatory variables, while heteroskedasticity will be corrected using robust standard errors. Autocorrelation in the time series data will be managed by applying Newey-West standard errors.

**Robustness Checks**

To test the stability and reliability of the results, various robustness checks will be conducted. Rolling regressions will be used to capture time-varying relationships between portfolio returns and macroeconomic variables. Additionally, sub-sample analyses—such as dividing the data into pre- and post-2008 financial crisis periods—will assess whether the identified relationships hold across different market regimes.

**Performance Metrics**

Portfolio performance will be evaluated using standard financial metrics, including annualized return, annualized volatility, Sharpe ratio, and maximum drawdown. Moreover, regression-based analyses will assess the portfolios' sensitivity to inflation and volatility, further supporting the assessment of their effectiveness as dual hedges.

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