The Inflation Hedging Potential of Commodities – a DCC-GARCH Approach

Exploring a DCC-GARCH approach, do commodities have the ability to hedge US inflation and what are their respective impacts on portfolio performance compared to Treasury Inflation-Protected Securities (TIPS)?

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Dissertation written under the supervision of
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Abstract

This thesis seeks to examine the inflation hedging ability of commodities in the US and their impact on an investment portfolio. It also aims to compare its inflation hedging performance to Treasury Inflation-Protected Securities (TIPS). First, a DCC-GARCH model is used to find dynamic conditional correlations between a selection of commodities and inflation. Secondly, a portfolio allocation exercise with a fixed weight allocated towards the commodity and, on the other hand, a Markowitz portfolio allocation is being conducted. The results come to the conclusion, that while some commodities do certainly have positive dynamic conditional correlations with inflation, they do not necessarily perform well in a portfolio setting given their volatility and unpredictability, specifally in times of crisis. However, Gold may indeed be used as an inflation hedge. Gold shows consistent positive correlations with inflation and good performance in a portfolio setting. Gold also outperforms TIPS in terms of real returns.

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Abstrato

O objetivo da presente tese é analisar a capacidade das comodidades nos Estados Unidos da América para servirem como proteção contra a inflação, bem como os respetivos impactos numa carteira de investimentos. Além disso, pretende-se comparar o desempenho dessas comodidades com o dos Títulos do Tesouro Protegidos contra a Inflação (TIPS), avaliando a sua eficácia como instrumentos de cobertura inflacionária.

Para tal, utiliza-se inicialmente um modelo DCC-GARCH para estimar as correlações condicionais dinâmicas entre uma seleção de comodidades e a inflação. Posteriormente, procede-se a um exercício de alocação de carteira, contrastando uma abordagem de alocação de peso fixo para as comodidades com uma alocação baseada no modelo de Markowitz.

Os resultados indicam que, embora algumas comodidades apresentem correlações condicionais dinâmicas positivas com a inflação, a sua elevada volatilidade pode comprometer o desempenho numa carteira de investimentos. No entanto, o ouro destaca-se como um ativo eficaz na proteção contra a inflação, evidenciando correlações positivas consistentes com a inflação e um desempenho robusto em contexto de carteira. Além disso, verificou-se que o ouro supera os TIPS em termos de retornos reais.

Título da Tese: O Potencial de Hedge contra a Inflação das Commodities – uma Abordagem DCC-GARCH

Autora: Sabrina Egartner

Palavras-chave: Inflação, Hedge contra a inflação, Commodities, Commodities energéticas, Metais preciosos, Metais industriais, Commodities agrícolas, Desempenho da carteira, Ativos de refúgio, Treasury Inflation-Protected Securities (TIPS), Agrupamento de volatilidade, Modelo DCC-GARCH, Correlações dinâmicas, Inflação nos EUA, Pandemia da COVID-19, Investidores institucionais, Carteira 60/40, Relação risco-retorno, Modelagem econométrica

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This journey has been both challenging and fulfilling, strengthening my resilience and knowledge within a field I am deeply interested in. I am very grateful for this experience and the support that eventually made this work possible.

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• In other ways, as described below:
    - Reviewing and improving own text
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Acronyms

ARCH	Autoregressive Conditional Heteroskedasticity
CAL	Capital Allocation Line
CME	Chicago Mercantile Exchange
CPI	Consumer Price Index
DCC	Dynamic Conditional Correlations
ECB	European Central Bank
FED	US Federal Reserve
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GFC	Global Financial Crisis
ICE	Intercontinental Exchange
IMF	International Monetary Fund
LME	London Metal Exchange
OLS	Ordinary Least Squares
PPI	Producer Price Index
RPC	Retail Price Index
SR	Sharpe Ratio
TIPS	Treasury Inflation-Protected Securities
TOCOM	Tokyo Commodity Exchange
UK	United Kingdom
US	United States of America
VIX	CBOE Volatility Index
WTI	Western Texas Intermediate

1 Introduction

We are currently experiencing the end tail of a global inflation surge driven by multiple factors, most notably the COVID-19 pandemic, that started in 2020 and the Russian invasion of Ukraine in 2022. Those events led to a significant rise in oil and energy prices, which have been key contributors to inflationary pressures observed worldwide. Inflation does not only lead to below-average returns and a devaluation of cash, but also has far-reaching effects on economies and the global economic system. Now, this is not only true for the latest period of economic woes. Inflation has been a concern for centuries, shaping economies and societies alike.

1.1 Motivation and Research Question

Traditional investments, such as stocks and bonds, typically suffer in high-inflation environments, negatively impacting traders, institutional investors, mutual funds, national economies, and private investors' portfolios.

To illustrate, rational investors intend to balance risk and return in their portfolios. Yet, periods of heightened inflation can substantially undermine such efforts. During the COVID-19 pandemic, inflation in the US surged to around 7% in 2021 (using CPI data from the US Bureau of Labor Statistics). Considering an institutional investor with a classic 60/40 portfolio (consisting solely of stocks and bonds) with an assumed total value of USD 100m, inflation has undesired effects on the portfolios' performance. Assuming this portfolio generates an annual return of 5%, a rise in inflation would shrink the real return to -2%. Hence this would yield in a negative return for the investor. Essentially, the portfolio's purchasing power declines, shrinking its real value from USD 100m to USD 98m in one year. This simplified scenario highlights the importance of hedging against inflation since the latter may notably erode returns.

Given this context, a critical question arises: Is there any asset that could be incorporated into an investment portfolio to counterbalance or hedge against inflation? This paper seeks to address this question by analyzing commodities such as Brent Crude Oil, WTI Crude Oil, Natural Gas, Gold, Silver, Nickel, Copper, Aluminum, Wheat (HRW), and Cocoa. Those commodities cover the most important commodities types of energy, precious metals, industrial metals, and agriculture. The motivation to analyze commodities stems from the frequent discussions that commodities – especially Gold – have the potential to be a safe haven asset and thus may hedge inflation. This paper tries to give a more in-depth and quantitative analysis of those beliefs by applying an advanced econometric model that accounts for volatility clustering. This paper explores the dynamic co-movements between inflation and commodity returns. It differentiates itself from the currently available literature on this topic by applying a DCC-GARCH model and looking specifically into a broader range of commodities that go beyond Gold or Silver. To get a good understanding of inflation hedging ability, the results will be compared to Treasury Inflation-Protected Securities (TIPS), which have the characteristics of an inflation-adjusted principal.

The specific research question this thesis tries to answer is therefore the following: Exploring a DCC-GARCH approach, do commodities have the ability to hedge US inflation and what are their respective impacts on portfolio performance compared to Treasury Inflation-Protected Securities (TIPS)?

1.2 Contribution to existing Literature

This thesis contributes to the existing literature by providing a deeper analysis of the inflation hedging capabilities of commodities with a special focus on the US. Thus, the use of a DCC-GARCH model offers a nuanced understanding of the dynamic relationships between commodities and inflation and thus may provide valuable insights for investors. It should also provide practical information for short to medium term investors, including institutional investors but also traders to make informed decisions in the future, given that they face an increasingly volatile market, not only in the US but globally.

2 Background

2.1 Inflation

Inflation is a key macroeconomic variable and indicator, measuring the diminishing purchasing power of a currency or income. It measures the price of a basket of goods for a given country over a given time period – monthly, semiannually or annually. Inflation is not necessarily bad and most economists see inflation as a vital stimulation for economic growth. However, if inflation is too high, it erodes purchasing power and makes necessities like food or electricity more expensive for daily use. Central Banks keep a strict eye on inflation developments across the globe and have tools at hand to react to inflation accordingly. Most Central Banks aim for an annual inflation target of about 2% and will adjust monetary policy to maintain this target when necessary. When inflation is too high, they react by increasing interest rates to cool down the economy. Contrarily, if they lower interest rates, they boost investment and spending behavior which should drive inflation. The Federal Reserve (FED) is the Central Bank that sets the interest rate in the US, while its European counterpart is the European Central Bank (ECB).

Figure 1 visualizes the average annual inflation rate in the US over the period from 1982 until 2024 derived from CPI data (Consumer Price Index for All Urban Consumer - seasonally adjusted) of the US Bureau of Labor Statistics. Crisis, like the Gulf-War, the Burst of the Dot-Com Bubble, the Post Sub-Prime Crisis or the COVID-19 Pandemic can have a significant impact on inflation. The most pronounced spike in US inflation has been seen after the outbreak of the COVID-19 pandemic in 2020, which led to global supply chain disruptions and spikes in prices. Inflation has risen up to 7% in 2021, marking the latest significant spike. Since then, inflation levels have slowly dropped and come back to the target level of approximately 2% in 2024. The FED has intervened by increasing interest rates progressively up to 5.33% in August 2023 and has recently started cutting again.

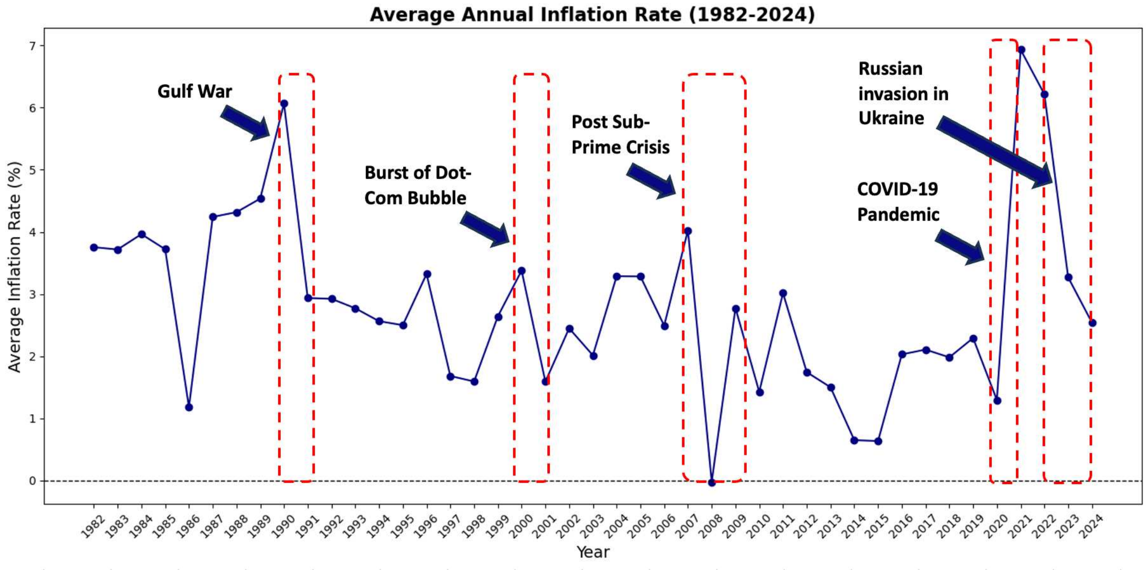

Figure 1 Average Annual US Inflation (1982 - 2024)

2.2 Commodities and Commodity Markets

Commodities are the raw materials or input-factors for a wide range of products, thus being vital to the overall economy. From the grain in our bread to the fuel in our cars, commodities have an impact on everyday life (James, 2016). Hence, it is useful to understand some key characteristics, behaviors, and classifications of different commodities to understand the underlying dynamics of commodity markets.

Commodities need to be distinguished from traditional asset classes because they cannot create future cash flows such as equities or bonds. While there are a range of possible classification systems for commodities, the most important in finance is the distinction between storable and non-storable commodities due to arising storage costs (Pirrong, 2011). Commodities - as used in this thesis - can be categorized into 4 core categories, listed in Table 1 below:

Commodity Category	Examples
Energy	Crude Oil, Natural Gas, Power, …
Precious Metals	Gold, Silver, Platinum, Palladium, …
Industrial Metals	Nickel, Aluminum, Copper, …
Agricultural	Wheat, Cocoa, Coffee, Sugar, …

Table 1 Commodity Categories

Additionally, demand and supply is subject to seasonality, supply chains (disruptions), weather as well as geopolitical events and conflicts. This implies an increased complexity in the pricing of commodities. According to James, resource prices have changed abruptly and decisively since the turn of the century and average commodity prices have more than doubled since. Strikingly, volatilities have shown three times the volatilities than in the 1990s (James, 2016).

In response to high volatility and price uncertainty of commodity markets, commodity derivatives markets have been established to provide suitable risk management and price hedging tools. The most prominent tools are commodity futures. Commodity futures are financial contracts to buy (sell) a fixed quantity of a specific commodity on a specific date at a given price. These contracts have the advantage, that they are traded on regulated exchanges and can therefore provide a higher degree of liquidity and regulation for investors. Future contracts do not expose to actual physical commodities, but are rather a bet on their future commodity prices (James, 2016). Today, most commodities are traded via regulated exchanges like the Chicago Mercantile Exchange (CME), Intercontinental Exchange (ICE), the London Metal Exchange (LME) or the Tokyo Commodity Exchange (TOCOM). Additionally, investable commodity indices like the S&P GSCI, commodity ETFs, and other commodity linked products have emerged in recent years to satisfy the increasing demand of private and institutional investors to diversify their portfolios (James, 2016).

Even though commodities exhibit significant higher volatilities than traditional asset classes, they are often seen as a portfolio diversifier. This stems from their exposure to certain market forces, for instance inflation (James, 2016). Investors therefore might look to invest into commodities in order to achieve their diversification objectives.

2.3 Treasury Inflation-Protected Securities

A common instrument that is designed to hedge inflation, are Treasury Inflation-Protected Securities (TIPS). TIPS are issued by the full faith and credit of the US government. Therefore, they can be considered a low-risk investments. Their coupon and principal payments are directly indexed to the CPI to protect investors from a decline in purchasing power. Since the par value of the bond is linked to inflation, the coupon payments and the final repayment increase in direct proportion to the CPI index. The interest on such bonds can therefore be seen as a risk-free, real interest rate (Bodie et al., 2021).

Since 1997, the US has issued 10-, 20-, and 30-year TIPS, also accessible through mutual funds and ETFs. Since its inception, the TIPS market has grown to about 8.6% of the entire Treasury debt market in 2018, according to a paper of D'Amico et. al. However, they also highlight that TIPS are less liquid than nominal government bonds and investors often demand a liquidity premium to hold them. This tends to narrow the yield spread between TIPS and nominal T-bonds. That liquidity difference partly explains why TIPS yields might converge with nominal yields, especially during times of low inflation volatility (D'Amico et al., 2018).

Despite the mentioned limitations, TIPS are a suitable benchmark to compare with commodities. Unlike TIPS, commodities react to global inflationary pressures and are driven by supply and demand factors, leading to greater price volatility. That volatility may allow commodities to potentially offer a broader and more responsive inflation hedge. The latter will be at the core of this thesis' research.

3 Literature Review

While commodities have been extensively analyzed as a potential inflation hedge, empirical evidence remains inconclusive. Despite the theoretical framework provided by the Fisher Hypothesis, studies have yielded mixed results. Such discrepancies can be attributed to variations in sample periods, geographic scope, and methodological approaches, ranging from basic regression models to more sophisticated econometric techniques. This may be attributed to the relatively low and straightforward storage costs of precious and industrial metals opposed to more complex and expensive storage requirements for oil, gas, or some agricultural products. Below is a summary of literature differentiating between papers that support, reject, or cannot find a final answer as to whether commodities hedge inflation. Additionally, some literature focuses on the performance of commodity futures within a portfolio. First, a deeper look into the fundamental Fisher hypothesis has to be made.

3.1 Fisher Hypothesis

The basis for inflation hedging is the Fisher Hypothesis, first introduced in 1930 by the US economist Irving Fisher. It essentially describes the relationship between nominal interest rates (i), real interest rates (r), and inflation (π). It states, that nominal interest rates should be expressed by the real interest rates plus the expected inflation rate (Fisher, 1930):

$$(1+i)=(1+r)*(1+\pi) \tag{1}$$

Fama and Schwert (Fama & Schwert, 1977) further concluded that this theorem can be applied to all assets. Therefore, if the information available at time t-1 is processed efficiently, the market will set the price of any asset j, so that the expected nominal return on the asset from time t-1 to t is the sum of the appropriate equilibrium expected real return plus the best possible assessment of the expected inflation rate $E_{t-1}(\pi)$. Note, that the inflation hedging performance of commodities in existing literature is typically assessed using real returns, including this thesis.

3.2 In favor of commodities' inflation hedging ability

An extensive study conducted by Worthington and Pahlavani in 2007 found that Gold has long-term inflation hedging capabilities in the US in the post-war period. They used data from 1945 to 2004 and 1973 to 2004. To account for structural changes over these periods, they apply a unit root testing procedure to allow for the timing of such events to be estimated endogenously. Finally, they apply a modified cointegration approach (Worthington & Pahlavani, 2007).

Similarly, Bampinas and Panagiotidis came to the result that Gold is an effective inflation hedge in both the UK and the US, though more so in the US. Silver in contrast does not provide the same protection in neither the US nor the UK. They made use of both a time-variant and a time-invariant cointegration framework for an extensive dataset spanning from 1791 until 2010 (Bampinas & Panagiotidis, 2015).

Aye et al. analyzed the inflation hedging ability of Gold and Silver in the UK and US, using more than two centuries of data (dating back to 1791) and using the retail price index (RPI) to derive a set of inflation measures. They applied a time-variant and a time-invariant approach. Their findings of the time-invariant approach suggest that Gold is more effective than Silver to hedge against headline, expected, and core inflation in the long run. Furthermore, they find a stronger time-invariant relationship between Gold and inflation in the US (long run beta of 1.36) than in the UK (long run beta of 1.16). In the time-variant framework, they find stronger long-term inflation hedging ability for Gold and Silver in both countries (Aye et al., 2017).

Leaving out Gold and Silver, Adekoya et al. have analyzed the commodities aluminum, iron, copper, lead, tin, nickel, and zinc for the 20 most industrialized courtiers in the world. They find that these commodities hedge inflation in at least one country in question, with lead and zinc exhibiting the weakest inflation hedging capabilities. Interestingly, tin hedges inflation in eleven countries which is more than any other of those metals. Their results improve after accounting for asymmetries. Furthermore, they find that no metal may hedge inflation in China, Indonesia, India, and Russia. Inflation hedging improves in the post-subprime crisis (Adekoya et al., 2023).

Spierdijk and Umar document that commodity futures do provide a favorable inflation hedge for the period from 1970 until 2011, however changing over time. They analyzed subsector future indices using a rolling window analysis (Spierdijk & Umar, 2014).

3.3 Mixed results on commodities' inflation hedging ability

Some studies report more mixed results regarding commodities' inflation hedging capabilities. Differences often come from different time scopes, economic regimes, or geographical differences.

In a working paper for the International Monetary Fund (IMF), Attié and Roache analyzed not only commodities as inflation hedges but also included Cash, Bonds, and Equities by using a simple regression model. They found, that commodities effectively hedge against inflation in the short term, they do not perform so well in the long term. Bonds on the other hand, seem to perform better. Furthermore, they suggest that tactical asset allocation may improve these results. Taking structural changes into account, they report inconclusive results (Attié & Roache, 2009).

Phochanachan et al. checked for the inflation-hedging potential of Gold, Oil, and Bitcoin by using monthly data from 2010 to 2021. They applied a Markov Switching Vector Autoregressive model for a stable and a turbulent market environment and came to a multi-dimensional result. First, the inflation hedging capabilities of all assets seem to be stronger short term than in the long term in both regimes. Also, the inflation hedge seems to be higher in a more stable market environment. Lastly, the responses of the assets to inflationary shocks are heterogeneous across the stable as well as the turbulent market setting (Phochanachan et al., 2022).

In contrast, Beckmann and Czudaj found that Gold can hedge inflation only in the long term. The effectiveness depends on economic regimes (normal or turbulent) and geography when applying a Markov-switching vector error correction model. Using data from 1970 until 2011, the effectiveness is generally stronger for the US compared to the UK, Japan, and the Euro Area. Additionally, they mention that the CPI adjustment is regime-dependent, concluding that the inflation-hedging ability of Gold strongly depends on the investment horizon (Beckmann & Czudaj, 2013).

Wang et al. explore the inflation hedging of Gold in the US and Japan from 1971 until 2010, using long and short term threshold models. Their findings suggest, that Gold hedges against inflation only during high-momentum periods in the US. In Japan it shows only partial effectiveness. One explanation for weak performance in Japan may be the price rigidity there. The authors also point out, that the inflation hedging ability is not absolute and varies widely in different market regimes and investment horizons (Wang et al., 2011).

In a more recent study, Liu et al. analyzed the GSCI Commodity Subsector Indices from 1995 to 2021. They demonstrate, that only industrial metal and precious metal futures provide an inflation hedge by using a Markov-switching vector error correction model. Industrial metals performed slightly better. Additionally, they included Stocks and Bonds to test the inflation-hedging reliability (Liu et al., 2023).

Finally, Zaremba et al. found in an extensive study, that across 50 commodities in 80 countries a majority of the commodities are effective in the long term and in the majority of countries. However, their effectiveness varies again on time horizon and geography (Zaremba et al., 2021).

3.4 No evidence of commodities' inflation hedging ability

In contrast to the studies mentioned above, Chua and Woodward find that Gold provides neither a full nor a partial hedge against inflation exploring. Their chosen method is a simple OLS regression with semiannual and monthly data from 1957 until 1980. They analyzed Canada, Germany, Japan, Switzerland, the UK, and the US. Since their analysis includes data from the Bretton-Woods period, the authors acknowledge that their findings may significantly be affected by it (Chua & Woodward, 1982).

Baur explores Gold and its relationship with major US economic and financial variables. This includes a variety of stock market indices, the VIX index, bond indices, the short term USD exchange rate, and CPI as an inflation measure. He applies both a simple and multiple OLS regression as well as a symmetric and asymmetric GARCH approach. The findings suggest that Gold seems to be primarily influenced by the short term USD exchange rate over the 30 years (1979 - 2011), while all other indicators play a minor role. This leads to the conclusion, that Gold may be a hedge against the US Dollar but not against inflation (Baur, 2011).

Furthermore, a recent study by Batten et al. examines the relationship between inflation and Gold using a range of advanced methodologies. The study finds no evidence of cointegration between Gold and inflation during the period from 1985 to 2012. Their results suggest that macroeconomic factors, such as monetary easing, should be considered when evaluating Gold's performance in hedging inflation. They find that Gold is specifically sensitive to reductions in interest rates (Batten et al., 2014).

3.5 Performance of portfolios including commodity futures

Several papers analyze the performance of commodities in portfolios (Jensen et al. 2000, Becker and Finnerty 2000, Baur and Lucey 2010, Akhtaruzzaman et al. 2021). For instance, Jensen et. al examine the role of commodity futures in portfolios consisting of stocks, bonds, T-bills, and real estate (REITS) by using data from 1973 to 1997. They found that a Markowitz Optimization algorithm allocates substantial weights to commodity futures for a range of risk levels. This may underscore their effectiveness within a portfolio (Jensen et al., 2000).

In a paper by Becker and Finnerty from 2000, the authors found that the inclusion of commodity index futures in stocks and bond portfolios improves the performance of the portfolio over a period from 1970 to 1990. They also found a particularly strong performance improvement in periods of high inflation, indicating that commodities hedge against inflationary pressures (Becker & Finnerty, 2000).

Baur and Lucey found that Gold acts as a safe haven for stocks in bear markets for around 15 trading days. However, they found no evidence of such for bonds (Baur & Lucey, 2010).

A recent study by Akhtaruzzaman et al. from 2021 particularly focused on the question of whether Gold acts as a hedge or safe haven in the COVID-19 crisis and its different phases. They analyzed the relationship between Gold and equity returns in the US, the Euro Area, Japan, and China using a DCC-GARCH model. Furthermore, they used high-frequency intraday data of commodity indices. They were then able to allocate Gold to a portfolio using a hedge ratio. Their findings suggest, that DCCs were negative during the period before global lockdowns started (December 2019 until March 16, 2020). This implies, that Gold was indeed a safe-haven asset in this period for equities. However, in the second phase when governments started to intervene with monetary and fiscal instruments, Gold was no longer a safe-haven asset and portfolio weights significantly decreased during that period (Akhtaruzzaman et al., 2021).

4 Data

This thesis uses monthly data from January 1982 until September 2024 both for commodity spot prices as well as CPI data. The starting year 1982 is determined by the availability of WTI crude oil prices within the dataset. Additionally, data for the S&P 500 Index, TIPS (5-year index) and Bonds (1-year T-Bill) is needed to perform the asset allocation exercise later on.

4.1 Data Description and Transformation

CPI data is from the US Bureau of Labor Statistics, retrieved from FRED. Specifically, this paper uses the Consumer Price Index for All Urban Consumers, seasonally adjusted (CPIAUCSL), which is a price index of a basket of goods and services paid by urban consumers in the US (US Bureau of Labor Statistics, 2024). The inflation measure is then calculated by annualizing the monthly log-returns of the CPI. Note, that this inflation measure includes energy as a major driver. However, tests with different measures have shown little deviations in terms of outcome and thus are not further presented in this paper. An additional analysis using the Producer Price Index (PPI) is provided in the appendix of this paper.

Commodity spot prices are taken from the Pink Sheet of the World Bank Commodity Price Database (World Bank, 2024) and filtered for ten specific commodities, namely Brent Crude Oil, WTI Crude Oil, Natural Gas, Gold, Silver, Nickel, Copper, Aluminum, Wheat (HRW), and Cocoa. Plots of each commodity's spot price since 1982 can be found in the appendix. Returns are calculated by taking monthly log-returns. Figure 2 below illustrates the cumulative returns for all commodities over the whole period from January 1982 until September 2024. Three major events have shaped commodity markets since the early 2000s: the 2008 Financial Crisis and the outbreak of the COVID-19 pandemic, followed by the 2022 Russian invasion of Ukraine. During the time from 2014 to 2016, a downturn in commodity prices was visible, often called a commodity slump. Most notably, crude oils have slumped during that period, with WTI prices falling from USD 105 down to USD 32 in a period of just 1.5 years. This explains the overall negative returns in that period. Other commodities show the same trend in that period. The commodity slump was followed by a phase of relatively low and stable prices during the 2016 US election and the US-China trade war. However, these trends shifted dramatically by late 2019, marking the early stages of the COVID-19 pandemic.

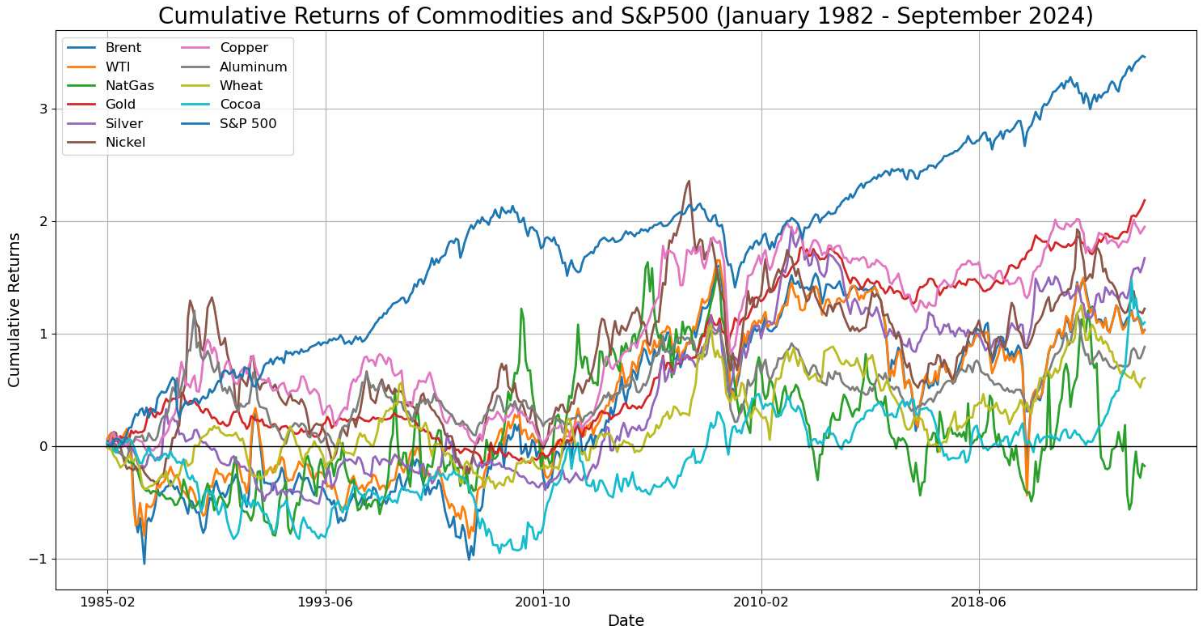

Figure 2 Cumulative Returns of Commodities from 1982 until 2024

In order to perform the asset allocation after retrieving the dynamic conditional correlations of the commodities with inflation, more data is needed. This includes retrieving commodity future data, risky and non-risky assets represented by a stock index, and a government bond. Additionally, TIPS data will be retrieved to get a suitable benchmark with regards to inflation hedging ability.

First, the risky asset is represented by the S&P 500 Index, which includes the 500 leading US companies and represents approximately 80% of the total US market capitalization (S&P Global, 2024). Monthly data is taken from the Yahoo Finance API. Secondly, data for bonds is represented by the 1-Year Treasury Bond (GS1), while the risk-free asset is captured by using the 3-Month Treasury Bond (TB3MS). Both are issued by the U.S. Department of Treasury and sourced from the FRED database. For TIPS, this thesis uses the 5-Year TIPS index (FII5), obtained from the Board of Governors of the Federal Reserve System through FRED database. Notably, TIPS data is available up to 2024. Commodity futures data is taken from Refinitiv Eikon Workspace and are available since November 2004 for most commodities, except for Aluminum and Nickel (available since May 2014 and March 2015, respectively). Where available, the asset allocation uses 1-month commodity futures.

4.2 Descriptive Statistics and Static Correlations

	Mean (%)	Volatility (%)	Skew	Kurt	Min (%)	Max (%)	25 Percentile (%)	50 Percentile (%)	75 Percentile (%)
INF	2.75	11.11	-0.96	9.12	-21.44	16.41	1.32	2.74	4.37
Brent	0.21	33.12	-0.56	3.64	-51.14	43.26	-5.1	0.8	6.27
WTI	0.21	33.38	-0.67	7.56	-59.26	54.74	-4.97	1.07	5.54
NatGas	-0.03	48.75	-0.26	3.27	-68.06	64.2	-6.96	-0.11	7.54
Gold	0.45	11.95	0.35	1.27	-12.48	16.01	-1.62	0.09	2.44
Silver	0.34	21.39	0.25	2.12	-21.43	26.84	-3.03	-0.17	3.53
Nickel	0.25	29.66	0.72	5.27	-38.24	58.11	-4.98	-0.45	5.25
Copper	0.4	21.31	-0.38	4.3	-35.01	24.92	-2.94	0.56	3.61
Aluminum	0.17	18.94	-0.58	3.63	-32.62	18.01	-2.85	0.14	3.34
Wheat	0.12	20.91	0.3	1.9	-21.92	22.92	-3.54	0	3.54
Cocoa	0.23	21.29	0.33	2.86	-25.63	31.77	-3.55	-0.02	3.69
SP500	0.73	15.37	-0.97	2.99	-24.54	12.38	-1.75	1.21	3.52

Table 2 Descriptive Statistics (Inflation, Commodities and S&P 500)

Table 2 reports descriptive statistics of all selected commodities, the S&P 500 index, as well as inflation between 1982 and 2024. While inflation is 2.72% on average and thus quite close to the FEDs target rate of 2%, the average returns of the commodities are only slightly positive, with the lowest average return of -0.03% for Natural Gas and the highest of 0.45% for Gold. The average monthly return for the S&P 500 is 0.73%. Given the very high volatilities of all commodities, the average return is not very indicative in this case. As mentioned before, high levels of uncertainty are characteristic for commodities because their prices depend on a wide range of factors.

Figure 3 illustrates the static correlation matrix between commodities and inflation (INF) returns over the whole period. Additionally, the correlation between inflation and the equity index S&P 500 is provided. The latter are however, not very indicative (even though slightly negative) and do not exhibit any correlation structure with both inflation and commodities. In order to potentially be an inflation-hedging asset, positive correlations are needed. While all commodities exhibit positive static correlations with inflation over the whole period, the only commodities with rather high correlations are Brent and WTI Crude Oil, followed by Copper. While this might be a fairly good approximation, it is not a reasonable indication for an inflation hedge.

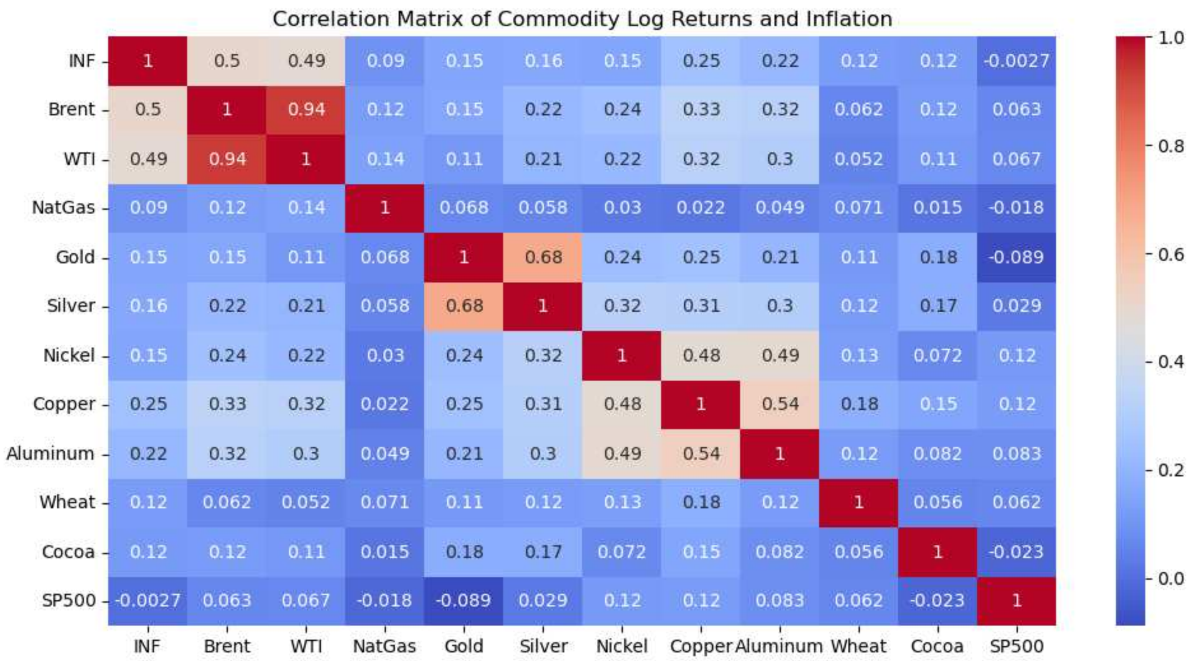

Figure 3 Static Correlations (1982 - 2024)

An easy approach to look at the relationship between inflation and commodities can also be presented by looking at individual scatterplots. They plot returns of each commodity and inflation in a graph with the intention of finding a consistent pattern. Such a graph is presented in the appendix. However, this relationship does not seem to be very strong for most commodities. Some slightly positive patterns can be identified, especially for the crude oil specifications, Brent, and WTI.

5 Methodology

The introduction of ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models by Bollerslev have been a major milestone in forecasting and modelling time-varying asset volatilities (Bollerslev, 1986). Volatility is a key risk measure that is widely used in Asset Management, Portfolio Optimization, Derivative Pricing, and Hedging Strategies. Using a GARCH model has the advantage over other common econometric models commonly used in asset allocation, that it is able to capture volatility clustering. Volatility clustering means that times of high (low) volatility are usually followed by high (low) volatility periods. This phenomenon is particularly observed in financial time series.

However, those models are only applicable to a single asset and thus limited in their usefulness within portfolios because of two main flaws. First, portfolio returns (and prices) depend on covariances between two assets, and second, those covariances vary over time. Therefore, one may consider using a multivariate GARCH (MGARCH) model, which has extended the base literature on ARCH and GARCH models.

5.1 DCC-GARCH Model

In 1999, Engle first introduced a dynamic conditional correlation (DCC) model which provides the flexibility of a univariate GARCH model coupled with a parsimonious parametric correlation model (Engle, 2002). In the context of inflation hedging, a DCC-GARCH model offers valuable insights into the dynamic co-movements between inflation and commodities. By employing this approach, this thesis tries to assess the potential of commodities to serve as effective inflation hedges. This should provide a robust framework for determining the optimal timing as well as its intensity for a commodity-based hedge. This model also enables to identify shifts in co-movement over time across different periods and under varying macroeconomic conditions. A DCC-GARCH model essentially undergoes two major steps. First, using a common GARCH model, the conditional volatilities of inflation and a commodity are estimated. Second, using the diagonal matrix with conditional volatilities, the adjusted time-varying correlation matrix can be retrieved. The latter represent the DCCs.

5.2 Model Specification

As mentioned, the first step is to estimate conditional volatilities h_t for each inflation and commodity time-series returns using a GARCH (1,1) model as specified by Bollerslev (Bollerslev, 1986):

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{2}$$

With mean:

$$r_t = \mu_t + \varepsilon_t \tag{3}$$

$$\varepsilon_t = \sqrt{h_t} z_t \qquad \varepsilon_t \sim N(0, h_t) \tag{4}$$

The conditional variance h_t is a function of past conditional variances h_{t-1} and past squared errors ε_{t-1}. With r_t representing the return of each asset, derived from the unconditional mean μ and an error term ε_t, that incorporates the conditional variance h_t. The error term is normally distributed with mean 0 and h_t as time-varying variance. A GARCH (p,q) uses p lags for the past squared errors and the q lags for past conditional volatilities. In the case of this thesis, using a GARCH (1,1), one leg each is used. The parameter α is similar to a shock parameter, or in other words, how the volatility reacts to recent returns and news, while β serves as a memory parameter, measuring how yesterday's volatility influences today's volatility. The parameters need to satisfy the following constraints:

$$\omega > 0,\ \alpha \geq 0 \text{ and } \beta \geq 0$$

And:

$$(\alpha + \beta) < 1$$

Where:

$$\omega = (1 - \alpha - \beta)V_L$$

Whereas, V_L represents the long-run, unconditional variance. If $(\alpha + \beta) = 1$, then a change in current variance h_t, has a direct effect on all future expectations (Cuthbertson & Nitzsche, 2004). The parameters ω, α and β are model parameters that are automatically estimated during the fitting process when making use of the fit() method in the arch package. The parameters α and β for each commodity with inflation are provided in the appendix.

Moving on to the second step, specific to the DCC-GARCH model. The conditional correlation matrix by Engle is defined by (Engle, 2002):

$$H_t = D_t R_t D_t \tag{5}$$

$$H_t = \begin{bmatrix} \sigma^2_{INF,t} & \cdots & \sigma_{INF,\ COCOA,t} \\ \vdots & \ddots & \vdots \\ \sigma_{COCOA,INF,\ t} & \cdots & \sigma^2_{COCOA,t} \end{bmatrix} \tag{6}$$

Where D_t is the diagonal matrix of conditional standard deviations by fitting the GARCH (1,1) for inflation and commodity return data:

$$D_t = \text{diag } \{\sqrt{h_{i,t}}\} \tag{7}$$

R_t is an adjusted time-varying conditional correlation matrix defined as:

$$R_t = \text{diag}\{Q_t\}^{-1}\ Q_t\ \text{diag}\{Q_t\}^{-1} \tag{8}$$

To estimate R_t, the dynamic correlation matrix Q_t needs to be estimated, with R being the weighted average of the dynamic variance-covariance matrix. Covariances are expected to revert to their mean in the long-term and Q_t is a positive definite matrix.

$$Q_t = (1-\lambda_1 - \lambda_2)R + \lambda_1 \varepsilon_{t-1} \varepsilon'_{t-1} + \lambda_2 Q_{t-1} \tag{9}$$

The coefficient λ_1 adjusts the disturbance in the residuals of the correlations ($\varepsilon_{t-1}\varepsilon'_{t-1}$) and coefficient λ_2 measures the persistence to the previous correlation matrix Q_{t-1}. Note that, λ_1 and λ_2 correspond to the traditional DCC parameters α and β respectivel. In order to optimize the model and retrieve the parameters λ_1 and λ_2, the log-likelihood function will be minimized using the minimize function of the scipy package. For this thesis the fitted parameters λ_1 and λ_2 are 0.0449 and 0.2635 respectively. While λ_1 is moderate, meaning shocks impact correlations moderately, λ_2 is rather low, indicating correlations do not have high persistence or memory. Since the sum of λ_1 and λ_2 is well below 1 (0.3084), the model can be considered stable and stationary.

The intuition behind applying a DCC-GARCH (1,1) model stems from previous studies which evaluated the suitability of econometric models. These studies consistently utilize GARCH models with parameters p=1 and q=1. They highlight their effectiveness in capturing time-varying volatility and correlations. For references, papers by Lai (Lai, 2019) or Chang et. al (Chang et al., 2012) came to such conclusions. Therefore, given the previous econometric literature, this thesis makes use of those insights and fits the GARCH(1,1) to similar data.

6 Empirical Results

6.1 DCC-GARCH

As mentioned, the first step of the DCC-GARCH model is to fit a GARCH model to the commodities' returns. This should allow for a better understanding of the underlying, dynamic volatilities. Again, this thesis uses a GARCH (1,1) model, indicating the use of one lag for both past squared errors and past conditional variances.

The figures below illustrate the monthly conditional volatilities of each commodity return series for the whole period (1982 – 2024). Volatility spikes during the Gulf War in the early 1990s, the post-subprime crisis in 2009, and the outbreak of the COVID-19 pandemic in 2020 can quickly be identified for most commodities. Interestingly, energy commodities (Brent, WTI, and Natural Gas) exhibit overall high positive volatilities compared to other commodities, not only in times of crisis. This seems to be rather reasonable for events like the Gulf War in 1990 and also for the Russian invasion in Ukraine in 2022, because they have an immediate connection to energy and specifically oil infrastructure. On the other hand, it is not so straightforward and intuitive for events like the COVID-19 pandemic or the subprime crisis. The biggest spike can be seen during the COVID-19 pandemic, where global supply chains were disrupted, firms had to stop production, and whole societies were in lockdown for prolonged periods of time. This consequently led to economic losses in most industries, and an inherent lower demand for oil and other energy products in energy-intensive industries. According to the International Energy Agency (IEA), international oil demand (excluding China) experienced a sharp decline in 2020, with demand growth plunging by 9 million barrels per day (mb/d). In contrast, global oil demand had shown steady positive growth in prior years, largely driven by China's increasing consumption. This shift highlights the significant disruption that hit oil markets during this period (IEA, 2024). On the other hand, Gold exhibits rather low conditional volatilities with only minor spikes over the whole period, indicating an absence of extreme price movements.

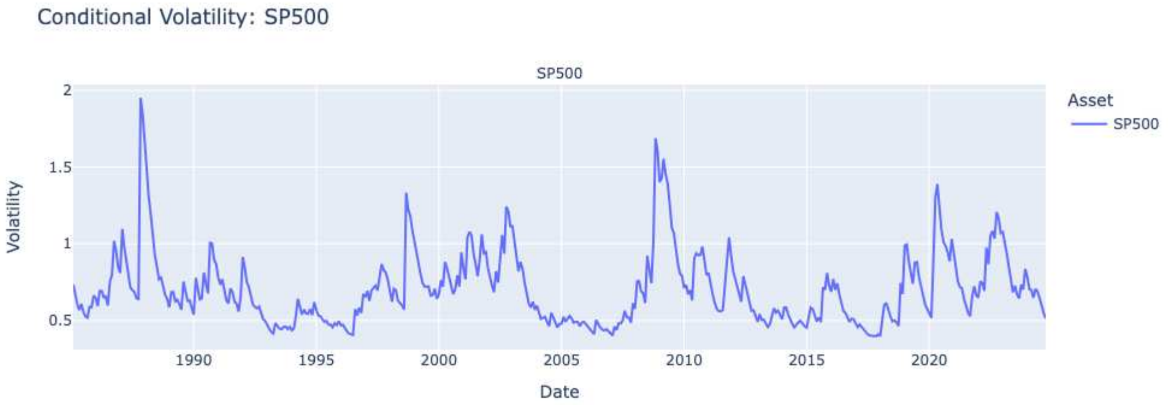

Figure 4 Conditional Volatility with Inflation (S&P500)

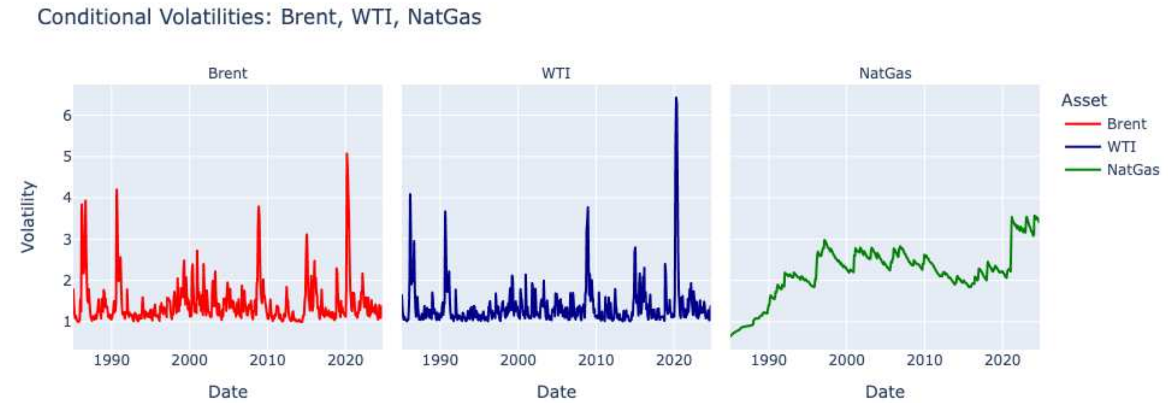

Figure 5 Conditional Volatility with Inflation (Energy Commodities)

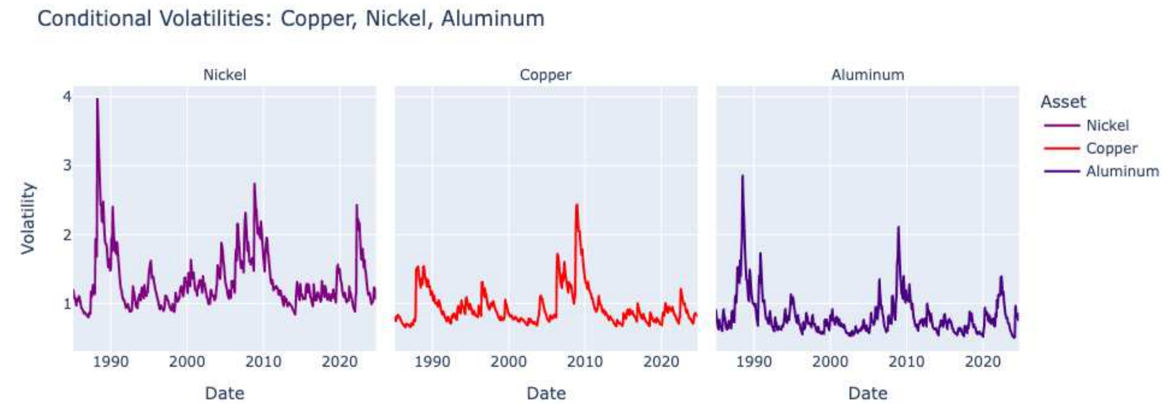

Figure 6 Conditional Volatility with Inflation (Industrial Metals)

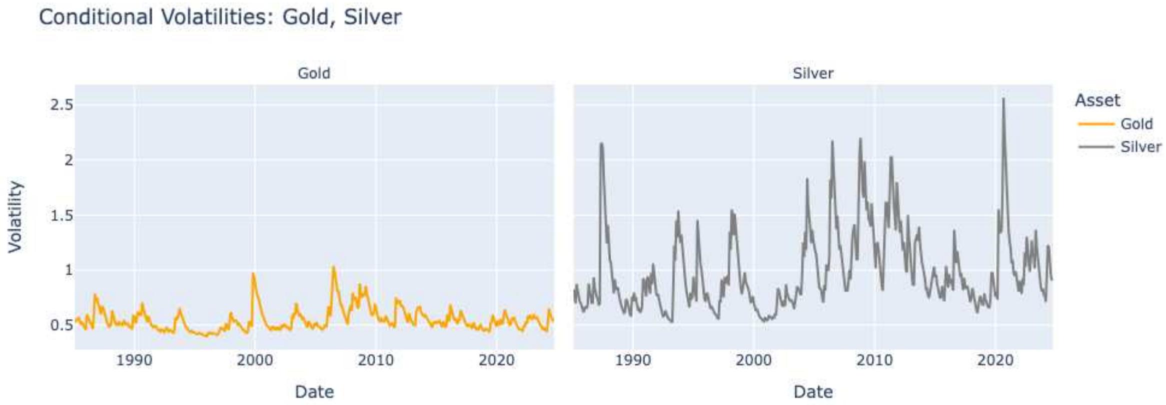

Figure 7 Conditional Volatility with Inflation (Precious Metals)

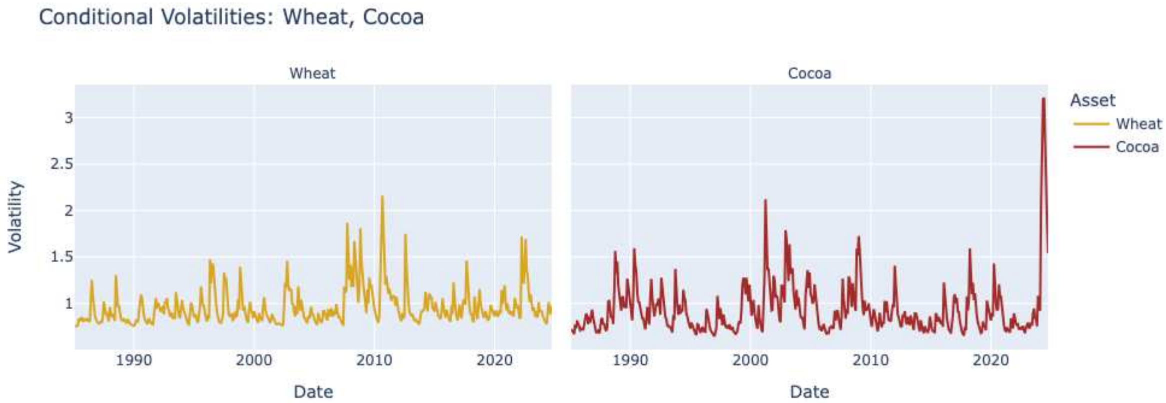

Figure 8 Conditional Volatility with Inflation (Agriculatural Commodities)

This thesis tries to explain the relationship between inflation and commodities using dynamic correlations. In order to provide a suitable inflation hedge, the commodity in question needs to be continuously positively correlated with inflation. As previously mentioned, all analyzed commodities exhibit those desired positive static correlations over the whole period. However, they are not very useful in determining their inflation hedging ability because they are static and barely significant, with correlations close to 0. Therefore, looking at dynamic correlations is much more useful in determining their inflation hedging effectiveness. For that, the DCC-GARCH model gives a good understanding of the co-movements of commodity returns and inflation. A graph including all DCCs is plotted in Figure 9 below. At first glance, it illustrates very clearly that the two crude oil types, Brent and WTI, outperform all other commodities. While the majority of correlations are positive, there are commodities that sporadically show negative correlation patterns, particularly in earlier years. The trend seems to be an overall slight increase in correlations since the 2000s for most commodities.

The following graphs and analysis use CPI as the inflation measure, as mentioned. However, the same exercise has been performed with the producer price index (PPI) as the inflation measure. A graph of those DCCs is provided in the appendix. The results using PPI are rather similar, even though they result in slightly higher correlations over time. Again, Brent and WTI crude oils exhibit the highest correlations with inflation. Acknowledging that the CPI measure here incorporates energy prices, a separate analysis with CPI excluding energy has shown no significant differences.

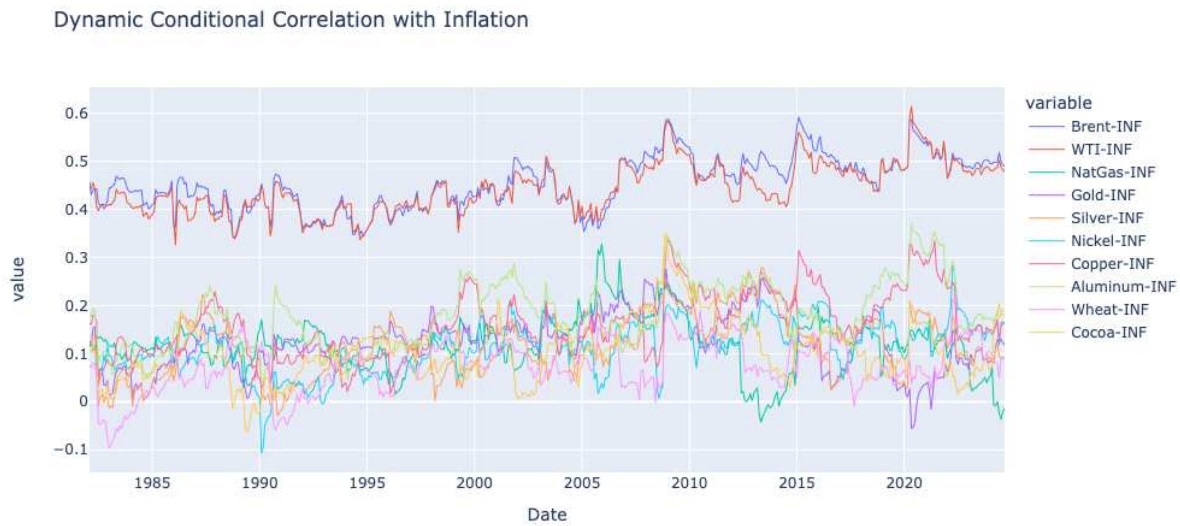

Figure 9 Dynamic Conditional Correlations with Inflation (All)

Given the complexity of the graph above, it is useful to plot each commodity class (energy, industrial metals, precious metals, and agriculture) separately. Additionally, in order to get a benchmark, the DCCs between the S&P 500 index and inflation are also plotted. The S&P 500 index is expected to be negatively correlated with inflation over the whole period, highlighting the necessity of hedging inflation risk. To mitigate this risk, asset classes demonstrating positive DCCs over time are of particular interest. This thesis focuses on commodities only. For a more detailed analysis, the appendix provides separate plots for each commodity, including the S&P 500 as a reference.

First, given the clear outperformance compared to all other commodity types, a closer look into energy commodities is made. As indicated before, Brent and WTI crude oil exhibit stronger dynamic correlations with inflation than other commodities. Brent and WTI correlations are higher over the whole period and indicate an increasing correlation pattern since the year 2005. This could be explained by the increased usage and demand of energy in the form of oil products. Another possible explanation could be the increased volatility of oil which, for instance, arises due to geopolitical tensions. Figure 10 clearly shows that they exhibit spikes during times of economic woes and periods that were characterized by inflation, like the global financial crisis in 2008 and, more so, the COVID-19 pandemic in 2020. Strikingly, the third energy commodity, Natural Gas, shows a different pattern with much lower DCCs. These findings suggest that crude oil may be a more effective inflation hedge than Natural Gas. While the DCCs are generally high for all three commodities, their volatilities are too. Hence, no direct conclusion can be taken with regards to their inflation hedging ability in a portfolio.

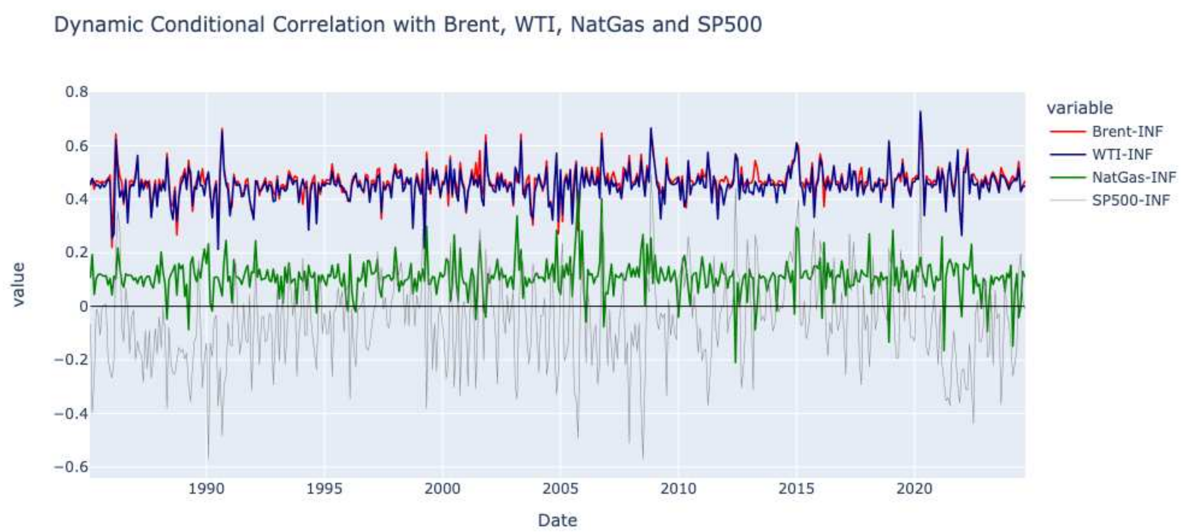

Figure 10 Dynamic Conditional correlations with Inflation (Energy Commodities)

The industrial metals, Nickel, Copper, and Aluminum, demonstrate a similar, though slightly different picture (see Figure 11). Again, one can identify an overall increasing correlation pattern since the early 2000s, however, slightly weaker than for crude oil. Diving deeper, Aluminum and Copper seem to have a positive correlation with inflation, yet not consistently. Looking at the latest inflation spikes, Aluminum's correlation with inflation has gone into the negative, indicating a potentially unreliable inflation hedging instrument. Similarly, Copper has shown such negative correlations in the 2008 financial crisis. One might still consider those metals as an inflation hedge and will therefore be further analyzed in a portfolio. Nickel on the other hand, does not show such high correlations as Copper or Aluminum. Additionally, correlations have repeatedly drifted into the negative in times of crisis, which may indicate poor inflation hedging performance in those periods.

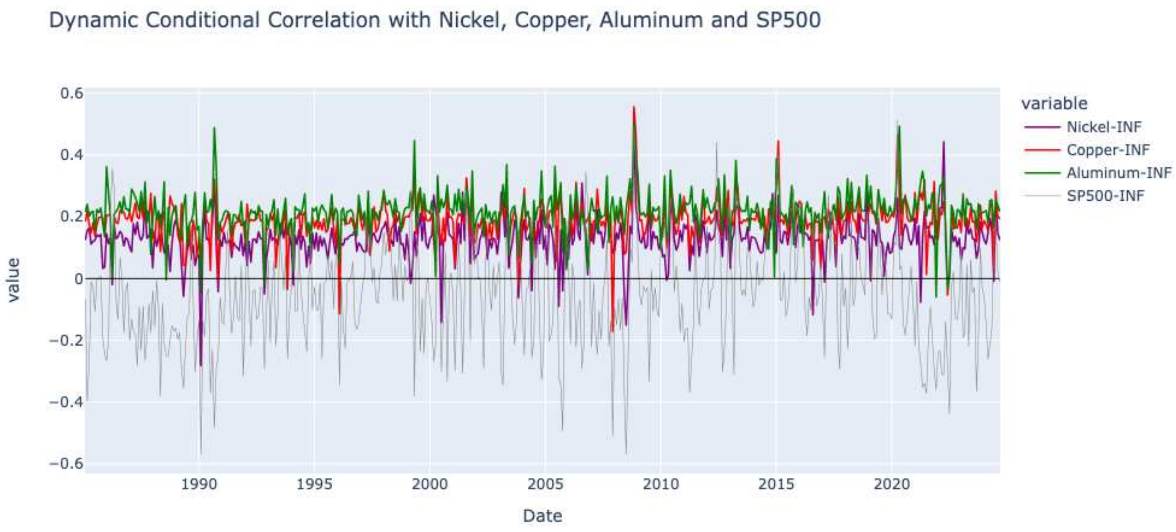

Figure 11 Dynamic Conditional correlations with Inflation (Industrial Metals)

Now, precious metals show a very different picture, indicated by Figure 12. Prior to the COVID-19 pandemic, Gold and Silver show similar correlation patterns with inflation. Then they show something very interesting since the COVID-19 pandemic. They seem to break their pattern of moving in line with each other. Gold's recent trend is particularly compelling, given the ongoing debate about its effectiveness as an inflation hedge. In this case, Gold has the lowest correlation with inflation in the short term. While this is not what this thesis is looking for, Gold is often considered a long-term investment and not necessarily a short term cushion. A striking aspect is the deeply negative correlation of Gold with inflation in the COVID-19 period. Compared to the Global Financial Crisis, this seems quite surprising since correlation dropped then, but remained positive. One could also argue that the year 2020 marks a point where Gold passed a significant turning point. As El-Erian wrote in a Financial Times Article in October 2024, Gold seems to have decoupled from its historical influences like interest rates or the US Dollar over a prolonged period of time (Financial Times, 2024).

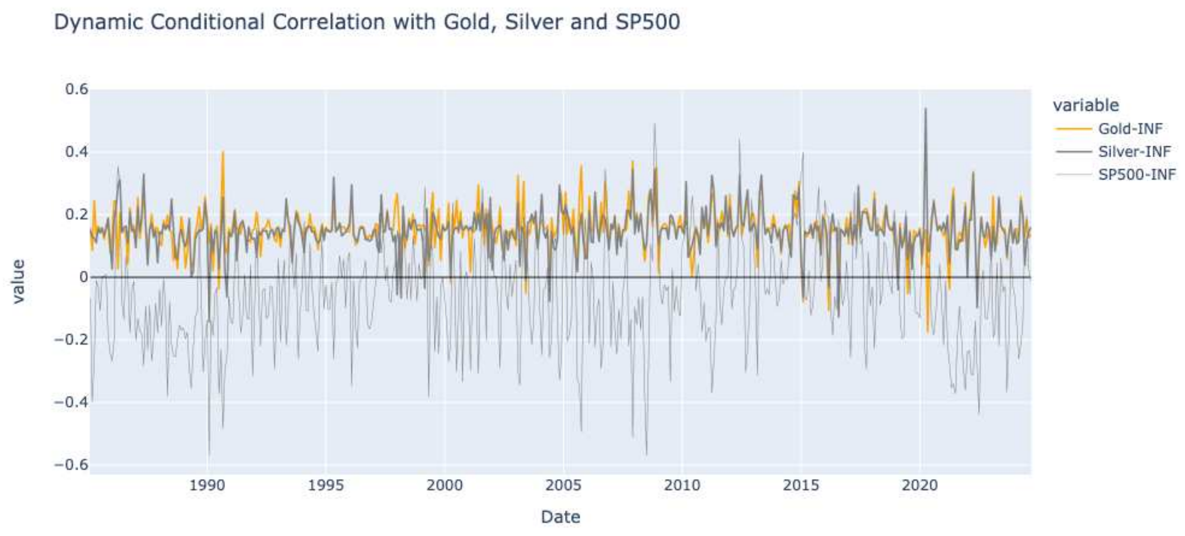

Figure 12 Dynamic Conditional correlations with Inflation (Precious Metals)

With regards to Wheat and Cocoa, we see slightly positive correlations with inflation, however, not as high as the other commodity classes (Figure 13). Spikes during crisis indicate some co-movement with inflation, though not as pronounced. Interestingly, Cocoa has recently seen spikes in DCCs, which is generally explained by a big price increase for Cocoa in recent years. The Wheat spike in 2022 can be explained by the Russian invasion of Ukraine, with Ukraine being a major Wheat and Corn exporter. This may have impacted supply chains not only in the Red Sea but also across land. Therefore, this can certainly not be seen as a consistent pattern and give useful insight into the future.

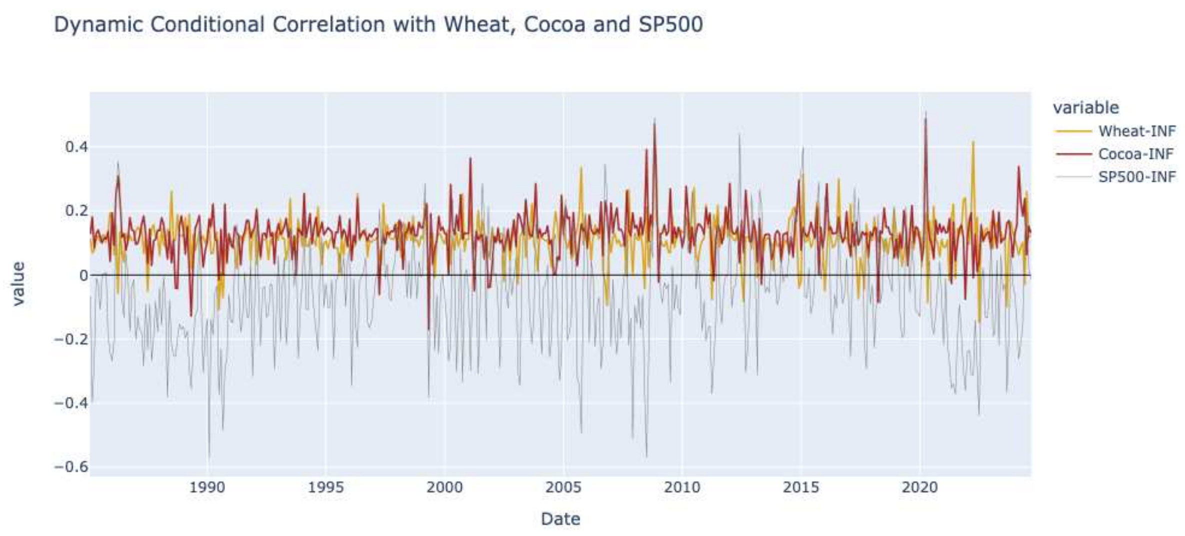

Figure 13 Dynamic Conditional correlations with Inflation (Agricultural Commodities)

In order to better understand and visualize the dynamic conditional correlations, a heatmap is useful. The heatmap in Figure 14 provides a year-to-year breakdown of DCCs with inflation from 1982 until 2024. Monthly conditional correlations are annualized in order to facilitate analysis and interpretation for the reader. Note, that darker shades of blue represent a higher degree of co-movement with inflation than lighter shades. This could be interpreted as very short term inflation hedging effectiveness. But this effectiveness is solely based on the derived conditional correlations between commodities and inflation, using the DCC-GARCH model.

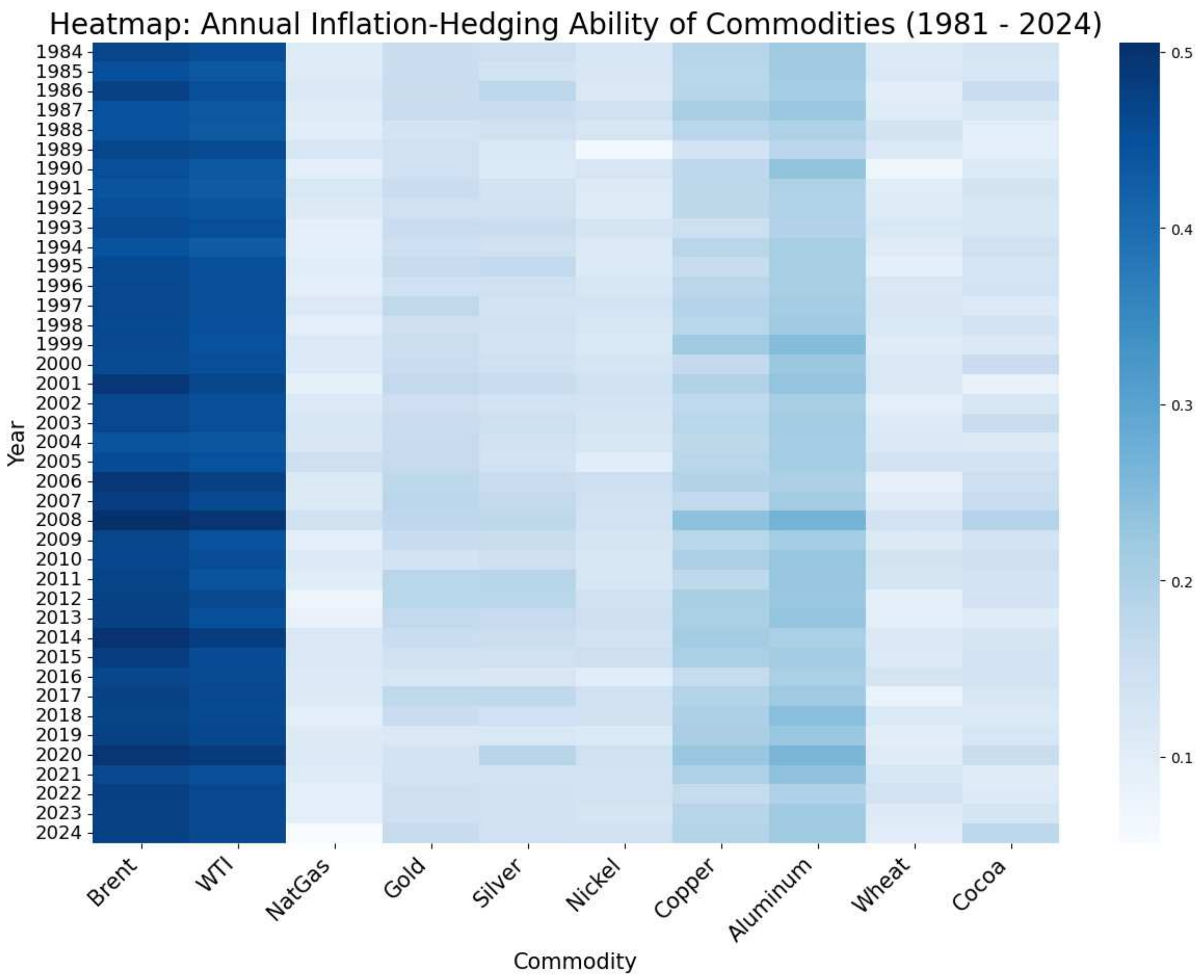

Figure 14 Heatmap of annual inflation hedging ability

The heatmap nicely illustrates how Brent and WTI crude oil significantly outperform all other commodities with regards to their DCCs. While the industrial metals copper and aluminum seem to exhibit slightly higher DCCs in later years, most other commodities do not or only sporadically find high conditional correlations.

Given the superiority of crude oils in terms of conditional correlations, it is also interesting to compare the two specifications, Brent and WTI. For that, another heatmap presenting only these two commodities is provided in the appendix. While both crude oils seem to be highly positively correlated and very much in line with each other, Brent's seems to be higher in specific years as well as in earlier years. Interestingly, both have very high and positive DCCs in the COVID-19 year 2020, marking the latest major inflation spike. This trend, with correlations becoming slightly stronger in recent years, is once again underscoring the pattern that have been observed before.

6.2 Asset Allocation

While the application of a DCC-GARCH model is academically interesting, its practicality is limited. Therefore, it is useful to explore how they behave in a hypothetical investment portfolio. This paper will apply a fixed-weight asset allocation and a Markowitz optimization to evaluate their benefits regarding inflation. This involves determining the optimal asset allocation that yields the highest Sharpe Ratio. The portfolios will consist of equities (represented by the S&P 500 index), government bonds (represented by the three-month T-Bill), and a portion allocated to commodity futures. Those portfolios will be benchmarked against a common 60/40 portfolio. A portfolio that uses TIPS as the inflation hedging instrument will also be included. This eventually leads to a comparable analysis of the effectiveness of commodities as an inflation hedge in a more practical setting.

Since this paper examines the dynamic co-movement between commodities and inflation, a significant limitation is the impact of storage costs, which can be substantial and vary widely across commodities. These costs add a layer of complexity and risk for investors. To address this issue, this section will use commodity futures rather than spot prices. Futures provide exposure to commodities without the need for physical storage. By using futures contracts investors can avoid the delivery of physical commodities, with the caveat that contracts must be closed or rolled over before expiration to prevent physical delivery. Therefore, the insights of this asset allocation are more suitable and impactful for professional investors with a sizable portfolio. This makes monitoring and managing future contracts more feasible compared to individual investors. Commodity future data is taken from Refinitiv Eikon Workspace and is available since November 2004 for all commodities, except Aluminum and Nickel (available since May 2014 and March 2015, respectively). Given that, these two industrial metals will not be analyzed going forward because the data is essential to retrieve the variance-covariance matrices.

6.3 Portfolio Analysis and Performance Measurements

The data will be segmented into periods of different levels of US inflation, some of them exceeding the FED's 2% target. This allows to make a more targeted and differentiated analysis of commodities and their performance in different inflation-characterized chapters since 2004. Most notably, the periods with the biggest inflation spikes are the Financial Crisis (September 2007 until December 2008), the Post Global Financial Crisis (January 2009 until December 2010), the COVID-19 pandemic (March 2020 until December 2021), and the Russian invasion of Ukraine (February 2022 until December 2023). An additional analysis for times, which have seen lower levels of inflation has been performed as well, and includes the Eurozone Crisis in 2011, the Commodity Slump in 2014 (oil price crashed to around USD 30 per barrel), the US election in 2016 (resulting in a win for the Republican Party), and the eventual trade war between the US and China. Note, that those periods are all chosen to be between one and two years. The reason for specifically looking into crises, such as the ones mentioned, is that investors are typically more concerned about inflation during times of crisis rather than in low, stable economic environments. While it is still important to hedge against inflation during those periods, it becomes an immediate priority in times of crisis with high inflation expectations. In order to get a timeframe beyond two years, the whole period from 2004 until 2024 will be explored, and thus may be of interest to investors focused on long-term inflation hedging insights.

The performance measurement of each portfolio will be measured in terms of real return, average excess return, and Sharpe Ratio. In order to evaluate inflation hedging performance, real portfolio returns are derived. Real returns offer an easy inflation-adjusted view of returns, highlighting whether the portfolio retains purchasing power. This helps evaluate whether a portfolio truly grows in value or simply keeps up with rising prices. Real returns are calculated as follows:

$$\text{Real Return}_P = \frac{1 + \text{Average Return}_P}{1 + \text{Average Inflation}} - 1 \qquad (10)$$

Average excess returns represent the average returns of a portfolio over the benchmark portfolio. In that case, the classic 60/40 portfolio is used as such a benchmark. Hence, positive average excess returns for any given portfolio (whether including TIPS or commodity futures as an inflation hedge) indicate outperformance or underperformance of a classic 60/40 portfolio. They are derived as follows:

$$\text{Average Excess Return}_P = \frac{1}{T}\sum_{t=1}^{T} \text{Return}_P \text{- Return}_{\text{Classic 60/40}} \tag{11}$$

Finally, Sharpe Ratios will be calculated. This ratio provides a risk-adjusted performance measure of the portfolios and is commonly used in Asset Management or Risk Management. High Sharpe Ratios indicate higher generated returns given the individual risk level of the investment, and vice versa. Sharpe Ratios (SR) are calculated as follows:

$$\text{Sharpe Ratio}_P = \frac{\text{Average Return}_p \text{ -Average Risk Free Rate}}{\text{Volatilty}_P} \tag{12}$$

6.4 Fixed-Weight Asset Allocation with single commodity asset

First, a fixed-weight asset allocation exercise will be conducted to gain insights into how commodities perform in a portfolio setting. This allows a targeted comparison of portfolios with equivalent allocations to either a commodity or TIPS. Again, the benchmark portfolio consists of the classic 60/40 allocation with 60% invested in a stock market index (S&P 500 index) and 40% into the 1-year Treasury Bill. Portfolios 2-12 use a 60/30/10 asset allocation with 10% allocated to the asset expected to hedge inflation (Figure 15).

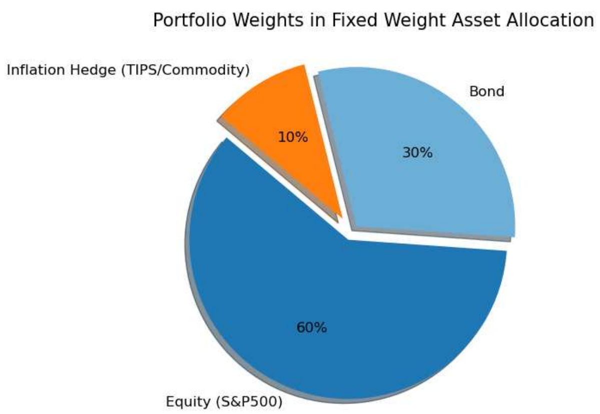

Figure 15 Fixed weight allocation

This is a common allocation for portfolios with exposure to alternative asset classes. For reference, according to global investment firm AllianceBernstein, a 10% allocation to a five-year TIPS index may improve risk-adjusted potential returns under the inflation regime in 2024 (Zhou & Rivers, 2024). Hence, this allocation can also be applied to commodities as inflation hedging instruments and provides a good starting point for a fixed-weight asset allocation.

Additionally, an equally weighted commodity portfolio is included, which represents an index of commodity futures consisting of the mentioned commodities. This should give an insightful summary of whether an index consisting of a range of commodities is more suitable due to diversification than a single commodity asset.

Figure 16 illustrates charts of the performance measures for each portfolio in the mentioned periods.

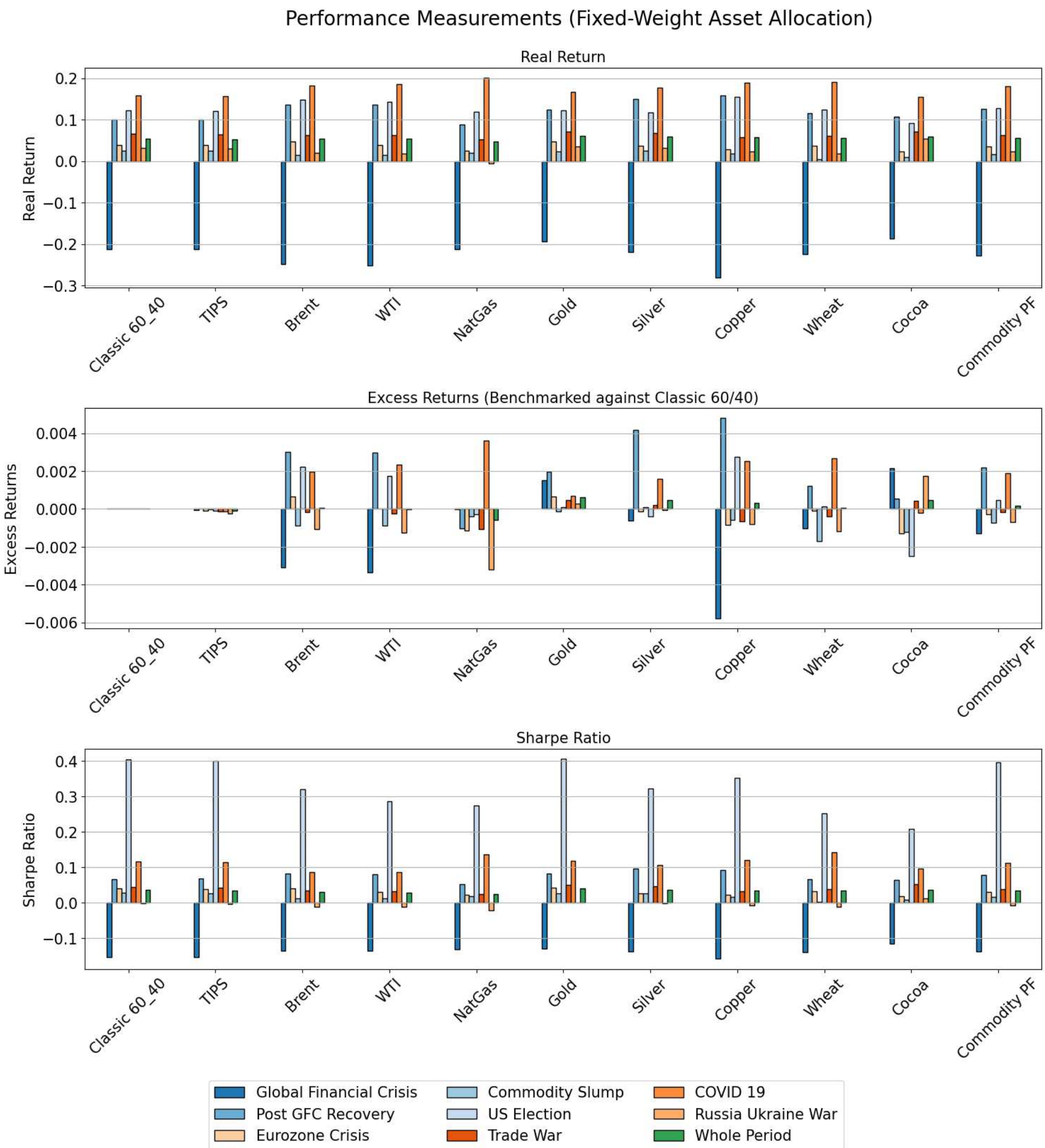

Figure 16 Performance of fixed-weights portfolios

The graph clearly shows negative real returns for all portfolios in the Global Financial Crisis (GFC). Thus, all portfolios, except those that use Gold or Cocoa futures, perform worse than the benchmark 60/40 portfolio during that time. Gold and Cocoa indicate a better performance during that period, even if only marginally better. In contrast, all portfolios exhibit positive real returns after the Global Financial Crisis. Excess returns of commodity portfolios over the benchmark portfolio vary widely. While the TIPS portfolio is only slightly worse than the benchmark portfolio in those periods, Gold performs mostly better or equally well. Portfolios including commodities other than Gold show changing but generally positive real returns, indicating that they work as an inflation hedge but have inconsistent performance compared to the classic 60/40 portfolio. In the low inflation period of the Post-GFC and commodity slump, the commodity portfolios seem to perform better than the benchmark. Also, during high inflation regimes like the COVID-19 pandemic they perform well, followed by a general slump during the Russian invasion of Ukraine.

With regards to the Sharpe Ratio (SR), Cocoa outperforms the 60/40 portfolio during the Global Financial Crisis, followed by Gold, Silver, and Natural Gas. Even though their SRs are better than the one for the benchmark, they are still negative, given the overall negative returns. The TIPS portfolio performs worse in this economic environment than the mentioned commodity portfolios. The worst portfolio in terms of SR is the copper portfolio. The Post-GFC shows the highest SR for the crude oils Brent and WTI, and the precious metals Gold and Silver. Hence, better than the benchmark and TIPS portfolios. During the COVID-19 pandemic, a different pattern arises, where most commodities outperform the TIPS portfolio but only partly outperform the 60/40 portfolio. The commodities that outperform are Natural Gas and Copper. No better SR than that of the 60/40 portfolio can be found for commodities in the latest crisis of 2022, and only Cocoa can keep up with the performance of the TIPS portfolio. Again, Cocoa has seen a price spike due to global supply shortages, which could explain their recent performance. The very high SR during the period of the US elections can be traced back to overall booming financial markets with low volatilities and stable inflation levels of around 2%.

Over the whole period from 2004 until 2024, the best performance can be found for Gold. Since it outperforms the benchmark 60/40 portfolio and delivers the highest average returns, one may consider it a safe haven over that period. The short term performance of the Gold portfolio delivers positive and comparably stable returns as well. One caveat, however, is that there are other portfolios that are at least as good or better in each of the examined periods.

In conclusion, while 60/30/10 commodity portfolios may not consistently outperform classic 60/40 portfolios during market crises, they have demonstrated superior performance as inflation hedges compared to Treasury Inflation-Protected Securities (TIPS). Moreover, commodities have historically exhibited higher returns than TIPS, albeit with increased risk.

While Sharpe Rations are comparable between TIPS and commodities, commodities often present slightly more favorable risk-adjusted returns. Especially, when comparing TIPS to Gold, it becomes clear that Gold is at least as good as TIPS or better. Therefore, risk-averse investors may prefer Gold futures over TIPS as a conservative inflation hedge, whereas risk-tolerant investors could consider commodities as a potentially higher-yielding alternative.

With regards to the commodity index, representing an equally weighted portfolio of all analyzed commodities, mixed results can be reported. While real returns are generally positive, excess returns over the benchmark portfolio remain unclear, even though they are better than TIPS. The gold portfolio clearly outperforms it in every period, therefore leading to the conclusion of insufficient inflation hedging performance in a portfolio setting. However, one may argue that a similar index could reduce transaction costs when investing via a passive investment vehicle. The latter remains outside the scope of this thesis and may pose an interesting topic for future research.

6.5 Markowitz Portfolio Optimization and Efficient Frontier

Instead of choosing an arbitrary set of weights for the risky assets in the asset allocation, investors may want to choose weights that optimize the risk-to-return relationship. In other words, they aim to maximize the Sharpe Ratio of their portfolio. A higher Sharpe Ratio means a more efficient portfolio, delivering greater returns for any given level of risk. This approach is a more realistic and widely adopted method in Portfolio and Risk Management. In 1952, Harry Markowitz revolutionized portfolio theory with the introduction of the efficient frontier. This frontier represents the lowest possible variance that can be achieved for any expected portfolio return. Portfolios on this frontier are considered efficient because they maximize return for a specific risk level. The optimal portfolio lies on the efficient frontier and is tangent to the Capital Allocation Line (CAL). The CAL represents the risk-return trade-off of a portfolio that combines a risk-free asset with a risky portfolio. The tangency portfolio maximizes the slope of the CAL, which is simply the Sharpe Ratio (Bodie et al., 2021).

In order to get reasonable weights which do not allocate extreme weights to a single risky asset, some constraints need to be implemented into the optimization process. To ensure a balanced and realistic portfolio without extreme weight allocations, the Markowitz Optimization is subject to the following set of constraints:

- Weight Summation: The sum of all asset weights must equal 100%.
- No Short-Selling: All weights must be non-negative.
- Mandatory Allocations: A minimum allocation is required for the S&P 500, the 1-year Treasury Bond, and either TIPS or one commodity future as an inflation hedge.

The optimization process was performed for each period, resulting in a time-varying optimal asset allocation that maximizes the Sharpe Ratio. The development of the optimal weights of the inflation hedge is plotted in Figure 17.

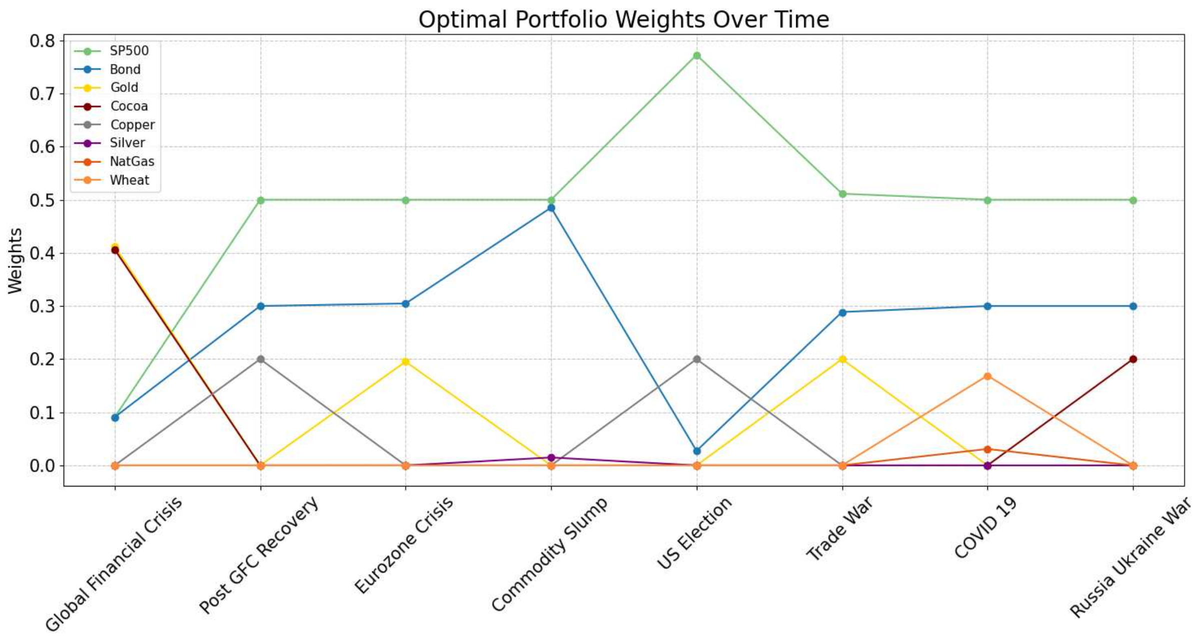

Figure 17 Optimal weight for third asset in Markowitz portfolio allocation next to S&P 500 Index and the 1-year T-Bill

Interestingly, the model consistently favored commodity futures over TIPS as the third risky asset (besides the S&P 500 and the 1-year Treasury Bond). Notably, Gold, Silver, Natural Gas, Copper, Cocoa, and Wheat were the chosen commodities included in the optimal portfolios. Additionally, the model exhibits a slight preference for Gold and Cocoa futures during periods of economic turmoil, such as the Global Financial Crisis (GFC) or the Russia-Ukraine War. It also slightly prefers Gold and Cocoa futures during moderate economic periods, like the Eurozone Crisis or the Trade War between the US and China. In contrast, Copper was primarily used in periods of low inflation, such as the Post-GFC period and the 2016 US election. Finally, Wheat emerged as the top-performing commodity during the COVID-19 pandemic. Overall, the results of the Markowitz Optimization are broadly consistent with the findings from the fixed-weight asset allocation.

Turning to the whole period (2004 until 2024), the allocation yielded in weights of 50% towards the S&P 500 index, 30% to the 1-year Treasury Bond, and 20% to the Gold future (Figure 18). Note, that the Optimization algorithm imposes a limit on the hedge asset to not exceed 20% of the overall portfolio. By removing this constraint, the investment in Gold will be higher, highlighting the attractiveness of Gold in long-term investment portfolios.

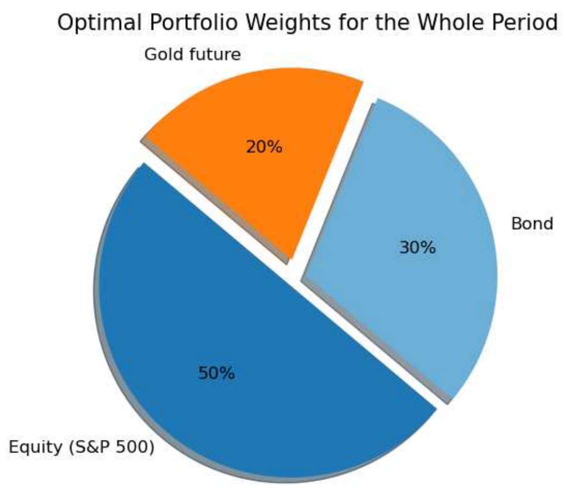

Figure 18 Optimal Portfolio Weights over the whole period (2004 - 2024)

Figure 19 shows the performance of the optimized portfolios in terms of real returns, excess returns over the 60/40 portfolio, and the Sharpe Ratios.

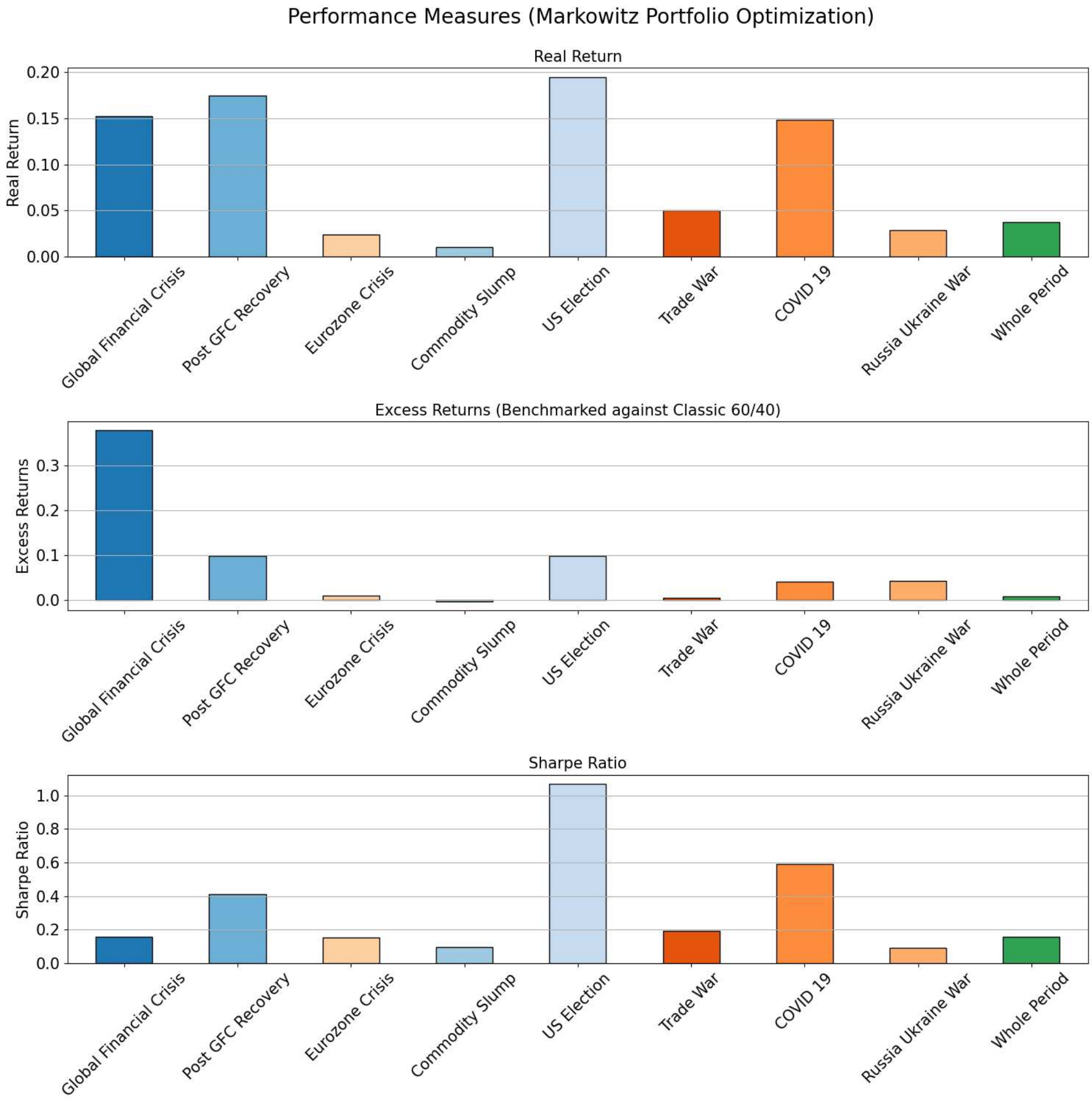

Figure 19 Performance of Markowitz Portfolios

The optimized portfolios realized consistent positive real returns, hence offsetting the effect of inflation. Additionally, all of them realized higher or the same returns compared to the benchmark 60/40 portfolio. This includes the most pressured inflationary periods, like the GFC or the COVID-19 pandemic.

Sharpe Ratios are consistently positive in all periods, despite being on a relatively low level. This is due to the constraints implemented in the optimization algorithm to ensure no extreme weights are allocated. Compared to the fixed weight allocation, the Sharpe Ratios from the Markowitz Allocation are significantly better, which is not surprising, given the underlying objective to maximize the Sharpe Ratio. The Sharpe Ratio during the US elections is again higher than in other periods and above 1. This can be explained by comparably low volatility and stable returns during that period.

6.6 Markowitz Portfolio Optimization Rolling-Window Backtest

Given that inflation hedging strategies vary depending on an investor's time horizon, it is crucial to backtest the Markowitz Optimization algorithm across a range of rolling window sizes. For instance, long-term investors may prioritize returns over periods longer than two years, while short term investors or traders might focus on shorter lookback windows to capture more immediate market trends. For this reason, a backtest for window sizes of 72, 48, 26, and 6 months was performed. The results are represented in the form of heatmaps in Figure 20. Heatmaps are particularly useful to present weight allocation for each commodity (or TIPS) over the analyzed period for a given lookback window. Hence, darker colors indicate more weight and, therefore, better Sharpe Ratios when a certain asset is included.

Overall, the results favor Gold in the long run and energy commodities in the medium term. For the short period, agricultural as well as a set of other commodities show good performance, including TIPS. While those results are not very consistent over time, one pattern generally arises: TIPS exhibit a steady decline in portfolio weights, whereas agricultural commodities like Cocoa and Wheat tend to see an increase in their allocation.

Figure 20 plots the mentioned heatmaps for the weight allocation by the algorithm using window sizes of 72, 48, 26, and 6 months. The appendix provides an additional analysis for window sizes of 96, 36, 3, and 2 months. However, the results largely align with the trends represented here and are therefore not needed to describe the findings.

Figure 20 Asset Allocation of the Markowitz Portfolio Optimization Rolling-Window Backtest (72, 48, 24, and 6 months)

6.7 Findings

After analyzing dynamic conditional correlations and the performance of commodities portfolios benchmarked to a TIPS portfolio and a classic 60/40 asset allocation, the results can be broken down into four main observations.

Firstly, Gold clearly outperforms in the long run compared to all other commodities (including TIPS), delivering stable and positive real returns in a portfolio setting. This is in line with the results of the DCCs, which yield rather low, positive but consistent conditional correlations between Gold and inflation. For instance, while DCCs between inflation and Brent crude oil are comparably high, they are much more volatile than DCCs between Gold and inflation. The results of the Markowitz Optimization, together with the fixed weight allocation, also yield positive real returns, and the Gold portfolio frequently outperforms the 60/40 benchmark portfolio as well as the TIPS portfolio. This indicates Gold's ability to hedge inflation and yield positive returns. It also underscores Gold's ability to maintain value over a long period of time and its diversification benefits. Hence, one can argue that Gold is a good long-term investment. As seen, the portfolio chosen by the Markowitz Optimization algorithm over the whole period from 2004 until 2024 allocates 20% to the Gold future. Those results are comparably stable and reliable when looking at other commodities.

Secondly, energy commodities have demonstrated the highest DCCs with inflation over time. This makes them a strong candidate as a good inflation hedge. However, the results of the portfolio allocations show a different picture due to the highly volatile nature of those assets. This characteristic often yields deeply negative excess returns, benchmarked to the 60/40 portfolio. When they are positive though, they clearly outperform that benchmark. In comparison, the Markowitz Optimization algorithm allocates portfolio weights to alternative commodities or TIPS to maximize the Sharpe Ratio, which primarily focuses on risk-adjusted returns. Due to their high volatility, energy commodities are not always the optimal choice, as increased volatility lowers the Sharpe Ratio. Eventually, if the algorithm selects Brent, WTI, or Natural Gas futures, it tends to do so more frequently in later periods. This is particularly true for lookback windows of 12 to 48 months. This pattern suggests that these assets may have shown improved performance during the medium term horizon in more recent periods. It is important to note, that these commodities remain highly volatile, making them unsuitable for risk-averse investors.

Following that, the agricultural commodities Cocoa and Wheat, are generally harder to categorize in terms of their inflation hedging ability and portfolio performance. Their dynamic conditional correlations with inflation are in the medium range, but unlike Gold, they are very volatile. Portfolios with 10% exposure to those commodities yield positive real returns in all periods except the Global Financial Crisis, thus hedging inflation. It is important to note that they are not always better than the benchmark portfolio. When the Markowitz algorithm selects those commodity futures, it seems to be rather erratic. Hence, no particular pattern can be found for those commodities apart from an indication of increasing weight allocation in more recent periods. This could indicate an increasing attractiveness leading up to the year 2024. But this can certainly not be generalized for future investments and may be an interesting topic for further observation and testing.

Lastly, the Markowitz Optimization algorithm rarely selects TIPS as the third asset to be included in the portfolio and rather prefers commodity futures. Now, while this is true for longer lookback periods (more than 12 months), it does select TIPS in shorter periods. A potential downside is that this was more pronounced during earlier periods, like the Global Financial Crisis. TIPS do not seem to perform particularly better than commodities in a portfolio setting, especially in more recent periods. While TIPS deliver the intended positive real returns in a portfolio with 10% exposure, their performance is slightly inferior to that of a classic 60/40 portfolio. It also significantly lags behind the portfolio that allocates 10% to Gold futures. Hence, commodities may work better as an inflation hedge than TIPS, particularly Gold.

In conclusion, commodities demonstrate consistent DCCs with inflation over time, with Brent and WTI crude oil showing the strongest correlations. However, those correlations are extremely volatile, eventually making crude oil an unreliable component in an investment portfolio. Overall, commodities have proven to be a viable and often superior alternative to TIPS in terms of real returns and inflation-hedging capabilities. This is particularly true since the Global Financial Crisis. The key drawback with this asset class is that they are highly volatile, which often prevents it from consistently outperforming a classic 60/40 portfolio. Among all commodities, Gold futures stand out as the only asset that consistently performs with regard to hedging inflation and performance in a portfolio. Especially for long-term investors who are trying to maximize Sharpe Ratios, Gold is a great addition to a portfolio.

7 Discussion and Limitations

7.1 Data availability and frequency

This thesis uses monthly commodity spot prices since January 1982, determined by the availability of WTI crude oil data. Given the focus on the inflation hedging capabilities of commodities in the US, WTI crude oil is supposed to be included in the analysis as the US crude oil specification. Similarly, data for asset allocation in the form of commodity futures are only available since November 2004, excluding Aluminum and Nickel. Given this, the findings of this thesis are limited to those periods. This makes results potentially subject to bias. Therefore, longer periods of data availability may change or support the suggested findings in this paper.

Another shortfall is data frequency. While this thesis strictly uses monthly data, it might be useful to explore both the DCC exploration as well as the asset allocation for shorter periods. This would imply a need for weekly, daily, or even intraday data. Hence, findings for short term data might oppose those that use monthly data. On the other hand, one might also consider longer periods, such as quarterly, semiannual, or yearly data.

Lastly, a broader range of different commodities could be considered. There is a range of other commodities that could be interesting to analyze as well. However, in order to make this work not too complex in terms of interpretation and recommendation, it is useful to select certain commodities beforehand.

7.2 Reverse Causality

One possible reason for significantly higher DCCs of energy commodities is endogeneity. Energy commodities are often a major reason for inflation spikes, as seen in the latest Russian invasion of Ukraine. The conflict triggered a spike in global oil and gas prices, which is a direct result of geopolitical uncertainty and tense relationships between Western countries and Russia. While inflation has already been high previously, this event certainly added to inflationary pressures. Hence, it can be argued that energy prices, like crude oil have actually caused inflation in the first place. This makes the exploration of hedging ability more complicated. Those dynamics underscore the complicated interplay between inflation and energy prices and add another layer of complexity in evaluating their inflation hedging effectiveness.

7.3 Commodity Markets and Commodity Dynamics

As mentioned, commodity markets are highly volatile and more risky than traditional asset classes such as bonds or stocks. Commodity prices do not always reflect true fundamental value but are often influenced by various factors. For instance, weather, speculation, or even manipulation. Naturally, the supply of commodities heavily relies on weather conditions. For example, natural disasters, storms, or heat may significantly affect the crop of, e.g., Wheat, Cocoa, or Orange Juice Concentrate. On the other hand, weather influences supply chains and eventually leads to delivery delays, constraints, or destruction. Following basic economic theory, those dynamics lead to rising market prices.

Another major influence that can certainly distort commodity prices is powerful traders with enough resources to influence the market price of a specific commodity. A well-known example of such an event is the so-called 'Silver-Tuesday'. This day refers to March 27, 1980, when the price of Silver collapsed after the Hunt brothers attempted to corner the silver market. Cornering the market means buying so much of a specific commodity that it becomes possible to influence its price. At some point, the Hunt brothers owned about one-third of the global supply of privately held silver (Investopedia, 2024), illustrating significant market power, distortion, and volatility. Hence, it is difficult to determine the inflation hedging ability of commodities due to the mentioned features and imperfections in the commodity markets. This leaves commodities highly volatile and unpredictable as an asset class.

7.4 Markowitz Optimization Algorithm

The Markowitz optimization algorithm is designed to maximize investors' Sharpe Ratio by changing the weights given to the S&P 500 index, the 1-year T-Bill, and an asset that is supposed to hedge inflation. The latter is either TIPS or a commodity future. The reason why only one asset is allowed for inflation hedging purposes, is to isolate its effect. However, in order to get meaningful results in this exercise, it is necessary to impose strict rules for the optimization process, which include a restriction on short-selling, a minimum exposure towards the S&P 500 index, and a mandatory allocation towards the inflation hedging asset. Without those constraints, the Markowitz Allocation would result in extreme weights towards T-Bills or the S&P 500 during times of crisis or calm economic periods, respectively. Allocating the total wealth to a single asset class would be the opposite of the desired diversification within a portfolio, which is why strict limitations have been imposed on the model.

Additionally, a no-short-selling constraint is introduced in order to make findings simpler and less complex. However, institutional investors and traders are professional investors who frequently short-sell assets in order to react quickly to certain market dynamics. Short-selling allows those investors to make a potential profit by not owning the asset in question at the exact time, leading to more flexibility. Therefore, the Markowitz allocation does not necessarily mirror a realistic portfolio strategy.

7.5 Potential inflation hedging strategy using expected inflation as signal

While the findings seem to be intriguing, it still remains unclear how a possible strategy could be applied by investors or traders. This has been tested using a signal based on expected inflation. The latter is indicated by the 1-year expected inflation from the Federal Reserve Bank of Cleveland, retrieved from Fred (EXPINF1YR). This indicator estimates the expected rate of inflation over the next year along with the inflation risk premium, the real risk premium, and the real interest rate (Federal Reserve Bank of Cleveland, 2025). The 60/40 portfolio serves as the baseline, with a 10% allocation to Gold futures when monthly expected inflation exceeds 2%. This has been done for 1, 2, 3, and 6 months rolling windows and is tested for all periods, as in the Asset Allocation (6.2). The key metric is the hedging success, measuring how often the strategy returns better real returns than the benchmark 60/40 portfolio.

Results can be found in the appendix, but they are inconsistent and not very indicative of a good strategy. However, the strategy has performed better in periods with very high inflation, like the Global Financial Crisis (64% success), the COVID-19 pandemic (12% success), or the beginnings of the Russia-Ukraine War (18% success). Despite this, all other periods do not show any hedging success, indicating a lack of consistency and robustness. Note, that this strategy has not been thoroughly tested and shall solely indicate how inflation hedging could potentially be deployed using an investment signal.

8 Conclusion

This thesis finds valuable insights into the question of whether commodities have the potential to hedge inflation in the US. Beyond analyzing Dynamic Conditional Correlations, it also explores commodities in portfolios. This should give some practical implications for real-life institutional investors and traders. Additionally, the results attempt to compare Treasury Inflation-Protected Securities (TIPS) and their respective contribution to a portfolio's risk-return profile.

As a general rule, commodities tend to positively correlate with inflation. But these correlations are neither stable nor predictable, sometimes showing erratic patterns. This volatility makes it strenuous to derive insightful implications for commodities, such as agricultural commodities or industrial metals. Strikingly, even though TIPS offsets the effects of inflation (as intended), Gold futures seem to be a better and more reliable alternative. The findings of this thesis suggest that while energy commodities such as WTI, Brent, or Natural Gas exhibit higher dynamic conditional correlations than other commodities, they do not consistently perform well in a portfolio setting. Gold, despite having lower dynamic conditional correlations with inflation, demonstrates robust performance across different periods. A portfolio that includes 10% Gold outperforms a classic 60/40 portfolio as well as a portfolio including 10% TIPS in terms of real returns. This is true over a long period since 2024, as well as shorter periods characterized by high inflation. This suggests that Gold offers the desired inflation-hedging capabilities while also positively contributing to portfolio diversification and performance.

In conclusion, commodities imply some potential to hedge inflation. However, their volatility limits a consistent conclusion. Only Gold stands out as a reliable option, delivering positive real returns that outperform TIPS in a portfolio. Hence, for investors seeking to protect their investment portfolio from negative inflation effects, Gold represents a powerful and viable alternative to TIPS. Lastly, there seems to be a slight trend of increased performance in recent years for most commodities, both in portfolios and in terms of Dynamic Conditional Correlations. Similar to what previous studies have found, the results are not very clear. However, one interesting finding is the role of Gold, showing stable and reliable returns. All of this makes commodities an interesting and contemporary topic for future research on inflation hedging.

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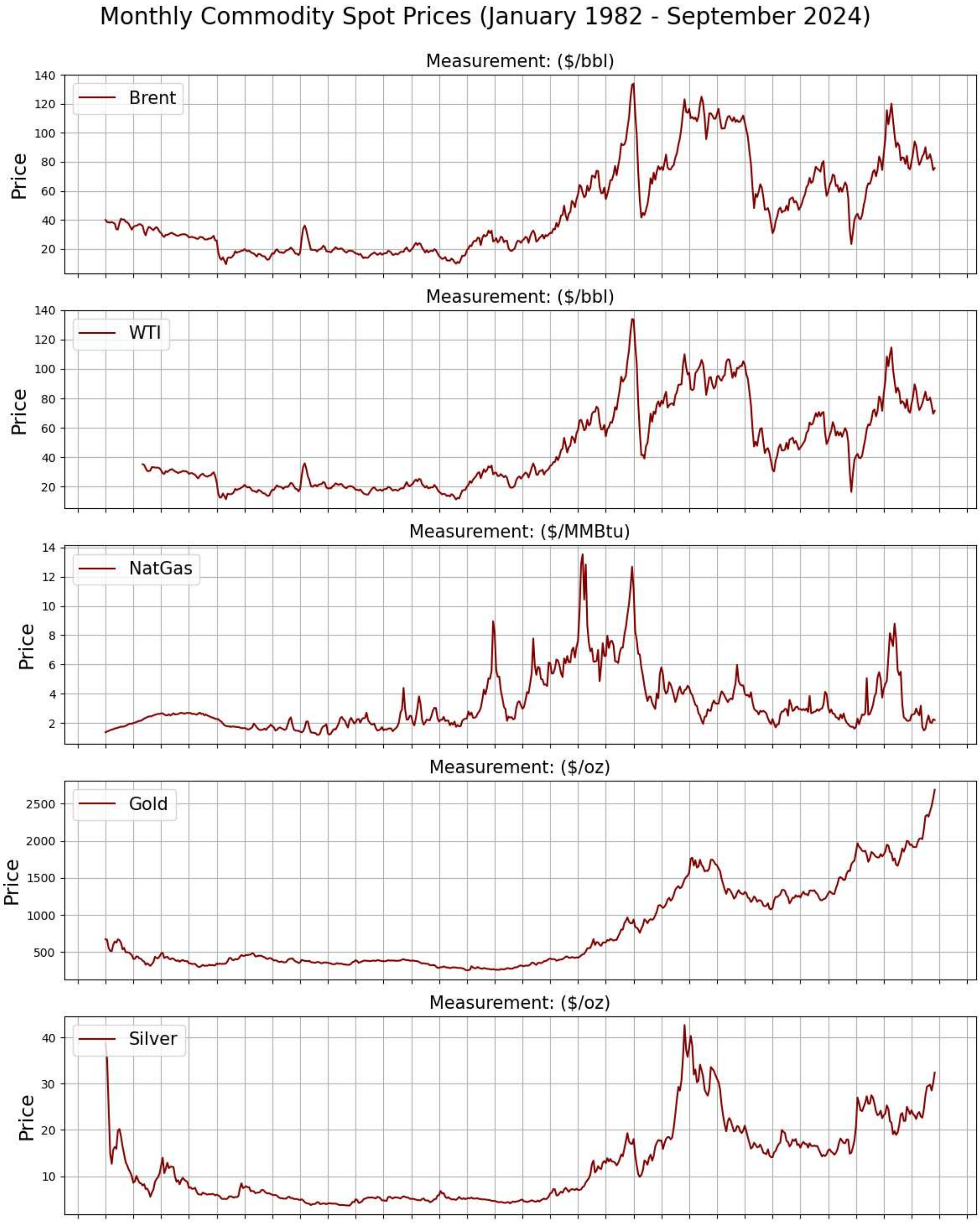
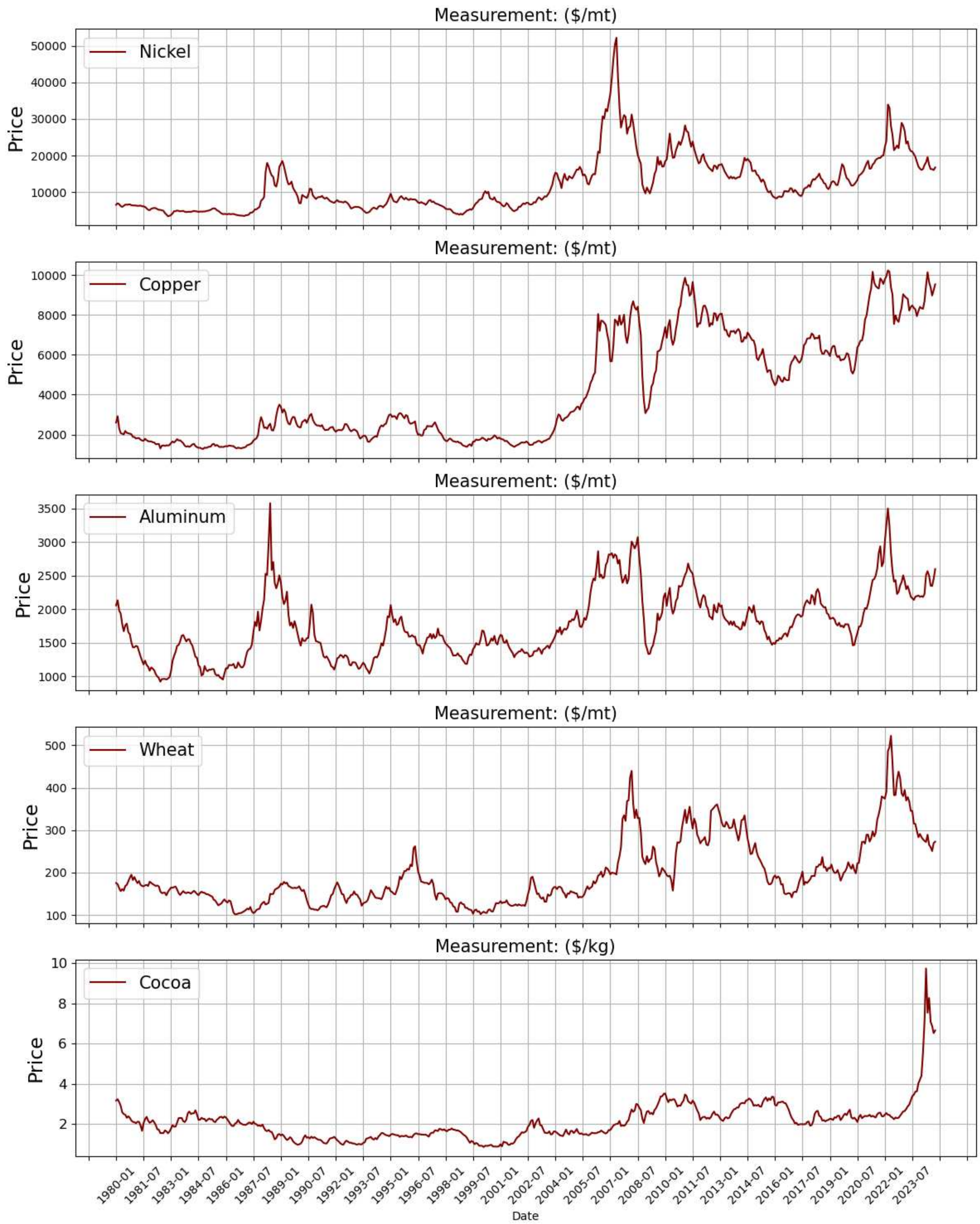
10 Appendix

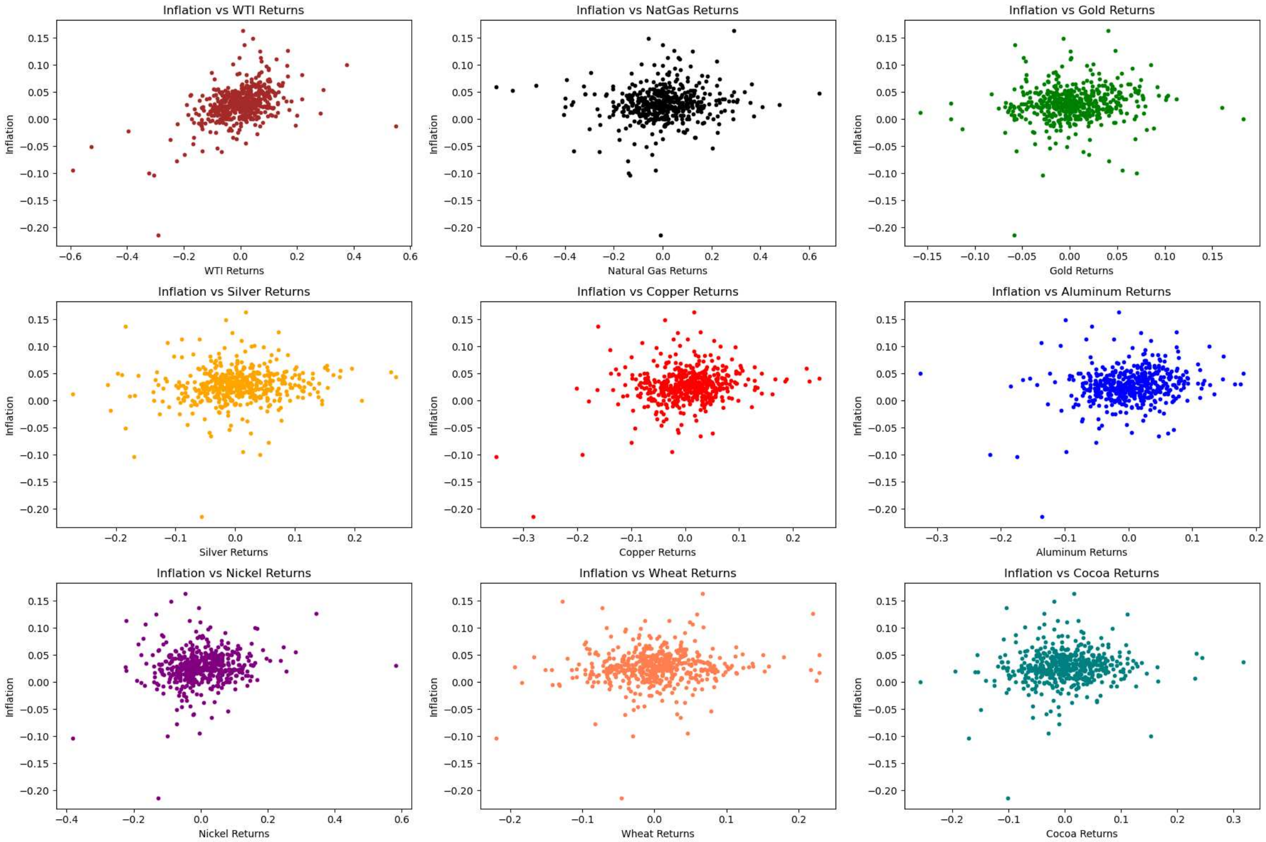
<u>Monthly commodity spot price development (part I)</u>



Monthly commodity spot price development (part II)



Scatterplot monthly inflation vs. commodity returns (1982-2024)



GARCH(1,1) Parameters

Asset	Alpha	Beta
Brent-INF	0.159633	0.341283
WTI-INF	0.375665	0.624335
NatGas-INF	0.819518	0.180482
Gold-INF	0.125647	0.874353
Silver-INF	0.099998	0.799988
Nickel-INF	0.231255	0.725737
Copper-INF	0.05	0.849994
Aluminum-INF	0.099999	0.799992
Wheat-INF	0.34165	0.506955
Cocoa-INF	0.09996	0.799683
SP500-INF	0.099987	0.799899

DCC Model Parameters

$\lambda_1 = 0.0449$

$\lambda_2 = 0.2635$

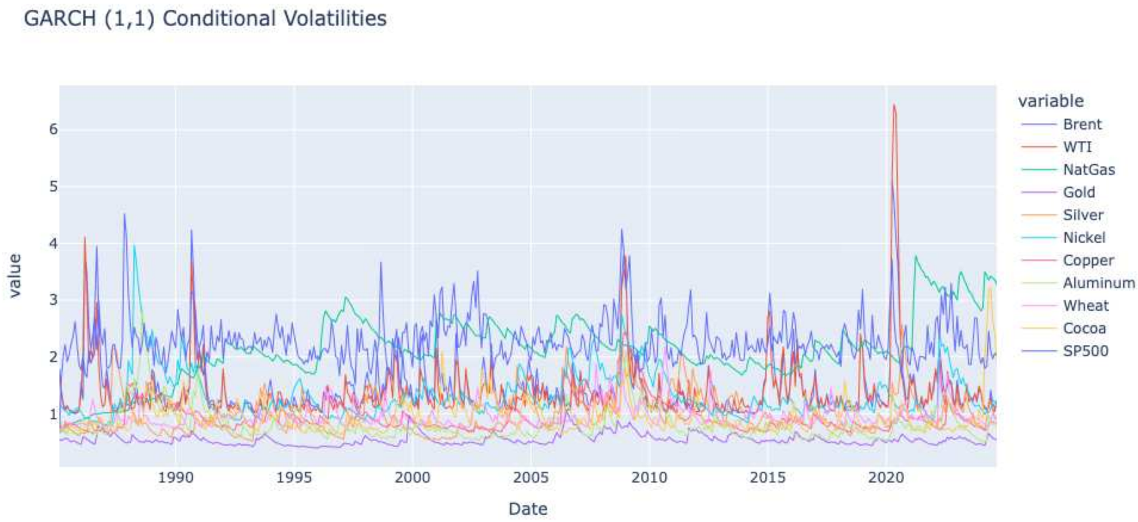
$\lambda_1 + \lambda_2 < 1$ (0.3084)

Note that, λ1 and λ2 correspond to the traditional DCC parameters α and β respectively and the difference is purely notational.

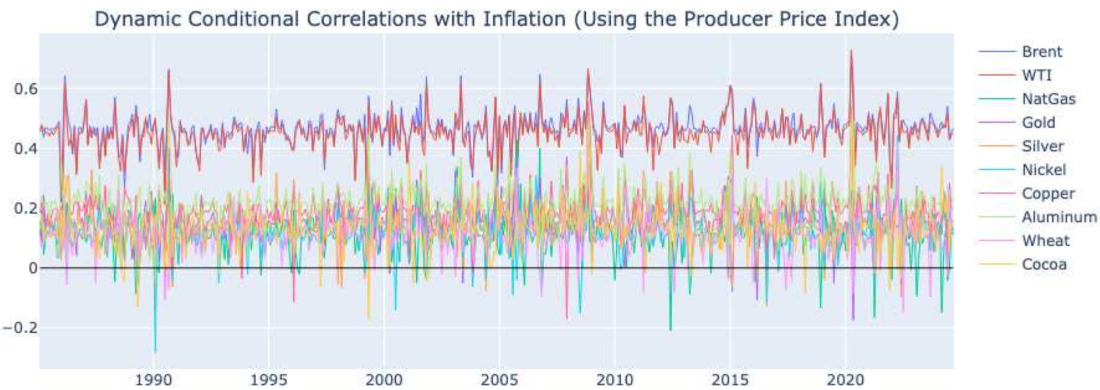
Annualized Dynamic Conditional Correlations with Inflation

Annualized Dynamic Conditional Correlations with Inflation (1984 - 2024)										
Year	Brent	WTI	NatGas	Gold	Silver	Nickel	Copper	Aluminum	Wheat	Cocoa
1984	0.468	0.455	0.107	0.155	0.149	0.127	0.187	0.218	0.111	0.130
1985	0.450	0.435	0.105	0.153	0.137	0.120	0.182	0.219	0.116	0.124
1986	0.476	0.454	0.115	0.155	0.179	0.119	0.186	0.212	0.101	0.153
1987	0.448	0.437	0.107	0.158	0.153	0.142	0.204	0.227	0.106	0.123
1988	0.446	0.434	0.103	0.132	0.142	0.125	0.181	0.196	0.133	0.097
1989	0.469	0.459	0.124	0.145	0.119	0.063	0.135	0.180	0.114	0.093
1990	0.453	0.438	0.095	0.144	0.111	0.126	0.175	0.236	0.070	0.113
1991	0.440	0.432	0.120	0.153	0.138	0.109	0.177	0.197	0.104	0.133
1992	0.451	0.441	0.108	0.145	0.143	0.105	0.176	0.192	0.106	0.123
1993	0.458	0.451	0.095	0.158	0.153	0.130	0.148	0.191	0.120	0.127
1994	0.445	0.430	0.098	0.150	0.142	0.112	0.181	0.206	0.105	0.142
1995	0.460	0.449	0.102	0.165	0.171	0.115	0.161	0.207	0.093	0.128
1996	0.462	0.452	0.097	0.145	0.141	0.122	0.181	0.205	0.118	0.131
1997	0.464	0.452	0.114	0.173	0.136	0.132	0.189	0.212	0.121	0.114
1998	0.460	0.449	0.097	0.149	0.140	0.127	0.183	0.221	0.119	0.132
1999	0.462	0.447	0.115	0.151	0.135	0.119	0.219	0.247	0.106	0.117
2000	0.458	0.453	0.111	0.153	0.144	0.129	0.167	0.224	0.118	0.157
2001	0.490	0.466	0.087	0.169	0.159	0.143	0.195	0.233	0.117	0.084
2002	0.461	0.451	0.114	0.150	0.138	0.132	0.173	0.205	0.097	0.121
2003	0.463	0.451	0.125	0.157	0.148	0.129	0.183	0.215	0.111	0.156
2004	0.440	0.438	0.121	0.164	0.145	0.125	0.176	0.210	0.117	0.112
2005	0.456	0.448	0.150	0.166	0.136	0.102	0.184	0.213	0.131	0.131
2006	0.490	0.474	0.112	0.176	0.157	0.150	0.193	0.202	0.085	0.150
2007	0.480	0.459	0.113	0.181	0.172	0.143	0.170	0.215	0.105	0.154
2008	0.505	0.494	0.143	0.175	0.176	0.135	0.238	0.267	0.136	0.188
2009	0.467	0.446	0.098	0.162	0.155	0.129	0.184	0.212	0.112	0.138
2010	0.466	0.454	0.111	0.138	0.149	0.123	0.200	0.229	0.133	0.150
2011	0.471	0.445	0.104	0.184	0.185	0.125	0.177	0.228	0.128	0.137
2012	0.476	0.462	0.071	0.182	0.181	0.142	0.206	0.226	0.094	0.136
2013	0.476	0.449	0.084	0.169	0.166	0.146	0.203	0.232	0.097	0.105
2014	0.499	0.482	0.116	0.152	0.152	0.136	0.213	0.203	0.117	0.130
2015	0.479	0.456	0.118	0.145	0.144	0.149	0.202	0.213	0.113	0.135
2016	0.465	0.458	0.111	0.124	0.120	0.102	0.163	0.203	0.130	0.135
2017	0.476	0.462	0.112	0.174	0.173	0.143	0.189	0.221	0.081	0.123
2018	0.471	0.460	0.096	0.154	0.145	0.139	0.202	0.246	0.111	0.114
2019	0.476	0.465	0.108	0.117	0.120	0.114	0.205	0.225	0.100	0.125
2020	0.494	0.486	0.114	0.131	0.185	0.144	0.228	0.260	0.105	0.155
2021	0.463	0.452	0.106	0.138	0.138	0.136	0.199	0.236	0.126	0.106
2022	0.479	0.464	0.096	0.149	0.139	0.137	0.164	0.196	0.136	0.111
2023	0.476	0.461	0.095	0.146	0.143	0.130	0.185	0.218	0.108	0.129
2024	0.473	0.461	0.051	0.160	0.144	0.142	0.189	0.220	0.103	0.176

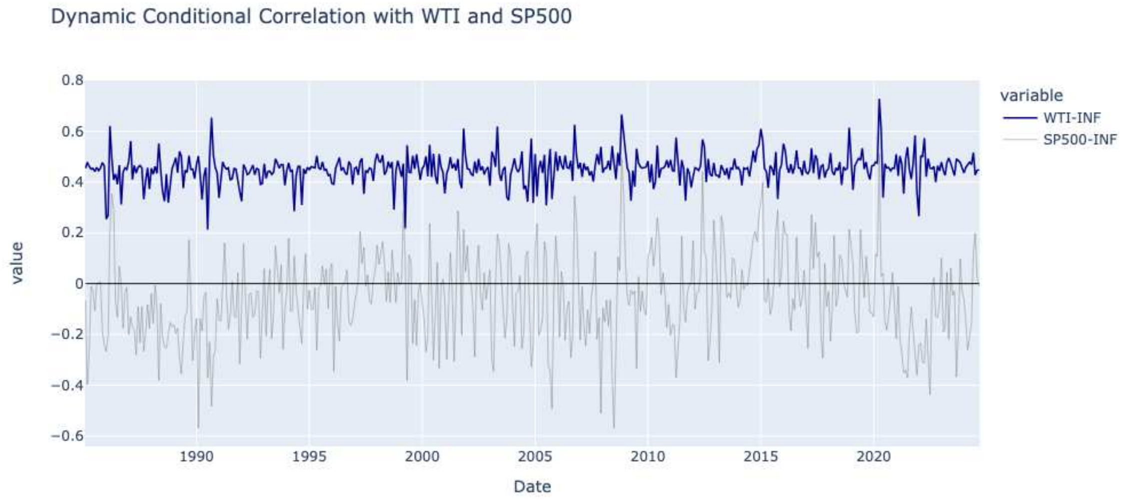
Dynamic Conditional Volatilities with Inflations

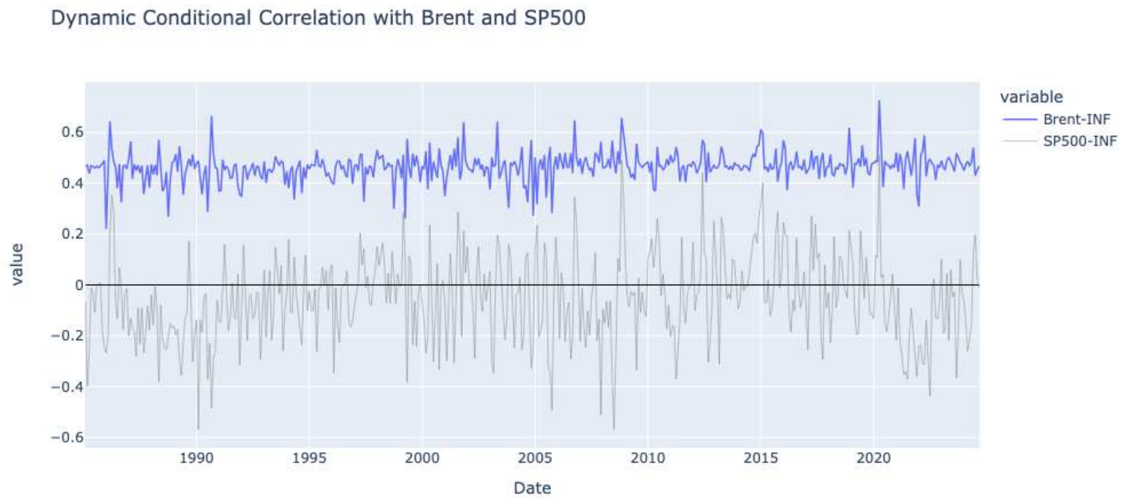


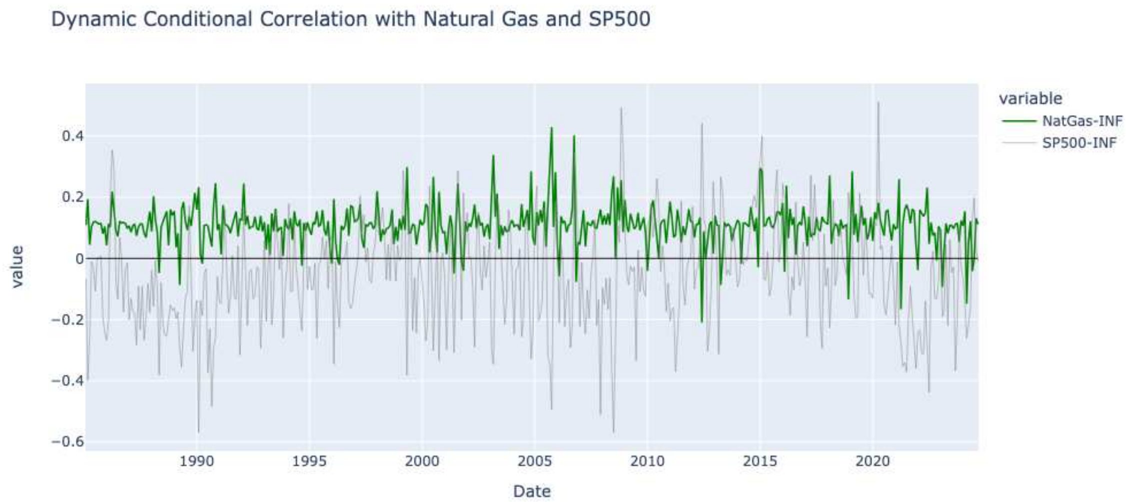
Dynamic Conditional Correlations with Inflations (using the PPI as inflation measure)



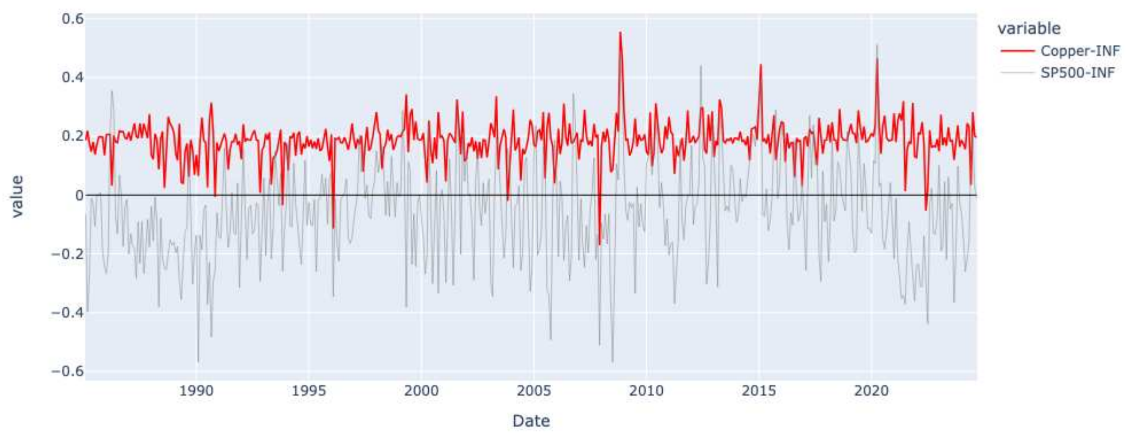
Dynamic Conditional Correlations with Inflations – individual plots



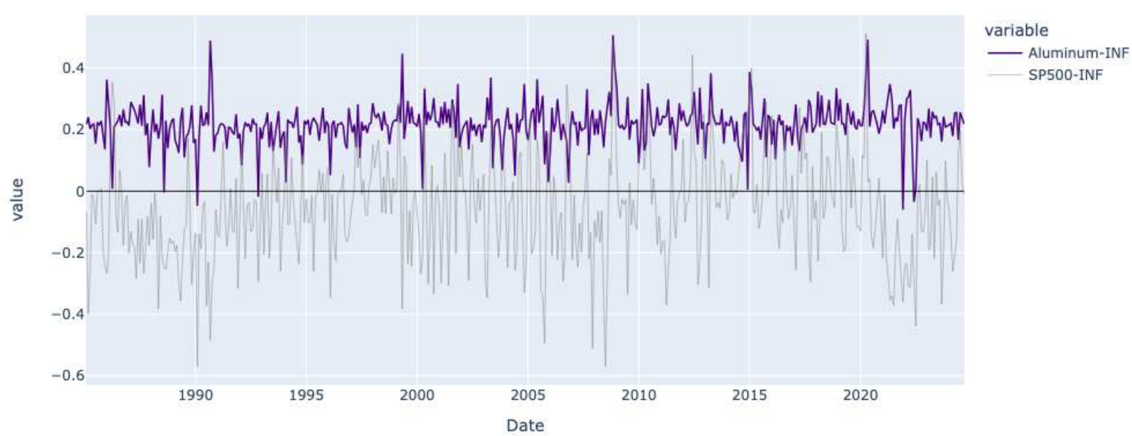




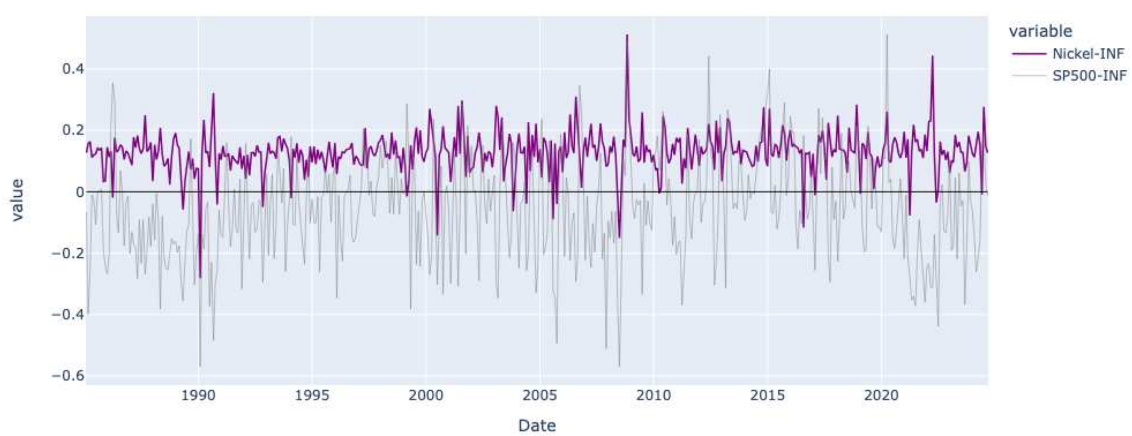
Dynamic Conditional Correlation with Copper and SP500

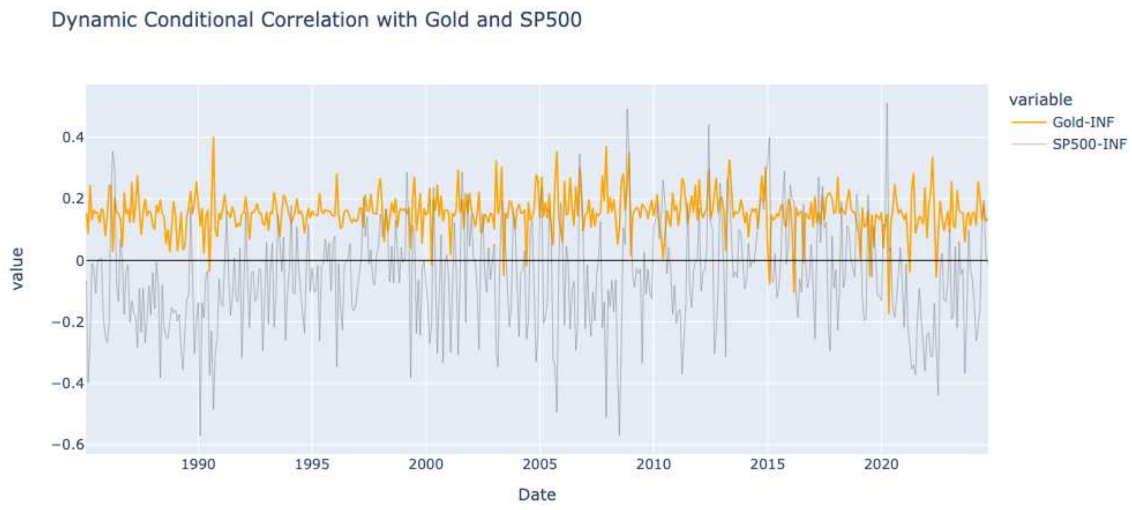


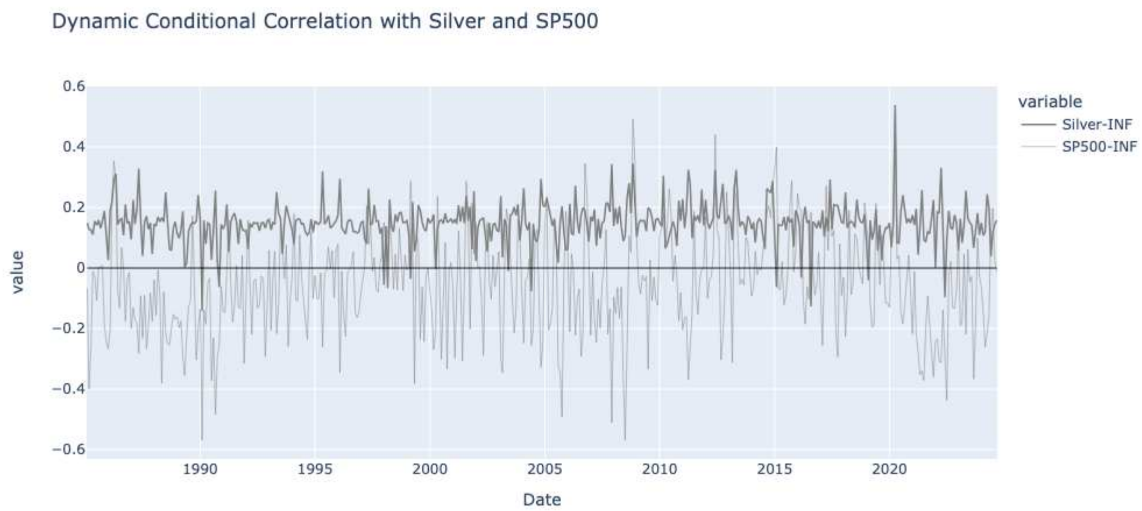
Dynamic Conditional Correlation with Aluminum and SP500

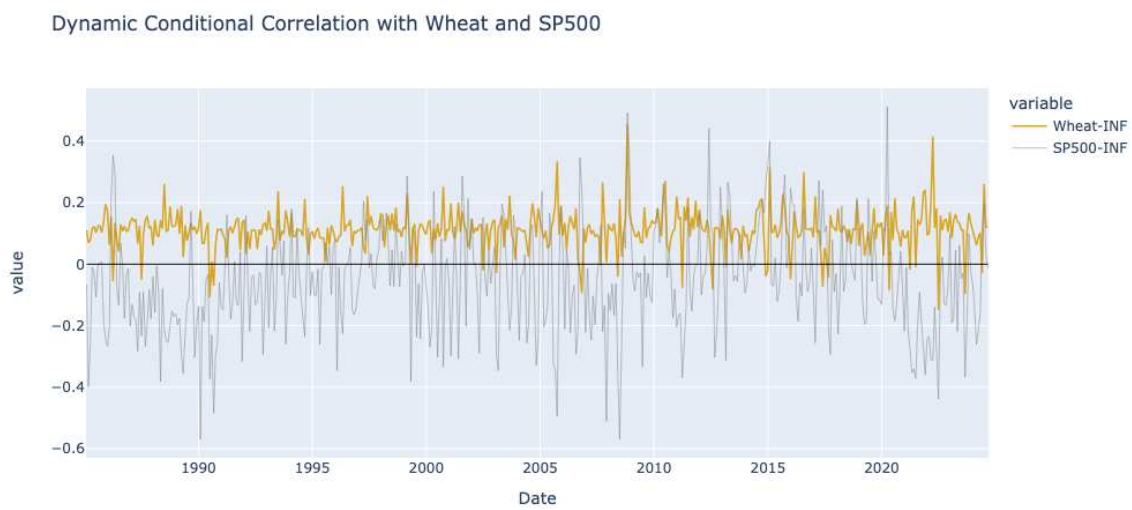


Dynamic Conditional Correlation with Nickel and SP500




Dynamic Conditional Correlation with Gold and SP500
variable
Gold-INF
SP500-INF
value
0.4
0.2
0
−0.2
−0.4
−0.6
1990
1995
2000
2005
2010
2015
2020
Date


Dynamic Conditional Correlation with Silver and SP500
variable
Silver-INF
SP500-INF
value
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
1990
1995
2000
2005
2010
2015
2020
Date


Dynamic Conditional Correlation with Wheat and SP500
variable
Wheat-INF
SP500-INF
value
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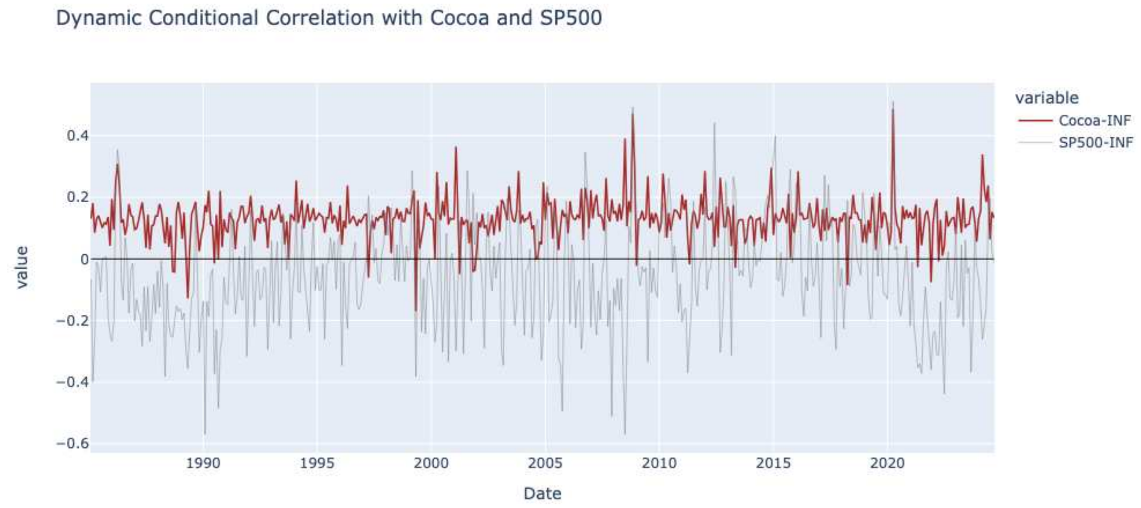
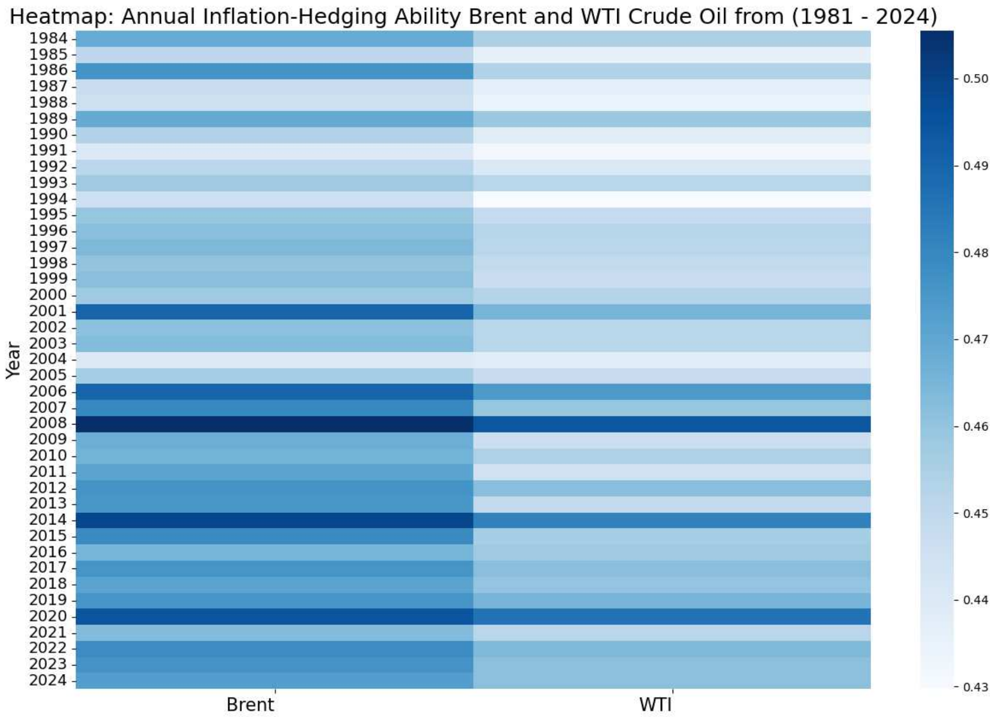
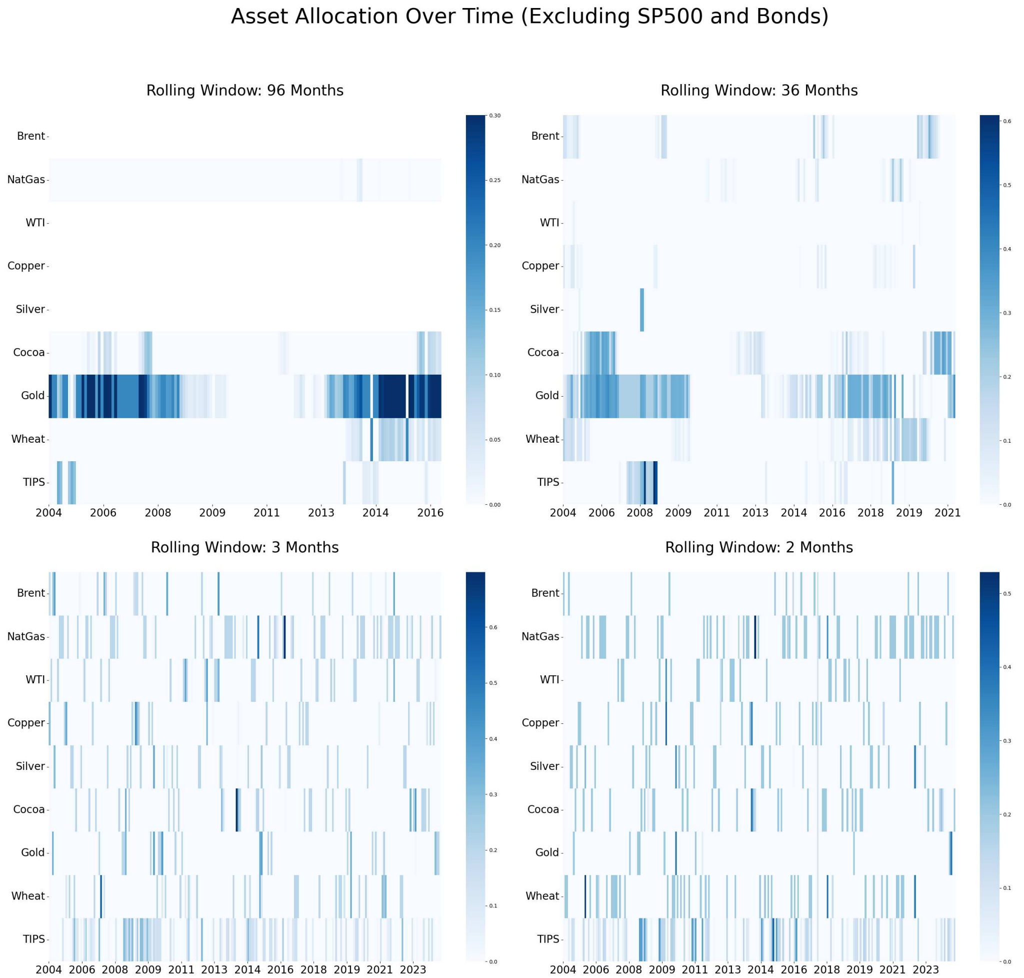
0.2
0
−0.2
−0.4
−0.6
1990
1995
2000
2005
2010
2015
2020
Date



<u>Heatmap of annual inflation-hedging ability of Brent and WTI crude oil</u>



Back-testing asset allocation (96, 36, 3 and 2 month rolling window estimation)



Testing a strategy that dynamically allocates to Gold futures using expected inflation as signal

Period	Rolling Window (months)	Avg. Real Return (Strategy)	Avg. Real Return (60/40)	Hedging Success Rate
Global Financial Crisis	1	-3.13%	-3.10%	18.75%
Global Financial Crisis	2	-6.80%	-6.72%	26.67%
Global Financial Crisis	3	-12.00%	-11.89%	28.57%
Global Financial Crisis	6	-26.35%	-26.43%	63.64%
Post GFC Recovery	1	-1.26%	-1.26%	0.00%
Post GFC Recovery	2	-2.23%	-2.23%	0.00%
Post GFC Recovery	3	-2.72%	-2.72%	0.00%
Post GFC Recovery	6	-5.49%	-5.49%	0.00%
Eurozone Crisis	1	-2.09%	-2.06%	0.00%
Eurozone Crisis	2	-4.21%	-4.15%	0.00%
Eurozone Crisis	3	-6.50%	-6.42%	0.00%
Eurozone Crisis	6	-11.59%	-11.43%	0.00%
Commodity Slump	1	-0.93%	-0.93%	0.00%
Commodity Slump	2	-1.97%	-1.97%	0.00%
Commodity Slump	3	-3.39%	-3.39%	0.00%
Commodity Slump	6	-6.99%	-6.99%	0.00%
US Election	1	-1.13%	-1.10%	0.00%
US Election	2	-2.33%	-2.26%	0.00%
US Election	3	-3.41%	-3.34%	0.00%
US Election	6	-5.53%	-5.45%	0.00%
Trade War	1	-1.41%	-1.40%	0.00%
Trade War	2	-2.80%	-2.79%	0.00%
Trade War	3	-4.10%	-4.08%	0.00%
Trade War	6	-8.06%	-8.02%	0.00%
COVID-19	1	-3.07%	-3.05%	4.55%
COVID-19	2	-5.83%	-5.78%	9.52%
COVID-19	3	-9.07%	-9.01%	10.00%
COVID-19	6	-18.23%	-18.16%	11.76%
Russia-Ukraine War	1	-4.38%	-4.35%	34.78%
Russia-Ukraine War	2	-8.46%	-8.39%	45.45%
Russia-Ukraine War	3	-12.45%	-12.38%	42.86%
Russia-Ukraine War	6	-21.32%	-21.07%	27.78%
Whole Period	1	-2.08%	-2.05%	9.62%
Whole Period	2	-4.09%	-4.01%	10.50%
Whole Period	3	-6.06%	-5.95%	10.13%
Whole Period	6	-11.61%	-11.41%	10.26%