Assessing Gold´s Protective Properties During Market Stress

Evidence from U.S. and Swedish Markets

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Abstract:

This thesis studies whether gold functions as a hedge, safe haven or a diversifier for equity investors in the United States and Sweden. Monthly return data covering the period from 2000 to 2024 are used to examine the relationship between gold, stock markets (S&P and OMXSPI), and oil. The analysis combines correlation measures with regression models based on stress indicators defined by the 10th and 5th percentiles of stock market returns. In addition, Vector Autoregression (VAR) models, impulse response functions, and Granger causality tests are employed to capture dynamic interactions between the assets. The empirical results provide little support for gold acting as either a hedge or a safe haven in the U.S. market. Gold returns are significantly negative during both moderate and extreme stock market downturns, indicating that gold tends to fall when U.S. equities decline. For the Swedish market, gold shows positive but statistically insignificant responses during stress periods, suggesting that it neither protects nor amplifies equity losses. Instead, gold appears to behave largely independently of the OMXSPI. The dynamic analysis confirms these findings, as gold does not respond significantly to negative stock market shocks in either country, while oil moves in line with the business cycle. Granger causality tests further show no predictive relationship between stock market returns and gold returns. Overall, the results indicate that gold does not function as a hedge or a safe haven in either market. Rather, its primary role is that of a diversifier, particularly in the Swedish context.

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1.Introduction

Financial markets can change very quickly, and when they do, many assets start moving in the same direction. This makes it harder for investors to protect their portfolios, especially during periods of market stress. Gold is often talked about as a "safe haven asset" that can protect investors when the stock market fall, but whether this is true is not obvious. To answer this, we need to study how gold moves in relation to other assets both under normal market conditions but also under periods of market stress.

Skepticism regarding gold's role as a safe haven has also been expressed by prominent investors. As Warren Buffett famously stated, "Gold gets dug out of the ground in Africa, or someplace. Then we melt it down, dig another hole, bury it again, and pay people to stand around guarding it. It has no utility" (Forbes, 2017). This quote highlights doubts about gold's fundamental value and stands in contrast to its widespread perception as a safe haven asset, thereby motivating the empirical analysis conducted in this study.

Accordingly, this study examines whether gold functions as a hedge, diversifier or safe haven. To investigate this, historical financial data covering the period (2000 – 2024) are analyzed using several econometric methods, including Vector Autoregression (VAR), Impulse Response Functions, and Granger Causality tests. By combining these approaches, the analysis evaluates both the average relationship between gold and other assets and how gold reacts to shocks during periods of market stress. The overall objective is to determine whether gold behaves in line with common investor beliefs by providing protection during turbulent periods, or whether it's safe haven properties are more limited.

1.1 Background

Financial markets often experience periods of volatility and uncertainty, during which the benefits of diversification tend to weaken as asset correlations increase (Hartmann et al., 2001). These conditions make it more difficult for investors to manage risk, especially during sharp market downturns when capital preservation becomes a priority. As a result, there is strong interest in identifying assets that can offer protection when traditional asset classes decline simultaneously.

Gold has long been viewed as a potential protective asset due to its historical role as a store of value and its relative independence from the financial system (Hillier et al., 2006). However, the extent to which gold effectively protects investors remains debated. Baur and Lucey (2010) highlight an important distinction between hedge assets that are uncorrelated or negatively correlated with the market on average and safe havens, which maintain this non-positive correlation during extreme market stress. Their findings suggest that gold may act as a safe haven, but only for short periods following market shocks.

Investors behavior during crises is closely connected to the concept of flight to quality. Where capital flows from risky assets into safer alternatives such as government bonds or gold (Mustafa et al., 2015). Understanding whether gold consistently attracts such flows is essential for evaluating its role in modern portfolio management. Given this context analyzing gold´s behavior using both average correlations and dynamic time-series methods is necessary to determine whether it functions as a hedge, a diversifier or a true safe haven.

1.2 Definitions

A clear distinction between a hedge, a diversifier and a safe haven is necessary to understand how gold behaves under different market conditions. These concepts describe how an asset move together with one another and whether they provide protection during periods of financial stress.

1.2.1 Hedge

"*A hedge is defined as an asset that is uncorrelated or negatively correlated with another asset or portfolio on average*" (Baur & Lucey, 2010)

Investopedia team (2025) explains a hedge as an asset or position used to reduce the risk of adverse price movements in another asset. In financial markets, a hedge typically shows zero or negative correlation with the asset it is meant to protect, meaning it does not usually move in the same direction. Hedging often involves taking an offsetting position, commonly through derivatives, to limit potential losses, although this protection usually comes at the cost of reducing potential gains. A perfect hedge, which eliminates all risk is largely theoretical.

1.2.2 Diversifier

"*A diversifier is defined as an asset that is positively (but not perfectly correlated with another asset or portfolio on average"* (Baur & Lucey, 2010)

According to Segal (2025), diversification is a risk-management strategy that reduces portfolio risk by spreading investments across a variety of assets. The idea is that different assets respond differently to market conditions, so poor performance in one investment does not necessarily coincide with poor performance in others. A diversified portfolio typically includes multiple asset classes such as stocks, bonds, or commodities and different securities within each class.

The effectiveness of diversification depends on the correlations between assets, the lower the correlation, the greater the potential risk reduction. While diversification cannot eliminate all risk, it helps smooth out unsystematic risk and limits the portfolios exposure to any single asset or sector.

1.2.3 Safe haven

A safe haven is defined as an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil" (Baur & Lucey, 2010)

Chen (2025) defines safe haven investments as an asset that is expected to retain or increase its value during periods of market turbulence. When other assets experience sharp declines, a safe haven provides stability by remaining uncorrelated or negatively correlated with the broader market. Investors often turn to a safe haven asset during times of financial stress to limit losses and preserve capital. Common examples include gold, government treasury bills and certain stable currencies such as the US dollar.

The effectiveness of a safe haven can vary across different market conditions, and its protective characteristics are only intended to appear during times of distress, not during normal or rising market. The perception of hedging and safe haven strategies suggests that they are often viewed as similar approaches with different labels. However, the essential difference lies in timing: a hedge provides protection on average over time, whereas a safe haven is expected to offer protection primarily during periods of extreme market stress.

1.3 Research questions

Based on the background, theoretical framework, and previous literature discussed in this study, the aim is to examine the role as a hedge, safe haven, and diversifier in equity markets. To address this objective, the following research questions are formulated.

1. Does gold act as a hedge against the stock market. During normal market conditions?
2. Does gold function as a safe haven during periods of financial stress or extreme negative stock market returns?
3. How does gold respond dynamically to stock market shocks over time?
4. Is there a predictive relationship between stock market returns and gold returns?

1.4 Ethical considerations

The ethical aspects of gold production are closely linked to broader discussions on environmental, social, and governance (ESG) factors in investment decisions. Although gold is widely regarded as a safe haven asset, its extraction is often associated with significant environmental damage and violations of labor rights, raising concerns from a sustainable finance perspective.

Gold mining is concentrated in countries where protections for workers rights are relatively weak. Several major gold producing countries rank low in the International Trade Union Confederation´s (ITUC) Global rights Index, which documents issues such as restrictions on unionization, unsafe working conditions, and violations of basic labor rights (ITUC, 2019). These constrictions highlight the social risks embedded in gold supply chains.

Environmental concerns are equally significant. Gold extraction is highly resource intensive and frequently involves the use of hazardous chemicals such as cyanide and mercury, which can contaminate water systems and cause long-term ecological damage. Acid mine drainage further contributes to environmental degradation, with substantial cleanup costs reported in affected regions (Bland, 2014).

In response to these challenges, initiatives such as Earthworks, Fairtrade, and Fair mined have been established to promote more responsible mining practices. These certification schemes aim to improve environmental standards, working conditions, and wage fairness within the industry. However, ethically verified gold represents only a small fraction of total global gold production, limiting its overall impacts (Earthworks, n.d; Fairtrade International, n.d.)

From an ESG and investment perspective, these ethical considerations are increasingly relevant as investors incorporate sustainability criteria alongside financial performance. While gold may serve as a hedge or safe haven in portfolios, its environmental and social footprint highlights the importance of considering ESG risks when evaluation gold an investment.

1.5 Disposition

The layout of the thesis is as follows. Chapter 1 introduces the background, key concepts, research questions, and ethical considerations. Chapter 2 reviews the relevant literature, while chapter 3 presents the theoretical framework. Chapter 4 formulates the hypotheses. Chapter 5 describes the methodology and econometric approach. Chapter 6 presents the data, and chapter 7 reports the empirical results. Chapter 8 provides a discussion of the findings, and chapter 9 concludes.

2. Literature review

Gold has historically been viewed as a store of value and a potential diversifier in investment portfolios. Prior research shows that gold often exhibits low or negative correlations with equity markets, making it attractive as hedge during normal market contains (Hillier et al., 2006). However, its behavior during crises is less consistent, which has led to a growing academic interest in whether gold can act as a safe haven. Particularly during periods of severe market stress.

Baur and Lucey (2010) provide one of the most influential frameworks for analyzing hedging and safe haven properties. They distinguish between three concepts: a hedge (uncorrelated or negatively correlated with stocks on average), a diversifier (positively but not perfectly correlated), and a safe haven (Uncorrelated or negatively correlated only during periods of extreme market stress). Their empirical findings suggest that gold acts as a hedge in normal periods and as a safe haven only for short intervals following extreme stock market declines.

Financial crises also trigger flight to quality behavior. In which investors shift capital from risky assets into safer assets such as gold, U.S. treasury bonds, safe haven currencies (Hartmann et al., 2001; Vayanos, 2004) This behavior highlights the importance of distinguishing between normal market conditions and periods of stress when evaluating the role of gold in financial markets.

Given these findings, the literature emphasizes the need for empirical methods that can capture not only average relationships but also how asset interactions evolve over time and in response to market shocks. In this context, Vector Autoregressive (VAR) models are a standard tool for analyzing dynamic relationships between multiple time series. In a VAR framework, each variable is modelled as a function of its own past values and the past values of all other variables in the system, treating all variables as endogenous.

Under the stability condition, a VAR admits a moving average representation, allowing researchers to analyze how innovations propagate through the system over time. This property forms the theoretical basis for impulse response analysis and related tools commonly used in research (Lütkhepohl, 2005)

3.Theory

This section presents the key theoretical concepts needed to understand how gold may function as a hedge, diversifier or a safe haven.

Modern Portfolio Theory (MPT), introduced by Harry Markowitz (1952), provides a theoretical framework for understanding how investors can construct portfolios that optimally balance risk and return. The theory is based on the idea that investors are risk-averse and therefore prefer portfolios that offer the highest possible expected return for a given level of risk, or alternatively, the lowest possible risk for a given level of expected return. Risk in MPT is measured by the standard deviation of returns, and a key insight of the theory is that the risk of a portfolio depends not only on the risk of the individual assets it contains, but also on the correlations between those assets.

A central implication of Modern Portfolio Theory is the importance of diversification. By combining assets whose returns are not perfectly correlated, investors can reduce overall portfolio risk without necessarily sacrificing expected return. Modern Portfolio Theory therefore emphasizes that investment decisions should be evaluated at the portfolio level rather than by considering assets in isolation. Assets that exhibit low or negative correlation with the broader market can improve portfolio efficiency and play an important role as diversifiers. MPT is widely used theoretical foundation for empirical studies of diversification, risk management, and asset allocation.

A well-established theoretical explanation for safe haven assets is provided by the flight to quality framework, which originates from financial economics and macro finance. This theory explains investor behavior during periods of heightened uncertainty, financial crises, or market stress, when investors reallocate capital away from risky assets toward assets perceived as safer, more liquid, and more reliable stores of value. (Hartmann et al., 2001; Vayanos, 2004)

According to this framework, increases in uncertainty or risk aversion led investors to reduce exposure to assets with high default risk, volatility, or information asymmetry, such as equities, and instead shift their portfolios toward assets with low credit risk and high liquidity, such as government bonds or gold. This reallocation process generates systematic price increases in safe assets during crisis periods, while risky assets experience sharp declines. As a result, safe haven assets tend to exhibit low or negative correlation with risky assets precisely during market downturns. (Baur & Lucey, 2010).

The flight to quality theory provides a behavioral and macro financial foundation for the safe haven concept by linking asset price movements to changes in investor risk preferences and market wide uncertainty. Importantly, it explains why traditional diversification benefits may break down during crises, as correlations among risk assets increase, while safe assets remain insulated from these dynamics. Safe haven assets therefore play a crucial role in preserving portfolio value and providing protection during periods of systemic stress.

This framework has been extensively applied in empirical research to study market reactions during financial crises, monetary policy shocks, and periods of extreme volatility. By showing shifts in investor behavior and capital flows under stress, the flight to quality theory offers a robust theoretical foundation for understanding why certain assets function as safe havens in financial markets.

4. Hypotheses

H1 (Hedge hypothesis)

H_0: Gold is uncorrelated or negatively correlated with stock market returns during normal market conditions.

H_1: Gold is positively correlated with stock market returns during normal market conditions

H2 (Safe haven hypothesis)

H_0: Gold does not decline during periods of stock market stress, implying a zero or positive average return in stress periods.

H_1: Gold declines during periods of stock market stress, implying a negative average return.

H3 (Dynamic response hypothesis)

H_0: A negative stock market shock leads to a non-negative response in gold returns over subsequent periods.
H_1: A negative stock market shock leads to a negative response in gold returns over subsequent periods.

H4 (Causality hypothesis)

H_0: Stock market returns do not Granger-cause gold returns.
H_1: Stock market returns Granger-cause gold returns.

5. Methodology

The methodology is chosen to address the research questions regarding whether gold functions as a hedge, whether it displays safe haven characteristics during periods of extreme stock market stress, whether stock market movements help predict gold returns, and how the relationships between the variables evolve over time.

The study is based on quantitative time series analysis. The first part of the analysis consists of descriptive statistics and regression analysis based on logarithmic monthly returns, where the assets risk and co-movement characteristics are identified and their behavior during stress periods is analyzed. The regression model equations are specified in Equations (1)-(2). Oil is included as a benchmark asset to provide a comparative reference for gold’s behavior during market stress. The second part consists of econometric time-series methods in the form of Vector autoregressive (VAR) models, Granger causality tests, and Impulse Response Functions (IRF) analysis. The VAR (1) system for the U.S. and Swedish markets is defined by Equations (3)-(5) and (6)-(8), respectively.

To examine whether the time series have unit roots, the Augmented Dickey-Fuller (ADF) test is applied to all variables. The test determines whether the variables are stationary or require transformation before inclusion in the VAR model. This procedure is consistent with the empirical approach used by Blau et al. (2021).

The optimal lag length of the VAR model is selected using standard lag order selection criteria, including the Akaike Information Criterion (AIC), the Hannan-Quinn Criterion (HQ), the Schwarz Bayesian Information Criterion (SBIC) and the final prediction Error (FPE), following Lütkepohl (2005). The lag order that minimizes these information criteria is chosen for the VAR estimation.

Model stability is a crucial requirement for valid inference in VAR analysis, as it ensures that the dynamic system is well-behaved and that the model contains meaningful information. The stability of the VAR model is therefore examined by analyzing the roots of the characteristic polynomial. Following Lüktepohl (2005), a VAR model is stable if all eigenvalues of the companion matrix have a modulus smaller than one.

5.1 Definition of Stress Periods and Dummy Variables

Following the methodology of Baur and Lucey (2010), market stress is defined using low percentiles of stock market returns. In this study, the 10th and 5th percentiles are used to identify periods of moderate and extreme market stress. For the U.S. market, these thresholds correspond to monthly S&P500 returns below –5.9 percent (10th percentile) and –8.4 percent (5th percentile). For the Swedish market, the corresponding thresholds are monthly OMXSPI returns below –6.7 percent (10th percentile) and –9.0 percent (5th percentile).

To construct the dummy variables, the 10th and 5th percentiles of the S&P500 and OMXSPI monthly returns were first identified. The percentiles are used to define periods of moderate and extreme market stress. Although the same percentile thresholds are applied across both markets, the corresponding return values differ between the U.S. and Swedish equity markets due to differences in volatility and return distributions. Using market-specific percentiles ensures that stress periods are defined relative to each market.

Based on these two thresholds, two dummy variables are created. The two dummy variables are used in separate regression models in order to avoid multicollinearity, as periods of extreme stress are nested within periods of moderate stress. Dummy10 is set to 1 when stock market returns (S&P500 or OMXSPI) fall to or below their respective 10th percentile, indicating periods of moderate market stress, and 0 otherwise. Dummy5 is defined using the 5th percentile and represents periods of extreme market stress. The dummy variables are therefore based purely on equity market returns and are common across all asset regressions.

5.2 Regressions analysis

OLS regressions were used to analyze the relationship between the dummy variables and the monthly returns of the assets. These regressions make it possible to observe whether an asset tends to rise or fall during periods when the S&P500 and OMXSPI experience moderate stress (defined by the 10th percentile) or extreme stress (defined by the 5th percentile). The regressions also provide statistical inference, indicating whether the estimated coefficients are significantly different from zero which allows a distinction between systematic relationships and results driven by random variation. To evaluate whether gold behaves as a hedge or a safe haven, two separate OLS regression models are estimated. The regression models are specified as follows:

$$r_{i,t} = \alpha_i + \beta_i \cdot Dummy10_t + \varepsilon_{i,t} \text{ (1)}$$

$$r_{i,t} = \alpha_i + \beta_i \cdot Dummy5_t + \varepsilon_{i,t} \text{ (2)}$$

The notation and variables used in the regression specifications are defined as follows. In equation (1) and (2), $r_{i,t}$ denotes the return on asset *i* (gold or oil) at time t. The parameter α_i is a constant term, while $\varepsilon_{i,t}$ represents an error term capturing unexplained variation. The coefficient β_i measures the asset's response during periods of market stress. $Dummy10_t$ is a dummy variable equal to one if stock market returns fall below the 10th percentile, representing periods of moderate market stress, and zero otherwise. Finally, $Dummy5_t$ represents periods of extreme market stress and is equal to one if stock market returns fall below the 5th percentile, and zero otherwise.

5.3 VAR Model Analysis

To analyze the dynamic relationships between stock markets, gold, and oil over time, this study employs a Vector Autoregressive (VAR) model. Following the VAR methodology described in Lütkepohl (2005), each variable in the VAR system is modeled as a function of its own past values as well as the past values of all other variables in the system. This framework allows the analysis of dynamic interactions among multiple time series. Separate VAR models are estimated for the United States and Sweden. The U.S. model includes returns on the S&P500, gold and oil, while the Swedish model replaces the S&P500 with the OMXSPI index. All variables are expressed as logarithmic monthly returns.

5.3.1 Model specification

Following the vector autoregressive framework described in Lütkepohl (2005), the dynamic relationship between stock market returns, gold returns, and oil returns are analyzed within a VAR framework. Based on the empirical specification of this study, a VAR model with one lag, VAR (1), is employed. The model treats all variables as endogenous, allowing each variable to depend on its own past values as well as the past values of the other variables in the system. This specification enables the analysis of short-run dynamic interactions among the variables based on the observed data.

The VAR (1) model is specified as:

$$Y_t = \nu + A_{1Yt-1} + \cdots + A_{pYt-p} + u_t.$$

Where Y_t is a 3 x 1 vector of endogenous variables observed at time $t,$ containing the returns of the stock market, gold and oil at the time t. Y_{t-1} denotes the one period lagged vector of endogenous variables capturing past information in the system. The vector υ denotes a 3 x 1 vector of intercept terms, while A_i is a 3 x 3 coefficient matrix summarizing the dynamic effects of lagged values on current values. Finally, u_t is a 3 x 1 vector of innovations representing unexpected shocks to the system.

Based on the VAR framework described in Lütkepohl (2005), the dynamic interactions among the variables in the VAR model are captured by the coefficient matrices A_i. Each coefficient matrix summarizes how lagged values of all variables in the system affect the current values of each variable.

$$A1 = \begin{bmatrix} \alpha 11 & \alpha 12 & \alpha 13 \\ \alpha 21 & \alpha 22 & \alpha 23 \\ \alpha 31 & \alpha 32 & \alpha 33 \end{bmatrix}$$

In a VAR (1) model, the coefficient A_1 is a 3 x 3 matrix. Its elements are denoted by α_{jk}. Where the index j = 1,2,3 refers to the equation (i.e. the dependent variable, corresponding to each element of Y_t), and the index k = 1,2,3 refers to the lagged explanatory variable in the system, that is, the corresponding component of the vector Y_{t-1}.

Each element α_{jk} therefore measures the effect of the lagged value of variable k on the current value of variable j. The coefficients associated with a variables own lagged values capture the persistence of that variable over time, while the coefficients on lagged values of the other variables describe cross-variable effects within the system. This structure allows the VAR model to account for both its own dynamics and interactions across markets.

Separate VAR (1) models are estimated for the United States and Sweden, where all variables are treated as endogenous. Estimating the models separately allows the dynamic relationships to differ across markets, reflecting potential structural and institutional differences between the U.S. and Swedish financial systems. Oil returns are included as a control variable to account for broader commodity market dynamics that may jointly affect both stock and gold returns. The VAR (1) model specifications for the United States and Sweden are presented below.

U.S. model (S&P500)

$lret_{sp500,t} = v_{sp500} + \alpha 11 lret_{sp500,t-1} + \alpha 12 lret_{Gold,t-1} + \alpha 13_{oil,t-1} + u_{sp500,t}$ (3)

$lret_{Gold,t} = v_{Gold} + \alpha 21 lret_{sp500,t-1} + \alpha 22 lret_{Gold,t-1} + \alpha 23_{oil,t-1} + u_{Gold,t}$ (4)

$lret_{Oil,t} = v_{Oil} + \alpha 31 lret_{sp500,t-1} + \alpha 32 lret_{Gold,t-1} + \alpha 33_{oil,t-1} + u_{Oil,t}$ (5)

Swedish model (OMXSPI)

$$lret_{OMXSPI,t} = v_{OMXSPI} + \alpha 11 lret_{OMXSPI,t-1} + \alpha 12 lret_{Gold,t-1} + \alpha 13_{oil,t-1} + u_{OMXSPI,t} \quad (6)$$

$$lret_{Gold,t} = v_{Gold} + \alpha 21 lret_{OMXSPI,t-1} + \alpha 22 lret_{Gold,t-1} + \alpha 23_{oil,t-1} + u_{Gold,t} \quad (7)$$

$$lret_{Oil,t} = v_{Oil} + \alpha 31 lret_{OMXSPI,t-1} + \alpha 32 lret_{Gold,t-1} + \alpha 33_{oil,t-1} + u_{Oil,t} \quad (8)$$

5.3.2 Pre-estimation diagnostics: Unit Root Tests

To ensure that the VAR model is estimated using appropriate time-series properties, Augmented Dickey-Fuller (ADF) tests are conducted to assess stationarity. This pre-estimation approach is consistent with the empirical approach in Blau et al. (2021), who examine the time-series properties of return data prior to VAR and Granger causality analyses.

5.3.3 Lag length selection

The lag length of the VAR models is selected using standard lag order selection criteria, following Lütkepohl (2005). The criteria used are the Akaike Information Criterion (AIC), the Hannon-Quinn Information Criterion (HQIC), the Schwarz Bayesian information criterion (SBIC), and the final prediction error (FPE). These criteria help determine how many lags should be included in the models.

5.3.4 VAR Stability Condition

According to Lütkepohl (2005), a VAR model is stable if its reverse characteristic polynomial has no roots on or inside the unit circle. Formally, this stability condition is expressed through the model's reverse characteristic polynomial, which is constructed from the coefficient matrices of the VAR. In practical terms, stability requires that all eigenvalues of the VAR system have a modulus strictly less than one, which is equivalent to the reverse characteristic polynomial having no roots on or outside the unit circle ($|z| \leq 1$). When this condition holds, the VAR model is dynamically stable, implying that impulse response functions are well defined.

It is important to distinguish this stability condition from unit root tests such as the Augmented Dickey-Fuller (ADF) test. While ADF tests are used to assess whether individual time series are stationary prior to model estimation, the VAR stability condition concerns the dynamic properties of the VAR system as a whole. Even if all variables are stationary, the interaction between them may still result in unstable system dynamics if the stability condition is violated. Therefore, testing the stability condition is a necessary step when working with VAR models, particularly when the analysis relies on impulse responses and dynamic interactions.

5.4 Granger Causality and Impulse Response Analysis

The VAR models are used for two main purposes. First, impulse response functions are derived to evaluate the dynamic response of gold returns to stock market shocks, addressing the dynamic response hypothesis (H3). Second, Granger causality tests are conducted to examine whether stock market returns help predict gold returns over time, corresponding to the causality hypothesis (H4).

Granger causality tests are performed within the VAR framework to assess whether past values of one variable improve the prediction of another variable, given the information provided by the other variables in the system (Lütkepohl, 2005). Within the VAR framework, Granger causality is tested by examining whether lagged coefficients are equal to zero. This hypothesis is evaluated using a Wald test, which follows a chi-square (χ^2) distribution under the null hypothesis (Lütkepohl, 2005). Large values of the Wald statistic lead to rejection of the null hypothesis (Buse, 1982). Statistical significance is assessed using the corresponding p-values.

The Impulse Response Function (IRF) analysis illustrates the dynamic effects of a shock in one variable on the other variables in the VAR system. Impulse response functions are estimated using orthogonalized shocks obtained through a Choleski decomposition. This approach requires specifying an ordering of the variables, which determines how shocks can affect other variables in the model within the same period. The chosen ordering is therefore important for the interpretation of the results (Lütkepohl, 2005).

This approach is consistent with Blau et al. (2021), who use impulse response functions to analyze how shocks to one financial variable affect other variables over time. In this study, the IRFs illustrate how shocks to the S&P500 and OMXSPI are transmitted to gold and oil over the following months, as well as how shocks in gold and oil affect equity markets. By examining the size of the responses, the direction in which they move, and how long they last, make it possible to evaluate how these assets react to stock market shocks. Impulse responses are presented together with confidence intervals to illustrate the uncertainty surrounding the estimated effects. An impulse response is typically regarded as statistically significant if the confidence interval does not include zero.

6. Data

Historical monthly data for gold and oil prices were collected for the period 2000-2024. This time interval was selected because it includes several major global crises, such as the IT crash, the 2008 financial crisis, the eurozone debt crisis, the Covid-19 pandemic, and the energy and inflation shocks of 2021-2022. Covering multiple crises allows the analysis to capture how assets behave both under normal market conditions and during periods of moderate and extreme stress. The data have been retrieved from investing.com, riksbanken.se, and swbf.se.

The S&P500 was chosen as the reference market because it is the most widely used equity index globally and often functions as an indicator of international risk aversion. When the S&P500 falls sharply, it often signals global financial stress, which makes it suitable for studying safe haven behavior. For Sweden, the OMXSPI is used as the reference equity market. The OMXSPI represents the broad Swedish stock market and captures overall equity market developments in a small open economy.

6.1 Sample Periods

This section presents descriptive data on major stock market downturns during the sample period from 2000 to 2024, which gives a total of 300 monthly observations. The identified crisis episodes illustrate how market crashes have unfolded over time in terms of timing and duration. These periods are summarized in Table 1 and are further visualized in Figure 1, which highlights how equity markets and gold have developed during major market stress events.

Table 1. Sample periods

Sample period	Start	End	Observations
Full period	2000-01-01	2024-12-01	300 months
Dotcom Crash	2000-03-01	2002-10-01	31 months
Global Financial Crisis	2007-07-01	2009-06-01	24 months
Eurozone Debt Crisis	2010-11-01	2012-08-01	22 months
Covid-19 Crisis	2020-02-01	2020-12-01	11 months
Energy & inflation	2021-01-01	2022-12-01	24 months

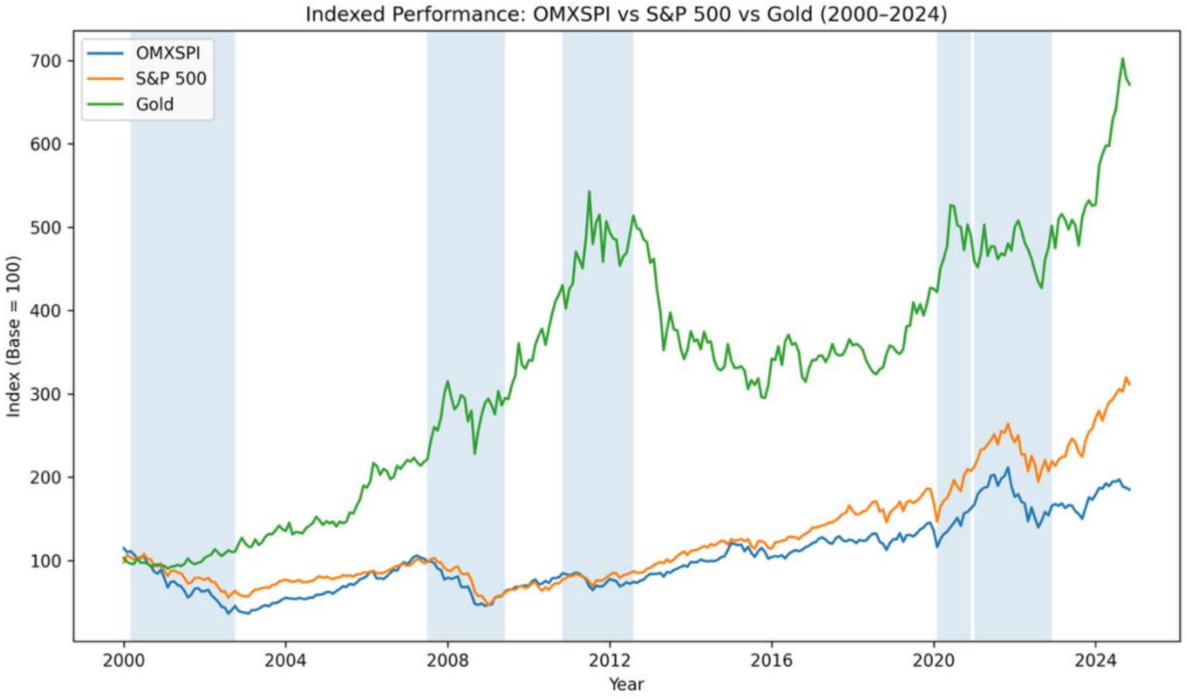


Figure 1. Indexed performance of OMXSPI, the S&P500, and gold from 2000 to 2024 (base = 100). Shaded areas indicate periods of major financial market stress.

6.2 Choice of Assets

The assets included in the study are gold and oil, which represent two distinct components of global financial markets. These assets were selected because they represent two different components of global markets and therefore provide complementary information about how markets behave during periods of stress.

Gold is commonly associated with the concept of a safe haven due to its perceived ability to preserve value during periods of severe financial market stress. Baur and McDermott (2010) define a safe haven asset as one that holds its value in adverse or "stormy" market conditions and argue that investors are most likely to seek such assets in response to sudden market shocks.

Since gold prices are quoted in U.S. dollars, the gold price series is converted to Swedish kronor when analyzing the Swedish market in order to ensure consistency across asset prices. The conversion is performed using the corresponding USD/SEK exchange rate prior to computing returns.

Previous research shows that oil prices are closely linked to global economic activity, and that their relationship with stock markets depends on the underlying source of economic shocks. In particular, Filis et al. (2011) show that the correlation between oil prices and stock markets strengthens in response to aggregate demand-side and uncertainty driven oil price shocks associated with global buisness cycle fluctuations and periods of geopolitical turmoil. Including oil allows for a clear comparison between an asset that may exhibit defensive characteristics (gold) and an asset that typically performs poorly during economically driven market downturns (oil).

7. Results and Analysis

7.1 Descriptive Statistics

This section presents descriptive statistics for the assets included in the study. Table 2 reports summary statistics for asset prices and monthly logarithmic returns, while Table 3 presents the pairwise correlation matrix across the assets.

Table 2. Summary statistics

Panel A. Asset Prices					
	Mean	**Std. Deviation**	**Minimum**	**Median**	**Maximum**
Gold price	1138.657	591.533	257.950	1219.045	2743.800
S&P 500	2116.562	1233.801	735.100	1490.250	6032.380
OMXSPI	457.221	231.063	134.370	376.120	1037.140
Oil	63.826	25.395	18.840	63.580	140.000

Panel B. Asset Returns					
Δ Gold	0.007	0.046	-0.184	0.006	0.121
Δ S&P 500	0.005	0.044	-0.186	0.011	0.119
Δ OMXSPI	0.004	0.053	-0.197	0.008	0.172
Δ Oil	0.003	0.109	-0.782	0.016	0.633

Notes: Panel A reports summary statistics for asset prices, while Panel B reports summary statistics for monthly logarithmic returns. Δ denotes monthly logarithmic returns. All statistics are based on data from 2000 to 2024.

Table 2 reports descriptive statistics for the monthly logarithmic returns of all assets included in the analysis. Both equity indices, the S&P500 and OMXSPI, exhibit positive mean returns of 0.005 and 0.004, respectively. The standard deviation of return is 0.044 for the S&P500 and 0.053 for OMXSPI.

Gold displays a mean monthly logarithmic return of 0.007, with a standard deviation of 0.046, suggesting that its volatility is broadly comparable to that of the equity indices. Oil has a lower average monthly return of 0.003 but is the most volatile asset in the sample, with a standard deviation of 0.109. Oil exhibits substantial variation in monthly logarithmic returns, with values ranging from a minimum of –0.780 to a maximum of 0.630. Overall, the descriptive statistics suggest that oil is substantially more volatile than both equities and gold, while gold combines relatively high average returns with volatility comparable to that of stock markets.

Table 3. Correlations matrix

Assets	S&P 500	OMXSPI	Gold	Oil
S&P 500	1.000			
OMXSPI	0.780	1.000		
Gold	0.070	0.016	1.000	
Oil	0.322	0.241	0.144	1.000

***Notes**: The table reports pairwise Pearson correlation coefficients based on monthly logarithmic returns. The sample period is 2000-2024.*

Table 3 reports the correlations across the assets included in the study. The S&P500 and OMXSPI exhibit a strong positive correlation (0.780), indicating a high degree of co-movement between the two equity indexes, while gold suggests low correlations with both equity indices, with correlation coefficients of 0.070 with S&P500 and 0.016 with OMXSPI.

Oil displays positive correlation with the equity indices, with values of 0.322 for the S&P500 and 0.241 for OMXSPI. Overall, the correlation between the S&P500 and OMXSPI is substantially higher than the correlation observed between the equity indices and the other assets, indicating strong co-movement between the two equity markets over the sample period. In contrast, gold exhibits low correlations with coefficients close to zero, indicating limited co-movement between gold and equities. Oil, by comparison, shows positive correlations with both equity indices. The correlation between gold and oil is also relatively low (0.144), suggesting limited co-movement between the two commodities.

7.2 Regression Results: Market Stress Analysis

This section presents the regression results from the market stress analysis. The estimates are obtained from separate OLS regressions in which asset returns, measured as monthly logarithmic returns, are regressed on dummy variables capturing periods of moderate and extreme stock market stress. The results are reported for gold and oil in relation to the S&P500 and OMXSPI and are presented separately for the United States and Sweden in Table 4.

Table 4 Market stress analysis

Dependent Variable	Stress Definition	Coefficient	Sign	p-value	Significance
Panel A: United States (S&P 500)					
Gold returns	Moderate stress	-0.098	Neg.	< 0.001	***
Gold returns	Extreme stress	-0.125	Neg.	< 0.001	***
Oil returns	Moderate stress	-0.175	Neg.	< 0.001	***
Oil returns	Extreme stress	-0.194	Neg.	< 0.001	***
Panel B: Sweden (OMXSPI)					
Gold returns	Moderate stress	0.018	Pos.	0.129	—
Gold returns	Extreme stress	0.011	Pos.	0.592	—
Oil returns	Moderate stress	-0.179	Neg.	< 0.001	***
Oil returns	Extreme stress	-0.197	Neg.	< 0.001	***

***Notes:** Dummy10 and Dummy5 indicate moderate and extreme market stress, defined as stock market returns below the 10th and 5th percentiles, respectively ***, **, and * denote statistical significance at the 1%, 5% and 10% levels.*

7.2.1 Gold and S&P500

Based on the regression specified in Equation (1), gold exhibits a negative and statistically significant relationship with U.S. stock market stress. During periods of moderate market stress, defined by the 10th percentile (Dummy10), the estimated coefficient for gold is (β = -0.098, p < 0.001), indicating that gold tends to decline when equity markets experience moderate downturns. This negative relationship becomes even stronger during periods of extreme market stress, defined by the 5th percentile (Dummy5), where the estimated coefficient is (β = -0.125, p < 0.001). Together, these results suggest that gold does not provide protection during either moderate or extreme U.S. stock market stress.

7.2.2 Oil and S&P500

The regression results indicate that oil returns decline significantly during periods of U.S. stock market stress. Under conditions of moderate market stress, oil exhibits a negative and statistically significant response, with an estimated coefficient of (β = -0.175, p < 0.001).

When market stress intensifies, the negative effect on oil returns becomes larger, as reflected by a larger and statistically significant coefficient during extreme stress periods ($\beta = -0.194$, $p < 0.001$). Overall, these findings suggest that oil is highly sensitive to equity market downturns and tends to perform poorly during both moderate and severe periods of U.S. stock market stress.

7.2.3 Gold and OMXSPI

For the Swedish equity market, the regression results indicate that gold displays a positive but statistically insignificant relationship with market stress. During periods of moderate market stress, the estimated coefficient for gold is positive but not statistically significant. ($\beta = 0.018$, $p = 0.129$). This pattern continues during periods of extreme market stress, where gold returns remain positive but statistically insignificant, with an estimated coefficient of ($\beta = 0.011$, $p = 0.592$). These results reveal that gold neither provides meaningful protection nor amplifies equity losses in the Swedish market during periods of market stress but instead behaves largely independently of OMXSPI movements.

7.2.4 Oil and OMXSPI

For the Swedish equity market, oil returns are negatively affected during periods of stock market stress. The results show that oil returns decrease significantly during moderate stress periods, with an estimated coefficient of ($\beta = -0.179$, $p < 0.001$). When market stress intensifies, the negative effect becomes slightly larger, as oil continues to exhibit a statistically significant decline during periods of extreme stress, with an estimated coefficient of ($\beta = -0.197$, $p < 0.001$). The estimates indicate that oil underperforms during both moderate and extreme periods of Swedish equity market stress.

7.2.5 Pre-estimation diagnostics: Unit Root Tests

Prior to estimating the VAR models, the stationarity properties of the return series are examined. Augmented Dickey-Fuller (ADF) unit root tests are conducted to ensure that all variables satisfy the stationarity requirements of the VAR framework. The test results for gold, stock market returns, and oil returns are reported in Table 5.

Table 5. Augmented Dickey – Fuller unit root test (AR (1) – AR (3))

Panel A. Gold and SP500

	AR(1)		**AR(2)**		**AR(3)**	
Statistic	ΔGold	ΔSP500	ΔGold	ΔSP500	ΔGold	ΔSP500
	[1]	[2]	[3]	[4]	[5]	[6]
T-value	-13.448	-12.785	-10.660	-9.237	-8.840	-7.662
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Critical value (1%)	-3.456	-3.456	-3.456	-3.456	-3.456	-3.456
Critical value (5%)	-2.878	-2.878	-2.878	-2.878	-2.878	-2.878
Critical value (10%)	-2.570	-2.570	-2.570	-2.570	-2.570	-2.570

Panel B. OMXSPI and Oil

	AR(1)		**AR(2)**		**AR(3)**	
Statistic	ΔOMXSPI	ΔOil	ΔOMXSPI	ΔOil	ΔOMXSPI	ΔOil
	[1]	[2]	[3]	[4]	[5]	[6]
T-value	-12.325	-12.471	-8.380	-10.278	-7.254	-9.838
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Critical value (1%)	-3.456	-3.456	-3.456	-3.456	-3.456	-3.456
Critical value (5%)	-2.878	-2.878	-2.878	-2.878	-2.878	-2.878
Critical value (10%)	-2.570	-2.570	-2.570	-2.570	-2.570	-2.570

To ensure that the vector autoregression is estimated on stationary time series, Augmented Dickey-Fuller (ADF) unit root tests are conducted for all return variables included in the analysis. The tests were performed using one lag, consistent with the chosen VAR (1) specification, and without a constant or deterministic trend. This choice is based on Sathyanarayana and Thangamuthu (2025), who note that when a time series shows no systematic pattern, the ADF test may be performed without an intercept or deterministic trend.

The results, reported in Table 5, show that the null hypothesis of a unit root is rejected for all return series at the 1 percent significance level. Test statistics are well below the corresponding critical values, indicating that gold returns, stock market returns (S&P500 and OMXSPI), and oil returns are stationary in levels.

Following Blau et al. (2021), ADF tests were also conducted using alternative lag lengths to ensure that the conclusion of stationarity is not driven by a particular lag specification. Accordingly, additional tests with two and three lags were performed as robustness checks. In all cases, the null hypothesis of a unit root is rejected. As a further robustness check, ADF tests including a constant and a deterministic trend were also conducted, with unchanged results, confirming that all return series are stationary in levels and suitable for VAR estimation.

7.2.6 Lag length selection

The lag length of the VAR models is selected using standard information criteria. Table 6 reports the values of the Akaike information Criterion (AIC), the Hannan-Quinn Information Criterion (HQIC), the Schwarz Bayesian information Criterion (SBIC), and the Final Prediction Error (FPE) for different lag orders for both the U.S. and Swedish models. The lag order selected by each cirterion is indicated by an asterisk.

Table 6. Lag-order selection criteria for the U.S. and Sweden VAR models.

Panel A. Lag-order selection - U.S. model

Lag	FPE	AIC	HQIC	SBIC
0	4.4e-08	-8.420	-8.404*	-8.381*
1	4.3e-08*	-8.446*	-8.385	-8.293
2	4.4e-08	-8.432	-8.324	-8.164
3	4.6e-08	-8.389	-8.236	-8.007
4	4.5e-08	-8.398	-8.199	-7.901
5	4.7e-08	-8.358	-8.112	-7.746
6	4.9e-08	-8.315	-8.023	-7.588
7	5.1e-08	-8.274	-7.937	-7.433

Panel B. Lag-order selection - Sweden model

0	6.7e-08	-8.005	-7.990*	-7.966*
1	6.5e-08*	-8.034*	-7.972	-7.881
2	6.8e-08	-7.997	-7.890	-7.730
3	6.9e-08	-7.982	-7.829	-7.600
4	6.7e-08	-8.001	-7.801	-7.503
5	6.9e-08	-7.974	-7.729	-7.362
6	7.3e-08	-7.926	-7.635	-7.199
7	7.6e-08	-7.874	-7.537	-7.033

Notes: An asterisk (*) denotes the lag order selected by the corresponding information criterion.

For the U.S. model, the lag-order selection results indicate mixed recommendations across criteria. As shown in table 6, both the AIC and the FPE reach their minimum values at lag 1 (AIC = -8.446 and FPE = 4.3), suggesting the inclusion of one lag. In contrast, the HQIC and SBIC favor a more predictive specification with zero lags. However, since a VAR (0) model would not allow for dynamic interactions between variables, a lag length of one is selected to capture short-run dynamics among stock returns, gold returns, and oil returns.

For the Swedish model, a similar pattern is observed. According to Table 6, the AIC and FPE are minimized at lag 1 (AIC = -8.034 and FPE = 6.5) while the HQIC and SBIC suggest zero lags. Based on these results, and to maintain consistency with the U.S. model, a lag length of one is chosen for the Swedish VAR as well

7.3 Empirical Results from the VAR model

This section presents the empirical results from the VAR analysis. The results are reported separately for the United States and Sweden, focusing on the statistical significance of the VAR equations and the dynamic interactions between stock markets, gold, and oil.

Table 7. VAR model results (U.S. and Sweden)

Panel A. United States (S&P 500, Gold, Oil)

	$lret_{sp500}$	$lret_{Gold}$	$lret_{Oil}$
$lret_{sp500,t-1}$	0.040	−0.010	0.421***
	(0.66)	(−0.16)	(2.86)
$lret_{Gold,t-1}$	−0.062	−0.108*	−0.051
	(−1.10)	(−1.85)	(−0.38)
$lret_{Oil,t-1}$	−0.018	−0.003	0.098
	(−0.71)	(−0.11)	(1.52)
Constant	0.005**	0.008***	0.001
	(2.00)	(3.05)	(0.15)
R^2	0.007	0.012	0.047
χ^2	2.10	3.65	14.75
p-value	0.553	0.302	0.002

Panel B. Sweden (OMXSPI, Gold, Oil)

	$lret_{OMXSPI}$	$lret_{Gold}$	$lret_{Oil}$
$lret_{OMXSPI,t-1}$	0.085	0.045	0.312***
	(1.45)	(0.88)	(2.61)
$lret_{Gold,t-1}$	0.009	−0.107*	−0.035
	(−0.13)	(−1.84)	(−0.25)
$lret_{Oil,t-1}$	−0.060**	−0.009	0.109*
	(−2.06)	(−0.37)	(1.85)
Constant	0.003	0.008***	0.002
	(0.97)	(2.99)	(0.27)
R^2	0.018	0.015	0.043
χ^2	5.40	4.41	13.36
p-value	0.145	0.221	0.004

Notes: *The table reports coefficient estimates from VAR (1) models estimated using monthly log returns. T-values are reported in parentheses. χ^2 statistics test the joint significance of lagged regressors in each equation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

7.3.1 VAR Results for the United States (S&P500)

The estimated VAR (1) results for the United States, as defined by Equations (3)-(5), are reported in Table 7 (Panel A) and provide insights into the short-run dynamic interactions between S&P500 returns, gold returns, and oil returns.

In the stock market equation ($lret_{sp500}$), the coefficient on lagged stock market returns is positive but statistically insignificant (β =0.040, t=0.66). Lagged gold returns exhibit a negative but insignificant coefficient (β =-0.062, t=-1.10), while lagged oil returns are also insignificant (β =-0.018, t=-0.71). Overall, these results indicate that past movements in gold and oil returns do not significantly explain short-run fluctuations in U.S. stock market returns.

In the gold equation ($lret_{Gold}$), lagged S&P500 returns are negative and statistically insignificant (β =0.010, t=-0.16). Lagged oil returns are also insignificant (β =-0.003, t=-0.11), suggesting that short-run dynamics in gold returns are not strongly driven by past movements in equity or oil markets.

In contrast, the oil equation ($lret_{Oil}$), exhibits a strong and statistically significant response to lagged stock market returns (β =0.421, t=2.86), while lagged gold and oil returns remain insignificant. This finding is consistent with oils procyclical nature and its close connection to economic activity.

7.3.2 VAR Results for Sweden (OMXSPI)

The estimated VAR (1) results for Sweden, as defined by Equations (6)-(8), are reported in Table 7 (Panel B), and describe the short-run dynamic interactions between, OMXSPI returns, gold returns, and oil returns.

In the stock market equation ($lret_{OMXSPI}$), the coefficient on lagged stock market returns is positive but statistically insignificant (β =0.085, t=1.45). Lagged gold returns are likewise insignificant (β =-0.009, t=-0.13), while lagged oil returns exhibit a negative and statistically significant coefficient (β =-0.060, t=-2.06). This indicates that past movements in oil returns have a significant short-run impact on Swedish stock market returns, while gold does not.

In the gold equation ($lret_{Gold}$), lagged OMXSPI returns are positive but statistically insignificant (β =0.045, t=0.88). Lagged gold returns are negative and weakly significant at the 10 percent level (β =-0.107, t=-1.84), suggesting limited short-run persistence in gold returns. Lagged oil returns are insignificant (β =-0.009, t=-0.37).

In the oil equation ($lret_{Oil}$), lagged OMXSPI returns exhibit a strong positive statistically significant effect (β =0.312, t=2.61), while lagged oil returns are weakly significant (β =0.109, t=1.85). In contrast, lagged gold returns remain statistically insignificant. Overall, these results highlight oils procyclical behavior and its close connection to equity market dynamics relative to gold.

7.4 VAR stability and roots of the characteristics polynomial

As a final diagnostic check, the stability of the estimated VAR models is examined. VAR stability requires that all roots of the characteristic polynomial lie inside the unit circle. This condition is assessed by inspecting the eigenvalues of the companion matrix, which are reported in Table 8, while the corresponding graphical representations are provided in Figures A1 and A2 in the appendix.

Table 8. Eigenvalue stability condition of the VAR model (U.S. and Sweden)

Panel A. Eigenvalue stability condition. U.S. model

Eigenvalue (Real part)	Eigenvalue (Imaginary part)	Modulus
-0.110	0.000	0.110
0.067	0.080	0.104
0.067	-0.080	0.104

Panel B. Eigenvalue stability condition - Sweden model

0.096	0.134	0.165
0.096	-0.134	0.165
-0.104	0.000	0.104

Figures A1 and A2 (see appendix) show the roots of the characteristic polynomial (eigenvalues) for estimated VAR (1) models for Sweden and United States. The figures illustrate the position of the eigenvalues relative to the unit circle, while the corresponding numerical values are reported in Table 8. Together, the figures and tables make it easier to assess whether the VAR models satisfy the stability condition.

For the Swedish model, shown in Figures A1 (appendix) and Table 8, all eigenvalues are located inside the unit circle. The largest modulus is 0.165, which is clearly below one. According to the stability criterion discussed in Lütkepohl (2005), this indicates that the Swedish VAR (1) model is stable.

A similar result is obtained for the U.S. model. As shown in Figure A2 (appendix) and Table 8, all eigenvalues lie inside the unit circle, with the largest modulus equal to 0.110. This confirms that the U.S. VAR (1) model also satisfies the stability condition.

7.4 Dynamic Analysis: Impulse Response Functions

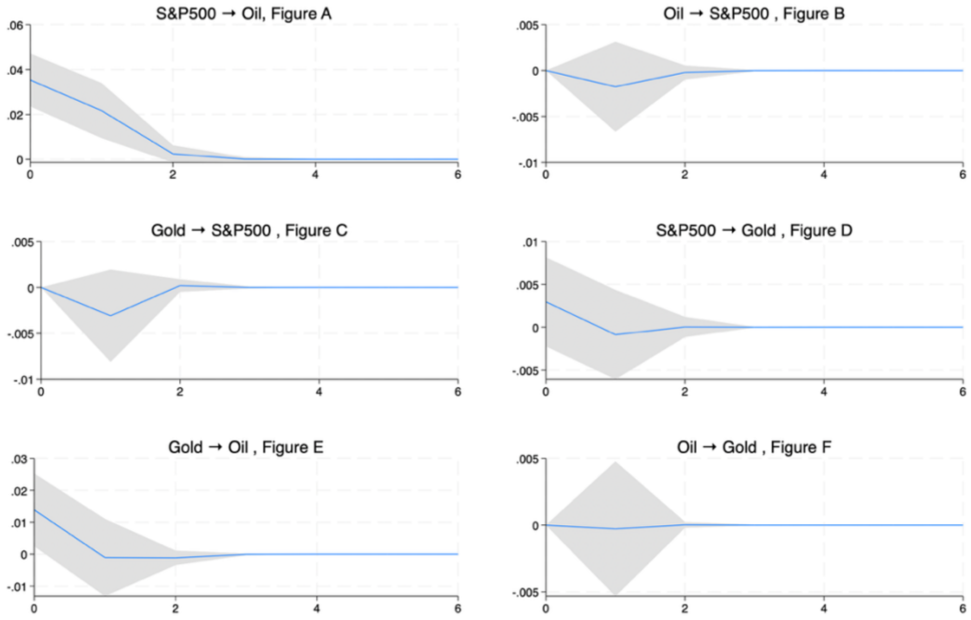
Impulse Response Functions (IRF) are applied within the VAR framework to trace the dynamic effects of a shock in one variable on the other variables in the system (Lütkepohl, 2005). In this study, the IRFs are used to examine how shocks to the equity market returns are transmitted to gold and oil returns over time.

In the IRF figures, the horizontal axis represents the number of months following the initial shock, and the vertical axis indicates the magnitude of the response in returns. Shaded areas indicate 95% confidence intervals.

7.5 Impulse Response Analysis: United States (S&P500)

This section presents the impulse response functions (IRFs) derived from the U.S. VAR (1) model, as defined by Equations (3)-(5). The IRFs illustrate the dynamic responses of U.S. equity market returns, gold returns, and oil returns. The analysis focuses on the direction, magnitude, and persistence of these responses over a six-month horizon. With particular attention to their statistical significance as indicated by the 95 percent confidence intervals.

Figure 2. Impulse Response Functions from the VAR model (United States)



Note: The shaded grey areas represent 95% confidence intervals, while the blue solid lines denote the orthogonalized impulse response functions (IRFs).

Gold and S&P500 (Figure 2c and 2d)

Figure 2c shows the impulse response of S&P500 returns following a shock to gold returns in the U.S. VAR (1) model. The response of S&P500 returns is slightly negative in the initial period, however, the effect is short-lived and fades within a few months. Importantly, the 95 percent confidence interval includes zero at all horizons, implying that the response lacks statistically significant. Overall, Figure 2c indicates that shocks to gold returns do not generate a clear or persistent dynamic effect on U.S. stock market returns in this specification.

Figure 2d shows the impulse response of gold returns following a shock to S&P500 returns in the U.S. VAR (1) model. Gold returns display a small initial response in the first period, but the effect quickly disappears. Across the entire time horizon, the 95 percent confidence intervals include zero, indicating that the response is not statistically significant. Taken together, Figures 2c and 2d indicate a weak and statistically insignificant dynamic relationship between gold and U.S. equity returns.

Oil and S&P500 (Figure 2a and 2b)

Figure 2a illustrates the impulse response of oil returns following a shock to S&P500 returns. The response is positive in the short run and strongest during the first few months, after which it gradually declines. In the first few months, the confidence intervals exclude zero, indicating a statistically significant short-run response of oil returns to stock market shocks.

In contrast, Figure 2b shows the impulse response of S&P500 returns following a shock to oil returns. The response is slightly negative in the initial period, after which the effect fades quickly. The confidence intervals include zero at all horizons, indicating that oil price shocks do not have a statistically significant effect on U.S. stock market returns. Overall, Figures 2a and 2b reveal an asymmetric relationship between oil and stock market returns, where equity market shocks have short-run predictive effects on oil returns, while oil price shocks do not significantly influence stock market returns.

Gold and Oil (Figure 2e and 2f)

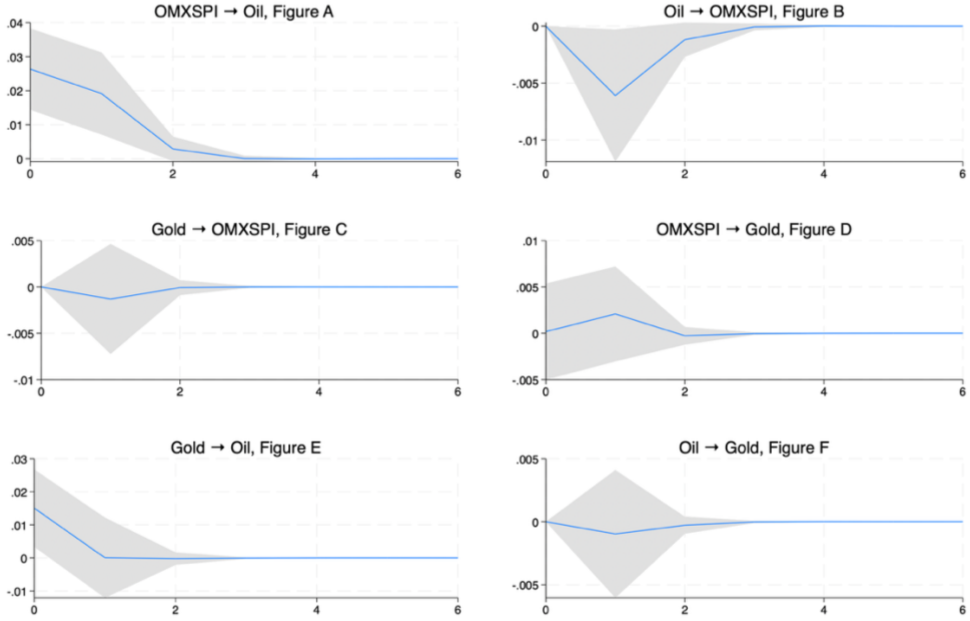
Figure 2e illustrates the impulse response of oil returns following a shock to gold returns. The response is slightly positive in the first period, but it diminishes rapidly and converges to zero within a short time-horizon. Importantly, the 95 percent confidence intervals include zero at all horizons, indicating that the response is not statistically significant. This suggests that shocks to gold returns do not generate a meaningful or persistent effect on oil returns in the VAR specification.

Similarly, Figure 2f shows the impulse response of gold returns following a shock to oil returns. The response is small in magnitude, short-lived, and statistically insignificant, as the confidence intervals include zero throughout the entire horizon. This indicates that oil price shocks do not have a significant dynamic effect on gold returns. Taken together, Figures 2e and 2f suggest that the dynamic relationship between gold and oil returns is weak and statistically insignificant in both directions.

7.6 Impulse Response Analysis: Sweden (OMXSPI)

This section presents the impulse response functions (IRFs) derived from the Swedish VAR (1) model, as defined in Equations (6)-(8). The IRFs illustrate the dynamic responses of Swedish equity market returns (OMXSPI), gold returns, and oil returns. The analysis examines the direction, magnitude, and persistence of these responses over a six-month horizon, with particular attention to their statistical significance as indicated by the 95 percent confidence intervals.

Figure 3. Impulse Response Function from the VAR model (Sweden)



Note: The shaded grey areas represent 95% confidence intervals, while the blue solid lines denote the orthogonalized impulse response functions (IRFs).

Gold and OMXSPI (Figures 3c and 3d)

Figure 3c shows the impulse response of OMXSPI returns following a shock to gold returns in the Swedish VAR (1) model. OMXSPI returns exhibit a slightly negative response in the first period. However, the effect is short-lived and quickly fades. Across all horizons, the 95 percent confidence intervals include zero, indicating that the estimated response is not statistically significant.

Figure 3d presents the impulse response of gold returns following a shock to OMXSPI returns. Gold returns display a small initial positive response, which rapidly declines and converges back to zero within a few months. Throughout the entire time horizon, the confidence intervals include zero, suggesting that the response lacks statistical significance.

Taken together, Figures 3c and 3d provide evidence of a weak and statistically insignificant dynamic relationship between gold and OMXSPI returns in the Swedish market.

Oil and OMXSPI (Figures 3a and 3b)

Figure 3a shows the impulse response of oil returns following a shock to OMXSPI returns. The response is strongest in the initial periods, after which the effect gradually weakens. In the first few periods, the confidence intervals exclude zero, indicating a statistically significant short-run response of oil returns to OMXSPI shocks.

Figure 3b shows the impulse response of OMXSPI returns following a shock to oil returns. The response is slightly negative in the initial period but fades quickly and stabilizes around zero. Throughout the entire time horizon, the confidence intervals include zero, indicating that oil price shocks do not have a statistically significant effect on OMXSPI returns. Taken together, Figures 3a and 3b reveal an asymmetric relationship between oil and Swedish equity returns, while oil price shocks do not significantly affect OMXSPI returns, stock market shocks influence short-run predictive effects on oil returns.

Gold and Oil (Figures 3e and 3f)

Figure 3e shows the impulse response of oil returns following a shock to gold returns. Oil returns respond positively in the initial period, and the response is statistically significant at the start, as the 95 percent confidence interval excludes zero. However, the effect is short-lived and fades within the first period and returns to zero. Beyond the initial horizon, the confidence intervals include zero, indicating that the response is no longer statistically significant.

Figure 3f presents the impulse response of gold returns following a shock to oil returns. Gold returns exhibit a small initial response, but the effect is short-lived, and statistically insignificant, as the confidence intervals include zero at all horizons.

7.7. Granger Causality Analysis

Granger causality tests are applied within the VAR framework to examine whether past values of one variable contain predictive information about another variable (Lütkepohl, 2005). In this study, Granger causality is used to assess whether equity-market returns help predict future movements in gold returns. A variable is said to Granger-cause another variable if its past values improve the prediction of the other variable beyond the information contained in its own past (Lütkepohl, 2005).

7.7.1 Granger Causality results: United States (S&P500)

This section presents the results from Granger causality tests based on the estimated VAR (1) models. The tests examine whether past values of one variable contain predictive information for another variable. Table 9 reports the Wald test statistics and corresponding p-values for pairwise Granger causality relationships for the United States and Sweden.

Tabel 9. Granger causality Wald tests

Panel A. Granger causality wald test (U.S. model)

Dependent variable	Excluded variable	χ^2	p-value
$lret_{sp500}$	$lret_{Gold}$	1.221	0.270
$lret_{sp500}$	$lret_{Oil}$	0.500	0.479
$lret_{sp500}$	$lret_{ALL}$	1.955	0.376
$lret_{Gold}$	$lret_{sp500}$	0.026	0.871
$lret_{Gold}$	$lret_{Oil}$	0.011	0.916
$lret_{Gold}$	$lret_{ALL}$	0.053	0.974
$lret_{Oil}$	$lret_{sp500}$	8.182	0.004
$lret_{Oil}$	$lret_{Gold}$	0.141	0.707
$lret_{Oil}$	$lret_{ALL}$	8.276	0.016

Panel B. Granger causality wald test (Sweden model)

$lret_{OMXSPI}$	$lret_{Gold}$	0.018	0.894
$lret_{OMXSPI}$	$lret_{Oil}$	4.253	0.039
$lret_{OMXSPI}$	$lret_{ALL}$	4.445	0.108
$lret_{Gold}$	$lret_{OMXSPI}$	0.776	0.378
$lret_{Gold}$	$lret_{Oil}$	0.140	0.708
$lret_{Gold}$	$lret_{ALL}$	0.803	0.669
$lret_{Oil}$	$lret_{OMXSPI}$	6.821	0.009
$lret_{Oil}$	$lret_{Gold}$	0.064	0.800
$lret_{Oil}$	$lret_{ALL}$	6.915	0.032

***Notes**: The table reports Granger causality Wald test results based on the estimated VAR (1) models. The null hypothesis is that the excluded variable does not Granger cause the dependent variable the* χ^2 *statistic tests the joint significance of the lagged coefficients of the excluded variable.* $lret_{ALL}$ *refers to a joint test of all other variables in the system. P-values are reported in the last column.*

Table 9 (Panel A) reports the results from the Granger causality Wald tests for the U.S VAR (1) model. For the S&P500 equation, neither lagged gold returns (χ^2 = 1.221, p = 0.270) nor lagged oil returns (χ^2 = 0.500, p = 0.479) are statistically significant. The joint test of lagged gold and oil returns is also insignificant (χ^2 = 1.955, p = 0.376). This suggests that past movements in gold and oil returns do not improve the prediction of U.S. stock market returns.

Similarly, no Granger causality is found for the gold equation. Lagged S&P500 returns (χ^2 = 0.026, p = 0.871), lagged oil returns (χ^2 = 0.011, p = 0.916) and the joint test of all variables (χ^2 = 0.053, p = 0.974) are all statistically insignificant. This indicates that past stock market and oil price movements do not help predict gold returns in the U.S. model.

In contrast the oil return provides evidence of Granger causality from the stock market. Lagged S&P 500 returns are statistically significant (χ^2 = 8.182, p = 0.004), whereas lagged gold returns are positive but statistically insignificant (χ^2 = 0.141, p = 0.707). Moreover, the joint Wald test of lagged S&P 500 and gold returns is significant. (χ^2 = 8.276, p = 0.016).

Taken together, these results indicate that past stock market returns contain predictive information for current oil returns in the United States.

7.7.2 Granger Causality results: Sweden (OMXSPI)

Table 9 (Panel B) presents the results from the Granger causality tests for the Swedish VAR (1) model. For the OMXSPI equation, lagged gold returns are statistically insignificant (χ^2 = 0.018, p = 0.894), indicating that past gold returns do not improve the prediction of Swedish stock market returns. In contrast, lagged oil returns are statistically significant (χ^2 = 4.253, p = 0.039), suggesting that past oil returns contain predictive information for OMXSPI returns. However, the joint test of lagged gold and oil returns is statistically insignificant (χ^2 = 4.445, p = 0.108), implying that the combined effect does not provide additional predictive power beyond the individual effect of oil.

For the gold equation, neither lagged OMXSPI returns (χ^2 = 0.776, p = 0.378) nor lagged oil returns (χ^2 = 0.140, p = 0.708) are statistically significant. The joint test is also insignificant (χ^2 = 0803, p = 0.067). These results indicate that past stock market and oil returns do not help predict gold returns in the Swedish model.

In the oil equation, lagged OMXSPI returns are statistically significant (χ^2 = 6.821, p = 0.009), while lagged gold returns are not (χ^2 = 0.064, p = 0.800). The joint test of lagged OMXSPI and gold returns is statistically significant (χ^2 = 6.915, p = 0.032). This suggests that stock market returns, and the system as a whole, contain predictive information for oil returns in Sweden.

Overall, the Granger causality results for Sweden indicate that predictive relationships are mainly present between stock market returns and oil returns, while gold returns appear largely independent within the Swedish VAR system.

8. Discussion

The findings of this study indicate that gold does not function as a hedge or a safe haven for equity investments in the U.S. or the Swedish market. The estimated VAR models and impulse response functions reveal largely insignificant relationships between gold returns and stock market returns. According to the definitions proposed by Baur and Lucey (2010), an asset qualifies as a hedge if it is uncorrelated or negatively correlated with equities on average, while a safe haven exhibits such properties specifically during periods of market stress. Based on these definitions, the empirical findings of this study do not support classifying gold as either a hedge or a safe haven for U.S. or Swedish equities.

However, the lack of strong and persistent co-movements between gold and equity returns suggests that gold may still provide diversification benefits. Low or unstable correlations are consistent with the role of a diversifier, particularly in portfolio construction, where diversification rather than protection during crises may be the primary contribution of gold.

While traditional safe haven theory emphasizes flight to quality behavior during periods of financial stress, the result of this study instead points toward the dominance of flight-to-liquidity dynamics. One possible explanation for the negative gold returns observed during periods of market stress, especially in the U.S. market is an increased demand for liquidity among investors during crises. In such environments, investors may seek to raise cash by selling even highly liquid and traditionally safe assets, including gold, in order to cover losses elsewhere in their portfolios. This behavior is consistent with a flight to liquidity mechanism and suggests that gold behaves more as a financial asset rather than a safe haven in the short-run.

The weaker and statistically insignificant relationship between gold and the Swedish equity market may be explained by factors not explicitly captured in the VAR specification. In particular, the model does not account for exchange rate dynamics. Since gold is priced in U.S. dollars, Swedish investors are exposed not only to changes in gold prices but also to fluctuations in the USD/SEK exchange rate. Consequently, exchange rate movements may influence how the relationship between gold and Swedish equity returns appears. Including an exchange rate variable in the VAR framework could therefore provide a more comprehensive understanding of how gold price shocks transmit to the Swedish stock market and potentially change the estimated impulse responses.

Another explanation for the limited protective role of gold observed in this study relates to a broader range of alternative assets. Investors today have access to a wider range of alternative assets that may compete with gold as potential hedges or safe haven. According to Baur et al. (2018), the statistical properties of Bitcoin suggest that its returns are largely independent of movements in traditional financial assets across both normal and periods of financial turmoil. Although Bitcoin is primarily used as a speculative investment rather than an asset used for everyday transactions in the real economy, the emergence of such alternatives may influence investor behavior during periods of uncertainty and reduce the relative importance of gold as a short-term protective asset in modern portfolios.

Finally, the results of this study align with earlier findings suggesting that golds primary contribution to portfolio management lies in diversification rather than crisis protection. Hillier, et al. (2006) document that gold and other precious metals exhibit low correlations with stock market returns, suggesting that they can provide diversification benefits in broad investment portfolios. At the same time, Hillier et al. (2006) document that the gold market is exceptionally liquid and that private investment demand for gold largely takes place through both physical holdings and financial instruments such as futures, options, and warrants. The high degree of liquidity and the extensive use of derivative trading imply that gold is actively integrated into financial markets. As a result, gold prices may at times become more closely linked to broader market dynamics, which may limit its effectiveness as a stable safe haven during equity market downturns.

9. Conclusion

This study analyzes how the relationship between stock markets, gold, and oil differs between normal market conditions and periods of market stress, and how these effects vary between the United States and Sweden during the period 2000-2024. These conclusions are based on evidence from descriptive statistics, market stress regressions, VAR models with impulse response functions, and Granger causality tests. A key finding is that asset behavior changes both in size and importance as market stress increases, and that these changes differ across countries.

Under normal market conditions, the results show limited interaction between stock markets and gold. Gold has low correlations with equity returns, shows no significant Granger-causal relationships, and exhibits weak dynamic links in the baseline VAR models in both countries. This finding is consistent with the hedge hypothesis (H1), providing mixed support for gold as a hedge, suggesting that gold generally moves independently of stock markets when market conditions are stable. Oil, on the other hand, shows stronger co-movements with equities, reflecting its close connection to economic activity and its procyclical nature.

When market stress is considered, these relationships change clearly. During periods of moderate market stress, gold returns in the U.S. decline by a noticeable and statistically significant amount. This negative effect becomes even larger during periods of extreme stress, indicating that the magnitude of golds response increases as market conditions worsen. These results contradict the safe haven hypothesis (H2) for the U.S. market, as gold does not protect investors during equity market downturns but instead tends to lose value when stress intensifies. In contrast, gold returns in Sweden remain statistically insignificant during both moderate and extreme stress, and the estimated coefficients are small. This suggests neither clear support nor rejection of the safe haven hypothesis for Sweden, with gold behaving largely independently of stock market movements.

Oil shows a consistently negative and economically large response to market stress in both countries. In the United States, oil returns fall substantially during periods of moderate stress, and the decline becomes even larger during extreme stress. These results indicate that oil performs poorly when equity markets are under pressure. The magnitude of this effect is even stronger in Sweden, where the estimated coefficients are larger during both moderate and extreme stress periods.

Comparing these two countries highlights clear differences. While oil responds negatively to market stress in both markets, the size of the effect is considerably larger in Sweden than in the United States. Gold, by contrast, shows a clear negative response to market stress in the U.S. but exhibits no statistically meaningful response in Sweden. These differences suggest that asset behavior during market stress depends on the specific market and its structure.

In summary, the results show that asset responses are not the same across all market conditions. Treating market stress as a single situation hides important differences between moderate and extreme stress periods, as both the size and significance of the effects increase when stress intensifies. Taken together, the evidence provides limited support for gold as a universal safe haven (H2), mixed support for its role as a hedge (H1), and little evidence of strong predictive causality from stock markets to gold returns (H4). By contrast, oil consistently behaves as a procyclical asset that performs poorly during periods of equity market stress. Clearly distinguishing between normal market conditions, moderate stress, and extreme stress is therefore crucial when analyzing asset behavior during financial downturns.

However, the conclusions should be read with consideration for the limitations of the study. In particular, market stress is identified using fixed percentile thresholds of stock market returns, which represents only one possible way of defining stressful market conditions. Alternative measures, such as volatility-based indicators, could capture different dimensions of market stress and potentially lead to different results. Moreover, the impulse response analysis relies on the specification of the VAR models and the set of included variables, meaning that omitted factors may influence the estimated dynamics. Finally, the focus on two equity markets and a limited set of assets, while allowing for a clear comparison, may limit the generalizability of the findings to other markets or asset classes.

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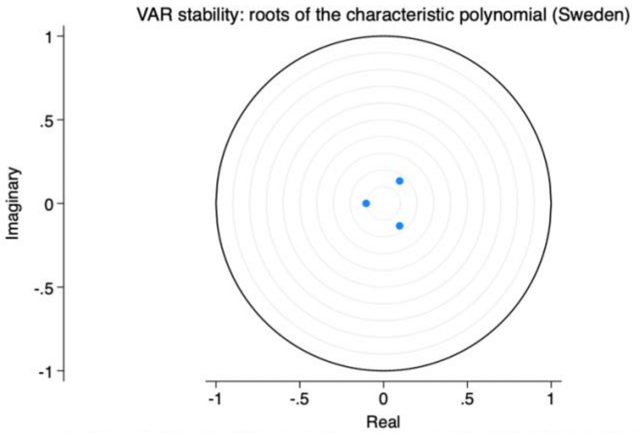
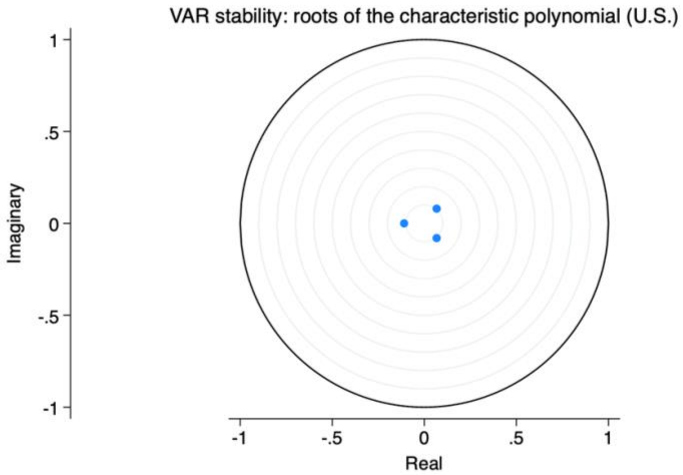
Appendix

Figure A1. Var stability: roots of the characteristic polynomial (Sweden model)



Notes: The figure is based on a VAR(1) model including OMXSPI returns (lret_omx), gold returns (lret_gold), and oil returns (lret_oil). All roots lie inside the unit circle, indicating that the VAR model is stable.

Figure A2. Var stability: roots of the characteristic polynomial (U.S. model)



Notes: The figure is based on a VAR(1) model including S&P500 returns (lret_sp500), gold returns (lret_gold), and oil returns (lret_oil). All roots lie inside the unit circle, indicating that the VAR model is stable.