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Dominik Novak*

The impact of macroeconomic measures on the valuation of listed equity in the US. Insights from high inflation periods

1. Introduction

Understanding and examining the empirical relationship between macroeconomic variables and stock prices is essential for both market participants and policymakers. Stock market fluctuations play a critical role in economic performance by influencing capital allocation, affecting the cost of equity, and contributing to overall economic growth.

According to the Efficient Market Hypothesis (EMH), capital markets rapidly incorporate new information, ensuring that stock prices consistently reflect all available information. Consequently, it is impossible for any investor to predict stock price fluctuations using readily available information (Fama 1970). The EMH, particularly its semi-strong form definition of price efficiency, posits that stock prices fully reflect all publicly available information, and historical data. Therefore, changes in macroeconomic variables are expected to be promptly incorporated into stock prices. If the assumptions of the EMH hold, policymakers can implement national macroeconomic policies without worrying about affecting capital formation and the stock trading process. Moreover, if stock prices accurately reflect the fundamental value of a company, as posited by the EMH, stock prices should be used as leading indicators for future economic activity, rather than macroeconomic variables.

Contrary to the conclusions of the EMH, evidence has accumulated over the past 40 years indicating that key macroeconomic variables can reliably predict stock price movements. E.F. Fama and G. Schwert (Fama, Schwert 1977), R.R. Nelson and S.G. Winter (Nelson, Winter 1977) and J.F. Jaffe and G. Mandelker

* University of Graz, Austria, e-mail: do.novak@edu.uni-graz.at, ORCID: 0009-0002-4431-4039

(Jaffe, Mandelker 1976) were among the first to challenge the conclusions of the EMH, strengthening the hypothesis that macroeconomic variables influence stock prices. Employing the Johansen cointegration procedure, there has been a growing body of literature investigating the relationship between stock prices and macroeconomic variables. Focusing on the US, O. Ratanapakorn and S.C. Sharma (Ratanapakorn, Sharma 2007) find that the S&P 500 index positively correlates with money supply, industrial production, inflation, exchange rates, and short-term interest rates, while negatively correlates with long-term interest rates from 1975 to 1999. Similarly, A. Humpe and P. Macmillan (Humpe, Macmillan 2009) analyse the period from 1965 to 2005 and identify comparable results. However, unlike O. Ratanapakorn and S.C. Sharma (Ratanapakorn, Sharma 2007), they find an inverse relationship between inflation and the S&P 500 index, indicating a potential dynamic relationship that has not yet been thoroughly investigated. Following the research of A. López-Villavicencio and V. Mignon (López-Villavicencio, Mignon 2011) and H. Loi and A.S. Abou-Zaid (Loi, Abou-Zaid 2016), the threshold level of inflation in the US ranges between 3% and 5%, beyond which inflation exerts significant negative effects on economic stability, disrupting the relationships between macroeconomic variables. Additionally, A. Brick and D. Nautz (Brick, Nautz 2008) find that stock market volatility and uncertainty increase when inflation exceeds a critical threshold of 4.4%. While a negative relationship between inflation rates and stock prices aligns with Fama's (1981) proxy hypothesis, the presence of an inflation threshold effect may indicate a shift towards the Fisher hypothesis (1930). This hypothesis suggests a positive relationship between inflation and stock prices, as equities are perceived as a hedge against rising price levels and economic uncertainty, given that equities represent real assets.

In light of these considerations, the conflicting findings across the empirical studies discussed above may be attributable to the inclusion of a significant inflationary period in both observation periods, neglecting potential non-linear threshold effects. Between 1970 and 1985, major oil-price shocks, triggered by OPEC-imposed oil embargos against the US, led to severe energy shortages. The shocks were followed by soaring inflation rates for over a decade, alongside declining GDP growth, a phenomenon known as stagflation (Dierks 2021). The presence of additional divergent empirical findings on the relationship between macroeconomic variables and stock prices (Fama 1990; Schwert 1990; Abdullah and Hayworth 1993; Dhakal et al. 1993) further highlights the nonlinearity of this relationship.

Thus, a gap in the literature exists regarding the analysis of the relationship between macroeconomic variables and stock prices, particularly in the context of high-inflation periods in the US. This paper explicitly investigates the cointegrating relationship during the high-inflation period from 1973 to 1982 using the Johansen cointegration procedure. Given the resurgence of supply-side inflationary pressures, driven by an oil-price shock in 2021, the analysis is extended to include the recent episode to enhance the robustness of the findings. This period, characterized by a preceding highly expansionary monetary policy, the economic fallout of the COVID-19 pandemic, including high unemployment rates and a sharp economic contraction, and surging energy prices due to the Russia-Ukraine conflict, which collectively contributed to rising inflation rates, is also analysed using the Johansen cointegration procedure. This comparative analysis will assess whether both inflationary periods exhibit similar empirical relationships, which would shed light into the contradicting results of empirical findings, as alterations may be attributable to neglected threshold effects of high inflation environments. In summary, this paper investigates the following research question:

- Does a cointegrating relationship exist between macroeconomic variables and the S&P 500 composite index during periods of high inflation from 1973 to 1982 and 2021 to 2024?
- How do the statistical direction and magnitude of the relationships between macroeconomic variables and the S&P 500 during 2021 to 2024 compare to those observed in 1973 to 1982?
- Does explicitly focusing on periods of high inflation help explain inconsistencies in the empirical literature regarding the relationship between macroeconomic measures and US stock prices, as potential threshold effects are taken into account in the analysis?

The paper is organized as follows: Section 2 reviews the existing literature relevant to this research field. Section 3 outlines the theoretical framework regarding the applied methodology. Section 4 discusses the financial and macroeconomic variables used in the analysis. Section 5 presents the econometric analysis of the relationships between these variables. Finally, Section 6 discusses the findings concerning the long- and short-term relationship dynamics during the periods of high inflation 1973 to 1982 and 2021 to 2024.

2. Literature review

Proponents of the EMH argue that only unanticipated changes in macroeconomic variables can influence stock prices, when investigating the impact of these variables on the stock market (Sorensen 1982; Davidson, Froyen, 1982; Pearce, Roley, 1983). Following this idea, P. Samuelson introduced the concept known as the Samuelson Dictum which suggests that the stock market might be “micro-efficient” but “macro-inefficient” (Samuelson 1998). According to this theory, the EMH empirically applies to individual stocks but not to composite indices. The Samuelson Dictum is supported by empirical evidence such as R.J. Shiller (Shiller 1981), J.Y. Campbell and R.J. Shiller (Campbell, Shiller 1988) and R. Cohen,

C. Polk, and T. Vuolteenaho (Cohen et al. 2005). Consistent with the Samuelson Dictum, this paper focuses on composite indices.

A substantial body of literature investigates the relationship between stock prices and a variety of macroeconomic and financial variables across different stock markets and time horizons. Existing financial theories offer numerous models that provide frameworks for analysing this relationship. Early research utilizes the Arbitrage Pricing Theory (APT) proposed by S.A. Ross (Ross 1976), which formulates asset returns as a linear function of various risk factors, including macroeconomic variables. Within a multivariate regression framework, the coefficients quantify the sensitivity to each factor. N.F. Chen et al. analysed monthly data in the US for the period between 1958 and 1984 (Chen et al. 1986). Y. Hamao replicated the study for the Japanese market as a test for robustness using monthly data for the period of 1975 to 1984 (Hamao 1988). The APT framework was also used by M.A. Martinez and G. Rubio to observe the Spanish stock market (Martinez, Rubio 1989). Moreover, significant contributions in this regard have been made by E.F. Fama (Fama 1981, 1990), S. Poon and S.J. Taylor (Poon, Taylor 1991), G.W. Schwert (Schwert 1990), W.E. Ferson and C.R. Harvey (Ferson, Harvey 1991), A. Black, P. Fraser and R. MacDonald (Black et al. 1997). In summary, research employing the APT framework has strengthened the hypothesis of an existing relationship between stock prices and several key economic indicators across several countries, including industrial production (as a measure of real economic activity), inflation rates, interest rates, the yield curve, and the risk premium.

In 1981, Clive W.J. Granger introduced the concept of cointegration, a significant advancement in the field of econometrics. The comprehensive formulation of this concept was later presented by R.F. Engle and C.W.J. Granger (Engle, Granger 1987) in their seminal paper. Cointegration involves identifying a linear combination of two I(d)-variables that yield a variable integrated of a lower order. This methodological breakthrough allows for the detection of stable long-run relationships among non-stationary variables. This is particularly important in economics, given that most financial and macroeconomic time series are non-stationary. Building on this foundational work, S. Johansen (Johansen 1988, 1991; Johansen, Juselius 1990) developed maximum likelihood estimators for cointegration vectors within an autoregressive framework. Using the cointegration approach and Vector Error Correction Models (VECM), a substantial body of literature challenges the assertions of the EMH and provides evidence that macroeconomic variables significantly contribute to predicting stock price movements. A. Nasseh and J. Strauss (Nasseh, Strauss 2000) investigated the influence of macroeconomic factors on stock prices, encompassing the stock markets in Germany, France, Italy, Netherlands, Switzerland, and the United Kingdom. Their findings reveal a lasting cointegrating relationship between the stock indices of each country and their respective domestic industrial production index, as well as long- and short-term interest and inflation rates. Further research to be mentioned in this regard includes T.K. Mukherjee and A. Naka (Mukherjee, Naka 1995), Y.-W. Cheung and L.K. Ng (Cheung, Ng 1998), M. Binswanger (Binswanger 2004), R. Kizys and C. Pierdzioch (Kizys, Pierdzioch 2009), and H.A. Bekhet and A. Matar (Bekhet, Matar 2013).

N. Apergis utilizes the Generalized Autoregressive Conditional Heteroskedastic model (GARCH) (Apergis 1998), introduced by T. Bollerslev (Bollerslev 1986), along with GARCH-X models. The GARCH-X model, which is an extension of the standard GARCH model proposed by S.-W. Lee and B.E. Hansen (Lee, Hansen 1994), enables the analysis of the relationship between short-run deviations from the long-run cointegrating equilibrium and volatility. N. Apergis finds significant short-run deviations between stock prices and various economic indicators, including money supply, commodity prices, oil prices, income and the exchange rate (Apergis 1998). N. Sariannidis et al. analysed the effects of various macroeconomic variables on the Dow Jones Sustainability index and the Dow Jones Wilshire 5000 index using a GARCH model and monthly data spanning from January 2000 to January 2008 (Sariannidis et al. 2010). Their findings indicate that fluctuations in crude oil prices have a negative impact on the US stock market, while changes in 10-year government bond yields exert a positive effect. Additionally, the analysis reveals that both macroeconomic indicators influence the stock market with a one-month lag.

A. Abhyankar, L.S. Copeland and W. Wong (Abhyankar et al. 1997), E. Maasoumi and J. Racine (Maasoumi, Racine 2002) emphasize the need for statistical methodologies capable of capturing potential nonlinear relationships between macroeconomic variables and the stock market. A body of research, exemplified by Z. Zeng (Zeng 2011), W. Mensi et al. (Mensi et al. 2014), and N. Naifar (Naifar 2016), investigates the impact of macroeconomic indicators on the stock market across various quantiles of the conditional distribution of the stock market index, using quantile regression methodology. Quantile regression offers the advantage of not requiring any distributional assumptions about the population and allows for the non-parametric estimation of arguments (Naifar 2016). S.J.H. Shahzad et al. (Shahzad et al. 2021) adopt the Quantile Autoregressive Distributed Lag (QARDL) approach established by J.C. Cho et al. to comprehensively investigate the short- and long-term linkages between macroeconomic variables and US stock prices amidst different states of the equity market (Cho et al. 2015).

3. Methodology

To address the research questions outlined in Section 1, this study follows a structured methodological framework, which is briefly introduced in this section. First, the stationarity of the time series is examined using the Augmented

Dickey–Fuller (ADF) test and the Phillips–Perron (PP) test. Second, potential cointegration relationships are identified through the Johansen cointegration test. Third, Granger-causal linkages between the time series are analysed using the Granger causality test. Finally, short-term dynamics are examined by means of VECMs, Impulse-Response functions, and Forecast Error Variance Decompositions (FEVDs). Following the estimation of the VECMs, diagnostic tests are conducted to ensure that the model assumptions hold. Residual autocorrelation is tested using the Breusch-Godfrey test (Godfrey 1988), residual heteroscedasticity is assessed with a multivariate Lagrange Multiplier (LM) statistic (Lütkepohl 1991), and residual normality is evaluated using the Lomnicki–Jarque–Bera test (Lomnicki 1961; Jarque, Bera 1987).

3.1. Unit root tests

Economic and financial variables often exhibit trending behaviour, rendering them non-stationary in their mean. Assessing the stationarity of time series data is essential prior to applying cointegration models to avoid spurious cointegrating relationships. In the context of this paper, the time series under consideration must be integrated of order one, denoted as I(1). E.S. Said and D.A. Dickey (Said, Dickey 1984) extend the basic autoregressive unit root test to include general ARMA(p,q) models with unknown orders, resulting in the development of the ADF test. The inclusion of higher-order lagged terms accounts for the complexity of the ARMA(p,q) model and helps to whiten the error term in the regression equation used for testing (Harris 1995). The ADF test is conducted by estimating the corresponding test regression model:

$$X_t = \beta' D_t + \phi X_{(t-1)} + \sum\nolimits_{(j=1)}^{p} \psi_j \Delta X_{(t-j)} + \varepsilon_t \tag{1}$$

D_t represents a vector of deterministic terms. The inclusion of p lagged difference terms, X_{t-j}, serves to approximate the ARMA structure of the errors. The number of lags is chosen such that the error term ε_t is serially uncorrelated. The null hypothesis denotes that the series X_t is non-stationary, which implies that $\phi = 1$. The ADF test employs the t-statistic and normalized bias statistic, both derived from the least squares estimates of the test regression model, and is expressed as follows (Zivot, Wang 2003):

$$ADF_t = t_{\phi=1} = \frac{\hat{\phi} - 1}{SE(\phi)} \tag{2}$$

P.C.B. Phillips and P. Perron (Phillips, Perron 1988) introduced the PP test, which differs from the ADF test primarily in its approach of addressing serial correlation and heteroskedasticity in the error terms. One key advantage of the PP test compared to the ADF test is its robustness to general forms of heteroskedasticity in the errors ε_t. The test is therefore used to verify the results of the ADF test (Zivot, Wang 2003).

3.2. Johansen cointegration test

C.W.J. Granger initially introduced the concept of cointegration (Granger 1981), which was subsequently elaborated upon by R.F. Engle and C.W.J. Granger in their seminal paper (Engle, Granger 1987). The essence of cointegration lies in discovering a linear combination β between two I(d) variables X_t and Y_t that result in a variable with a reduced order of integration $X_t - \beta Y_t = I(d - b)$. Whereas the R.F. Engle and C.W.J. Granger (Engle, Granger 1987) procedure is suitable for single equation models, the Johansen cointegration test (Johansen 1988; Johansen, Juselius, 1990; Johansen 1991) represents the most widely used approach in this field of research, providing a framework for investigating cointegrating relationships in multivariate systems (Holden, Perman 1994). In the case of multivariate systems, each component of the vector X_t where $t = 1, 2, \ldots, T$ and X_t is a $(K \times 1)$ matrix, can be defined as follows:

$$X_{i,t} = TD_{i,t} + z_{i,t}, \text{ for } \quad i = 1,...,K;\ t = 1,...,T \tag{3}$$

In this regression model, the deterministic component is represented by $TD_{i,t}$, while $z_{i,t}$ represents the stochastic component, modelled as an ARMA process. In the context of multivariate systems, it is assumed that the maximum number of unit roots present in the series $X_{i,t}$ is one, with all remaining roots lying outside the unit circle.

The foundation of a VECM is a VAR model of the order p:

$$X_t = \Pi_1 X_{t-1} + ... + \Pi_K X_{t-p} + \mu + \phi D_t + \varepsilon_t, t = 1,...,T \tag{4}$$

Where X_t defines the $(K \times 1)$ vector of time series at period t, the matrices $\Pi_{(i=1,\ldots,p_i)}$ are the $(K \times K)$ coefficient matrices of the lagged endogenous variables. The coefficients μ and D_t assign the vectors for constants and non-stochastic variables like seasonal dummies or intervention dummies. ε_t represents the error terms, which are independent stochastic vectors with a mean of zero and a variance of 1. While the VAR model is sufficiently general to encompass variables exhibiting stochastic trends, it is not adequately suited for investigating cointegrating relations, as these relations are not explicitly represented in VAR models. Rather, VECMs, which are derived from the levels VAR model by subtracting X_{t-1} from both sides and rearranging terms, are applied. S. Johansen and K. Juselius (Johansen, Juselius 1990) developed maximum-likelihood estimators for the cointegrating vectors within the β matrix of a VAR model. The Johansen cointegration test employs canonical correlation analysis to reduce the dimensionality of the data, effectively transforming information from T observations in a K-dimensional space into a lower-dimensional space defined by r cointegrating vectors. This dimensionality reduction is achieved by regressing ΔX_t on the lagged differences of X_t, with the resulting residuals referred to as $R_{0,t}$. Subsequently, X_{t-p} is regressed on the lagged differences of X_t, from which residuals are obtained. The vectors $R_{0,t}$ and $R_{1,t}$, derived from these regressions, are then utilized to calculate the product moment matrices (Johansen 1995):

$$\hat{S}_{ij} = \frac{1}{T}\sum_{t=1}^{T} R_{i,t} R_{j,t} \tag{5}$$

with $i, j = 0, 1$. S. Johansen (Johansen 1995) defined the likelihood-ratio test statistic for H0: at most r cointegrating vectors by:

$$-2\ln(Q) = -T\sum_{i=r+1}^{n}\left(1-\hat{\lambda}_i\right) \tag{6}$$

where the eigenvectors relating to the r largest eigenvalues form the solution to the equation and the maximum likelihood estimation of β is obtained:

$$\left|\lambda \hat{S}_{11} - \hat{S}_{10}\hat{S}_{00}^{-1}\hat{S}_{01}C'\right| = 0 \tag{7}$$

S. Johansen established critical values for the trace statistic at different quantiles and up to five cointegrating relationships (Johansen 1988). In a related study, S. Johansen and K. Juselius developed the maximum eigenvalue statistic to determine the presence of r versus $r + 1$ cointegrating ranks (Johansen, Juselius 1990). They also provided critical values for different model specifications, such as a deterministic constant or a trend.

$$-2\ln(Q; r \mid r+1) = -T\ln\left(1-\hat{\lambda}_{r+1}\right) \tag{8}$$

After the cointegrating rank r has been determined, the cointegrating vector is obtained by:

$$\hat{\beta} = \left(\hat{v}_1, \ldots, \hat{v}_r\right), \hat{v}_r = C'^{-1} e_i \tag{9}$$

The vectors e_i represent the eigenvectors associated with the eigenvalues of Equation (7). The loadings matrix α is determined by β and is defined as follows:

$$\hat{\alpha} = -\hat{S}_{01}\hat{\beta}\left(\hat{\beta}'\hat{S}_{11}\hat{\beta}\right)^{-1} \tag{10}$$

In the concluding step of the Johansen cointegration procedure, the variance-covariance matrix of the K-dimensional error process ε_t is derived. The matrix is specified as follows:

$$\hat{\Sigma} = \hat{S}_{00} - \hat{S}_{01}\hat{\beta}\hat{\beta}'\hat{S}_{10} \tag{11}$$

3.3. Granger causality analysis

C.W.J. Granger introduced a causality concept based on the predictive power of past values of a time series X_{t-1} for forecasting future values of another time series Y_t (Granger 1969). $H_{<t}$ denotes the history of all pertinent information available up to time $t-1$, whereas $P(X_t \mid H_{<t})$ is the optimal prediction of X_t, given $H_{<t}$. CW.J. Granger specifies X_t as causal for Y_t if:

$$var\left[Y_t - P(Y_t \mid H_{<t})\right] < var\left[Y_t - P(Y_t \mid H_{<t} \setminus X_{<t})\right] \tag{12}$$

This implies that incorporating the history of X_t reduces the variance of the optimal prediction error for Y_t. Based on the idea that predictability suggests causation, C.W.J. Granger stated that the ability of X_t to predict Y_t indicates a causal effect. Later theoretical considerations suggest that the test is not fully adequate for establishing strict causal relationships. This inadequacy stems from the potential for a *post hoc ergo propter hoc* fallacy, where one might incorrectly infer causation merely because one event follows another. Therefore, it is common practice to claim that variable X_t Granger-causes variable Y_t, rather than claiming a direct causal link.

4. Data and motivation

N.-F. Chen et al. suggest that a Present Value Model (PVM) can be used to justify the selection of macroeconomic variables that act as systematic risk factors influencing stock returns (Chen et al. 1986). In this framework, $E_t(d_{t+i})$ denotes the anticipated annual real dividend per share, and refers to the projected discount rate or cost of capital.

$$P_t = \sum_{i=1}^{\infty} \frac{E_t\left(d_{t+i}\right)}{\left(1 + E_t r\right)^i} \tag{13}$$

Therefore, any macroeconomic variable that affects expected future dividends or the discount rate has the potential to influence stock returns. Since the primary focus of this paper is to analyse the relationship between stock prices and macroeconomic variables during inflationary periods in the US, the analysis includes monthly observations from August 1973 to August 1982, representing the first subsample, and from January 2021 to June 2024, representing the second subsample. For the remainder of this paper, the periods under examination will be referred to as High-Inflation Period 1 (109 observations) and High-Inflation Period 2 (42 observations). During these periods the inflation rate consistently exceeds 3%, coinciding with beginning threshold effects of high inflation rates (López-Villavicencio, Mignon 2011; Loi, Abou-Zaid 2016).

Given the recent onset of High-Inflation Period 2, no additional data is available. Thus, the results of the Johansen cointegration test will be validated using an Autoregressive Distributed Lag (ARDL) model and the Bounds Test proposed by M.H. Pesaran et al., which is widely acknowledged for its robustness at shorter timeframes (Pesaran et al. 2001). The composite S&P 500 index serves as the benchmark for assessing US stock price performance, given its data availability across both subsamples. Monthly closing prices of the S&P 500 are obtained from Thomson Reuters Datastream.

Considering the PVM according to N.-F. Chen et al. (Chen et al. 1986), the long-term government bond yield, the inflation rate, the industrial production rate, which serves as a proxy for economic growth, and the narrow money supply are identified as significant determinants of expected stock prices. The variables are expressed in natural logarithmic form, both in levels and first differences. In the case of variables exhibiting evident seasonal patterns, seasonally adjusted data is used. The time series data for the macroeconomic variables is obtained from the Federal Reserve Bank of St. Louis database. Before providing a detailed discussion of each variable, Table 1 presents an overview of the time series adopted in this paper.

Table 1

Description of financial and macroeconomic variables

Variable	Definition
Stock price (S&P 500)	Monthly closing values of the float-adjusted market cap-weighted index for all shares listed in the S&P 500
Money Supply (M1)	Monthly real narrowly defined money supply (seasonally adjusted)
Inflation (INF)	Monthly consumer price index for all urban consumers (seasonally adjusted)
Long-Term Interest Rate (LTI)	Monthly market yield on US treasury securities at 10-year constant maturity
Industrial Production (IP)	Monthly industrial production index (seasonally adjusted)

Notes: All variables are converted into natural logarithm

Money supply is anticipated to influence stock prices through several mechanisms. According to D. Dhakal et al. (Dhakal et al. 1993), an expansion in the money supply can lead to a heightened inflation rate, increased uncertainty about future inflation rates, and therefore rising interest rates. As per Equation (13), an elevated discount rate triggered by the rising interest rates would result in a decrease in the expected stock price P_t. Conversely, an increase in the money supply can also act as a catalyst for economic growth, enhancing expected cash flows and future dividend payments per share $E_t(d_{t+i})$, driving up expected stock prices P_t. Portfolio-balance theory, as suggested by the quantity theory of money, indicates that a larger money supply may encourage investors to reallocate their portfolios, shifting from non-interest-bearing assets to financial instruments like equities (Friedman 1961; Friedman, Jacobson-Schwarz 1963).

The relationship between inflation and stock prices remains a subject of both empirical and theoretical debate. Following the Fisher hypothesis (1930), D. Abdullah and S. Hayworth find a positive association between stock prices and inflation, suggesting that equities act as a hedge against inflation (Abdullah, Hayworth 1993). Conversely, the PVM proposes that inflation may negatively impact expected stock prices, since an increase in the nominal risk-free rate leads to a higher discount rate, reducing the present value of future cash flows. E.F. Fama interprets the Phillips Curve framework to suggest a positive relationship between inflation and the stock market (Fama 1981). Further, R. DeFina states that an increasing inflation rate results in declining corporate income due to immediate rising costs and slowly adjusting output prices, thereby reducing profits and ultimately the stock price (DeFina 1991). Empirical research focusing on the US stock market also yields conflicting findings (Bodie 1976; Nelson, Winter 1977; Toyoshima, Hamori 2011). Hence, the results of this research will contribute to the existing body of empirical evidence and help to clarify the divergent findings regarding the relationship between inflation rates and US stock prices, especially by focusing on potential threshold effects during periods of elevated inflation rates.

The interest rate directly affects the discount rate $E_t r$ by increasing the nominal risk-free rate in Equation (13), which in turn leads to a reduction in the expected stock price P_t. Additionally, a rise in interest rates can elevate financing costs, thereby reducing a firm's profitability and the market value of its shares (Bulmash, Trivoli 1991).

Industrial production is considered a key indicator of real economic activity, as it tends to capture variations in economic performance more effectively than other metrics such as the gross domestic product or private investment (Nasseh, Strauss 2000; Ratanapakorn, Sharma 2007; Bhuiyan, Chowdhury 2020). In theory, an increase in industrial output suggests a buildup of tangible assets, which enhances the economy's productive capacity. As firms expand their ability to generate future cash flows, this growth positively influences expected stock prices (Maysami et al. 2004).

Figure 1 illustrates the time series included in the analysis. The shaded areas highlight the specific subsamples beginning in 1973 and 2021.

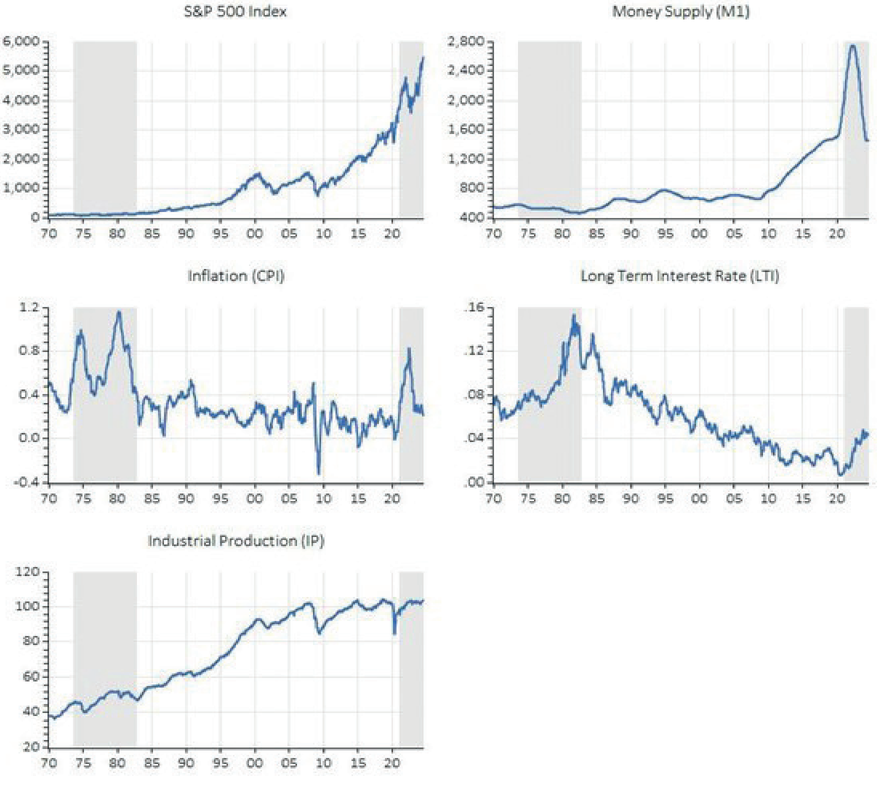

Figure 1. Graphical representation of financial and macroeconomic time series data

5. Empirical results

This section reports the results of the econometric analysis examining the relationship between stock prices and macroeconomic variables in the US, using the Johansen cointegration test. The decision to apply the Johansen cointegration procedure to separate subsamples, rather than the extended period from 1970 to 2024, is motivated by the presence of multiple economic crises, outliers, and regime shifts throughout the full timeframe. These factors ought to be controlled, as they complicate the interpretation of financial and economic data and may introduce unintended parameter shifts in the VAR model (Juselius 2006).

5.1. Unit root tests

The first step is to determine the order of integration of each time series, as the Johansen procedure requires variables to be integrated of order one. The results of the ADF and the PP test are presented in Table 2.

Table 2

ADF test results for US variables

ADF test for US variables August 1973 – August 1982		
Variables	At level	At first difference
S&P 500	−3.0936	−8.6854***
IP	−1.5708	−5.7040 ***
LTI	−1.7219	−8.7665 ***
INF	−1.2689	−4.7321 ***
M1	−2.7952	−7.7800 ***
ADF test for US variables January 2021 – June 2024		
Variables	At level	At first difference
S&P 500	−0.7614	−5.5176***
IP	−2.5724	−12.3041 ***
LTI	−1.4704	−5.1528 ***
INF	−0.1482	−5.1201 ***
M1	−2.4931	−2.5069

Notes: (***) denotes significant at the 1% level. The one-sided p-values are obtained from MacKinnon (1996). The time series are expressed in natural logarithmic form

Given the characteristics of the variables analysed in this paper, the null hypothesis for the ADF test assumes the presence of a unit root, including both a constant and a time trend. The number of lags for the test regression is determined using the Schwarz Information Criterion (SIC). Based on the results of the ADF test, all time series are integrated of order one, except for the money supply in High-Inflation Period 2. As a result, the Johansen cointegration procedure cannot be applied to analyse the relationship between the money supply and stock prices in the second subsample. As illustrated in Figure 1, money supply exhibits significant volatility during the second subsample, largely attributable to the extensive interventions by the Federal Reserve's Quantitative Easing measures during the COVID-19 pandemic. A visual inspection of the time series suggests that it remains non-stationary even after first differencing, confirming the unit root test results.

Table 3

PP test results for US variables

PP test for US variables August 1973 – August 1982		
Variables	At level	At first difference
S&P 500	−3.1165	−10.1739 ***
IP	−1.3849	−5.7412 ***
LTI	−2.0691	−7.3968 ***
INF	−1.2054	−4.6503 ***
M1	−2.4339	−7.8100 ***
PP test for US variables January 2021 – June 2024		
Variables	At level	At first difference
S&P 500	−0.9511	−5.5213***
IP	−2.3874	−12.3041 ***
LTI	−1.4704	−4.3093 ***
INF	−0.1482	−5.1201 ***
M1	−2.4931	−2.5069

Notes: (***) denotes significant at the 1% level. The one-sided p-values are obtained from MacKinnon (1996). The time series are expressed in natural logarithmic form

Given the robustness of the PP test (Tab. 3) to various forms of heteroscedasticity in the error terms, the results serve as a validation of the findings from the ADF test. The optimal bandwidth selection for the spectral density estimation of the PP test is based on the Newey–West Bandwidth estimation (Newey, West 1994). Both the ADF and PP unit root tests yield consistent results.

5.2. Johansen cointegration test

After assessing the stationarity of the time series, the Johansen cointegration test is applied to examine whether an equilibrium relationship exists between the US stock market and the selected macroeconomic variables. The optimal lag length is identified using the Akaike Information Criterion and the Schwarz Information Criterion. Additionally, the lag length is validated through a visual inspection of the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the residuals from the VECM. Adding too many lags can be detrimental, as it makes diagnosing regime shifts or non-constant parameters more challenging. According to K. Juselius (Juselius 2006), a well-specified model rarely requires more than two lags. Based on the information criteria and Juselius's (Juselius 2006) rule of thumb, a lag length of 2 is determined to be optimal for modelling High-Inflation Period 1. Due to the shorter time frame of High-Inflation Period 2, a lag length of 1 is identified as optimal. The λ-trace and λ-max statistics are used to determine the number of cointegrating vectors. The results for the λ-trace and λ-max statistics for both subsamples are summarized in Table 4 and 5.

Table 4

Unrestricted cointegration rank test (λ-trace)

Unrestricted Cointegration Rank Test (λ-trace) for August 1973 – August 1982				
Hypothesized No. of CE(s)	Eigenvalue	Trace statistic	0.05 critical value	Probability value
None *	0.297185	78.44205	69.81889	0.0087
At most 1	0.224066	41.05996	47.85613	0.1868
At most 2	0.086608	14.16899	29.79707	0.8310
At most 3	0.042164	4.566393	15.49471	0.8530
At most 4	6.69E-07	7.09E-05	3.841465	0.9944
Unrestricted cointegration rank test (λ-trace) for January 2021 – June 2024				
Hypothesized No. of CE(s)	Eigenvalue	Trace statistic	0.05 critical value	Probability value
None *	0.710153	77.91396	47.85613	0.0000
At most 1	0.318421	28.37792	29.79707	0.0722
At most 2	0.247362	13.04422	15.49471	0.1132
At most 3	0.041067	1.677373	3.841465	0.1953

Notes: (*) denotes rejection of the null hypothesis at the 5% level. The *p*-values are obtained by J.G. MacKinnon, A.A. Haug and L. Michelis (MacKinnon et al. 1999). CE(s) denotes Cointegrating Equations

The λ-trace statistic results presented in Table 4 indicate the presence of one cointegrating vector at the 5% significance level in both subsamples at the null hypothesis of at most r cointegrating vectors.

Table 5

Unrestricted cointegration rank test (λ-max)

Unrestricted cointegration rank test (λ-max) for August 1973 – August 1982				
Hypothesized No. of CE(s)	Eigenvalue	Max–Eigen statistic	0.05 critical value	Probability value
None *	0.297185	37.38209	33.87687	0.0183
At most 1	0.224066	26.89097	27.58434	0.0611
At most 2	0.086608	9.602596	21.13162	0.7810
At most 3	0.042164	4.566322	14.26460	0.7953
At most 4	6.69E-07	7.09E-05	3.841465	0.9944
Unrestricted cointegration rank test (λ-max) for January 2021 – June 2024				
Hypothesized No. of CE(s)	Eigenvalue	Max–Eigen	0.05 critical value	Probability value
None *	0.710153	49.53604	27.58434	0.0000
At most 1	0.318421	15.33370	21.13162	0.2662
At most 2	0.247362	11.36685	14.26460	0.1368
At most 3	0.041067	1.677373	3.841465	0.1953

Notes: (*) denotes rejection of the null hypothesis at the 5% level. The *p*-values are obtained by J.G. MacKinnon, A.A. Haug, L. Michelis (MacKinnon et al. 1999). CE(s) denotes cointegrating equations

The results of the λ-max statistics align with the λ-trace statistics, strengthening the conclusions.

5.3. Vector Error Correction Models (VECM)

This section describes the VECM for High-Inflation Period 1 and 2. The VECM suggests that variations in one variable are influenced by the extent of disequilibrium in the cointegrating relationship, as indicated by the error correction term, and by fluctuations in other explanatory variables. Thus, the VECM is effective in identifying both long- and short-term Granger causality, given that variables are cointegrated. The short-run Granger-causal dynamics of the variables are examined using the Granger causality approach discussed in Section 3.3. The magnitude is analysed with Impulse-Response functions and FEVDs.

5.3.1. High-Inflation Period 1 (1973 to 1982)

The observation period follows a phase of expanding federal spending, driven by increased military expenditures for the Vietnam War, social welfare programs aimed at alleviating poverty, and the collapse of the Bretton Woods system. The oil embargo imposed by OPEC in response to the Yom Kippur War and the Iran-Iraq War led to a sharp rise in oil prices, reaching 39.5 USD per barrel. Escalating energy costs exacerbated inflationary pressures and contributed to a prolonged wage-price spiral, while real GDP contracted. Table 6 presents the normalized cointegrating coefficients from the VECM. The full VECM specification for High-Inflation Period 1 is provided in Appendix A1.

Table 6

Normalized cointegrating coefficients – High-Inflation Period 1

Normalized cointegrating coefficients (CE)					
S&P 500	IP	LTI	INF	M1	C
1.000000	−2.167218	−0.329622	−4.085554	5.807458	−12.21825
–	(0.56753)	(0.21401)	(1.04025)	(1.38087)	–
–	[−3.81872]	[−1.54023]	[−3.9274]	[4.20564]	–

Notes: The VECM is specified with a lag length of 2, based on the ACF, PACF and chosen information criteria; *t*-values are in square brackets while SEs are in parentheses

Given the volatile environment during the observation period, this paper incorporates dummy variables to account for additive outliers and extreme observations to improve the quality of the VECM. Such extraordinarily large shocks violate the normality assumption of VECMs and thus need to be addressed in the model development (Juselius 2006). According to the results outlined in Table 6, the impact of industrial production, long-term interest rates, inflation and the narrow money supply during High-Inflation Period 1 can be expressed with the following normalized cointegrating equation:

$$S\&P500 = 12.21825 + 2.167218IP + 0.329622LTI + 4.085554INF - 5.807458M1$$

The cointegrating equation reveals a statistically significant positive equilibrium relationship between stock prices and industrial production, consistent with established theory and empirical evidence (Fama 1990; Ratanapakorn, Sharma 2008; Humpe, Macmillan 2009). This finding supports the notion that real economic activity influences expected cash flows, causing stock prices to move in the same direction (Mukherjee, Naka 1995). Moreover, the negative effects of inflationary periods on economic growth rates, as examined by A. López-Villavicencio and V. Mignon (López-Villavicencio, Mignon 2011), do not lead to deviations in the relationship between industrial production and stock prices.

The findings on the equilibrium relationship between the inflation rate and stock prices in the US are statistically significant and align with the Fisher hypothesis (1930), indicating a positive relationship. O. Ratanapakorn and S.C. Sharma (Ratanapakorn, Sharma 2007), whose dataset includes High-Inflation Period 1, along with the empirical findings of D. Abdullah and S. Hayworth (Abdullah, Hayworth 1993) also report a positive equilibrium relationship. In contrast, A. Humpe and P. Macmillan (Humpe, Macmillan 2009) analyse the period from 1965 to 2005, encompassing the dataset used in this paper, while extending it by 23 years beyond the conclusion of High-Inflation Period 1 in 1982. Their findings suggest a negative relationship between inflation rates and stock prices, indicating that the positive correlation observed between inflation rates and stock prices may be specific to periods of high inflation. Furthermore, the results confirm that hedging against price level increases is a stronger determinant than withdrawal from capital markets due to heightened uncertainty caused by rising inflation rates, which would otherwise lead to declining stock prices.

Due to the expansive monetary policy of the Federal Reserve to finance the Vietnam War prior to High-Inflation Period 1, decreases in money supply may have positively influenced the expectations of market participants and thus resulted in increasing stock prices. These reductions in the money supply may have also been interpreted as a signal of the end of the Vietnam War. Hence, this paper reports a statistically significant negative relationship between the real narrow money supply and stock prices. The observed relationship is strengthened by the overall decline in the real money stock in the US, which decreased from 572.7 billion USD to 462 billion USD over the period under review, while on average the S&P 500 experienced an increase.

Considering the documented outcomes concerning inflation rates, whereas individuals may perceive equities as a hedge against heightened price levels during inflationary periods and an increased inflation rate results in increasing long-term interest rates, the analysis indicates a positive but statistically insignificant equilibrium relationship between stock prices and long-term interest rates.

5.3.1.1. GRANGER CAUSALITY ANALYSIS

The test statistics for High-Inflation Period 1 are provided in Appendix A2 and the results are qualitatively summarized in Figure 2.

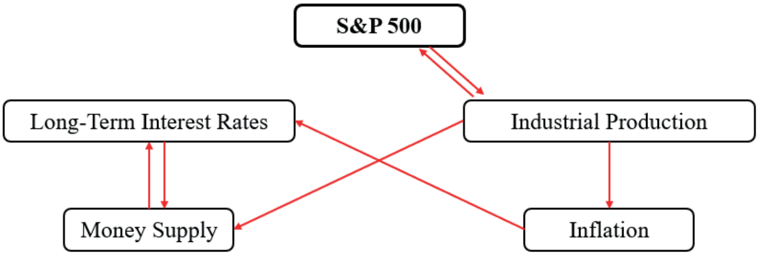

Figure 2. The arrows outline the significant short-term Granger causality channels deviated from the VECM and denote the direction of the Granger causation

As shown in Figure 2, stock prices and industrial production exhibit bidirectional Granger causality. Additionally, past values of industrial production influence both the inflation rate and the money supply. The inflation rate influences the long-term interest rate and there is evidence of bidirectional Granger causality between the long-term interest rate and the money supply. The results indicate that market participants respond sensitively to short-term fluctuations in industrial production. Consequently, during High-Inflation Period 1, market participants were facing stagnating real economic growth, which explains the importance of short-term fluctuations of the industrial production rate for investment decisions. Furthermore, industrial production also exerts a direct or indirect influence on all other macroeconomic variables in the model. The absence of direct short-term Granger causality from other macroeconomic factors to stock prices may be explained by the tendency of stock prices to follow a random walk, particularly in the short run (Fama 1970). Nonetheless, the Johansen cointegration test results confirm the existence of a long-term equilibrium relationship over the observation period, suggesting that short-term deviations are systematically corrected.

5.3.1.2. IMPULSE-RESPONSE ANALYSIS

The impulses and responses are derived from a Cholesky decomposition of the error variance-covariance matrix (Durlauf, Blume 2010). The results are illustrated graphically in Figure 3, while the statistical details of the Impulse-Response functions are provided in Appendix A3.

The responses of the US stock prices to a one-standard-deviation exogenous shock are presented for a period of 12 months. Given the highly volatile economic conditions during the observed inflationary period, heightened nervousness among market participants makes market overreactions likely, which is also confirmed by the Impulse-Response functions in Figure 3. As demonstrated in the first graph of Figure 3, a shock to stock prices results in an immediate 4% response, which stabilizes at 2% in the subsequent periods. This outcome is consistent with the findings of O. Ratanapakorn and S.C. Sharma (Ratanapakorn, Sharma 2007), who observe that stock prices tend to heavily depend on themselves in the second half of the 20th century. Aligning with the observed results concerning the short-term relationship between stock prices and industrial production, a shock results in a swift and continuous 1% increase in stock prices. The periodic response of stock prices to shocks in long-term interest rates and inflation rates is nearly identical, stabilizing at 0.72% and 1%, respectively. This is consistent with the theoretical expectation that long-term interest rates are strongly influenced by inflation and inflation expectations. As discussed in the Granger causality analysis, the inflation rate Granger-causes the interest rate in the short-term, further strengthening these findings. A one-standard-deviation shock in the money supply results in a 0.76% decrease in stock prices within a period of 12 months, contradicting the findings of O. Ratanapakorn and S.C. Sharma (Ratanapakorn, Sharma 2007), and A. Humpe and P. Macmillan (Humpe, Macmillan 2009). This discrepancy is most likely attributable to High-Inflation Period 1 beginning in 1973 as discussed in Section 5.3.1.

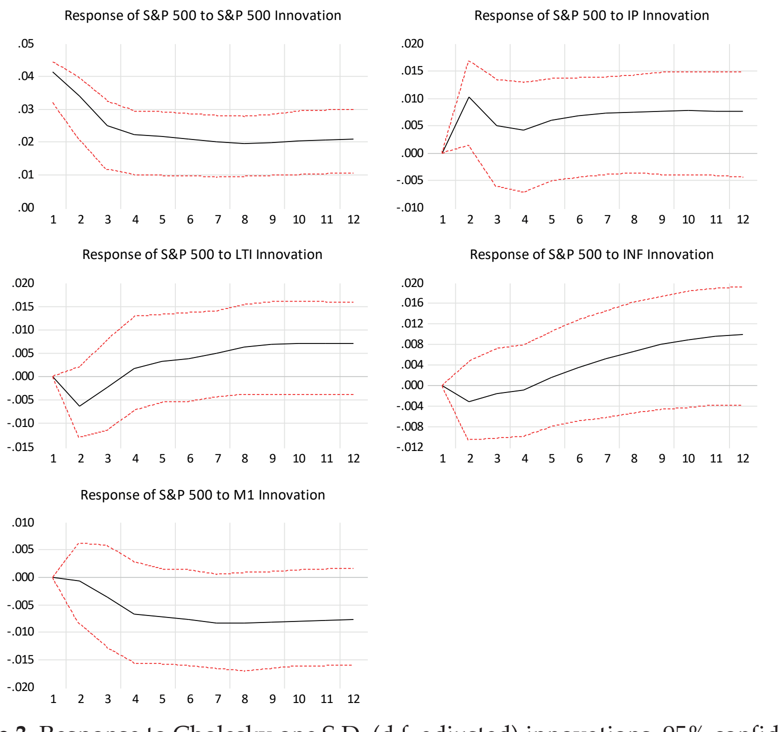

Figure 3. Response to Cholesky one S.D. (d.f. adjusted) innovations, 95% confidence interval using standard percentile bootstrap with 999 bootstrap repetitions

5.3.1.3. FORECAST ERROR VARIANCE DECOMPOSITION

Figure 4 presents the stacked graphs of the variance decomposition of the S&P 500 using Cholesky factors within a time period of 24 months.

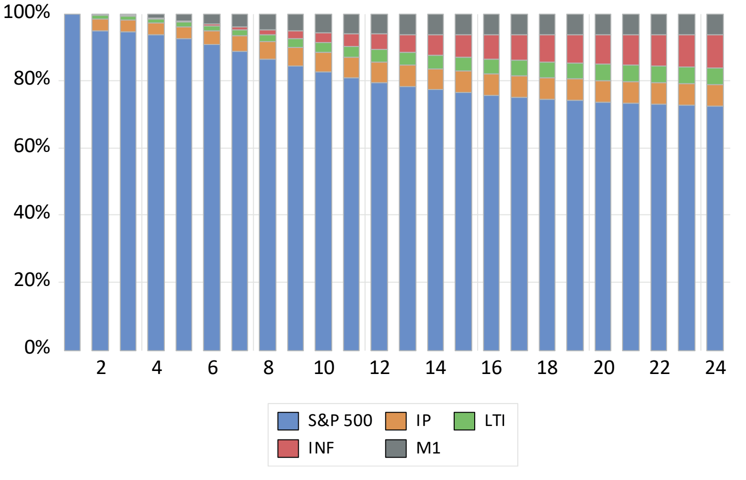

Figure 4. Variance decomposition of the S&P 500 using one S.D. Cholesky (d.f. adjusted) factors; Cholesky ordering: S&P 500, IP, LTI, INF, M1; the statistical outputs are given in Appendix A4.

In line with the Impulse-Response functions presented in Section 5.3.1.2, the variance decomposition indicates a strong dependence of stock prices on their own historical variance. Consistent with the findings of O. Ratanapakorn and S.C. Sharma (Ratanapakorn, Sharma 2007), 72% of the variance is explained by a one-standard-deviation shock of stock prices over a 24-months test period. The contribution of industrial production to the variation in the stock prices is beginning in the second period and converges at around 6.4%. The impact of an inflation rate shock on the stock price variation becomes noticeable after 6 months, increasing rapidly to 10.3% within 24 months. This trend supports the notion of equities serving as a hedge against rising inflation rates and suggests a significant capital reallocation to equities following an inflation shock. The long-term interest rate accounts for 5% of the variation in stock prices, while the money supply explains 6.3%. According to the FEVD, the inflation rate plays a significant role in explaining stock price variations, appearing with a noticeable lagged effect. This is supported by the fact that inflation Granger-causes long-term interest rates. Consequently, the combined effect of long-term interest rates and inflation rates accounts for 15.3% of stock price variation within 24 months.

5.3.1.4. DIAGNOSTIC TEST RESULTS

Diagnostic checks are conducted to assess whether the residuals ε_t satisfy the model assumptions, thereby ensuring that the model adequately represents the data-generating process. The results indicate that there is no evidence of residual autocorrelation (Appendix A5), non-normality (Appendix A6), or heteroscedasticity (Appendix A7).

5.3.2. High-Inflation Period 2 (2021 to 2024)

The surge in inflation rates between January 2021 and June 2024 can primarily be attributed to supply-side factors. On the demand side, private household consumption expenditures exhibited greater resilience than initially expected as the economic impact of COVID-19 waned. This resilience was further bolstered by the stronger-than-anticipated global economic recovery (Nagel 2022). On the supply side, deglobalization trends and lockdown-induced supply shortages led to declining global trade volumes. Additionally, Russia's invasion of Ukraine and the ensuing economic sanctions against Russia triggered inflationary pressures. As major exporters of oil and commodities, disruptions in Russian and Ukrainian exports further intensified global price volatility (World Bank 2022). Renewed pandemic outbreaks, particularly China's zero-COVID policy, further disrupted global supply chains, predominantly the semiconductor industry, which led to a shortage of microchips. Moreover, economic growth weakened as post-pandemic catch-up effects dissipated. The US economy faced persistent supply chain bottlenecks and declining market sentiment, fuelled by ongoing uncertainty stemming from both the pandemic and geopolitical tensions (World Bank 2022). Rising interest rates also exerted downward pressure on global economic growth. Consequently, while the sharp economic contraction caused by COVID-19 was swiftly reversed, overall growth remained below historical trends, with forecasts consistently falling short of expectations (Stiglitz, Regmi 2022). In response to the pandemic-induced economic downturn, the Federal Reserve implemented an extensive Quantitative Easing programme, significantly increasing US money supply. While Quantitative Easing stabilized the economy in the short term, its long-term effects on inflation rates remain uncertain. Although economic growth fell short of pre-crisis trend forecasts, the US economy exhibited greater stability than expected compared to Europe, mitigating the risk of stagflation.

Table 7 states the normalized cointegrating coefficients of the VECM. The complete VECM specification for High-Inflation Period 2 can be found in Appendix B1.

Table 7

Normalized cointegrating coefficients – High-Inflation Period 2

Normalized cointegrating coefficients (CE)				
S&P 500	IP	LTI	INF	C
1.000000	15.62142	0.793329	−10.80900	−20.00373
–	(1.79269)	(0.10483)	(1.05548)	–
–	[8.71398]	[7.56765]	[−10.2408]	–

Notes: The VECM is specified with a lag length of 1, based on the ACF and PACF of the VECM and selected information criteria; t-values are in square brackets while SEs are in parentheses

Consistent with High-Inflation Period 1, dummy variables are incorporated to strengthen the accuracy of the VECM (Juselius 2006). The VECM results in Table 7 illustrate the effects of industrial production, long-term interest rates, and inflation rates on stock prices from January 2021 to June 2024, as represented by the following normalized cointegrating equation:

$$S\,\&\,P500 = 20.00373 - 15.62142IP - 0.793329LTI + 10.80900INF$$

Comparable to the findings of High-Inflation Period 1, a significant positive correlation between the inflation rate and stock prices is observed during High-Inflation Period 2. These findings strengthen the argument made by D. Abdullah and S. Hayworth (Abdullah, Hayworth 1993) and are consistent with the Fisher hypothesis (1930). The positive correlation between inflation rates and stock prices also aligns with economic standard theory, suggesting that economic growth comes with rising inflation rates, as far as a positive relationship between economic growth and stock prices is assumed. Furthermore, both subsamples yield consistent results, emphasizing the importance of accounting for threshold effects of high-inflation periods when analysing the impact of macroeconomic variables on the stock market.

During High-Inflation Period 1, a positive correlation between long-term interest rates and share prices is observed, whereas a negative correlation emerges during High-Inflation Period 2. This reflects the significant shift in the strategic direction of the US monetary policy, which has increasingly prioritized price stability over time. Historically, US monetary policy has been characterized as a “go/stop” approach, oscillating between concerns about unemployment and inflation, which, in hindsight, often resulted in accommodative policies (Goodfriend 2004; Blinder 2013). According to Bernanke (2003), this approach was largely driven by a simplistic interpretation of the Phillips curve. In contrast to 1973, the Federal Reserve now operates under clear mandates for price stability and follows transparent operating procedures, which are regularly communicated and justified in monetary policy decision meetings (Bordo et al. 2007; Eichengreen 2024). These policy enhancements have led to better-anchored inflation expectations and more stable long-term forecasts for the broader economic outlook. As a result, market participants may now place greater emphasis on long-term interest rates when making capital market decisions, as these rates provide a more reliable indicator of long-term economic conditions with less noise than during the inflationary phase in 1973. The negative relationship between long-term interest rates and stock prices is consistent with standard PVM theory, where a decrease in long-term interest rates directly reduces the discount rate $E_t r$, leading to higher expected stock prices P_t. The observed negative relationship is consistent with prior studies by O. Ratanapakorn and S.C. Sharma (Ratanapakorn, Sharma 2007) and A. Humpe and P. Macmillan (Humpe, Macmillan 2009).

This paper identifies a negative correlation between industrial production and stock prices, which contradicts with the findings of O. Ratanapakorn and S.C. Sharma (Ratanapakorn, Sharma 2007), A. Humpe and P. Macmillan (Humpe, Macmillan 2009), and standard economic theory. An analysis of the time series data reveals that the 45.43% rally in the US market from October 2022 to June 2024 coincided with a stagnating decrease in the industrial production rate of −0.18%. This finding underscores the pronounced economic stagnation, especially in the industry sector and highlights the growing disconnect between market participants' investment decisions and actual economic growth during High-Inflation Period 2. Consistent with the findings of E.M. Bhuiyan and M. Chowdhury (Bhuiyan, Chowdhury 2020) and P. Young (Young 2006), this paper strengthens the conclusion that the positive relationship between industrial production and stock prices no longer persists in recent US data.

5.3.2.1. GRANGER CAUSALITY ANALYSIS

Appendix B2 presents the short-run causal relationships between the selected variables, with a qualitative summary provided in Figure 5 below.

As illustrated in Figure 5, past values of the long-term interest rate, industrial production, and the inflation rate help to predict future stock prices in the short term. In other words, these variables Granger-cause stock prices, while during High-Inflation Period 1, only industrial production directly Granger-caused stock prices. This shift may be largely attributed to the steady improvement in access to capital markets and the ability to make investment decisions anytime and anywhere due to computerized stock exchanges. Consequently, stock prices now respond more sensitively to changes in these macroeconomic variables in the short term.

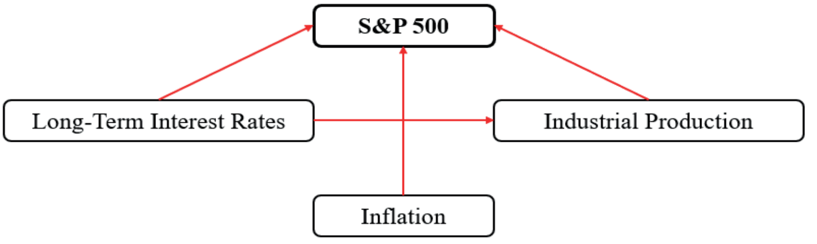

Figure 5. The arrows outline the significant short-term Granger causality channels deviated from the VECM and outline the direction of the Granger-causation

Another key difference between High-Inflation Period 1 and 2 is the absence of Granger causality from the inflation rate to the long-term interest rate in the latter period. This result is unsurprising given the significant shift in the monetary policy strategy, as discussed in Section 5.3.2. The new policy approach plays a crucial role in anchoring long-term inflation expectations, leading to a more stable and reliable long-term interest rate. In contrast, during High-Inflation Period 1 the long-term interest rate was highly dependent on short-term inflation dynamics according to the Granger causality analysis.

5.3.2.2. IMPULSE-RESPONSE ANALYSIS

The functions are computed over a 12-month period using a Cholesky decomposition of the error variance-covariance matrix (Durlauf, Blume 2010). The results of the Impulse-Response analysis are presented in Appendix B3 and illustrated in Figure 6.

Consistent with the findings of High-Inflation Period 1 and related studies such as O. Ratanapakorn and S.C. Sharma (Ratanapakorn, Sharma 2007), US stock prices exhibit strong self-dependence between January 2021 and June 2024. According to Figure 6, a one-standard-deviation shock to the S&P 500 leads to a 4% increase in stock prices, which stabilizes at 4.3% in the following periods. As discussed in Section 5.3.2, the relationship between industrial production and stock prices appears to be disconnected in the second subsample. During High-Inflation Period 2, a one-standard-deviation shock in the industrial production rate results in a slight decrease of 0.25% in stock prices over a 12-month period. The contradicting findings in the cointegrating vector presented in Table 7 can therefore be explained by the significantly reduced impact of industrial production shocks compared to High-Inflation Period 1. E.M. Bhuiyan and M. Chowdhury (Bhuiyan, Chowdhury 2020) report mixed results regarding the direction of industrial production's influence on stock prices, as their analysis examines the impact of macroeconomic variables across several S&P 500 sector indices. Moreover,

P. Young (Young 2006) argues that the positive relationship between industrial production and stock prices no longer holds when using more recent US data. One possible explanation is the growing dominance of the non-manufacturing sector in the US, which is 5.5 times larger than the manufacturing sector by the end of 2019. As a result, industrial production may no longer accurately reflect overall economic activity (Ha et al. 2022). A one-standard-deviation shock to the long-term interest rate leads to a sustained decrease in stock prices, stabilizing at 2.4% over a 12-month period, while a shock to the inflation rate has no significant impact on stock prices. Improvements in monetary policy strategy allow better anchored inflation expectations, contributing to reduced volatility in long-term interest rates. As a result, market participants increasingly factor long-term interest rate trends into their capital investment decisions, as these rates tend to be less volatile than inflation rates, particularly during periods of high uncertainty. Moreover, the combined impact of the pandemic and the war in Ukraine pushed long-term interest rates to a 10-year high, substantially increasing corporate financing costs and affecting stock market performance. Subsequent interest rate cuts boosted cash flows, thereby raising expected stock prices. The results are consistent with those reported by N.-F. Chen et al. (Chen et al. 1986) for the US, and by M. Asprem (Asprem 1989) for Germany, the Netherlands, Switzerland, Sweden, and the UK.

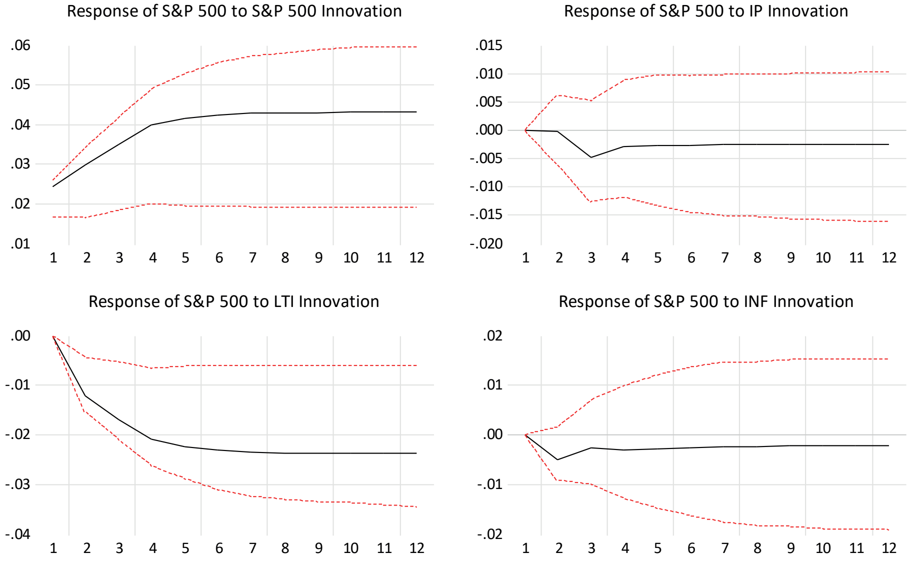

Figure 6. Response to Cholesky one S.D. (d.f. adjusted) innovations, 95% confidence interval using standard percentile bootstrap with 999 bootstrap repetitions.

5.3.2.3. FORECAST ERROR VARIANCE DECOMPOSITION

Figure 7 displays the stacked graphs representing the variance decomposition of the S&P 500, based on Cholesky factorization.

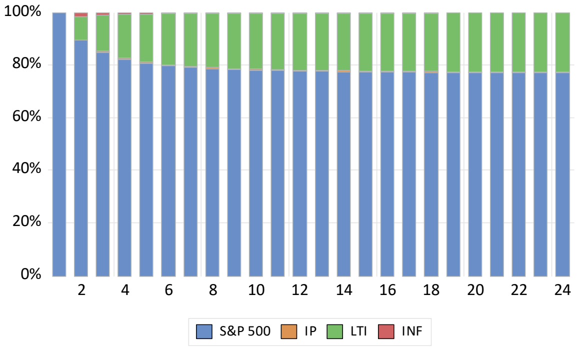

Figure 7. Variance decomposition of the S&P 500 using one S.D. Cholesky (d.f. adjusted) factors; Cholesky ordering: S&P 500, IP, LTI, INF; the statistical outputs are given in Appendix B4

Aligning with the results of High-Inflation Period 1, Figure 7 demonstrates that stock prices remain relatively exogenous to other variables, with 77% of their variance explained by their own shocks even after 24 months. These findings confirm that the self-dependence of stock prices has persisted over time. Consistent with the Impulse-Response function results, the long-term interest rate accounts for a considerable amount of 23% of the variation in stock prices. In contrast, a one-standard-deviation to industrial production and the inflation rate does not explain any considerable variation in stock prices, according to the results of the FEVD.

5.3.2.4. DIAGNOSTIC TEST RESULTS

Diagnostic checks are performed to evaluate whether the residuals ε_t adhere to the model assumptions, ensuring an appropriate representation of the data-generating process. The results provide no evidence of residual autocorrelation (Appendix B5), non-normality (Appendix B6), or heteroscedasticity (Appendix B7).

5.3.2.5. AUTOREGRESSIVE DISTRIBUTED LAGS MODEL – ROBUSTNESS CHECK

Due to the limited sample size of High-Inflation Period 2, which meets the minimum required number of observations, the equilibrium relationship identified by the Johansen test and the corresponding VECM is confirmed, using an ARDL model and the Bounds test, as proposed by M.H. Pesaran et al. (2001). A. Haug (Haug 2002) emphasizes that the ARDL bounds testing approach is particularly robust for small sample sizes. Additionally, ARDL models accommodate variables with different orders of integration, which enables the inclusion of oil price dynamics in the model (Nkoro, Uko 2016). The long- and short-run parameters of the ARDL(1, 6, 4, 4, 6) model are presented in Appendix B7. The direction of the long-run estimates aligns with the results of the Johansen test, reinforcing the overall findings of High-Inflation Period 2.

Table 8

ARDL cointegrating equation – High Inflation Period 2

Normalized cointegrating coefficients (CE)					
S&P 500	IP	LTI	INF	OIL	C
1.000	−21.7645	−0.3989830	9.1572	0.3620	54.0035
–	(3.6834)	(0.1482)	(1.2537)	(0.0598)	(16.1572)
–	[3.3423]	[−2.6924]	[7.3044]	[6.0567]	[3.3424]

Notes: The ARDL(1, 6, 4, 4, 6) can be found in Appendix B7; the lag length is based on AIC; *t*-values are in square brackets while SEs are in parentheses

As expected, a positive relationship between oil prices and the stock market is observed, driven by the strong influence of oil prices on inflation rates and the examined positive link between inflation and the US stock market during inflationary periods. Post-estimation tests indicate no issues with autocorrelation, heteroscedasticity, or non-normality of residuals. Additionally, plotting the cointegrating vector alongside the S&P 500 visually highlights the cointegrating relationship during High-Inflation Period 2 (Fig. 8).

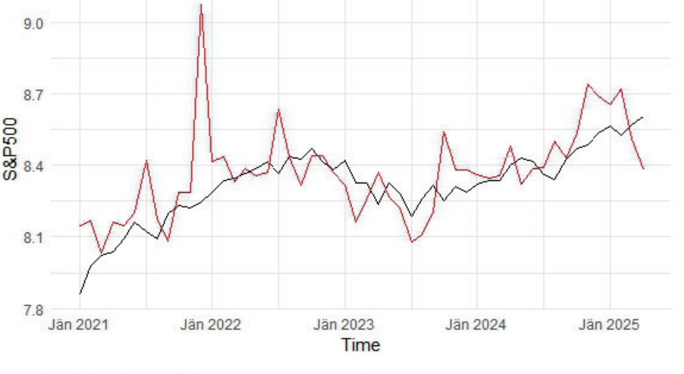

Figure 8. The black (red) line represents the S&P 500 (cointegrating equation)

6. Discussion

To obtain a deeper understanding of the impact of macroeconomic variables on US stock prices, particularly during periods of elevated inflation, a comparative analysis was conducted on the direction and magnitude of these relationships for two distinct periods: August 1973 to August 1982 (High-Inflation Period 1) and January 2021 to June 2024 (High-Inflation Period 2). Following the work of A. López-Villavicencio and V. Mignon (López-Villavicencio, Mignon 2011) and H. Loi and A.S. Abou-Zaid (Loi, Abou-Zaid 2016), inflation rates above a threshold level of 3% to 5% are associated with significant adverse effects on economic stability in the US, disrupting relationships among macroeconomic variables. Similarly, A. Brick and D. Nautz (Brick, Nautz 2008) highlight the relationship between inflation dynamics and stock market volatility, emphasizing that volatility and uncertainty in financial markets notably increase once inflation surpasses a critical threshold of 4.4%. In light of the conflicting empirical literature, this paper analyses periods of elevated inflation and the corresponding non-linear threshold effects, which provides further insights into the dynamic relationship between macroeconomic variables and stock prices in the US. Incorporating the findings of the research mentioned above, the subsamples exhibit inflation rates of above 3%. The recent period of elevated inflation rates is driven by supply chain disturbances caused by the pandemic and supply shocks to global energy and food prices resulting from Russia's invasion in the Ukraine, closely mirroring the oil shocks of 1973 and 1979. Overall, both subsamples feature huge energy and commodity price shocks and were preceded by highly accommodative monetary policies. In addition to the sharp rise in inflation, the US economy has been recovering from the pandemic-induced global recession of 2020, similar to its recovery following the global recession in 1975.

To address the issue of spurious correlations encountered when analysing time series with classical linear regression, this study employs the Johansen cointegration procedure in conjunction with VECMs for each subsample. In conclusion, this paper finds that there is an equilibrium relationship in both high-inflation periods between stock prices and macroeconomic variables that represent industrial production, long-term interest rates, inflation and the narrow money supply. The presence of cointegration and Granger causality suggests that the US stock markets may not be fully efficient according to the EMH proposed by E.F. Fama (Fama 1970). Consequently, future fluctuations in stock prices could potentially be forecasted using the information provided by macroeconomic variables (Ratanapakorn, Sharma 2007). However, as the results of this paper demonstrate, both the direction and magnitude of the correlation between stock prices and macroeconomic factors fluctuate and exhibit nonlinear threshold effects, complicating the reliability of forecasts.

Focusing on High-Inflation Period 1, this paper finds a positive equilibrium relationship between stock prices and industrial production, the long-term interest rate, and the inflation rate, while a negative equilibrium relationship is observed with the narrow money supply. Consistent with the findings of O. Ratanapakorn and S.C. Sharma (Ratanapakorn, Sharma 2007) and A. Humpe and P. Macmillan (Humpe, Macmillan 2009), rising industrial production, as a proxy for economic activity, is associated with higher stock prices, which aligns with standard economic theory. Given the ongoing debate regarding the relationship between inflation and stock prices, this paper reports a positive relationship, which strengthens the empirical findings of D. Abdullah and S. Hayworth (Abdullah, Hayworth 1993) and aligns with the suggestions of the Fisher hypothesis (1930). The hypothesis indicates that equities are seen as a hedge against rising inflation, as they represent claims on real assets. The negative relationship between the narrow money supply and stock prices contradicts economic standard theory and the findings of similar empirical research. However, no study has specifically focused on high-inflation periods yet. Therefore, this negative correlation may be considered a unique characteristic of High-Inflation Period 1. Given the accommodative monetary policy implemented to finance the Vietnam War, reductions in the money supply may have been perceived as a signal of the war's end and potential future increases in economic activity, which in turn has raised expectations for higher stock prices in the US. The Granger causality analysis, along with the Impulse-Response functions and the FEVD in Section 5.3.1, suggest that industrial production has a direct short-term impact on stock prices, explaining 6.4% of the stock price variance following a one-standard deviation shock in the industrial production rate. Additionally, the findings indicate that the long-term interest rate highly depends on the inflation rate in the short term. Combined shocks in the long-term interest rate and inflation rate account for 15.3% of the variation in stock prices over a 24-month test period.

During High-Inflation Period 2, this paper identifies a negative equilibrium relationship between stock prices and both the industrial production and the long-term interest rates. However, the positive relationship between inflation rates and stock prices remains consistent across both observation periods. The narrow money supply was excluded from the VECM for High-Inflation Period 2 because the time series is not integrated of order one, thus failing to meet the requirements of the Johansen cointegration test. Consistent with the theoretical PVM, declining long-term interest rates are associated with rising stock prices during High-Inflation Period 2, in line with the empirical findings of A. Humpe and P. Macmillan (Humpe, Macmillan 2009), and E.M. Bhuiyan and M. Chowdhury

(Bhuiyan, Chowdhury 2020). In contrast to the findings from High-Inflation Period 1 and standard economic theory, this study reports a negative relationship between stock prices and industrial production, which can be attributed to the fact that by the end of 2019, the non-manufacturing sector in the US was 5.5 times larger than the manufacturing sector. These results support E.M. Bhuiyan and M. Chowdhury's (Bhuiyan, Chowdhury 2020) hypothesis that industrial production is no longer a reliable indicator of economic activity due to the transformation of the US economy into a service-oriented one in recent years. The Impulse-Response functions and FEVD analysis indicate that long-term interest rates exert the most substantial influence on stock price movements compared to other macroeconomic factors in the short term. Following a one-standard-deviation shock in long-term interest rates, these rates account for approximately 23% of the variation in stock prices during High-Inflation Period 2.

The observed positive relationship between inflation rates and stock prices in the US across both inflationary periods adds further insights to the contradicting results of empirical findings, as alterations may be attributable to neglected threshold effects of elevated inflation periods. The findings therefore confirm that hedging against price increases influences market behaviour more than uncertainty-driven withdrawals, which would result in depressing stock prices. The deviating results regarding the long-term interest rate in High-Inflation Period 1 and 2 reflect the significant shift in the strategic direction of the US monetary policy, which has increasingly prioritized price stability over time, whereas the monetary policy was largely driven by a simplistic interpretation of the Phillips curve in the past, resulting in highly accommodative policies. In contrast, the Federal Reserve now follows transparent operating procedures, leading to better-anchored inflation expectations and more stable long-term forecasts for the broader economic outlook, making the long-term interest rate a more reliable indicator for investment decisions (Eichengreen 2024). Further, the negative relationship reported in High-Inflation Period 2 follows the assumption of the PVM theory, which is also widely used in practice today.

It is important to acknowledge that both VECMs address highly volatile periods, and the results may be influenced by market overreactions driven by heightened uncertainty in the US markets. Nevertheless, both models pass all diagnostic checks, indicating that they provide a reasonable approximation of the data-generating process. Future research could be enhanced by incorporating sector-specific indices instead of the composite index, allowing for a more detailed analysis of the interdependencies at the level of individual sectors. Given that industrial production is no longer a reliable indicator of economic growth in the US, using alternative benchmarks could provide clearer insights into the relationship between economic activity and stock price movements.

Appendix A – High-Inflation Period 1

Appendix A1

The VECM is specified with a lag length of 2, based on the ACF and PACF of the residuals of the VECM, and the results of various information criteria. The *t*-values are in square brackets while SEs are in parentheses; included observations: 106. The VECM is derived from the cointegrating equation obtained using the Johansen method, as presented in Table 4 and Table 5. The cointegrating vector, detailed in Table 6, is normalized with respect to S&P 500

Error correction:	D(S_P500)	D(IP)	D(LTI)	D(INF)	D(M1)
CointEq1	–0.133433	0.041821	0.091992	0.006290	0.002207
	(0.05306)	(0.00965)	(0.04199)	(0.00286)	(0.00504)
	[–2.51462]	[4.33397]	[2.19096]	[2.20111]	[0.43817]
D(S_P500(-1))	–0.134320	–0.041377	0.019963	0.007248	0.007329
	(0.09307)	(0.01693)	(0.07365)	(0.00501)	(0.00883)
	[–1.44315]	[–2.44465]	[0.27106]	[1.44596]	[0.82965]
D(S_P500(-2))	–0.054301	–0.016147	0.081084	0.001100	0.005817
	(0.09229)	(0.01678)	(0.07303)	(0.00497)	(0.00876)
	[–0.58835]	[–0.96207]	[1.11031]	[0.02209]	[0.66410]
D(IP(-1))	1.186209	0.295593	0.334227	–0.064065	0.137756
	(0.54185)	(0.09854)	(0.42875)	(0.02918)	(0.05143)
	[2.18919]	[2.99984]	[0.77954]	[–2.19549]	[2.67873]
D(IP(-2))	–1.073299	–0.062285	–0.388515	0.047539	–0.083136
	(0.50346)	(0.09156)	(0.39838)	(0.02711)	(0.04778)
	[–2.13183]	[–0.68030]	[–0.97525]	[1.75337]	[–1.73988]
D(LTI(-1))	–0.219559	0.035722	0.199617	0.002867	–0.038044
	(0.12942)	(0.02354)	(0.10241)	(0.00697)	(0.01228)
	[–1.69647]	[1.51780]	[1.94925]	[0.41136]	[–3.09724]
D(LTI(-2))	0.026715	0.029909	–0.188014	0.009308	–0.005677
	(0.12804)	(0.02328)	(0.10132)	(0.00690)	(0.01250)
	[0.20864]	[1.28448]	[–1.85573]	[1.34994]	[–0.46717]
D(INF(-1))	–1.955988	0.046702	2.764330	0.599203	–0.337728
	(1.81570)	(0.33019)	(1.43670)	(0.09778)	(0.17232)
	[–1.07727]	[0.14144]	[1.92408]	[6.12802]	[–1.95984]

Appendix A1 cont.

D(INF(-2))	1.198010	–0.364692	0.298720	0.153802	0.329741
	(1.91870)	(0.34892)	(1.51821)	(0.10333)	(0.18210)
	[0.62439]	[–1.04520]	[0.19676]	[1.48848]	[1.81077]
D(M1(-1))	0.615509	0.2960351	2.395700	–0.012962	0.405238
	(1.10646)	(0.20121)	(0.87551)	(0.05959)	(0.10501)
	[0.55629]	[1.47126]	[2.73636]	[–0.21754]	[3.85896]
D(M1(-2))	–0.219001	–0.242777	–1.166334	–0.019469	–0.140238
	(1.09195)	(0.19857)	(0.86403)	(0.05880)	(0.10364)
	[–0.20056]	[–1.22260]	[–1.34988]	[0.33108]	[–1.35319]
C	0.009957	0.019777	–0.022457	0.001519	0.004277
	(0.01478)	(0.00269)	(0.01169)	(0.00080)	(0.00140)
	[0.67370]	[0.73566]	[–1.92025]	[1.90785]	[3.04920]
D1974M8	–0.186373	–0.001114	0.029079	0.006592	0.001960
	(0.03222)	(0.00586)	(0.02549)	(0.0174)	(0.0306)
	[–5.78451]	[–0.19019]	[1.14061]	[3.79945]	[0.64103]
D1981M05	0.017569	–0.003290	–0.021330	–0.000417	–0.015349
	(0.04439)	(0.00807)	(0.03512)	(0.00239)	(0.00421)
	[0.39582]	[–0.40760]	[–0.60732]	[–0.17438]	[–3.64349]
D1973M11	–0.100100	–0.004740	–0.043208	–0.001570	0.000299
	(0.04419)	(0.00804)	(0.03497)	(0.00238)	(0.00419)
	[–2.26507]	[–0.58976]	[–1.23562]	[–0.65949]	[0.07141]
R-squared	0.417074	0.526891	0.372317	0.548464	0.392058
Adj. R-squared	0.327393	0.454105	0.275750	0.478997	0.298528
Sum sq. resids	0.156600	0.005179	0.098048	0.000454	0.001411
S.E. equation	0.041483	0.007544	0.032825	0.002234	0.003937
F-statistic	4.65646	7.238901	3.855541	7.895303	4.191802
Log likelihood	195.0200	375.7034	219.8365	504.6987	444.6336
Akaike AIC	–3.396604	–6.805724	–3.864839	–9.239597	–8.106295
Schwarz SC	–3.019703	–6.428823	–3.487938	–8.862696	–7.729393
Mean dependent	0.000930	0.000442	0.006171	0.007189	0.005241
S.D. dependent	0.050582	0.010210	0.038570	0.003095	0.004701

Appendix A2

Granger causality test results; 2 degrees of freedom; H0: X does not Granger-cause Y, H1: X Granger-causes Y; the theoretical framework is outlined in Section 3.3

Granger causality tests Included observations: 106			
Dependent variable: D(S_P500)			
Excluded	Chi-sq	df	Probability value
D(IP)	6.540981	2	0.0380
D(LTI)	2.881905	2	0.2367
D(INF)	1.160585	2	0.5597
D(M1)	0.326173	2	0.8495
All	9.936059	8	0.2695
Dependent variable: D(IP)			
Excluded	Chi-sq	df	Prob.
D(S_P500)	6.649587	2	0.0360
D(LTI)	4.693972	2	0.0957
D(INF)	1.431374	2	0.4889
D(M1)	3.246351	2	0.1973
All	16.60394	8	0.0345
Dependent variable: D(LTI)			
Excluded	Chi-sq	df	Prob.
D(S_P500)	1.275422	2	0.5285
D(IP)	1.111749	2	0.5736
D(INF)	6.378853	2	0.0412
D(M1)	8.492610	2	0.0143
All	18.44566	8	0.0181
Dependent variable: D(INF)			
Excluded	Chi-sq	df	Prob.
D(S_P500)	2.094724	2	0.3509
D(IP)	5.631183	2	0.0599

Appendix A2 cont.

D(LTI)	2.224969	2	0.3287
D(M1)	0.140581	2	0.9321
All	9.086394	8	0.3351
Dependent variable: D(M1)			
Excluded	Chi-sq	df	Probability value
D(S_P500)	1.068563	2	0.5861
D(IP)	7.607063	2	0.0223
D(LTI)	10.53973	2	0.0051
D(INF)	4.507709	2	0.1050
All	24.08702	8	0.0022

Appendix A3

Impulse-Response functions, response to Cholesky one S.D. (d.f. adjusted) Innovations, 95% confidence interval using standard percentile bootstrap with 999 bootstrap repetitions; Cholesky ordering: S&P 500, IP, LTI, INF, M1

Period	S_P500	IP	LTI	INF	M1
1	0.041483	0.000000	0.000000	0.000000	0.000000
	(1.0E–05)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
2	0.034078	0.010238	–0.006234	–0.003144	–0.000609
	(2.3E–05)	(1.8E–05)	(1.4E–05)	(1.4E–05)	(1.4E–05)
3	0.024908	0.004968	–0.002360	–0.001623	–0.003555
	(2.8E–05)	(2.6E–05)	(2.3E–05)	(1.6E–05)	(2.3E–05)
4	0.022176	0.004181	0.001822	–0.000923	–0.006636
	(2.4E–05)	(2.4E–05)	(2.2E–05)	(1.8E–05)	(2.2E–05)
5	0.021652	0.005909	0.003233	0.001594	–0.007256
	(2.5E–05)	(1.8E–05)	(1.8E–05)	(2.1E–05)	(2.0E–05)
6	0.020852	0.006815	0.003836	0.003510	–0.007688
	(2.7E–05)	(1.7E–05)	(1.9E–05)	(2.5E–05)	(2.0E–05)

Appendix A3 cont.

Period	S_P500	IP	LTI	INF	M1
7	0.019974	0.007290	0.005078	0.005152	–0.008284
	(2.7E–05)	(1.8E–05)	(2.2E–05)	(2.7E–05)	(2.1E–05)
8	0.019933	0.007528	0.006278	0.006693	–0.008413
	(2.6E–05)	(1.9E–05)	(2.3E–05)	(2.9E–05)	(2.1E–05)
9	0.020710	0.007675	0.006884	0.007946	–0.008225
	(2.6E–05)	(2.0E–05)	(2.3E–05)	(3.0E–05)	(2.2E–05)
10	0.020530	0.007722	0.007064	0.008885	–0.008003
	(2.6E–05)	(2.1E–05)	(2.3E–05)	(3.1E–05)	(2.2E–05)
11	0.020710	0.007657	0.007122	0.009557	0.007818
	(2.6E–05)	(2.1E–05)	(2.4E–05)	(3.2E–05)	(2.2E–05)
12	0.021026	0.007544	0.007150	0.010027	–0.007636
	(2.6E–05)	(2.2E–05)	(2.4E–05)	(3.3E–05)	(2.2E–05)

Appendix A4

Forecast error variance decomposition of the S&P 500
using one S.D. Cholesky (d.f. adjusted) factors;
Cholesky ordering: S&P 500, IP, LTI, INF, M1

Period	S.E.	S_P500	IP	LTI	INF	M1
1	0.041483	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.055101	94.93001	3.452176	1.280078	0.325504	0.012234
3	0.060844	94.61232	3.497892	1.200252	0.338089	0.351446
4	0.065265	93.77525	3.450503	1.121126	0.313836	1.339280
5	0.069490	92.77525	3.766820	1.205440	0.329481	2.271619
6	0.073459	90.76586	4.231408	1.351399	0.523150	3.128183
7	0.077262	88.73574	4.715516	1.653673	0.917636	3.977433
8	0.081043	86.53977	5.148625	2.103126	1.516053	4.692428
9	0.084867	84.43377	5.512918	2.575760	2.259093	5.218458
10	0.088707	82.54357	5.803664	2.991620	3.070818	5.590332
11	0.092519	80.89371	6.020225	3.342825	3.889988	5.853250

Appendix A4 cont.

12	0.096274	79.47582	6.173741	3.638739	4.677109	6.034591
13	0.099960	78.27426	6.280282	3.883029	5.409231	6.153199
14	0.103566	77.26440	6.353472	4.079893	6.074925	6.227314
15	0.107082	76.41481	6.403110	4.237831	6.671615	6.272630
16	0.110506	75.69506	6.436379	4.366148	7.202514	6.299905
17	0.113827	75.07982	6.458709	4.472039	7.673628	6.315808
18	0.117078	74.54877	6.474016	4.560638	8.091869	6.324710
19	0.120232	74.08543	6.484920	4.635906	8.464135	6.329614
20	0.123306	73.67662	6.493102	4.700980	8.796849	6.332454
21	0.126302	73.31210	6.499636	4.758213	9.095708	6.334345
22	0.120228	72.98403	6.505197	4.809280	9.365604	6.335885
23	0.132087	72.68638	6.410187	4.855383	9.610660	6.337385
24	0.134883	72.41445	6.514830	4.897410	9.833420	6.338988

Appendix A5

Null hypothesis: no serial correlation at lag h; (***), (**) and (*) would indicate significance at 1%, 5% and 10%

VEC residual serial correlation Breusch–Godfrey LM test						
Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	28.57714	25	0.2820	1.152780	(25, 306.1)	0.2826
2	21.20750	25	0.6810	0.845499	(25, 306.1)	0.6815
3	33.07956	25	0.1291	1.344050	(25, 306.1)	0.1296
4	28.27527	25	0.2953	1.140053	(25, 306.1)	0.2960

Appendix A6

Null hypothesis: residuals are multivariate normal; orthogonalization: Cholesky (Lütkepohl); (***), (**) and (*) indicate significance at 1%, 5% and 10%

Residual normality tests orthogonalization: Cholesky (Lütkepohl)			
Component	Jarque–Bera	df	Prob.
1	0.570503	2	0.7518
2	0.022949	2	0.9886

Appendix A6 cont.

Residual normality tests orthogonalization: Cholesky (Lütkepohl)			
Component	Jarque–Bera	df	Prob.
3	0.611199	2	0.7367
4	0.426156	2	0.8081
5	2.856881	2	0.2397
Joint	4.487688	10	0.9227

Appendix A7

Null hypothesis: residuals are homoscedastic, cross terms are included; (***), (**) and (*) indicate significance at 1%, 5% and 10%

VEC residual heteroskedasticity tests					
Dependent	R-squared	F(81,24)	Prob.	Chi-sq(81)	Prob.
res1*res1	0.691333	0.663627	0.9106	73.28135	0.7170
res2*res2	0.793601	1.139257	0.3707	84.12174	0.3842
res3*res3	0.764925	0.964136	0.5677	81.08203	0.4765
res4*res4	0.695056	0.675344	0.9011	73.67590	0.7057
res5*res5	0.825971	1.406268	0.1737	87.55288	0.2899
res2*res1	0.773243	1.010373	0.5114	81.96376	0.4492
res3*res1	0.851690	1.701524	0.0709	90.27917	0.2252
res3*res2	0.805770	1.229194	0.2902	85.41160	0.3473
res4*res1	0.903414	2.771398	0.0031	95.76188	0.1256
res4*res2	0.883722	2.251884	0.0135	93.67457	0.1587
res4*res3	0.892430	2.458145	0.0075	94.59754	0.1433
res5*res1	0.804942	1.222717	0.2955	85.32381	0.3497
res5*res2	0.731301	0.806411	0.7652	77.51790	0.5890
res5*res3	0.873359	2.043367	0.0251	92.57610	0.1785
res5*res4	0.878587	2.144108	0.0186	93.13025	0.1683
Joint Test					
Chi-sq	df	Prob.	–	–	–
1286.090	1215	0.0766*	–	–	–

Appendix B – High-Inflation Period 2

Appendix B1

The VECM is specified with a lag length of 1, based on the ACF and PACF of the residuals of the VECM and the results of various information criteria; *t*-values are in square brackets while SEs are in parentheses; included observations: 42. The VECM is derived from the cointegrating equation obtained using the Johansen method, as presented in Table 4 and Table 5. The cointegrating vector, detailed in Table 7, is normalized with respect to S&P 500

Error correction:	D(S_P500)	D(IP)	D(LTI)	D(INF)
CointEq1	–0.151945	–0.032954	–0.205987	–0.002577
	(0.03761)	(0.00820)	(0.10787)	(0.00441)
	[–4.03974]	[–4.01654]	[–1.90955]	[–0.58456]
D(S_P500(-1))	–0.101817	–0.030851	–0.433174	–0.016812
	(0.14771)	(0.03222)	(0.42363)	(0.01731)
	[–0.68930]	[–0.95749]	[–1.02252]	[–0.97110]
D(IP(-1))	2.147195	–0.067339	–1.181910	0.030116
	(0.57277)	(0.12494)	(1.64269)	(0.06713)
	[3.74882]	[–0.53898]	[–0.71950]	[0.44864]
D(LTI(-1))	–0.098876	0.023849	0.302763	0.007363
	(0.04849)	(0.01058)	(0.13906)	(0.00568)
	[–2.03923]	[2.25495]	[2.17721]	[1.29570]
D(INF(-1))	–3.544199	0.334519	–1.133020	0.415773
	(1.52212)	(0.33202)	(4.36542)	(0.17839)
	[–2.32847]	[1.00753]	[–0.25954]	[2.33066]
C	0.025042	–3.15E–05	0.019052	0.002398
	(0.00796)	(0.00174)	(0.02283)	(0.00093)
	[3.14555]	[–0.01815]	[0.83445]	[2.57049]
D_2022M09	–0.074028	0.008956	0.230958	0.002460
	(0.02696)	(0.00588)	(0.07733)	(0.00316)
	[–2.74567]	[1.52287]	[2.98681]	[0.77835]
D_2022M04	0.021205	0.001147	0.246716	–0.003413
	(0.02636)	(0.00575)	(0.07561)	(0.00309)
	[0.80438]	[0.19952]	[3.26319]	[–1.10458]

Appendix B1 cont.

Error correction:	D(S_P500)	D(IP)	D(LTI)	D(INF)
D_2022M11	0.086561	–0.002319	–0.047313	–0.002809
	(0.02626)	(0.00573)	(0.07531)	(0.00308)
	[3.29637]	[–0.40480]	[–0.62823]	[–0.91273]
R-squared	0.593893	0.574297	0.527525	0.319273
Adj. R-squared	0.489091	0.464438	0.405596	0.143601
Sum sq. resids	0.018378	0.000874	0.151167	0.000252
S.E. equation	0.024348	0.005311	0.069831	0.002854
F-statistic	5.666824	5.227586	4.326495	1.817442
Log likelihood	96.95189	157.8583	54.80742	182.7067
Akaike AIC	–4.397595	–7.442914	–2.290371	–8.685334
Schwarz SC	–4.017597	–7.062917	–1.910373	–8.305336
Mean dependent	0.008312	0.002163	0.030746	0.004300
S.D. dependent	0.034064	0.007257	0.090575	0.003084

Appendix B2

Granger causality test results; 1 degree of freedom; H0: X does not Granger-cause Y, H1: X Granger-causes Y; the theoretical framework is outlined in Section 3.3

Granger causality tests Included observations: 40			
Dependent variable: D(S_P500)			
Excluded	Chi-sq	df	Prob.
D(IP)	14.05362	1	0.0002
D(LTI)	4.158454	1	0.0414
D(INF)	5.421754	1	0.0199
All	19.90509	3	0.0002
Dependent variable: D(IP)			
Excluded	Chi-sq	df	Prob.
D(S_P500)	0.916781	1	0.3383
D(LTI)	5.084798	1	0.0241
D(INF)	1.015107	1	0.3137
All	12.68443	3	0.0054

Appendix B2 cont.

Dependent variable: D(LTI)			
Excluded	Chi-sq	df	Prob.
D(S_P500)	1.045547	1	0.3065
D(IP)	0.517677	1	0.4718
D(INF)	0.067363	1	0.7952
All	2.277201	3	0.5169
Dependent variable: D(INF)			
Excluded	Chi-sq	df	Prob.
D(S_P500)	0.943038	1	0.3315
D(IP)	0.201274	1	0.6537
D(LTI)	1.678840	1	0.1951
All	4.295823	3	0.2312

Appendix B3

Impulse-Response functions, Response to Cholesky one S.D. (d.f. adjusted) Innovations, 95% confidence interval using standard percentile bootstrap with 999 bootstrap repetitions; Cholesky ordering: S&P 500, IP, LTI, INF, M1

Period	S_P500	IP	LTI	INF
1	0.024348	0.000000	0.000000	0.000000
	(5.6E–06)	(0.00000)	(0.00000)	(0.00000)
2	0.029710	–0.000182	–0.012163	–0.004978
	(2.3E–05)	(8.2E–06)	(8.2E–06)	(7.4E–06)
3	0.035014	–0.004798	–0.016956	–0.002662
	(3.8E–05)	(1.8E–05)	(1.5E–05)	(1.7E–05)
4	0.040038	–0.002839	–0.020789	–0.003042
	(5.7E–05)	(2.5E–05)	(2.6E–05)	(3.0E–05)
5	0.041670	–0.002631	–0.022332	–0.002821
	(7.4E–05)	(3.1E–05)	(3.7E–05)	(4.4E–05)
6	0.042431	–0.002614	–0.023073	–0.002570
	(8.7E–05)	(3.5E–05)	(4.5E–05)	(5.4E–05)
7	0.042816	–0.002562	–0.023442	–0.002418
	(9.7E–05)	(3.7E–05)	(5.1E–05)	(6.0E–05)

Appendix B3 cont.

Period	S_P500	IP	LTI	INF
8	0.042982	–0.002540	–0.023614	–0.002321
	(0.00010)	(3.8E–05)	(5.6E–05)	(6.5E–05)
9	0.043053	–0.002532	–0.023693	–0.002261
	(0.00011)	(3.9E–05)	(6.0E–05)	(6.8E–05)
10	0.043082	–0.002529	–0.023728	–0.002227
	(0.00011)	(4.0E–05)	(6.3E–05)	(7.0E–05)
11	0.043094	–0.002527	–0.023743	–0.002208
	(0.00012)	(4.1E–05)	(6.5E–05)	(7.2E–05)
12	0.043097	–0.002527	–0.023750	–0.002197
	(0.00012)	(4.1E–05)	(6.7E–05)	(7.3E–05)

Appendix B4

Forecast error variance decomposition of the S&P 500 using one S.D. Cholesky (d.f. adjusted) factors; Cholesky ordering: S&P 500, IP, LTI, INF

Period	S.E.	S_P500	IP	LTI	INF
1	0.024348	100.0000	0.000000	0.000000	0.000000
2	0.040599	89.51853	0.002005	8.975874	1.503589
3	0.056497	84.63654	0.722354	13.64269	0.998419
4	0.072419	82.07884	0.593320	16.54372	0.784120
5	0.086570	80.60620	0.507559	18.23136	0.654881
6	0.099200	79.68381	0.455989	19.29432	0.565880
7	0.110615	79.06794	0.420384	20.00879	0.502886
8	0.121049	78.63421	0.395065	20.51403	0.456698
9	0.130687	78.31544	0.376483	20.88632	0.421757
10	0.139677	78.07282	0.362359	21.17019	0.394634
11	0.148127	77.88267	0.351305	21.39292	0.373102
12	0.156123	77.72997	0.342438	21.57193	0.355666
13	0.163729	77.60477	0.335175	21.71876	0.341298
14	0.170997	77.50034	0.329120	21.84127	0.329275

Appendix B4 cont.

15	0.177969	77.41191	0.323995	21.94501	0.319077
16	0.184677	77.33610	0.319603	22.03397	0.310324
17	0.191150	77.27038	0.315795	22.11110	0.302731
18	0.197411	77.21286	0.312463	22.17859	0.296085
19	0.203480	77.16210	0.309523	22.23815	0.290218
20	0.209372	77.11698	0.306910	22.29111	0.285002
21	0.215104	77.07660	0.304571	22.33849	0.280334
22	0.220686	77.04026	0.302466	22.38114	0.276133
23	0.226131	77.00737	0.300561	22.41973	0.272331
24	0.231447	76.97747	0.298829	22.45482	0.268875

Appendix B5

Null hypothesis: no serial correlation at lag h; (***), (**) and (*) indicate significance at 1%, 5% and 10%

VEC residual serial correlation Breusch–Godfrey LM test						
Lag	LRE* stat	df	Probability value	Rao F-stat	df	Probability value
1	10.87733	16	0.8170	0.664707	(16, 74.0)	0.8187
2	15.67656	16	0.4758	0.987603	(16, 74.0)	0.4791
3	10.65809	16	0.8301	0.650408	(16, 74.0)	0.8317

Appendix B6

Null hypothesis: residuals are multivariate normal, orthogonalization: Cholesky (Lütkepohl); (***), (**) and (*) indicate significance at 1%, 5% and 10%

Residual normality tests orthogonalization: Cholesky (Lütkepohl)			
Component	Jarque–Bera	df	Probability value
1	1.044168	2	0.5933
2	1.682823	2	0.4311
3	0.335947	2	0.8454
4	2.215305	2	0.3303
Joint	5.278242	8	0.7275

Appendix B7

Null hypothesis: residuals are homoscedastic, cross terms are included
(*) indicates significance at 10%

VEC residual heteroskedasticity tests					
Dependent	R-squared	F(23,16)	Probability	Chi-sq(23)	Probability
res1*res1	0.659348	1.346469	0.2731	26.37393	0.2835
res2*res2	0.376804	0.420613	0.9716	15.07214	0.8920
res3*res3	0.812660	3.017660	0.0133	32.50640	0.0901*
res4*res4	0.866874	4.529873	0.0015	34.67497	0.0560*
res2*res1	0.398549	0.460972	0.9560	15.94197	0.8577
res3*res1	0.659109	1.345038	0.2739	26.36437	0.2840
res3*res2	0.521448	0.758010	0.7343	20.85794	0.5898
res4*res1	0.844793	3.786442	0.0042	33.79172	0.0682*
res4*res2	0.422077	0.508058	0.9326	16.88306	0.8150
res4*res3	0.829921	3.394518	0.0074	33.19684	0.0777*
Joint test					
Chi-sq	df	Probability	–	–	–
224.6920	230	0.5864	–	–	–

Appendix B8

Restricted equilibrium correction form of the ARDL(1, 6, 4, 4, 6) model and long-run coefficients. Bounds F test according to M.H. Pesaran et al. (Pesaran et al. 2001), for each stochastic simulation, 70.000 iterations were used and the exact sample used was T = 42 observations; χ^2_{sc} (6) is the test statistic of the Breusch–Godfrey LM test for serial correlation of order up to 4. The expression χ^2_{FF} (1) is the test statistic of the RESET test for functional form misspecification, based on the power of 2 (tests for higher single and multiple powers pass too). The Jarque–Bera test statistic for normality is represented by χ^2_N (2) and χ^2_H (1) is the test statistic of the Breusch–Pagan test for heteroskedasticity; significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

Long- and short-run coefficients of ARDL(1, 6, 4, 4, 6) model				
Coefficient	Estimate	Std. error	*t*-value	Probability
Short-run coefficients				
d(IP)	−0.352851	0.990674	−0.356	0.724700
d(L(IP, 1))	9.410795	2.364507	3.980	0.000522 ***
d(L(IP, 2))	8.032368	1.976786	4.063	0.000421 ***

Appendix B8 cont.

d(L(IP, 3))	5.207626	1.294310	4.023	0.000466 ***
d(L(IP, 4))	3.730699	1.042913	3.577	0.001454 **
d(L(IP, 5))	2.438721	0.811998	3.003	0.005990 **
d(INF)	1.417206	0.700907	2.022	0.054006 .
d(L(INF, 1))	−5.870541	1.301093	−4.512	0.000132 ***
d(L(INF, 2))	−2.768873	1.093135	−2.533	0.017960 *
d(L(INF, 3))	−2.854211	1.010018	−2.826	0.009136 **
d(LTI)	−0.311630	0.089518	−3.481	0.001851 **
d(L(LTI, 1))	0.358921	0.090849	3.951	0.000562 ***
d(L(LTI, 2))	0.098062	0.085958	1.141	0.264758
d(L(LTI, 3))	0.211789	0.088214	2.401	0.024120 *
d(OIL)	0.077444	0.078366	0.988	0.332507
d(L(OIL, 1))	−0.323061	0.092580	−3.490	0.001812 **
d(L(OIL, 2))	−0.269166	0.105332	−2.555	0.017071 *
d(L(OIL, 3))	−0.195183	0.069718	−2.800	0.009719 **
d(L(OIL, 4))	−0.202859	0.075608	−2.683	0.012749 *
d(L(OIL, 5))	−0.002807	0.075080	−0.037	0.970472
ect	−0.627782	0.115546	−5.433	1.22e-05 ***
χ^2_{sc} (6) = 10.312 (0.1121)	χ^2_N (2) = 3.8946 *(0.1427)*	*adj.* $R^2 = 0.596$	–	–
χ^2_{FF} (1) = 0.93048 (0.3469)	χ^2_H (1) = 16.121 (0.9112)	–	–	–
Long-run coefficients				
(Intercept)	54.0035552	16.15721749	3.342380	0,00324***
IP	−21.7644995	3.68339411	−5.908816	0,0000088530***
INF	9.1571821	1.25366102	7.304353	4.614034e-07***
LTI	−0.3989830	0.14818725	−2.692424	0.01400820**
OIL	0.3620217	0.05977196	6.056715	6.397132e-06***
Bounds F-test with intercept (case 2)			–	–
statistic	Lower-bound I(0)	Upper-bound I(1)	Probability value	–
3.935898	2.840369	3.920781	0.0491442	–

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Summary

While the relationship between stock prices and macroeconomic indicators in the US has been widely examined, conflicting findings in the empirical literature suggest the presence of nonlinear dynamics that remain insufficiently explored. Following the work of A. López-Villavicencio and V. Mignon (2011), and A. Brick and D. Nautz (2008), inflation rates above a threshold level of 3% to 5% are associated with significant adverse effects on economic stability and stock market volatility. Therefore, there is a notable gap in the literature regarding the interactions between macroeconomic measures and stock prices during periods of elevated inflation, focusing on potential threshold effects. This study examines these relationships using monthly data from August 1973 to August 1982, representing High-Inflation Period 1, and from January 2021 to June 2024, representing High-Inflation Period 2. The analysis compares the direction and magnitude of the relationships across both periods. The results confirm that hedging against price level increases is a stronger determinant than withdrawal from capital markets due to heightened uncertainty caused by rising inflation rates, which would otherwise lead to declining stock prices. Additionally, the results highlight a strategic shift in US monetary policy, leading to better-anchored inflation expectations. The analysis also indicates that industrial production has become a less reliable proxy for economic activity in recent years, reflecting the US economy's transition towards a service-oriented structure. Overall, the observed cointegration between stock prices and macroeconomic variables challenges the assumptions of the Efficient Market Hypothesis.

JEL codes: C32, C58, E52

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