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Price and income elasticities of fruit demand in Poland: Evidence from Household Budget Data

1. Introduction

High fruit consumption plays a vital role in shaping public health, improving quality of life, and supporting socio-economic development. As a rich source of essential nutrients, fruits are crucial in the prevention of non-communicable diseases such as cardiovascular conditions, diabetes, and obesity. Research shows that increasing daily intake of fruits and vegetables to 800 grams significantly reduces the risk of cardiovascular diseases and reduces overall mortality (Aune et al. 2017). Similarly, Lee et al. (2019) emphasize the importance of fruit and vegetable consumption in reducing the risk of developing metabolic syndrome. Meanwhile, as indicated by Statistics Poland (GUS) data presented in Table 1, the average daily fruit consumption in Poland deviates substantially below the recommendations of the World Health Organization (WHO) and the Food and Agriculture Organization (FAO), which advise a minimum daily intake of 400 grams of fruit per person (Caprile, Rossi 2021).

Low levels of fruit consumption in households stand in contrast to Poland's national production potential. According to data provided by Statistics Poland (GUS), annual fruit harvests in the country ranged between 4.92 million and 5.36 million tonnes between 2021 and 2023. According to Eurostat data (Eurostat 2022), in 2022 Poland held the second position among EU member states in fruit and nut production (excluding citrus), contributing 20.3% to the total EU output

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in this sector. Apple production dominates the domestic fruit sector, and Poland, being one of the world's largest producers and exporters of concentrated apple juice, effectively leverages its processing industry to manage production surpluses. According to the Ministry of Agriculture and Rural Development, the value of fruit and fruit product exports in the 2022/23 season reached €2.8 billion, representing a 9% increase compared to the previous season.

Table 1

Descriptive statistics of fruit consumption by socio-economic group and educational level (kg/person/month)

Household category	Mean	Median	Standard deviation
By socio-economic group			
Pensioners and retirees	5.21	4.14	4.35
Self-employed	4.06	3.17	3.58
Employees	3.86	3.00	3.40
Non-labor income sources	3.49	2.56	3.72
Farmers	3.43	2.60	3.53
By educational level of the household head			
Higher education	4.71	3.60	4.09
Secondary education	4.48	3.45	3.95
Below secondary education	3.99	3.03	3.57

Despite Poland's strong position as a fruit producer and exporter, the level of domestic fruit consumption does not reflect either the market's potential or public health expectations. An additional challenge is that a significant share of fruit consumption in Poland consists of imported fruits (such as citrus fruits and bananas), which not only limits opportunities to support the domestic market, but at the same time contributes to a higher carbon footprint and hampers the development of sustainable consumption practices.

Efforts to increase fruit consumption in Poland, as well as to shift its structure, above all require a better understanding of the economic mechanisms that influence consumer decision-making. In this context, the analysis of complete demand models can be particularly helpful, as they make it possible to determine how changes in the prices of individual products and in consumers' income levels related to demand for various types of fruit. This, in turn, allows for the estimation of which products are more sensitive to price or income changes, and therefore which interventions (e.g., price reductions, subsidies, informational campaigns) are likely to be most effective in improving consumption levels (Wolak 2015).

Contemporary empirical studies also reveal significant relationships between fruit consumption and socio-economic factors such as household structure, age, or health-related needs (Mauramo et al. 2023). Understanding these relationships is important not only from a public health perspective, but also for designing effective policies that support the agricultural sector, prevent food waste, and promote responsible consumption

Although numerous applications of complete demand models for analysing fruit consumption can be found in the global literature (e.g., Peltner, Thiele 2021; Iqbal et al. 2023), there is still a notable absence of advanced demand analyses based on complete demand system estimations for the Polish fruit market – despite its significant economic and dietary relevance. This study seeks to fill this clear research gap.

The analysis is based on unit-level data from the 2022 Household Budget Survey conducted by Statistics Poland. Six fruit categories were considered: citrus fruits, bananas, apples, berries, stone fruits, and other fruits. To estimate income and price elasticities of demand, the QUAIDS model (Quadratic Almost Ideal Demand System) was employed, accounting for zero expenditures and the influence of selected demographic variables. The results indicate that fruit demand is sensitive to changes in both prices and income, particularly in the case of imported fruit.

The rest of the article is structured into following sections. Section 2 presents a literature review focused on methods of analysing fruit demand and the econometric models, including the QUAIDS model. Section 3 discusses the study's methodology, covering data sources, the procedure for determining unit prices, and the specifics of the applied model, including the calculation of price and income elasticities. Section 4 outlines the results of the model estimation, including an analysis of the obtained elasticity values and their potential implications. The article concludes with a summary of the main findings and recommendations for future research and the practical application of the results.

2. Literature review

The academic literature pays considerable attention to both the theoretical foundations of consumption modelling and empirical analyses of demand for various categories of food products. In addition to studies covering a spectrum of food items (e.g., Mjeda et al. 2020; Korir et al. 2020), particular interest has been given to those product groups whose consumption can be relatively easily influenced by government policies, primarily through fiscal instruments such as indirect taxation. Many examples include numerous analyses concerning alcohol (e.g., Gil, Molina 2009; Aepli 2014) and sugar-sweetened beverages (e.g., Caro et al. 2017; Segovia et al. 2020; Wolak 2021), the consumption of which is often subject to regulation due to its adverse health effects.

In this context, it appears justified to extend the analytical perspective to include products whose consumption may bring potential health benefits. A good example is fruit. In this case, government action aims not so much to limit consumption as to support it, both by promoting healthy eating habits and by strengthening the position of domestic producers.

The literature includes studies that examine fruit demand using a demand system approach. Mekonnen et al. (2012), using annual data from 1980 to 2007 on per capita fruit consumption in the United States, estimated a QUAIDS model that incorporated three product groups: fresh fruit, fruit juices, and processed fruit. Their findings indicate that demand for all the categories considered was price inelastic, and the relationships between them were complementary. This result is particularly relevant in the context of designing policies to promote fruit consumption, as it shows that increased demand for one form of fruit encourages consumption of the others. Demand analyses based on household budget expenditure data have also been conducted for selected developing countries, for example Malaysia (Ashagidigbi et al. 2019) and Pakistan (Iqbal et al. 2023). The authors of these studies, using different specifications of the AIDS (Deaton, Muellbauer 1980) or QUAIDS (Banks et al. 1997) models, came to fairly similar conclusions. Fruits were found to be normal goods with price-inelastic demand, and various demographic factors (including place of residence, household size, as well as the age or gender of the household head) were shown to significantly influence consumption levels.

In the Polish literature, there is a noticeable lack of studies devoted to the demand for distinct categories of fruit. Most of them focus on general analyses of food demand, in which fruit constitutes only one of many product categories considered (e.g., Gulbicka, Kwasek 2006; Kwasek 2008; Stanisławska, Wysocki 2011), or is limited to estimating income elasticities using nonlinear demand models (Dorosz, Dudek 2020). Previous approaches rarely incorporate the a priori conditions derived from microeconomic theory, which limits the ability to comprehensively capture the structure of fruit consumption.

In response to these limitations, the present study proposes the application of a complete demand system model that enables a more detailed analysis of the interrelationships among selected product categories. Although such models have been employed in Polish research, for example, in the analysis of household consumption expenditure structures (Gostkowski 2018) or specific product groups such as alcohol (Gurgul, Wolak 2008), staple food products (Dudek 2008), or sugar-sweetened beverages (Wolak 2021), they have not yet been applied to the study of fruit demand. As a result, this area remains underexplored in the Polish context.

3. Methods

This chapter presents the methodological framework adopted in the study. It begins with a description of the data source and construction of the price variables used in the analysis. Subsequently, demographic controls and their integration into the demand model are discussed. The core of the methodology involves the specification of a QUAIDS model adapted to handle zero expenditures, estimated in two stages. Finally, formulas for computing demand elasticities are outlined based on the estimated model coefficients.

3.1. Data set

The empirical part of this study is based on anonymized unit-level data obtained from the Household Budget Survey conducted by Statistics Poland (GUS) in 2022. This survey is carried out annually using a representative sampling method. In 2022, the sample covered 28,383 households, described by a wide range of demographic and socio-economic characteristics. Each participating household recorded, for a selected month, information on income received as well as the quantities purchased and total expenditures on selected categories of goods. This study used data on the quantities purchased in the following six fruit categories:

- citrus fruits (e.g., oranges, pomelo, grapefruit, lemons, mandarins),
- bananas,
- apples,
- berries (e.g., gooseberries, chokeberries, blueberries, bilberries, blackberries, raspberries, currants),
- stone fruits (e.g., peaches, apricots, nectarines, sweet cherries),
- other fruits (e.g., grapes, watermelons, melons, pomegranates).

Monthly household-level consumption data by fruit category are presented in Table 2.

Table 2

Descriptive statistics of unit prices by fruit category (PLN per kg)

Fruit category	Mean	Median	Standard deviation
Citrus fruits	1.92	0.99	2.77
Bananas	1.79	1.18	2.05
Apples	2.38	1.45	3.29
Berries	1.14	0.30	2.32
Stone fruits	0.85	0.00	2.16
Other fruits	1.14	0.00	2.33

3.2. Unit prices

There is an ongoing debate in the literature regarding the validity of using unit prices, defined as the ratio of expenditures to quantities purchased, as a proxy for market prices. While A. Deaton recognized the potential of unit values to approximate actual market prices, he also pointed out the limitations of this approach due to quality effects and demographic differences among households (Deaton 1988). A major methodological contribution was made by T.L. Cox and M.K. Wohlgenant, who suggested adjusting for product quality by regressing unit prices on selected household characteristics (Cox, Wohlgenant 1986). Their approach has since been extended in various contexts.

Deaton's framework (Deaton 1988, 1990) for analysing demand using household-level data relies on the assumption of price constancy within local markets. While this assumption simplifies empirical implementation, it may not accurately reflect price variation actually faced by households, particularly in regions with imperfect market integration or limited data granularity. Recognizing this limitation, L.V. Hoang proposed an alternative approach by incorporating regional average prices to better capture the effective prices consumers are exposed to (Hoang 2009). This modification allows for more accurate estimation of demand parameters by accounting for intra-regional price dispersion, and has since informed subsequent studies aiming to improve the robustness of demand system estimation using survey data. Nowadays, such adjusted approaches, tailored to the specific structure of the data, are widely adopted in demand analyses (Majumder et al. 2012; Aepli 2014; Wolak 2021).

The present study follows this line of methodology. It is assumed that quality effects are influenced by household income and selected demographic characteristics (i.e., household size, income and squared income, number of children, and the educational level of the household head). These effects are modelled as the deviation between the unit price paid by a household and the regional average unit price, accounting for temporal variation. To estimate adjusted market prices, the following regression equation is proposed

$$v_i - (v_i)_{median} = \alpha_i D_l + \gamma_i D_q + \delta_i x + \theta_i x^2 + \sum_{j=1}^{n} b_i Z_{ij} + \varepsilon_i \tag{1}$$

where:

- v_i – denote the unit value (unit price) paid by a household for product *i* in quarter *q* and region *l*,
- D_l – be a categorical variable for region,
- D_q – be a categorical variable for quarter,
- x – represents household income,
- Z_{ij} – be a set of demographic characteristics of household *j*.

The estimation of Equation (1) was performed separately for each of the six fruit categories using a robust M-estimator, which reduces the influence of outliers (Aepli, Finger 2013). Quality-adjusted prices, accounting for regional and temporal differences, were computed using the following formula

$$(p_i)_{med} = (v_i)_{med} + (\varepsilon_i)_{med} \tag{2}$$

where:

- $(v_i)_{med}$ – is the median unit value paid by households for product *i* in quarter *q* and region *l*,
- $(\varepsilon_i)_{med}$ – is the median of the residuals from Equation (1) for households that purchased product *i* in the same quarter and region.

3.3. Demographic variables

The literature identifies two main approaches for incorporating demographic variables into the QUAIDS model equations. The scaling approach, proposed by R. Ray, involves adjusting household income through a demographic scaling function (Ray 1983). This allows the model to account for differences in household composition and size.

The translating approach (Pollak, Wales 1981), which can be expressed by Equation (3).

$$\alpha_i = \alpha_i' + \sum_{k=1}^{K} \eta_{ik} Z_k \tag{3}$$

The household characteristics Z_k are introduced into the model by modifying the constant term α_i. Although the translating approach is more restrictive than the scaling approach, it enables direct modelling of the impact of household characteristics on consumption structure. Moreover, it is better suited to data with zero expenditures and allows for theoretically consistent estimation of the model (Caro et al. 2021).

3.4. QUAIDS model with zero-expenditures

Failure to account for zero expenditures in demand analysis can lead to biased estimates. For this reason, the literature proposes several techniques to address this issue. D. Heien and C.R. Wessells introduced a two-step procedure in which a probit model is first estimated to determine the probability of purchasing a given good (Heien, Wessells 1990). In the second step, an inverse Mills ratio is added to the demand model, and the parameters are estimated accordingly.

J.S. Shonkwiler and S.T. Yen proposed a refinement of this approach, offering a more consistent and less error-prone two-step estimation method (Shonkwiler, Yen 1999). In their procedure, probit models are estimated in the first stage to predict the probability of purchasing each product. If y_{ij} denotes the expenditure of household j on good i, new variables are generated according to Equation (4).

$$y_{ij}^{*} = \begin{cases} 1 & if \;\; y_{ij} > 0 \\ 0 & if \;\; y_{ij} = 0 \end{cases} \tag{4}$$

The newly constructed binary variables are then used to build probit models that explain the probability of expenditure on good i based on selected household characteristics.

$$y_i^{*} = \sum_{k=1}^{K} \theta_{ik} Z_{ik} + \varepsilon_i \tag{5}$$

In the second stage, using the results of the probit regressions (4), values of the probability density function ϕ_i and the cumulative distribution function Φ_i are computed. These are then incorporated into the demand system equations to adjust for the presence of zero expenditures. For QUAIDS, the equation for the i-th good in the system takes the following form

$$w_i^{*} = \Phi_i M_i + \delta_i \phi_i + u_i \tag{6}$$

where M_i represents the i-th equation of the original QUAIDS model, in which demographic variables are incorporated using the translating approach.

$$\alpha_i + \sum_{i=1}^{n} \gamma_{ij} \ln p_j + \beta_i \ln\left(\frac{m}{a(\mathbf{p})}\right) + \frac{\lambda_i}{b(\mathbf{p})}\left[\ln\left(\frac{m}{a(\mathbf{p})}\right)\right]^2 + \sum_{k=1}^{K} \eta_{ik} Z_k \tag{7}$$

In Equations (5)–(7), ln p_j denotes the logarithm of prices within the corresponding category of fruit, m represents total household expenditure on fruit, and Z_k refers to the demographic variables under consideration $a(p)$ and $b(p)$ are price indices. The symbol Φ_i denotes the cumulative distribution function value from the probit model, while ϕ_i refers to the value of the probability density function. The parameters α_i, γ_{ik}, β_i, η_{ik} and δ_i are estimated model coefficients, and u_i represents the error term.

3.5. Demand elasticities in the QUAIDS model

One of the main objectives of estimating demand system parameters is to derive income and price elasticity values based on the estimated coefficients. In the censored version of the QUAIDS model, elasticity measures are computed using formulas derived from the estimated model parameters (Caro et al. 2021). The income elasticity of demand is defined by the following identity (8).

$$\eta_i = 1 + \frac{1}{w_i^*}\left\{\Phi_i\left(\beta_i + \frac{2\lambda_i}{b(\mathbf{p})}\ln\left(\frac{m}{a(\mathbf{p})}\right)\right) + \theta_{i,\ln(m)}\phi_i\left[w_i - \delta_i y_i^*\right]\right\} \tag{8}$$

The uncompensated (Marshallian) price elasticity of demand is calculated using the following formula

$$\varepsilon_{ij}^{M} = -\delta_{ij} + \frac{1}{w_i^*}\left\{\Phi_i\left[E_{ij}\right] + \theta_{i,\ln(p_j)}\phi_i\left[w_i - \delta_i y_i^*\right]\right\} \tag{9}$$

$$\eta_i = 1 + \frac{1}{w_i^*}\left\{\Phi_i\left(\beta_i + \frac{2\lambda_i}{b(\mathbf{p})}\ln\left(\frac{m}{a(\mathbf{p})}\right)\right) + \theta_{i,\ln(m)}\phi_i\left[w_i - \delta_i y_i^*\right]\right\} \tag{10}$$

where δ_{ij} is the Kronecker delta, taking the value of 1 when $i = j$ and 0 otherwise.

Estimates of the compensated (Hicksian) price elasticity of demand are obtained by applying the Slutsky equation (Banks et al. 1997).

$$\varepsilon_{ij}^{H} = \varepsilon_{ij}^{M} + \eta_i w_j \tag{11}$$

4. Results and discussion

In the first stage of the empirical analysis, in accordance with the approach described in Section 3.1 and based on Equation (1), unit prices for individual fruit categories were estimated, adjusted for quality and differentiated by region and quarter. To ensure price consistency within local markets, households were grouped according to voivodeship, type of settlement, and rural area delimitation. The calculations also accounted for selected demographic variables, such as household size, the number of children under the age of 18, and the educational level of the household head. The estimated unit prices are presented in Table 3.

Table 3

Descriptive statistics of unit prices by fruit category

Fruit category	Mean	Median	Standard deviation
Citrus fruits	7.09	7.26	1.10
Bananas	5.70	5.77	0.55
Apples	2.92	2.98	0.33
Berries	12.73	12.74	3.17
Stone fruits	11.33	11.74	3.87
Other fruits	5.95	6.29	1.28

Next, using the price data presented in Table 3 along with information on the quantity of consumption for each fruit category, budget shares were calculated for all six defined categories. These are presented in Table 4. As can be observed, the largest portion of the fruit-related household budget in Poland is allocated to imported goods (citrus fruits and bananas) followed by domestically harvested fruits such as berries and apples.

Table 4

Descriptive statistics of budget shares by fruit category

Fruit category	Mean	Median	Standard deviation
Citrus fruits	0.24	0.17	0.25
Bananas	0.21	0.16	0.22

Table 4 cont.

Apples	0.16	0.09	0.20
Berries	0.19	0.09	0.24
Stone fruits	0.11	0.00	0.18
Other fruits	0.10	0.00	0.15

The analysed data show the presence of so-called zero expenditures, meaning that during the reference period some households did not report any purchases in specific fruit categories. Depending on the type of fruit, the proportion of zero expenditures ranged from 23.5% for citrus fruits to as high as 60.0% for stone fruits.

As a result, in the next stage of the analysis, a QUAIDS model adapted to handle zero expenditures was estimated. In the first step, following Equation (5), probit models were estimated. This was followed by the estimation of the system of equations – Equation (7), with parameter restrictions imposed to ensure that the conditions of adding-up, homogeneity, and symmetry of substitution effects were satisfied.

The model also included a demographic variable representing the number of household members being fed. Estimation was carried out using a nonlinear least squares method, following the approach presented by Caro et al. (2021). Finally, based on Equations (8– 10), uncompensated price and income elasticities of demand were computed for each fruit category. The results are presented in Table 5 and 6.

Table 5

Uncompensated price elasticities of fruit demand

	Citrus fruits	Bananas	Apples	Berries	Stone fruits	Other fruits
Citrus fruits	−3.07	0.87	−0.43	0.25	0.11	0.48
Bananas	0.41	−1.58	1.30	−0.66	2.55	2.44
Apples	−0.30	−0.07	−1.02	0.15	0.27	0.13
Berries	2.17	−0.95	0.69	−0.63	0.01	0.00
Stone fruits	4.27	−1.96	1.77	0.72	−1.62	−2.38
Other fruits	0.43	−0.52	0.19	0.09	−0.09	−0.95

Table 6

Income elasticities of fruit demand

Fruit category	Demand elasticities
Citrus fruits	1.09
Bananas	2.36
Apples	0.73
Berries	1.76
Stone fruits	1.94
Other fruits	1.37

The own-price Marshallian elasticities of demand, presented in Table 5, indicate that an increase in the price of each fruit category leads to a decline in demand. In three out of six cases, the decrease in demand is more than proportional to the price change, with elasticity values for citrus fruits (−3.07), bananas (−1.58), and stone fruits (−1.62). Demand for apples (−1.02) and other fruits (−0.95) is approximately unit elastic, while berries (−0.63) are the only category exhibiting inelastic demand.

The estimated income elasticities indicate that all considered fruit categories can be classified as normal goods. Apples show the lowest income elasticity (0.73), whereas other categories – including bananas (2.36), which appear most sensitive to changes in household income – demonstrate a more than proportional response of demand to income variation.

These findings may serve as a foundation for developing a comprehensive strategy aimed at increasing fruit consumption in Poland. Given the relatively high estimates of price elasticity, well-designed price incentives could be an effective tool of public policy. In particular, the government, drawing on the provisions of the revised EU VAT Directive, could follow the example of Ireland and consider reducing the VAT rate on fresh fruit to 0%. Such a policy, if fully reflected in retail prices, could significantly stimulate demand across all analysed fruit categories.

At the same time, due to the relatively high income elasticities, it would be advisable to consider expanding the "Fruit and Vegetables at School" programme to include students in upper primary and secondary schools. Such an intervention could not only support local producers but also promote healthy eating habits among adolescents and, in the longer term, contribute to an overall increase in fruit consumption in Poland.

5. Conclusion

The aim of this study was to analyse household demand patterns for selected fruit categories in Poland, with particular focus on their sensitivity to changes in prices and income. To estimate income and price elasticities of demand for six fruit categories (citrus fruits, bananas, apples, berries, stone fruits, and other fruits), the QUAIDS model was employed, using data from the 2022 Household Budget Survey conducted by Statistics Poland.

The findings from this analysis may serve as a basis for designing effective strategies and promotional campaigns aimed at increasing fruit consumption. Due to the limited number of studies focusing on the Polish market, a broader comparison of results with previous years or analogous studies could not be performed. In the future, it would be particularly valuable to investigate fruit demand across income groups or to focus on specific demographic segments.

At the same time, several limitations of this study should be acknowledged. First, fruit consumption is known to exhibit strong seasonal variation. Incorporating calendar effects, such as holidays or harvest periods, into future models could enhance the precision of estimates. Second, the use of scanner data, such as retail transaction records, could provide more accurate and timely insights into consumer responses to price changes and promotional campaigns. Incorporating these elements in future research would significantly strengthen the empirical foundation of demand analyses and align them more closely with contemporary approaches in consumer microeconomics.

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Summary

The aim of this article is to provide an empirical analysis of fruit demand in Polish households using the QUAIDS model. Based on unit-level data from the 2022 Household Budget Survey conducted by Statistics Poland (GUS), income and price elasticities were estimated for six fruit categories: citrus fruits, bananas, apples, berries, stone fruits, and other fruits. The estimation employed the two-step procedure developed by J.S. Shonkwiler and S.T. Yen, accounting for demographic variables and the issue of zero expenditures. The results indicate high sensitivity of fruit demand to changes in both prices and income, particularly for imported fruits. The article provides recommendations for public policy aimed at supporting the domestic fruit market and promoting healthy dietary habits.

JEL codes: D12, Q18, I18

Keywords: *fruit demand, QUAIDS model, demand elasticities, household consumption*

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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

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(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:

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

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:

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

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:

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

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.

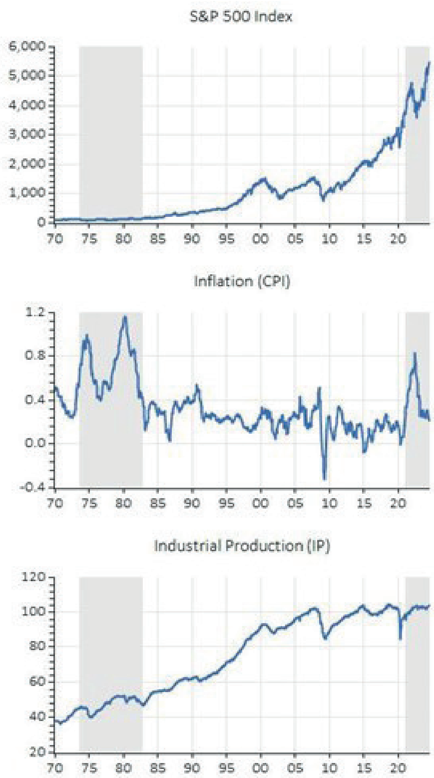

Figure 1. Graphical representation of financial and macroeconomic time series data

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.

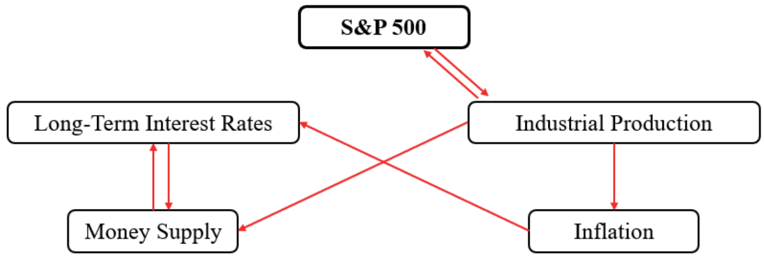

Figure 2. The arrows outline the significant short-term Granger causality channels deviated from the VECM and denote the direction of the Granger causation

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.

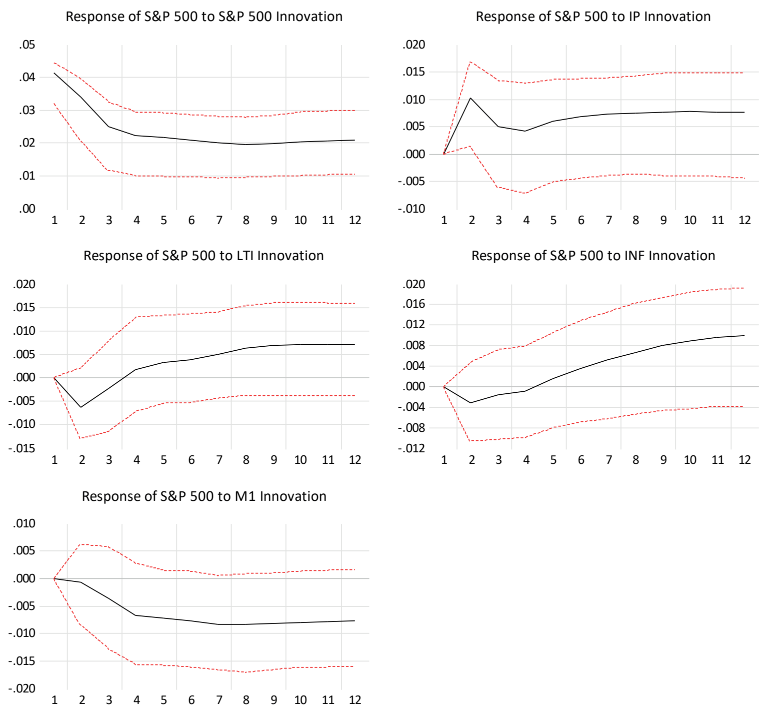

Figure 3. Response to Cholesky one S.D. (d.f. adjusted) innovations, 95% confidence interval using standard percentile bootstrap with 999 bootstrap repetitions

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.

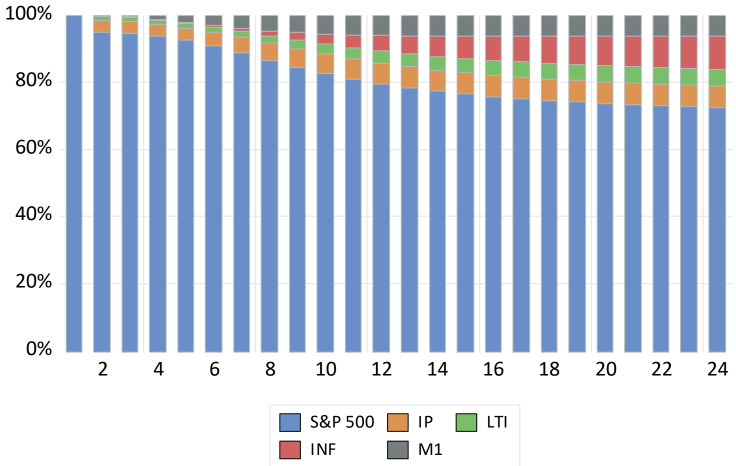

Figure 4. Variance decomposition of the S&P 500 using one S.D. Cholesky (d.f. adjusted) factors; Cholesky ordering: S&P 500, IP, LTI, INF, M1; the statistical outputs are given in Appendix A4.

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.

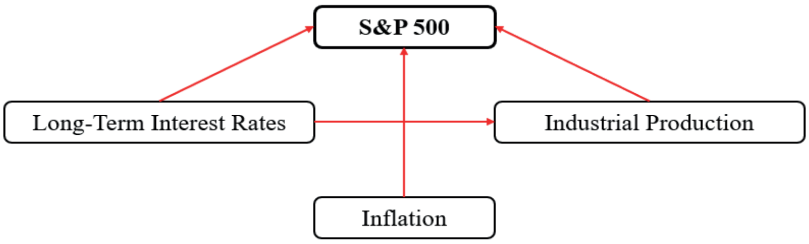

Figure 5. The arrows outline the significant short-term Granger causality channels deviated from the VECM and outline the direction of the Granger-causation

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.

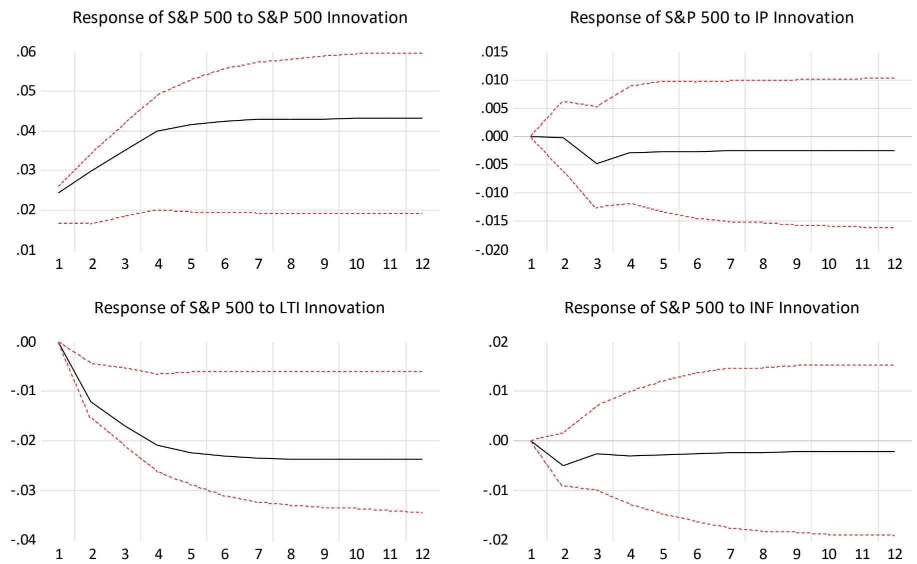

Figure 6. Response to Cholesky one S.D. (d.f. adjusted) innovations, 95% confidence interval using standard percentile bootstrap with 999 bootstrap repetitions.

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.

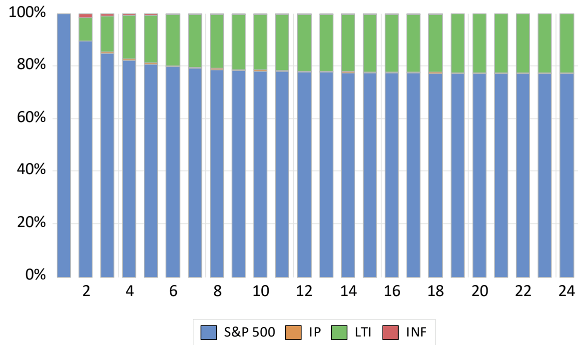

Figure 7. Variance decomposition of the S&P 500 using one S.D. Cholesky (d.f. adjusted) factors; Cholesky ordering: S&P 500, IP, LTI, INF; the statistical outputs are given in Appendix B4

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).

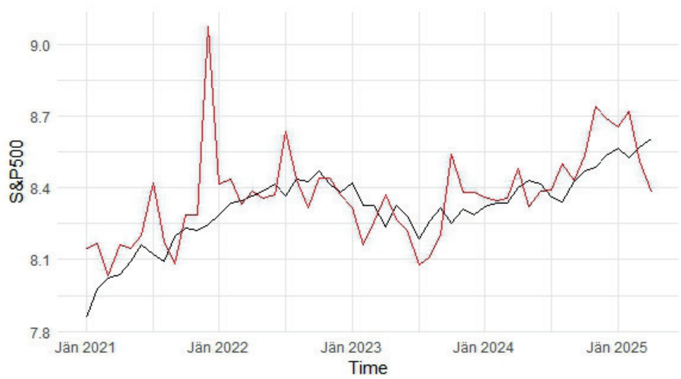

Figure 8. The black (red) line represents the S&P 500 (cointegrating equation)

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

Keywords: *cointegration, macroeconomic variables, stock market, inflation*

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The potential of artificial intelligence adoption for managerial decision making: A rapid literature review

1. Introduction

The rapid development of Artificial Intelligence (AI) technologies has undoubtedly changed the landscape of business, with increased interest in it also being seen in academia. The popularization and extensive interest in its potential, especially related to language-based communication, have made many professionals fearful of the consequences for their jobs. AI has tremendous potential for the replacement of human-conducted tasks in a wide range of business, intellectual and even social applications (Dwivedi et al. 2021). It promises a leap forwards, in a manner akin to the introduction of machines replacing physical workers during the Industrial Revolution. AI not only poses challenges to the way enterprises operate, introducing new work methods, and workplaces but also from the perspective of enterprise management. While there is a general sense of optimism, albeit mixed with legal and ethical problems, the application of AI in management is referred to as being limited to routine decisions (Feuerriegel *et al.*, 2022). In the work of M. Sieja and K. Wach (Sieja, Wach 2023), the clusters of opportunities of **generative artificial intelligence** are related to automated content generation, new product design, optimisation of workflows, customer experience, and data synthesis. Only a few works analyse the strategic level of research focus which is set also by V. Ratten (Ratten 2024) as a future research agenda. There is no information on how AI could help a manager make better decisions and if it is possible to "replace" the manager in this task. As at the moment we speak in academia about an AI spring (Arsenyan, Piepenbrink 2023) it is important to raise the question: "How can managers benefit from this technology?".

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AI is presented as a candidate to improve decision-making in organizations by the better analytical capabilities it can supply and which leads to valuable insights from big data. In turn, this could lead to more informed decisions being done in less time (Shick et al. 2023). AI systems can collect and organize data, analyse it, and offer decision alternatives (Prasanth et al. 2023). By the automation of receptive tasks, AI has more time for strategic planning and also prioritised soft skills in managers' work (Mkhize et al. 2023), representing a change in the profile of a future manager. On the other hand, there are survey results where workers strongly believe that "robots will one day replace their managers" (Schawbel 2019). The main work of a manager is to effectively use resources to achieve goals (Nićin et al. 2018; Tovmasyan 2017). They are responsible for planning, organizing, motivating, and controlling the activities within the organization (Tovmasyan 2017). In general, managers primarily engage in the efficient utilization of resources, decision-making and enhancing organizational value through their actions and choices (Chapman 2001).

Taking into account some concerns about the use of AI in management and beyond, the overall purpose of the work is to indicate the possibilities of using AI to support an enterprise's decision-making processes. The article raises the following explanatory research questions:

RQ1: In what ways does AI support managers for decision-making purposes?
RQ2: How do current studies highlight the potential future application of AI for decision-making purposes?

The primary focus of the article will be on the rapid literature review and exploring the directions of research development within the analysed context, aiming to highlight the practical opportunities that can impact a manager's work.

2. Research methodology

The conducted study employs a rapid literature review (Smela et al. 2023) done systematically. This stage aims to answer the question of what are the primary applications of artificial intelligence in the context of management and decision-making (RQ1) and also to find the potential of future AI utilization for purposes strictly related to managerial decision-making (RQ2).

Before starting a rapid systematic review the initial graphic analysis of keywords related to AI study in the context of management was done with the use of the Scopus database and the search: "artificial intelligence" and "management" for the newest data were conducted (Fig. 1). The search was limited to the years

2010–2024 and to articles and conference materials in English within the fields of Business, Management, and Accounting. The study allows distinct four clusters of topics based on keywords within the broader context of AI and management. The first cluster encompasses main categories such as economics, finance, and management science, highlighting the foundational aspects of AI applications. The second cluster explores specific topics directly related to machine learning, risk management, and the development of big data and Industry 4.0, illustrating the intersection of AI with contemporary technological advancements. The third cluster focuses on the relationship between AI and broadly described algorithms and optimization models. It emphasize the diverse applications of AI across various computational frameworks. The fourth and prominently visible cluster revolves around decision-making support systems, indicating a central theme in the management application of AI models.

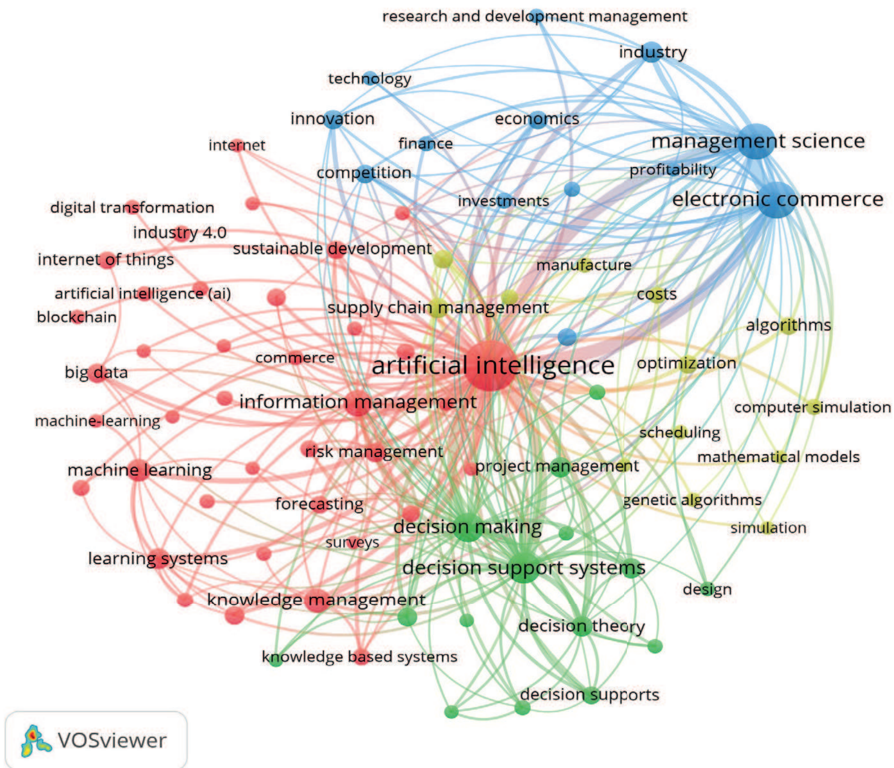

Figure 1. Visualization of keyword connections in the literature on artificial intelligence in management

Taking into consideration the popularity of the topic and the number of papers related to artificial intelligence, the decision was made to focus on the latest works which are literature reviews. Taking into account the results presented in Figure 1 it is justified to include two keywords for systematic literature review: "decision making" or "decision support". An additional requirement regarding the quantity of citations was introduced to ensure that only significant academic works were included. Given the widespread interest in the topic and the need to synthesize key elements, such a strict constraint will help emphasize the most significant and widely explored research directions. Subsequently, the received papers underwent selection based on a thorough examination of the topics addressed by the authors in this article. A presentation of the subsequent steps of rapid systematic review and the number of results can be found in Table 1.

Table 1

The subsequent steps of a rapid systematic literature review and the number of results

Review steps	Number of results	
	Scopus	Web of Science
1. Results for: "artificial intelligence" AND "management" and "decision making" OR "decision support"	15097	7993
2. Limited to English language and years 2020–2024	4989	4408
3. Limited to: "Business, Management and Accounting" (Scopus) „Management" and „Business" (WOS)	570	469
4. Narrowing to literature reviews and open access	16	27
5. More than 10 citations	8	15
6. Number of literature reviews with no duplicates	22	
7. Number of literature reviews after abstract verification	8	

3. Literature review

The first analysed paper is the review done by R. Costa et al. (Costa et al. 2020) where the focus lies on the understanding of the impact of AI tools on the development of business functions. The findings within the work suggest that AI tools are commonly utilized by commercial managers and play a supportive role in their functions. The findings underscore the significant impact of AI systems on the professional development of commercial managers, enabling better decision-making and fostering improved customer relationships.

The second examined work highlights the potential benefits of incorporating machine learning (ML) in information systems research (Abdel-Karim et al. 2021). ML is presented as a solution for a potential increase in the relevance of findings. Based on a literature review and a survey of information system researchers, an assessment was conducted to understand the reasons behind the limited adoption of ML methods. One of them is a deficiency in understanding it. This may block researchers from familiarizing themselves with and applying these methodologies. At the same time, a lack of understanding leads to a reduction in confidence in the reliability of the results obtained by ML.

The study of Z. Doborjeh et al. (Doborjeh et al. 2022) aims to review and analyse established AI methods in the tourism sectors while also identifying their applications in these industries. It proposes personalized AI modelling for smart tourism platforms to enhance decision-making processes. By emphasizing the importance of utilizing appropriate AI algorithms and interdisciplinary technologies, the paper provides decision-makers with insights into selecting suitable AI approaches. It is done mainly by the use of AI for predicting tourism choice behaviour patterns more accurately.

The next examined paper, by R.E. Bawack et al. (Bawack et al. 2022), provides a comprehensive bibliometric study and review of the research of AI in e-commerce. It emphasises that this area focuses on recommender systems. Key research themes include sentiment analysis, trust, personalization, and optimization. It suggests that firms aiming to leverage AI in e-commerce needs to hold ownership of customer data specialized AI algorithms, and proficiency in analytics which cannot be easily imitated by their competitors. The research underscores the importance of these discoveries for managers, emphasizing the opportunity to improve recommender systems' quality by integrating tailored AI algorithms that optimize, personalize, establish trust, and analyse sentiments.

The fifth review examined explores the growing role of people analytics in organizations and its impact on decision-making processes (Giermindl et al. 2022). The study places significant importance on the potential of learning algorithms to enhance decision-making by providing more reliable and superior outcomes in contrast to human decision-making. Autonomous analytics stands apart from other systems due to its capacity for continuous learning and adaptation with each use. As a result, it increases precise estimations and evaluations. Unlike traditional deterministic processes, algorithms in this category are not strictly predictable or repeatable. While descriptive, predictive, and prescriptive analytics supplement decision-making, autonomous analytics operates at a higher level by autonomously driving decision-making processes, including the execution of tasks and entire workflows, thereby reducing the need for human intervention. This shifts decision-making authority from humans to AI-enabled systems, allowing autonomous analytics to substitute humans in decision-making processes entirely. The paper urges for thorough research to comprehend the adverse effects and guarantee the future of work and human decision-making influenced by people analytics.

The next paper raises the question of supply chain resiliency post-COVID-19 in which effective decision-making plays a vital role. In the context of this review the article does not offer valuable implications as the main result in it is a proposition for further investigation of "the enablers of a sustainable supply chain and propose an AI-based decision model to overcome the challenges that occur due to pandemics" (Naz et al. 2022).

The research conducted by B. Rolf et al. (Rolf et al. 2023) acknowledges decision-making as a high-complexity process in the context of supply chain management. The primary application of reinforcement learning (related to AI and ML) in supply chains is inventory management, given its crucial role in synchronizing supply chain processes. This underscores the significance of inventory management as a central area due to its pivotal role in synchronizing the supply chain processes. Inventory management and transportation planning are highlighted as examples of short-term tasks which "require frequent and fast decision-making". It's an important part of the design of the supply chain that influences the success of the company. In this field managerial-level decisions play a key role and support by AI is crucial to foster competitiveness in this sector.

The last analysed work of G. Giuggioli and M. Pellegrini (Giuggioli, Pellegrini 2023) is the recognition of four advantageous consequences of artificial intelligence (AI) on entrepreneurship: empowering novel prospects, amplifying decision-making, ameliorating efficacy, and expediting education and inquiry in entrepreneurial undertakings. The paper emphasizes how AI enhances decision-making processes for entrepreneurs by enabling better predictions and, consequently, more informed and effective decisions. It serves well especially when AI enables entrepreneurs during the opportunity recognition phase of the entrepreneurial process.

In summary, the results do not identify specific applications directly related to decision-making. Analysed works focus on the supportive role of AI (Costa et al. 2020; Giermindl et al. 2022; Giuggioli, Pellegrini, 2023), especially through the increased relevance of findings with the use of big data analysis (Abdel-Karim et al. 2021). It allows for forecasting possible future scenarios, and preparing decision proposals (Giermindl et al. 2022). AI shows potential, especially in data-driven decision-making (Rolf et al. 2023). It is evident from the literature that AI enables more informed and effective decision-making by providing better predictions and insights, ultimately empowering entrepreneurs and decision-makers across diverse sectors. AI will become an important asset for tourism (Doborjeh et al. 2022), e-commerce (Bawack et al. 2022), supply chain management (Rolf et al. 2023) and many others. Responding to RQ1: "In what ways does Artificial Intelligence (AI) support managers for decision-making purposes?" it is noteworthy that the primary way is to make managers more informed due to improved predictions resulting from AI implementation (Giuggioli, Pellegrini 2023). So, it's important to note that in current research, AI primarily supports analysis processes. However, there is still the necessity for further development of AI technologies (Costa et al. 2020).

Surprisingly, the highlighted works do not provide a clear answer to RQ2, which necessitates indicating potential future applications of AI for decision-making purposes. There is a need for further research focused on future applications of AI in decision-making beyond the current support in providing more accurate information, also focusing on quicker decision-making processes.

4. Discussion

Criticism and discussion regarding the results may primarily be linked to the use of the rapid review method. The author intended to select the most popular journals, and it is possible that the latest studies were not included due to the requirement of 10 citations. Such a limitation allowed to find key and recognized trends in the research. However, additional review of the abstracts of papers rejected by this selection does not allow for the conclusion that results regarding the answer to RQ2 would have been found.

It seems that the main reason that stops the presence in research is the lack of understanding of AI, coupled with the limited ability to hold AI accountable for decisions made (Abdel-Karim et al. 2021). It's difficult to imagine a scenario where, under legislation, the owner of AI would be held criminally responsible. This poor ability to hold AI accountable is one of the problems in the Harvard Business Review report but the same report indicates that 78% of surveyed managers believe that they will be able to trust the advice of intelligent systems in making decisions (Feuerriegel et al. 2022). Such high results primarily stem from the widespread popularity of AI as a tool for delegating administrative tasks. This would allow the manager to focus on judgment and assess the potential of the proposed solutions, taking into account the history and culture of the organization. The human factor would therefore be responsible for empathy and reflection on the ethics of undertaken actions. Since, according to the study, more than half of managers at various levels of the organization spend more than half of their time on administrative and control tasks – freeing this time would also allow for the design of new solutions in the enterprise and the development of the social network around the entity (Kolbjørnsrud et al. 2016). Nevertheless, AI adoption is well-known for its problems with reliability, verification and the interpretation of results obtained through ML as well as any standardisation of its usage (Abdel-Karim et al. 2021).

From the methodological point of view, researchers must identify what they mean by AI. Even this paper includes numerous terms such as Machine Learning and Information Systems, which are directly related to AI but may not necessarily be strictly focused on it. It is important to differentiate between different types of AI used in their studies to avoid ambiguity (Bawack et al. 2022).

Other challenges are related to the dimension of the sensitive and personal data. It challenges the ethical implications of allowing it to be analysed by an AI system (Giermindl et al. 2022). Ethical problems are also widespread on the issue of increasing moral inequality triggered by the decision-making process of AI. This has the potential to a reduction in ethical decision-making options (Villegas-Galaviz, Martin 2023). Here again, arises the issue of transparency in the AI evaluation process. It is important to ensure that AI decisions are understandable and justifiable to those impacted by them (Milian, Bhattacharyya 2023).

Referring to the lack of an indication in the papers of an answer to RQ2, this could be judged a surprising result, especially given the hopes placed on AI by managers. Nevertheless, AI is expected to play a crucial role in decision-making in the future. The ability to process vast amounts of information and complex situations is a promising aid . However, its absence necessitates further investigation.

5. Conclusions

This study delves into the role of AI in supporting managerial decision-making processes, addressing two key research questions: (RQ1) In what ways does AI support managers for decision-making purposes? (RQ2) How do current studies highlight the potential future application of AI for decision-making purposes? The answer to both questions was investigated by a rapid literature review. The results show that AI doesn't replace managers but offers substantial opportunities to mitigate their workload. The answer to RQ1 is that the most popular use of AI is in support activities. AI enables more informed and effective decision-making by providing better predictions and insights. This is the basis for decisions to be made. This signifies the promising role of AI in enriching decision-making processes and fostering innovation and efficiency within organizations. Because of that, AI is an important topic in research in the context of computer science, business, and management as based on ecommerce (Bawack et al. 2022). However, regarding the RQ2, despite the prevailing optimism regarding AI's potential, the review underscores a lack of clear indications concerning its future applications in decision-making beyond its current supportive function. This indicates a deficiency in understating and projection of further trajectory of AI's influence and predicting its changing role and consequences.

This study contributes to the range of rapidly developing AI literature with an overview of the most promising possibilities for using AI in a manager's work. As businesses in a volatile and uncertain world should navigate the complexities, understanding AI advantages and possibilities may be considered essential for staying competitive by enabling the potential of technological innovation in the realm of business management. The study conducted is a rapid literature review, which has its limitations. While it quickly provides answers to the research question, which aligns with the exploratory nature of the study, there is a possibility that significant works related to the chosen topic may have been missed.

The study reveals some future research directions. The main one is related to the investigation of potential future applications of AI for decision-making purposes. It should consider the advancement in AI technology and trends in the adoption of it. Another research can address the challenges associated with AI implementation, ways to ensure accountability and ethical AI use in decision-making processes. It would also be interesting to pursue an investigation of the effectiveness of AI-driven decision-making systems on examples of different organizational contexts. Another intriguing research question for further research are stated in the work of R.E. Bawack et al. (Bawack et al. 2022): How is AI affecting managerial mindsets and actions in e-commerce? Of course, the question is also important from the point of view of other areas than e-commerce. The research directions could focus on investigating the intersection of AI with business goals and strategies, addressing the lack of attention given to this area in academic literature (Rajagopal et al. 2022).

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Summary

The article aims to investigate how Artificial Intelligence (AI) can support managers in making decisions. The methodology employed for this purpose involves a rapid literature review process. It is done in two stages that involve the graphic analysis of keywords, the systematic manner for rapid literature review and a directed search through online scientific article databases in pursuit of answers to the research questions. As a scientific basis for article selection, Scopus and Web of Science were chosen. The study indicates that AI supports decision-making processes by providing managers with more informed insights and predictions because of high data analysis capabilities. However, there is a lack of clear indication regarding the potential future applications of AI for decision-making purposes other than a supportive role. The study highlights the importance of AI in managerial decision-making processes. It particularly enhances analytical capabilities which led to the improvement of decision outcomes. It also stressed out the need for further research on future applications of AI in managerial decision-making contexts. The main concerns tackled challenges related to its adoption, such as reliability, accountability and ethical considerations.
This article contributes to the literature by conducting a rapid literature review of the current state of research of AI applications for managerial decision-making. It highlights gaps in research on the future of AI for decision-making and emphasizes the need for additional research in this area.

JEL codes: M10, M19

Keywords: *artificial intelligence, decision-making, decision-support*

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The impact of Ukrainian immigration on inter-voivodship migration in Poland – an attempt to estimate the regional "displacement" effect using the input-output method

1. Introduction

The migration crisis caused by Russia's invasion of Ukraine in February 2022 was undoubtedly the greatest post-World War II humanitarian and logistical challenge for EU countries (and especially for Central and Eastern European countries). It is estimated that in the initial phase of the armed conflict (by March 2022), around 10 million Ukrainian citizens left their homes (Polska Agencja Prasowa 2022) with more than three million of them choosing to flee the war abroad (UNHCR 2022). Finally, by 31 December 2023, according to UNHCR data, nearly six million Ukrainians were in European countries (Operational Data Portal. Ukraine Refugees Situation 2023). These figures show the huge scale of emigration of Ukrainians, which could significantly affect local labour markets and internal migration in individual EU countries.

Poland took on the greatest burden of helping migrants. It is estimated that by October 2022, approximately 3.8 million people had crossed the Polish-Ukrainian border, of which as many as 1.5 million remained in Poland, and their stay being implicitly temporary (Uchodźcy z Ukrainy w Polsce 2022). Numerous community initiatives and more formalised foundations from all over the country made numerous efforts to accommodate migrants in private homes, hotels, hostels, motels, tourist shelters or even wedding halls. Despite the nationwide nature of the campaign, the distribution of Ukrainian citizens across the country turned out to

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be uneven. This was mainly due to the individual preferences of the immigrants, who mainly chose large urban centres such as Warsaw, Kraków, Wrocław and Poznań (Bugdalski 2022). These cities provide more convenient access to all kinds of services and are characterised by capacious labour markets with a diverse and large number of vacancies. The presence of family and friends in Poland and the similar cultural and linguistic background of Poland and Ukraine were also significant in terms of the choice of temporary residence (Długosz et. al 2022).

The main goal of the study is to construct inter-voivodeship migration tables for Poland using the input-output approach and to estimate the regional "displacement" effect of the population associated with the huge inflow of Ukrainian immigrants recorded in 2022. Achieving this goal will allow answering the following main research question: Was the ability of individual voivodeships to absorb Ukrainian immigrants, measured by the strength of the so-called "displacement" effect, spatially differentiated in 2022?

However, it should be noted that the model used for answering this question greatly simplifies the reality, treating the inflow of migrants as the only factor causing internal migration. Other potential internal migration factors, such as the situation of the local labour market (e.g. wages, unemployment rate, level of development of economic infrastructure) or quality of life (e.g. housing conditions, access to education and health care, possibility of satisfying higher needs), are ignored. The results obtained in the simulations based on the model should therefore be treated with some reserve, as it has not been investigated (e.g. using surveys) what proportion of internal migration is actually caused by the mass inflow of immigrants and what is due to other factors. The author bases his inference on the literature on the subject and on the assumption that increased immigration to a given region may cause supply shocks in the local labour market, which further imply the migration of people with a lower occupational and economic standing.

Nevertheless, the construction of migration input-output tables for Poland can be both an interesting descriptive exercise and an attempt to fill the gap in officially published statistical data – the lack of data on the geography of internal temporary migration and the regional distribution of immigrants has been recognised and a method for estimating them has been proposed. In addition, the paper may provide a useful information for policymakers and for employees of the Office for Foreigners, who control and shape the size of the flow of immigrants to Poland.

The article is divided into six sections, with the next one containing a literature review. The third section describes the input-output method adapted to the study of inter-regional migration flows and explains the operation of the "displacement" effect. Parts four and five describe the data sources and the results of the study. The final section analyses the results obtained and outlines their contribution to the practice and directions for further research.

2. Literature review

The uneven distribution of Ukrainian immigrants across the provinces of Poland in 2022 may produce economic and social effects of varying intensity. Studies of the impact of immigration on basic socio-economic variables tend to focus on filling the supply gap in the labour market (cf. Saleheen, Shadforth 2006; Blau et al. 2011; Jarecki 2017) or the level of the unemployment rate and resident[1] wages (cf. Longhi et al. 2010; Giulietti et al. 2013; Edo 2015;). The impact of immigration on domestic interregional migration is less frequently addressed in the research. This type of analysis emphasises the importance of the migratory adjustment mechanism in local labour markets as a response to the inflow of immigrants to a region. First of all, it has been noted that an increase in immigration to a given region may cause an outflow of both low-skilled and low-paid labour, as well as better-educated and better-paid labour, with stronger effects observed for the first group (Frey 1995; Wright et al. 1997; White, Liang 1998). The qualifications of immigrants are not insignificant, as some studies indicate an intensification of interregional migration of local labour with similar qualifications to those of immigrants (Walker et al. 1992).

Researchers of the problem of interregional migration have noted that the inflow of immigrants to a given region can cause the so-called "push out" or "displacement" effect. It consists in forcing residents to migrate to other regions in the country as a result of the emergence in a given region of labour market competitors (immigrants) with similar skills (Walker et. al, 1992; Hatton, Tani 2005). This effect may be in the form of a fading impulse. It consists in the fact that the initiating inflow of migrants to the *j*-th region triggers a "displacement" of some of its residents to the other regions. The "displaced" internal migrants from the *j*-th region settle in the other regions and begin to "push out" the existing residents – then there is a secondary "push out" effect, which is weaker than the initiating effect. Residents from these regions go on to other regions and the aforementioned effect continues until it expires (Vázquez et al. 2011).

The "push out" effect can be quantified using modified input-output methods. The modifications are that input-output tables attempt to capture interregional migrant flows in place of traditional inter-industry flows, a method that was originally developed by Garin and Lowry (Rogers 1966; Gordon, Ledent 1980). Today, in an era of mass immigration, the use of input-output analysis in this area is slowly starting to regain the interest of researchers. For example,

[1] Residents are further defined as all natural persons living in a given region. This concept corresponds to the definition of residents formulated by the Central Statistical Office of Poland (cf. *Residents…* 2025).

E.V. Vázquez et al. (Vázquez et al. 2011) built a migration input-output model for Spain, which experienced (similarly to Poland in 2022) a large inflow of immigrants in 2005, amounting to 700,000 persons. In this study, a clear spatial differentiation of the "push out" effect was observed. The regions with the largest urban centres turned out to be the most capable of absorbing immigrants and at the same time having the least force to displace natives to other regions. At the other end of the spectrum were regions with relatively low economic growth, low GDP per capita and high unemployment rates. Similar conclusions were reached by F.S. Perobelli et al. (Perobelli et al. 2015), additionally emphasizing the concentration of neighbouring regions with low absorption capacity of immigrants in the northern and northeastern regions of the country (Brazil). However, the study revealed some exceptions to the main rule, e.g. Sao Paulo state. Despite its good economic condition, it recorded a high level of the "displacement" effect – this was explained by the huge attractiveness of this region for immigrants (over 20% share in their reception countrywide), which creates strong competitive pressure on the labour market and encourages the population living there to migrate. In other studies, like Ç. Değer et al. (Değer et al. 2016), there are also observations that do not fit into the generally prevailing trends. The Turkish Nevşehir region is an example here – the high absorption capacity of Syrian refugees was achieved artificially thanks to the migration policy applied, which consisted of housing assistance and registration of immigrants' places of residence.

The above examples of research show that it would be worth examining the strength of the interregional "push out" effect using another country (such as Poland) as an example, to confirm the high absorption capacity of immigrants by regions that are relatively more economically developed. An additional argument for estimating the "push out" effect at the regional level is the fact that the literature on this subject is not numerous and requires supplementation.

3. Capturing interregional migration and "displacement" effect in the input-output approach

3.1. Interregional input-output migration model

For a given moment in time (e.g. one year), migration flows occurring in N geographical units (hereafter referred to as regions) forming a compact system (country) can be captured in a modified input-output table like in Table 1.

Table 1

Migration flows in terms of input-output method

<table>
<tr><td colspan="3" rowspan="3"></td><td colspan="4">Region j-th [migrating to]</td><td rowspan="2">Outflow of population to other regions</td><td rowspan="2">Migration abroad (emigration)</td><td rowspan="2">Total net migration</td><td rowspan="2">Total inflow of migrants to the i-th region</td></tr>
<tr><td rowspan="2">region 1</td><td rowspan="2">region 2</td><td rowspan="2">…</td><td rowspan="2">region N</td></tr>
<tr><td>e</td><td>a</td><td>nm</td><td>x</td></tr>
<tr><td rowspan="4">Region i-th [migrations from]</td><td colspan="2">region 1</td><td colspan="4" rowspan="4">m_{ij}</td><td>$\sum m_{1j}$</td><td>a_1</td><td>nm_1</td><td>x_1</td></tr>
<tr><td colspan="2">region 2</td><td>$\sum m_{2j}$</td><td>a_2</td><td>nm_2</td><td>x_2</td></tr>
<tr><td colspan="2">…</td><td>…</td><td>…</td><td>…</td><td>…</td></tr>
<tr><td colspan="2">region N</td><td>$\sum m_{Nj}$</td><td>a_N</td><td>nm_N</td><td>x_N</td></tr>
<tr><td colspan="2">Inflow of people from other regions</td><td>$\boldsymbol{n}'$</td><td>$\sum m_{i1}$</td><td>$\sum m_{i2}$</td><td>…</td><td>$\sum m_{iN}$</td><td colspan="4"></td></tr>
<tr><td colspan="2">Number of immigrants admitted</td><td>$\boldsymbol{f}'$</td><td>f_1</td><td>f_2</td><td>…</td><td>f_N</td><td colspan="4"></td></tr>
<tr><td colspan="2">Total inflow of migrants to j-th region</td><td>$\boldsymbol{x}'$</td><td>x_1</td><td>x_2</td><td>…</td><td>x_N</td><td colspan="4"></td></tr>
</table>

Source: own study.

In the place of the I quadrant of the input-output table, showing the production demand of a branch of the economy for the goods and services of other branches, a matrix of inter-regional migrant flows is placed $\boldsymbol{M} = [m_{ij}]_{N \times N}$. The elements of this matrix define the number of internal migrants from region *i*-th coming to region *j*-th. The diagonal of the matrix $\boldsymbol{M}$ contains only zeros, as no case of internal migration is allowed here. For each *j*-th region, the inflow of internal migrants from the other regions can be determined by considering the matrix $\boldsymbol{M}$ vertically. The result of these considerations is a vector $\boldsymbol{n}'$ consisting of the elements $[n_j]_{1 \times N}$, where $n_j = \sum_{i=1}^{N} m_{ij}$. In addition to internal migrants, external migrants (immigrants) may also flow into the j-th region, and their number is determined by the vector $\boldsymbol{f}' = [f_j]_{1\times N}$. This variable is exogenous. The sum of the vectors $\boldsymbol{n}'$ and $\boldsymbol{f}'$ determines the total inflow of migrants to the j-th region:

$$\boldsymbol{x}' = \boldsymbol{n}' + \boldsymbol{f}' \tag{1}$$

The vectors $\boldsymbol{n}'$, $\boldsymbol{f}'$ and $\boldsymbol{x}'$ form a quasi-III quadrant of the input-output table are similar to vectors from the quadrant that concentrate the generated income in individual sectors of the economy. It is worth mentioning that the vector $\boldsymbol{x}'$ can be treated as a result vector, whereby it is not the total output of the productive activity of individual economic sectors (as in the traditional input-output approach), but the total inflow of migrants to subsequent regions.

There are four vectors in place of the II quadrant of the input-output table: population outflow from the i-th region to the other regions $\boldsymbol{e}$, foreign migration (emigration) $\boldsymbol{a}$, total net migration $\boldsymbol{nm}$ and, the vector discussed earlier in its non-transposed form, the total inflow of migrants to the i-th region $\boldsymbol{x}$. The outflow of population from the i-th region to other regions is determined by horizontally summing the population moving from the i-th region to the other regions, i.e. $e_i = \sum_{j=1}^{N} m_{ij}$. This creates the vector $\boldsymbol{e} = [e_i]_{N\times 1}$. In addition to internal migrants, foreign migrants (emigrants) may also flow out of the i-th region, and their number is determined by the vector $\boldsymbol{a} = [a_i]_{N\times 1}$. This variable, like $\boldsymbol{f}'$, is exogenous in nature. Another vector is the balancing item – total net migration $\boldsymbol{nm} = [nm_i]_{N\times 1}$. Total net migration can be written as:

$$\boldsymbol{nm} = \boldsymbol{x} - (\boldsymbol{e} + \boldsymbol{a}) \tag{2}$$

is therefore the difference between the total inflow and total outflow of population from a given region.

By transforming Equation (2), it is possible to obtain the total population inflow to the region in a horizontal orientation:

$$\boldsymbol{x} = \boldsymbol{nm} + (\boldsymbol{e} + \boldsymbol{a}) \tag{3}$$

Interregional migrant flows, like intermediate consumption in economic sectors in Leontief's classical input-output model (cf. Plich, Skrzypek 2016: 23), can be represented using the corresponding coefficients, hereafter referred to as migration coefficients (in the traditional sense of input-output tables, input-output coefficients or otherwise direct coefficients are considered here). The elements of the matrix of migration coefficients $\boldsymbol{D}$ are formed by dividing each i-th row of the matrix $\boldsymbol{M}$ by the total inflow of migrants to the i-th region, that is:

$$\boldsymbol{D} = [d_{ij}]_{N\times N}, \text{ where } \forall i = 1,\dots,N \quad d_{ij} = \frac{m_{ij}}{x_i} \tag{4}$$

These coefficients are interpreted as the number of internal migrants leaving the j-th region per one person arriving in the i-th region. For example if the value of the coefficient d_{ij} is 0.003, this means that for every 1,000 people arriving in the i-th region, there are (through the action of the adjustment mechanism) three migrants "pushed" out of the j-th region. Obviously, the diagonal elements of matrix $\boldsymbol{D}$ are zeros, as migration within a given region (e.g. migration from Zakopane to Krakow within the same małopolskie voivodeship) is not taken into account as interregional migration. In addition, as in the case of traditional input-output coefficients, migration coefficients must meet the conditions: $d_{ij} \le 1$ and $\sum_{j=1}^{N} d_{ij} \le 1$. These conditions boil down to the fact that the number of migrants "pushed" to the j-th region from the i-th region and the sum of all "pushed" migrants from the i-th region (the total outflow of people from the i-th region to the other regions) cannot be higher than the total inflow of migrants to the i-th region.

By transforming Equation (4) accordingly and writing the result in matrix form, the following relationship is obtained (cf. Vázquez et al. 2011: 194):

$$\boldsymbol{n}' = \boldsymbol{x}'\boldsymbol{D} = \begin{bmatrix} x_1 & \dots & x_N \end{bmatrix} \begin{bmatrix} 0 & d_{12} & \cdots & d_{1N} \\ d_{21} & d_{22} & \cdots & d_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ d_{N1} & d_{N2} & \cdots & 0 \end{bmatrix} = \begin{bmatrix} n_1 & \dots & n_N \end{bmatrix} \tag{5}$$

Inserting relationship (5) into Equation (1), we obtain equations (model) of the total inflow of migrants to each region of the country in a given time period $\boldsymbol{t}$ (for simplicity, the time sub-script is omitted further):

$$\boldsymbol{x}' = \boldsymbol{x}'\boldsymbol{D} + \boldsymbol{f}' \tag{6}$$

The system of equations (6) can be written in the form:

$$(\boldsymbol{I} - \boldsymbol{D})\boldsymbol{x}' = \boldsymbol{f}' \tag{7}$$

where $\boldsymbol{I}$ is the unit (identity) matrix. Assuming that there is an inverse matrix to the matrix $(\boldsymbol{I} - \boldsymbol{D})$, the model eventually takes the following form:

$$\boldsymbol{x}' = \boldsymbol{f}'(\boldsymbol{I} - \boldsymbol{D})^{-1} \text{ or } \boldsymbol{x}' = \boldsymbol{f}'\boldsymbol{L} \tag{8}$$

The elements of the matrix $(\boldsymbol{I} - \boldsymbol{D})^{-1}$ are the time-constant parameters of the model[2], while $\boldsymbol{f}'$ is an exogenous variable representing the inflow of immigrants to a region. Thus, the model makes the total population inflows (inward and outward) to subsequent regions conditional on changes in the number of immigrants arriving in these regions. The model makes sense if the sum of each row of the matrix $\boldsymbol{D}$ is less than unity[3]. The elements of the $(\boldsymbol{I} - \boldsymbol{D})^{-1}$ matrix are interpreted analogously to the elements of the Leontief inverse matrix (cf. Miller, Blair 2009: 21), hence it can be denoted similarly as the $\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{D})^{-1}$ matrix. The matrix $\boldsymbol{L}$ is referred to as the matrix of total migration coefficients for the purposes of the study.

Model (8) can be used to forecast the total inflow of migrants to individual regions of a country ($\boldsymbol{x}'$) when the future values of the exogenous inflow vector of immigrants ($\boldsymbol{f}'$) are known. Unfortunately, a weakness of the model (8) is its focus on an annual period of analysis, which results from the frequency of the publication of statistical data and the very construction of regional migration flow tables, which require the collection and balancing of large amounts of information. In reality, adjustments in the local labour market caused by a sudden increase in immigration are sometimes longer than a 1-year period, and the emergence of incentives forcing residents to migrate to other regions may be a long-term nature.

Another weakness of the model (8), as already mentioned in the introduction, is its simplifying assumption that immigration is the only factor significantly influencing internal migration (immigrant-driven intermigration model). Other covariates, such as differences in income, housing conditions and access to educational and health services, are excluded from the analysis. The next difficulty is the limited possibility of verifying the correctness of the model, i.e. whether immigration actually significantly affects internal migration. Unfortunately, an analysis of data from the last 10 years has shown that the assumption of positive net migration has not been met in every period. This fact makes comparative analysis difficult – it can only be done under conditions of exceptional inflows of migrants into the country (this was the case in 2015 and in 2022). Limiting ourselves solely to periods of exceptional immigration inflows does not allow

[2] The general description of the model includes time-constant parameters. For the purpose of the comparative analysis of the "push out" effect in 2022 and 2015 (see Section 5.1), a matrix of total migration coefficients was estimated for both periods.

[3] A similar thing happens in the input-output model, where final demand must be greater than zero (which is always true). In the migration model, the issue is not always conclusively determined, as net migration (found in the second quadrant of Table 1) can be negative (more migrants leave than arrive in a region). However, in the case of a massive inflow of Ukrainian migrants to the regions (as in the case of the migration crisis caused by Russia's invasion of Ukraine), the mathematical condition mentioned in this section is met.

for the verification of the thesis that increased immigration does indeed affect internal migration.

3.2. The effect of "pushing out" residents by immigrants

The elements of the matrix $\boldsymbol{L} = [\delta_{ij}]_{N\times N}$ from Equation (8) are the partial derivatives of x_i relative to f_j, i.e. $\frac{\partial x_i}{\partial f_j}$. The parameter δ_{ij} thus shows the total population inflow to the *i*-th region induced by the arrival of an additional one immigrant to the *j*-th region. This coefficient not only takes into account the initiating inflow of migrants to a region, but also the indirect effects, i.e. the migration of residents from region to region and their "pushing out" of further migrants, which also cause (but already smaller) "pushing out" effects, etc. until they expire. An alternative notation of Equation (8), using matrix algebra techniques, may be helpful in understanding this mechanism (see Tomaszewicz 1994: 67–68):

$$\boldsymbol{x}' = \boldsymbol{f}' + \boldsymbol{f}'\boldsymbol{D} + \boldsymbol{f}'\boldsymbol{D}^2 + \ldots = \boldsymbol{f}'\left(\boldsymbol{I} + \boldsymbol{D} + \boldsymbol{D}^2 + \ldots\right) \tag{9}$$

At the beginning, there is an impulse that initiates internal migration in the form of region j receiving a given number of migrants f_j. This is noticed by the residents of region *j*-th and they start to migrate to other regions, and their "distribution" between regions takes place according to the elements of the matrix **D**. The arrival of residents from the *j*-th region is observed by residents in the other regions. The latter also start migrating and there is a redistribution of migrants according to the matrix **D**, then these migrations produce a secondary "push out" effect, etc. Eventually, the migratory movements stop and the system finds its equilibrium.

For each region, a total "push out" effect can be determined, i.e. the total number of population inflows to all regions caused by the receiving of one additional immigrant by the *i*-th region. The "push out" or "displacement" indicator is written with the formula:

$$\boldsymbol{p} = \left(\boldsymbol{I} - \boldsymbol{D}\right)^{-1}\mathbf{i} \tag{10}$$

where **i** is a vector of ones of dimension N. In other words, the vector ***p*** is the sum of consecutive rows of the matrix of total migration coefficients ***L***. The indicator of the "displacement" of residents by a region due to the admission of additional immigrants is used to analyse the ability to absorb immigrant supply shocks. Regions with a higher level of this indicator will be more susceptible to such shocks, as local labour market conditions and increased competition in the labour market stimulate more internal migrants. Regions with a relatively low level of this indicator have a greater capacity to absorb additional immigrants – here labour markets are characterised by high capacity, the competitive pressure from immigrants is lower and the "push out" effect on residents is weaker. Of course, these relations occur with other conditions unchanged (*Ceteris paribus*) and with the assumption that the main driver of internal migration is the inflow of immigrants.

The comparability of the level of the $\boldsymbol{p}$ indicator between regions is facilitated by relating the value of the indicator to the average. This operation can be written with the formula (cf. Vázquez et. al 2011: 196):

$$\boldsymbol{p}^* = \frac{(\boldsymbol{I}-\boldsymbol{D})^{-1}\mathbf{i}}{\boldsymbol{i}'(\boldsymbol{I}-\boldsymbol{D})^{-1}\mathbf{i}}. \tag{11}$$

The average for all regions takes a standardised value of 1. The value of the $\boldsymbol{p}^*$ index for each region shows its deviation from the average.

4. Data sources and data collection issues

4.1. Description of real and estimated data

In order to construct the table of interregional migration flows (see Table 1), appropriate data are needed to complete the matrix $\boldsymbol{M}$ and the vectors $\boldsymbol{a}$ and $\boldsymbol{f}'$. Not all of the data functions directly in domestic or European migration statistics and this requires the researcher to make appropriate estimates under conditions of limited information. The most important data sources and how to obtain data not present in official statistics are discussed below. Regions will hereinafter be referred to as voivodeships, and their number in Poland is N = 16.

The core of the migration data is actually registered data collected by Główny Urząd Statystyczny (the Central Statistical Office) within of Bank Danych Lokalnych (the Local Data Bank) – internal and external migration in 2022. For the purpose of the comparative analysis (see Section 5.2), analogous data from 2015 were also used. Within the BDL, data on inter-voivodeship migration for permanent residence (registrations) are available, which were used to develop a matrix of inter-voivodeship migration for permanent residence. It should be noted that there is no data on inter-voivodeship migration for temporary residence in the BDL. The statistical office only provides information on the total number of admitted internal migrants in a given province without indicating their regional origin (see Table 2).

Table 2

Main data used to build the inter-regional input-output migration table for 2022 and 2015

No.	Voivodeship	2022			2015		
		Number of internal mi-grants admit-ted (temporary migration)	Estimated number of Ukrainian immigrants admitted	Emigra-tion for permanent residence	Number of internal mi-grants admit-ted (temporary migration)	Estimated number of Ukrainian immigrants admitted	Emigra-tion for permanent residence
		n_j	f_j	a_i	n_j	f_j	a_i
1	Dolnośląskie	32 761	84 759	1 356	47 127	2 460	2 105
2	Kujawsko-Pomorskie	22 359	15 967	640	36 153	460	988
3	Lubelskie	20 724	69 872	512	27 725	1 952	599
4	Lubuskie	13 303	28 813	404	18 050	591	771
5	Łódzkie	20 562	67 231	484	35 234	726	654
6	Małopolskie	38 790	161 354	1 407	59 028	2 272	1 631
7	Mazowieckie	58 069	303 378	889	73 697	9 161	861
8	Opolskie	11 958	12 005	979	17 900	679	1 583
9	Podkarpackie	23 214	49 343	759	31 470	1 411	820
10	Podlaskie	12 377	13 206	226	18 340	251	455
11	Pomorskie	23 357	60 628	1 182	33 664	824	1 548
12	Śląskie	42 589	61 828	2 133	68 801	1 233	3 785
13	Świętokrzyskie	11 191	18 488	243	15 289	607	307
14	Warmińsko-Mazurskie	15 151	10 685	676	25 145	333	1 034
15	Wielkopolskie	36 698	57 386	948	54 381	993	1 302
16	Zachodniopomorskie	20 615	50 783	795	31 919	935	1 586
Total		403 718	1 065 726	13 633	593 923	24 887	20 025

In order to estimate the matrix of inter-voivodeship migrations for temporary residence ***M***, the number of migrants for temporary residence was distributed among voivodeships after fixed shares according to the matrix of migration for permanent residence. This assumes that the directions and structure of migrants for temporary and permanent residence are similar (see next section). Actual data on internal migration show a similar spatial pattern, i.e. in 2022 and in 2015, the largest number of internal migrants was received by the Mazowieckie Voivodeship, while the smallest number was received by the Świętokrzyskie Voivodeship, but in 2015 the scale of internal migration was noticeably higher than in 2022 (by approximately 190,000 persons).

Model (8) is based on the simplifying assumption that internal migration is mainly caused by the inflow of immigrants represented by the vector $\boldsymbol{f}'$. In this study, the flow of immigrants should be identified with Ukrainians arriving in Poland. The focus on Ukrainian citizens in Poland was dictated by the domination of the immigration stream by Ukrainians[4] and their cultural and professional proximity to Poles. This proximity means that Ukrainian citizens have the right qualifications to start working in various professions, speak Polish communicatively (unlike, for example, most immigrants from Asian countries) and assimilate well in the country. The above factors may indicate high competitiveness of Ukrainians on the labour market with respect to Polish citizens. It is presumed that this group of immigrants has the greatest impact on the emergence of regional "push out" effects.

When examining the issue of Ukrainian immigration, it should be noted that there were problems in finding relevant data in the case of determining how many Ukrainian immigrants decided to stay in Poland and what number were received by individual voivodeships. Reports on migration of Ukrainian citizens, press articles or data from Urząd do spraw Cudzoziemców (the Office for Foreigners) were not consistent in this respect. For example, think-tanks and media reports indicated that up to 1.5 million migrants were estimated to have temporarily decided to stay in Poland in 2022 (cf. *Uchodźcy z…*, 2022: 5). Unfortunately, it was not specified here how many migrants were received by individual voivodeships. Data from the Office for Foreigners should be considered more precise, indicating that in 2022 the number of Ukrainian citizens with a valid residence permit (temporary and permanent residence, refugee status, temporary protection, etc.) increased by approximately 1.065 million compared to the previous year (Urząd do spraw Cudzoziemców 2024). This total number of migrants was taken in the input-output tables for 2022 (see the total row in Table 2) and treated as a stream of immigration

[4] According to the Urząd do spraw Cudzoziemców (the Office for Foreigners), Ukrainians accounted for 95% of the stream of all immigrants in 2022. The rate in 2015 was 68% (Urząd do spraw Cudzoziemców 2024).

of Ukrainian citizens to Poland. This stream was further distributed among the provinces using regional data on issued decisions on permanent residence (according to fixed shares) from the same source. It was assumed that the directions and structure of immigration for permanent and temporary residence are similar to each other, analogous to the data on internal migration. This assumption is based on the aforementioned studies by B. Bugdalski (Bugdalski 2022) and P. Długosz et al. (Długosz et al. 2022), suggesting that new Ukrainian immigrants often go to places where earlier immigrants from this country have already settled.

According to the estimates in Table 2, the most popular direction of immigration of Ukrainian citizens in 2022 was the Mazowieckie Voivodeship (about 303,000 immigrants), while the least popular direction of immigration was the Warmińsko-Mazurskie Voivodeship (about 11,000 persons). In 2015, the overall scale of migration of Ukrainian citizens to Poland was much smaller than in 2022 and amounted to only about 25,000 persons. At the same time, it should be emphasised that since 2015, the number of Ukrainians migrating to Poland has systematically increased, which can be considered as the beginning of intensification of this phenomenon. As in 2022, Ukrainians most often chose the Mazowieckie Voivodeship as their immigration direction (approximately 9,000 persons). In contrast, the least popular immigration direction was the Podlaskie Voivodeship (approximately 300 persons). The distribution of immigrants between provinces should be considered highly uneven in both 2022 and in 2015.

Actual data from the Central Statistical Office on the number of emigrants from Poland originating from individual voivodeships were also used to construct inter-regional input-output tables for 2022 and 2015. This data was used to supplement the vector $\boldsymbol{a}$. The year 2015 was characterised by a higher scale of emigration from Poland than the year 2022. The analysis of the actual recorded data of the Central Statistical Office shows that 20,000 residents emigrated permanently from Poland in 2015 while 14,000 in 2022. Despite the differences in the level of the studied phenomenon in the indicated years, one can notice a certain similarity in the regional distribution of emigrants – the largest number of emigrants came from the Śląskie Voivodeship. On the other hand, the smallest number of emigrants was recorded in the Świętokrzyskie Voivodeship (for 2015) and in the Podlaskie Voivodeship (for 2022).

4.2. The limitations of estimated migration data

The assumption made in the study that the structure and directions of internal migration for temporary and permanent stay are similar is questionable. This highly simplifying assumption was dictated by the lack of disaggregated spatial data on temporary migration. An argument for assuming the same structure of the interregional migration matrix for permanent and temporary residence is the fact that, in 2022, the structure of the vector of the total population inflow to individual voivodeships for permanent residence and the analogous vector for temporary residence was very similar – the average absolute difference between the individual elements of the vectors was only about 1.6 percentage points.

The assumption that the directions and intensities of internal migration for permanent and temporary residence are similar is difficult to base on adequate research in the literature, as there is not a large number of publications addressing this topic. Some of the few publications, such as M. Bell and G. Ward (Bell, Ward 2000) or Y. Liu and W. Xu (Liu, Xu 2017), even indicate that the directional choices of internal migration for temporary and permanent residence may be different. These studies concerned large, heterogeneous countries in terms of their level of economic development, such as Australia or China, which are difficult to juxtapose spatially with Poland's economy. Poland does not have huge desert areas or areas of forced internal immigration as a result of the introduction of migration policies. Nevertheless, the above-mentioned studies emphasise that intensive immigration to metropolitan areas for permanent and temporary residence is observed, which would confirm the important role of the Mazowieckie Voivodeship (and Warsaw) in both types of migration.

On the other hand, one can also find examples of studies confirming a positive correlation between the directions of temporary and permanent migration. Silvestre (Silvestre 2007) points to the occurrence of such a phenomenon in Spain in the 1930s, when workers willingly migrated to economically fast-growing provinces (Barcelona, Vizcaya and Zaragoza) for both permanent and temporary residence. On the basis of national research, similarities in the directions of permanent and temporary migration can be seen in the destination choices of Polish emigrants. According to a study by A. Zborowski and J. Gałka (Zborowski, Gałka 2008), between 2003 and 2006, emigrants for temporary and permanent residence most often chose the same destinations, i.e. Germany, the United Kingdom, Ireland and the Netherlands. Admittedly, these are not internal migrations, but it may be assumed that Poles are guided by similar criteria, e.g. economic, in their choices of permanent and temporary migration. Of course, any judgements on the destination choices of internal migration for permanent and temporary residence should be supported by in-depth research.

Another problem related to the estimation of data on migrants is the approach to estimate the size of the immigrant stream (the number of Ukrainian citizens coming to Poland) adopted in the paper. The approach shown in the previous section is not accurate, as it is more in the nature of a simplified economic estimate than an accurate demographic analysis. The stream, as in economic sciences, has been treated as a change in the stock, here as the change in the number of Ukrainian citizens with a valid residence permit compared to the previous year. Focusing on the change in stock status has its advantages and disadvantages. The advantage is the simplicity and speed of the estimates, while the disadvantage is the inclusion in the register of persons obtaining a permanent residence permit (who have been living in Poland for a minimum of five years) and persons leaving Poland, i.e. "outflowing" from the stock (analogous to economic depreciation). The estimated stream is therefore not exactly a stream of *strictly* migrant inflows. In order to estimate this stream more accurately, it would be necessary to carry out detailed demographic analyses by reviewing the number of temporary residence permits issued, the number of work permits received in Poland for Ukrainian citizens or (especially for recent years) the number of Ukrainians with Polish temporary protection (UKR PESEL status). The problem of access to certain data, the time-consuming process of collecting them and their questionable reliability, however, led to the decision to use a simple economic approach.

5. Results

5.1. The "displacement" effect in 2022

The results of the construction of the "push out" indicator for each voivodeship, which was estimated according to Equation (10), were as follows: Dolnośląskie 1.354, Kujawsko-Pomorskie **1.865**, Lubelskie 1.462, Lubuskie 1.519, Łódzkie 1.410, Małopolskie 1.246, Mazowieckie 1.211, Opolskie **1.868**, Podkarpackie 1.473, Podlaskie **1.742**, Pomorskie 1.407, Śląskie 1.586, Świętokrzyskie **1.983**, Warmińsko-Mazurskie **2.208**, Wielkopolskie 1.436, Zachodniopomorskie 1.407. Please note that **bold** highlights five largest values, whereas shading highlights five smallest values. The average level of the p indicator for the country was 1.574, with a standard deviation of 0.272 and a coefficient of variation of 17.3%.

It turns out that the regions with the highest level of the p indicator are the Warmińsko-Mazurskie, Świętokrzyskie, Opolskie, Kujawsko-Pomorskie and Podlaskie voivodeships. Therefore, it can be expected that these regions show the lowest possibilities of absorbing Ukrainian immigrants, and the potential supply shocks caused by them in the labour market (triggering increased internal migration) are relatively the strongest. On the other hand, the regions with the lowest level of the "push out" indicator are the Mazowieckie, Małopolskie, Dolnośląskie, Pomorskie and Zachodniopomorskie voivodeships. The applied migration model shows that the indicated voivodeships are characterised by a high potential to absorb Ukrainian immigrants, and the possibility of labour market turbulence affects internal migration to a relatively lesser extent.

The values of the indicator $\boldsymbol{p}$ for 2022 have a relatively low statistical variability (measured by a coefficient of variation) of about 17%. The average indicator for the whole country is 1.574 which means that for every additional 1,000 immigrants admitted in a hypothetical averaged region, the total inflow of internal migrants to all regions is 574 people. In other words, each inflow of an additional portion of 1,000 Ukrainian immigrants into Poland results in an internal migration movement in which 574 people leave their home regions in successive iterations of the "push out" effect.

The results of the voivodeships in relation to the "push out" indicator can be detailed by multiplying all the values of the matrix $\boldsymbol{L}$ (see Equation 8) by 1000. The results of this operation are presented in Table 3. In this way one obtains the total inflow of migrants to individual voivodeships caused by the admission of an additional 1,000 Ukrainian immigrants in the i-th voivodeship. For example the value 49 for i = 2 and j = 1 is interpreted as the total inflow of internal migrants to the Dolnośląskie Voivodeship due to the admission of an additional 1,000 immigrants by the Kujawsko-Pomorskie Voivodeship.

On the diagonal of Table 3, there are values greater than 1,000. These values for the i-th region include not only the initiating inflow of 1,000 migrants from outside to a given region, but also the induced internal migration inflow from the other regions. For example, for i = 1 and j = 1 the value 1,017 means that as a result of the inflow of 1,000 immigrants to the Dolnośląskie Voivodship, an additional 17 internal migrants arrived to this region from other regions and whose migration was due to the "displacement" effect.

Columns A and B are summarised in the right-hand side of the table. Column A contains the total population inflow to all regions resulting from the i-th region receiving an additional 1,000 migrants, and is therefore the sum of the rows (from j = 1 to 16) in the presented matrix. If 1,000 is subtracted from the values in column A, the result of this operation will be the total inflow of internal migrants to all regions, which is the consequence of the "displacement" effect. Column B, on the other hand, details the number of all residents of the i-th region who have migrated to the other regions due to the inflow of 1,000 immigrants to that region. The values in this column are not the result of adding/subtracting the values found in the rows of the presented matrix, but are derived from the numerical solution of the model and should be treated as additional information.

Demonstrating the mechanism of the "push out" effect will be easier when two extreme cases of voivodeships are contrasted. In the case of the constructed table of migration flows for the year 2022, these will be the Warmińsko-Mazurskie and Mazowieckie voivodeships. Thus, according to the results of the model (8), the admission of an additional 1,000 migrants in the Warmińsko-Mazurskie Voivodeship (with the highest level of "push out" indicator) causes the largest total (after the cessation of the "displacement" effect) inflow of internal migrants to the Mazowieckie (250 persons) and Pomorskie (242 persons) voivodeships. From the respective values of matrix **D** (see equation 4) it follows that in the first wave of migration 817 persons are "pushed out" from the Warmińsko-Mazurskie Voivodeship, of which 212 persons and 179 persons move to the Mazowieckie and Pomorskie voivodeships respectively. In the end, the total number of all "pushed out" residents from the Warmińsko-Mazurskie Voivodeship after the cessation of the effect is 841 people (per additional 1,000 admitted Ukrainian immigrants). The inflow of population to all regions together resulting from the admission of an additional 1,000 immigrants in the Warmińsko-Mazurskie Voivodeship is 2,208 persons, of whom 1,208 persons are the inflows caused by internal migration.

According to the simplified reasoning of the cause-effect relationship between inflows of immigrants and internal migration, the admission of an additional 1,000 immigrants in the Mazowieckie Voivodeship (with the lowest "push out" indicator) triggers the highest total inflow of internal migrants to the Lubelskie and Łódzkie voivodeships, but it is only 26 and 19 people respectively. Matrix **D** (see equation 4) shows that in the first wave 132 people are "pushed out" from the Mazowieckie Voivodeship, of which 23 people move to the Lubelskie Voivodeship and 16 people migrate to the Łódzkie Voivodeship. The total number of all "pushed out" residents from the Mazowieckie Voivodeship is 134 persons (per additional 1,000 admitted Ukrainian immigrants), so only an extra 2 persons will be "pushed out" from this Voivodeship as a result of the second and further waves of interregional migration. The population inflow to all regions together resulting from the admission of an additional 1,000 immigrants in the Mazowieckie Voivodeship is 1,211 persons, of whom 211 persons are the inflows caused by internal migration.

The analysis of the data collected in Table 3 shows that the strongest interregional (bilateral) "displacement" effects are observed in the case of the inflow of immigrants to the Opolskie, Podlaskie and Warmińsko-Mazurskie voivodeships. Disregarding the impact of other variables on internal migration, the admission of an additional 1,000 immigrants by these voivodeships results in the internal migration of more than 200 persons in the following directions: Opolskie – Dolnośląskie, Opolskie – Śląskie, Podlaskie – Mazowieckie, Warmińsko-Mazurskie – Mazowieckie and Warmińsko-Mazurskie – Pomorskie. On the other hand, the weakest interregional "displacement" effects are recorded in the Lubuskie, Małopolskie and Mazowieckie voivodeships. Here, the inflow of an additional 1,000 immigrants may entail internal migration of no more than four persons in the following directions: Lubuskie – Świętokrzyskie, Małopolskie – Lubuskie, Małopolskie – Podlaskie, Małopolskie – Wielkopolskie, Mazowieckie – Lubuskie and Mazowieckie – Opolskie.

Table 3

Total effect of "pushing out" residents from individual voivodeship estimated for the admission of an additional 1,000 immigrants by *i*-th voivodeship

			Total population inflow to the *j*-th region																A. Population inflows to all regions in total (tsum 1-16)	B. Total number of people 'pushed out' of the *i*-th region
			Dolnośląskie	Kujawsko-Pomorskie	Lubelskie	Lubuskie	łódzkie	Małopolskie	Mazowieckie	Opolskie	Podkarpackie	Podlaskie	Pomorskie	Śląskie	Świętokrzyskie	Warmińsko-Mazurskie	Wielkopolskie	Zachodniopomorskie		
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16		
Host *i*-th region for 1000 immigrants	Dolnośląskie	1	1 017	13	11	34	19	24	34	33	15	5	15	42	6	7	55	25	1 354	236
	Kujawsko-Pomorskie	2	49	1 025	23	21	46	36	132	13	18	20	125	49	10	46	198	54	1 865	611
	Lubelskie	3	27	14	1 009	8	17	46	156	7	56	12	20	34	11	10	20	14	1 462	338
	Lubuskie	4	99	22	12	1 011	15	19	38	10	12	5	20	30	4	7	137	78	1 519	367
	Łódzkie	5	45	21	14	9	1 007	29	86	14	14	8	20	53	13	9	49	17	1 410	284
	Małopolskie	6	16	7	10	4	8	1 016	27	7	35	4	8	70	13	4	11	7	1 246	162
	Mazowieckie	7	11	15	26	4	19	14	1 016	3	11	16	15	16	8	15	14	9	1 211	134
	Opolskie	8	202	23	24	23	41	75	64	1 016	35	9	23	219	13	14	58	31	1 868	604
	Podkarpackie	9	33	10	49	7	15	142	66	9	1 012	8	13	52	21	8	18	11	1 473	342
	Podlaskie	10	29	34	39	11	24	33	257	8	19	1 017	65	37	7	100	39	23	1 742	505
	Pomorskie	11	21	57	15	10	14	19	55	6	12	14	1 019	28	5	41	45	45	1 407	256
	Śląskie	12	61	20	22	13	40	129	64	43	37	10	23	1 028	27	14	32	23	1 586	412
	Świętokrzyskie	13	59	22	55	12	68	197	194	17	104	14	26	132	1 010	14	37	23	1 983	717
	Warmińsko-Mazurskie	14	46	119	40	21	36	46	250	14	26	129	242	65	11	1 030	83	51	2 208	841
	Wielkopolskie	15	67	55	10	35	30	21	45	11	11	7	26	32	5	10	1 024	45	1 436	296
	Zachodniopomorskie	16	39	30	12	45	15	17	45	7	10	6	40	27	5	10	89	1 011	1 407	279

5.2. Comparison of the "push out" effect – 2015 vs. 2022

The results of a comparative analysis of the spatial distribution of the "displacement" effect in 2022 and 2015 for the Polish voivodeships are presented below. The year 2022 and 2015 are very important periods in the history of the phenomenon of immigration of Ukrainian citizens to Poland. In 2015, this phenomenon intensified as a result of the outbreak of the Russian-Ukrainian conflict in the Donbas and Lugansk regions the year before. At that time, Poland saw the first refugees from the area of hostilities, in addition to economic migrants (linked to the strong fall in Ukraine's real GDP in 2015). In turn, in 2022, there was an unprecedented inflow of Ukrainian citizens to Poland in excess of one million people. In the author's opinion, these two notable periods are worth comparing in terms of the differences in the spatial and quantitative inflow of Ukrainian immigrants to Poland and the effects of this inflow in the form of "push out" effects.

The spatial variation of the "push out" indicator in relation to the national average (***p**** index) in 2022 and 2015 is shown in Figure 1. Both in 2022 and in 2015, the voivodeships falling in the first quartile group of the value of the ***p**** index were the Dolnośląskie, Małopolskie and Mazowieckie voivodeships. Assuming the strong relationship between internal migration and the inflow of immigrants, it can be concluded that the regions with the highest capacity to absorb Ukrainian citizens have not changed over the past seven years.

In 2015, the Wielkopolskie Voivodeship also belonged to this group of voivodeships, but in 2022 it lost its potential through the intensification of the "push out" effect. In 2022, the voivodeships in the first quartile group were characterised by a value of ***p**** between 10 and 23% lower than the national average. In 2015, this group recorded values of this indicator from 18 to even 30% lower than the national average.

Larger differences between 2022 and 2015 occur in the last quartile group of the index ***p****. Only the Warmian-Masurian Voivodeship and the Świętokrzyskie Voivodeship were present in it both in 2022 and in 2015. In 2015, additionally, the Lubelskie Voivodeship and the Lubuskie Voivodeship were also among the voivodeships with the highest "push out" indicator. However, the results for these regions in 2022 can be interpreted as an improvement in the absorption capacity of immigrants by reducing the "displacement" power of residents. On the other hand, in 2022, the last quartile group of the ***p**** indicator also included, in addition to the Warmińsko-Mazurskie and Świętokrzyskie Voivodeships – the Kujawsko-Pomorskie Voivodeship and the Opolskie Voivodeship. According to the mechanism of the model (8), it is concluded that in 2022 in these regions the possibility of absorbing immigrants has decreased through the intensification of the "displacement" effect.

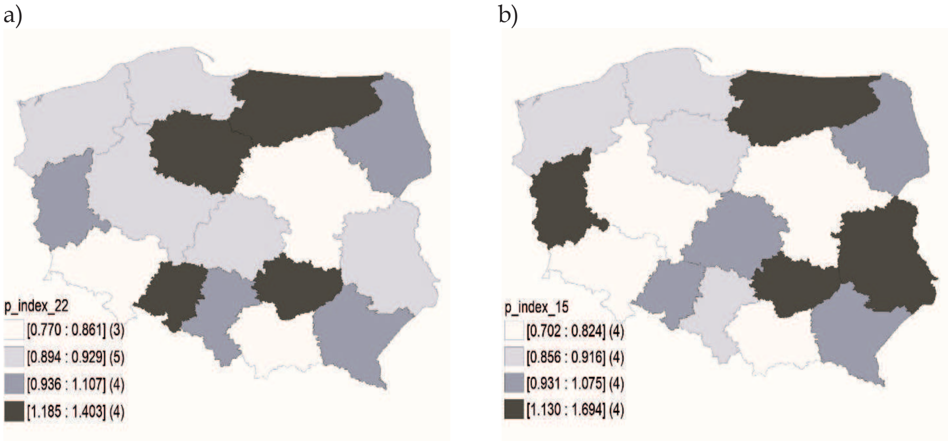

Figure 1. Spatial variation of the ***p**** index in 2022 (a) and 2015 (b)

Voivodeships in the last quartile group in 2022 were characterised by an index value ***p**** from 19% to 40% higher than the national average. In 2015, this group recorded values of this indicator from 13% to even 69% higher than the national average. Taking into account the results for the first quartile group and the coefficients of variation of the ***p**** index, it can be concluded that in 2015 the regions of Poland were more differentiated in terms of the strength of the "displacement" effect than in 2022.

6. Conclusions

In response to the research question formulated, the answer is: yes, the measurement of the "displacement" effect using the input-output method showed a noticeable spatial differentiation in the ability of individual voivodeships to absorb Ukrainian immigrants in 2022. In other words, the study revealed strong variation of the strength of the impact of the inflow of Ukrainian immigrants on the dislocation of residents in individual provinces. It turned out that the voivodeships characterised by the highest "push out" indicator are at the same time voivodeships with a relatively high level of unemployment rate and below the average wages, e.g. the Świętokrzyskie or Warmińsko-Mazurskie voivodeships.

This may indicate that the inflow of immigrants provides a strong incentive for residents to migrate from regions with unfavourable local labour market conditions. Such markets are more susceptible to immigrant supply shocks, and this probably manifests itself in more residents choosing to leave the region rather than compete with immigrants. These results are consistent with the results of the studies by E.F. Vázquez et al. (Vázquez et al. 2011), F.S. Perobelli et al. (Perobelli et al. 2015) and Ç. Değer et al. (Değer et al. 2016) conducted using the input-output method.

Voivodeships with large urban centres, such as Mazowieckie, Małopolskie and Dolnośląskie, are the least susceptible to labour market shocks. The absorption capacity of Ukrainian immigrants by these voivodeships may be the highest and this can be evidenced by the low values of the "push out" indicator. It is noteworthy that these regions are generally characterised by very low unemployment rates and relatively high average wages. They are also the regions with a very developed service sector. The aforementioned factors presumably have a negative impact on the strength of the "push out" effect. According to the mechanism of the introduced input-output model, each successive "portion" of immigrants arriving in these regions is associated with relatively weak internal migration – the total number of people "pushed out" from these regions did not exceed 240 per 1,000 additional Ukrainian immigrants. Arguably, the earlier inflow of Ukrainian immigrants to these regions before 2022 is also not insignificant. The earlier immigrants have already managed to find their way in the local labour markets and, through an extensive network of contacts with friends and family, using their acquired competences, may help the "new" Ukrainian immigrants of 2022 to assimilate better. Hence, among other things, we observed the differences between the spatial differentiation and strength of the "displacement" effect in 2022 and in 2015.

The analysis of the elements of the matrix of total migration coefficients showed that the strongest interregional "push out" effects are observed for pairs of neighbouring voivodeships, while the weakest – for pairs of non-neighbouring and significantly distant voivodeships. This is due to the preferences of "displaced" residents – when migrating, they usually choose the voivodeships that are geographically closest and strongly linked economically and infrastructurally to their home region.

There is an interesting juxtaposition of results for the Śląskie Voivodeship, which does not fit the pattern mentioned above. In this voivodeship, there are no noticeable problems with unemployment and there is no low level of wages. Nevertheless, the strength of the "push out" effect is high there. The explanation for this phenomenon can be linked to the structure of the Śląskie Voivodeship's economy, which relies heavily on industrial activity. Ukrainian immigrants, eagerly employed in the industrial sector, may constitute noticeable competition for residents of the Śląskie Voivodeship with similar qualifications, which is why they are probably more often "pushed out" to other voivodeships as a result of losing the competitive battle on the labour market. Similarly to the Śląskie Voivodeship, economically well-developed Sao Paulo state did not follow the general trend, and F.S. Perobelli et al. (Perobelli et al. 2015) attributed the reasons for this situation to economic decentralization and the decline in this state's share in the generated GDP. The same features can be used to describe the Śląskie Voivodeship – it lost its importance due to the declining importance of coal mining in the national economy, and the voivodeship's share in GDP is also on a downward trend (see BDL).

The study revealed a paradox consisting of a relatively strong "displacement" effect and a relatively small number of immigrants going to the eastern provinces directly bordering Ukraine, i.e. the Podkarpackie and Lubelskie voivodships. This regularity applies to both 2022 and 2015. The geographical proximity of these provinces, in a situation where Ukrainian immigrants are fleeing military action to seek their first peaceful place of residence, seems to be a logical choice. Nevertheless, it was estimated that around 49,000 Ukrainian migrants entered the Podkarpackie Voivodeship in 2022, and 70,000 in the Lubelskie Voivodeship, with a regional average of 67,000. Mobility and the possibility of free movement to provinces with a better capacity to absorb migrants was probably more important for migrants than the geographical proximity of the Podkarpackie and Lubelskie voivodeships. In addition, it can be stated with a high degree of probability that in these voivodeships, economic incentives of other regions with better conditions on the labour market were stronger than good logistical preparation for the reception of migrants in 2022 and 2015. So, the high unemployment rate and low wages could stimulate a stronger "push out" effect of residents than in other more economically developed voivodeships. For this reason, the capacity to absorb Ukrainian migrants of Podkarpackie and Lubelskie should be considered low. It is worth noting that a similar paradox can be observed in the results of Ç. Değer et al. (Değer et al. 2016) analyses, where regions close to or bordering Syria were less able to absorb Syrian immigrants than the more developed western regions.

The study contributes to academic practice, in particular to the popularization of the input-output method in the field of demography. The study also indicates, although imperfectly, the methods of estimating migration data that are not available in officially registered statistical data. Unfortunately, the greatest weaknesses of the study are: the assumptions of the model (8) that greatly simplify reality, basing this model largely on estimated data and the limited ability to verify the correctness of the formulated model. After all, the results of this study may be implemented within the framework of migration policy. The conducted analysis indicate regions in Poland where better conditions should be created on local labour markets so that supply shocks caused by the mass inflow of immigrants are as small as possible. This refers primarily to the Warmińsko-Mazurskie, Świętokrzyskie, Opolskie and Kujawsko-Pomorskie voivodeships. Levelling out income differences, creating new job vacancies, ensuring favourable conditions for housing construction and increasing access to educational and health services would probably help to mitigate the "displacement" effect in these voivodeships and to reduce the variation in the strength of the effect across the country.

The study of the impact of Ukrainian immigration on inter-provincial migration in Poland using the input-output method can be expanded to other areas in the future. It is, for example, possible to use model (8) to forecast internal migrations resulting from the (predetermined) expected inflow of Ukrainian immigrants in the coming years. The input-output method can also be used in a broader context – the study of the impact of Middle East and Sub-Saharan immigration on international migration within the EU. Using the method in a broader context would allow for better identification of regions with a greater potential to absorb immigrants across the European Union, which could be useful in the framework of the effective implementation of the Migration Pact.

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Summary

The aim of the article is to estimate the strength of the "displacement" effect of the residents of Polish voivodeships to other regions of the country and determine the regional differentiation caused by the mass inflow of immigrants from Ukraine to Poland in 2022. The study used a modified input-output method, which allows for capturing and balancing both internal and external migration. The first stage of the study consisted in constructing inter-voivodeship migration tables, taking into account the inflow of immigrants from Ukraine. In the second stage of the study, the "displacement" effect was measured using the input-output method, which showed its strong spatial differentiation – the strongest effect was observed in voivodeships with a relatively higher level of the unemployment rate and lower wages (i.e. Warmińsko-Mazurskie and Świętokrzyskie), while the weakest – in voivodeships with large urban centres and capacious labour markets (i.e. Mazowieckie, Małopolskie, Dolnośląskie). The study also revealed a paradox, namely that the eastern provinces closest to Ukraine (i.e. Podkarpackie, Lubelskie) showed a relatively weak capacity to absorb Ukrainian immigrants, whose admission could cause greater disruptions in the local labour markets in these regions than in more distant provinces. The construction of the migration input-output tables was mainly based on data from the Bank Danych Lokalnych Głównego Urzędu Statystycznego (Local Data Bank of Central Statistical Office of Poland) and the Office for Foreigners for the years 2022 and 2015.

JEL codes: R23, C67, D57, J61

Keywords: *immigration, interregional migration, input-output methods, displacement effect*

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