The effect of inflation on US insurance markets

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17 March 2025

Abstract

We analyze the effects of inflation on the US insurance industry. The analysis is based initially on a VAR (Vector AutoRegressive) model. The shock of the COVID-19 pandemic had a significant positive *short-term* impact on inflation, probably explained by the recent contractionary of the Fed monetary policy against inflation. We then analyze the characteristics of the U.S. inflation rate series observed over the 1973-2023 period in order to capture and model the effect of inflation on the insurance industry. Two important conclusions emerge from this analysis: The US inflation rate series is characterized by non-linear dynamics (asymmetry) and a random trend. The results obtained led us to select the two-regime Markov model to analyze the impact of inflation on the various fundamental indicators of insurance company performance in the US. We show that performance indicators are differently affected by inflation in the Life and P&C insurance sectors according to the inflation regime considered.

Keywords: Inflation, US insurance industry, Markov model, COVID-19 pandemic, Life insurance, P&C insurance, AM Best, American Council of Life Insurers.

JEL codes: B22, E3, E4, G22, G52

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The authors thank Claire Boisvert for her contribution to the preparation of the report. Financial support from the SCOR Corporate Foundation for Science and SSHRC Canada is acknowledged.

1. Introduction

In many countries, inflation is a major concern for politicians and decision-makers because of the adverse effects that uncontrolled inflation can have on economic stability. Given that the insurance industry is a key component of the economy, owing to the volume of premiums collected, claims paid, and investments made, it is important to know how variations in inflation could affect the financial stability of the insurance industry. To answer this question, we analyze the US insurance industry.

The study is based initially on a VAR (Vector AutoRegressive) model. We use this model to analyze the impulse response functions of inflation to shocks observed in the United States over the last 51 years (1973-2023 period), namely the oil shocks of the 1970s, the 1979 monetary policy reform led by Paul Volcker, and the COVID-19 pandemic. This empirical analysis shows that the 1970s oil shocks had a significant positive long-term impact on inflation, while the monetary policy shock of 1979 (significant increase in the key interest rate by the Fed) had a significant negative long-term impact on inflation. The shock of the COVID-19 pandemic, by comparison, had a significant positive *short-term* impact on inflation, probably explained by the recent contractionary of the Fed monetary policy against inflation.

Second, we analyze the characteristics of the U.S. inflation rate series observed over the 1973-2023 period in order to capture and model the effect of inflation on the insurance industry. Two important conclusions emerge from this analysis: The US inflation rate series is characterized by non-linear dynamics (asymmetry) and a random trend. To take these two characteristics into account, we have drawn on two approaches most commonly used in econometrics to address the issue of the presence of a stochastic trend and the presence of a non-linear trend in macro-econometric and financial series. The first approach is based on the use of processes with stochastic non-linearity in variance (GARCH models) and the second is based on the use of processes with stochastic non-linearity in the mean such as the regime-switching model. For the application of processes with stochastic non-linearity in variance, we chose the EGARCH (1,1) model of the large

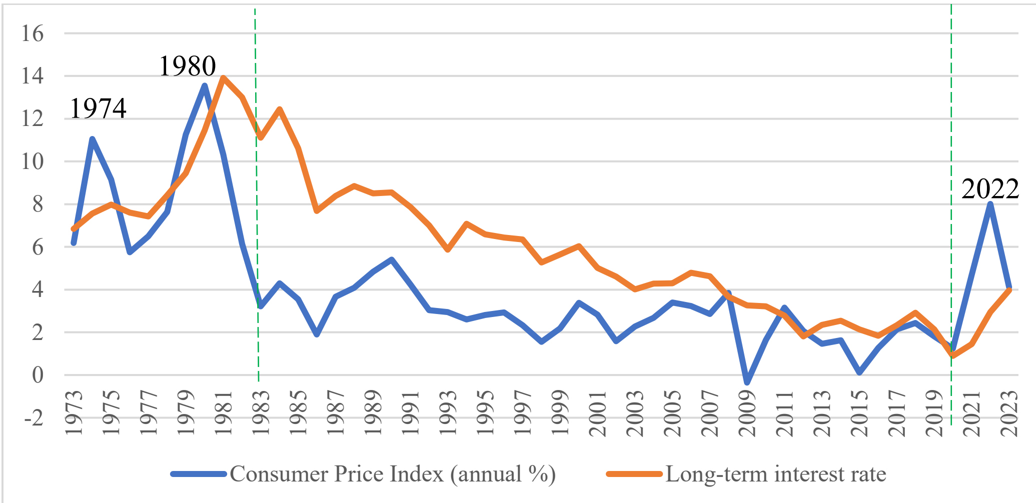
GARCH class. For the application of processes with non-linearity in the mean, we chose the Markovian regime model. We then carried out a specification test with the information criteria of Akaike (1969, AIC), Schwarz (1978, SIC), and the LR statistic (Log likelihood ratio) in order to choose which of the two models was best suited to the US inflation rate data. The results obtained led us to select the two-regime Markov model.

In the third part of our study, we analyze the impact of inflation on the various fundamental determinants of insurance company performance in the US. To do this, we measured the performance of insurance companies with seven performance measures. The first is the Combined ratio. It measures the operating cost management efficiency of the insurance business (insurance business performance). The second is the Net investment income to Total assets ratio, which isolates the performance of the investment business. The third is the Operating ratio, which indicates insurers' overall performance (for the insurance business and investment business combined). The fourth is Return on assets (ROA), which describes insurers' financial profitability. The fifth is the Capital to Total assets. It measures the return on shareholders' equity invested in total assets. Finally, we considered variations in insurance premiums and claims costs. We show that these performance indicators are differently affected by inflation in the Life and P&C insurance sectors and according to the inflation regime considered.

The rest of the document is organized as follows. Section 2 analyzes the main characteristics of the US inflation during the 1973–2023 period and presents the motivation of our study. Section 3 reviews the significant contributions in the literature on inflation in the insurance sector. Section 4 presents the main indicators of performance studied while Section 5 is dedicated to the characteristics of inflation during the period of analysis. We then study the non-linear stochastics processes of inflation in Section 6 and analyze the effects of inflation on the insurance industry using the Markov model in Section 7. Section 8 concludes the report.

2. US inflation rate trend and research motivation

Figure 1: Trends in inflation rate (annual CPI rate)
and the nominal rate of LT (10-year) government bonds,
1973-2023 analysis period



Source: World Bank.

Figure 1 shows that the United States has experienced three inflationary thresholds since 1973. The first threshold was observed in 1974. It is linked to a first oil shock, in 1973. The second threshold, the most important of this period, was observed in 1980. It is linked to a second oil shock, in 1979. The third threshold, seen in 2022, is associated with the COVID-19 pandemic of 2020-2023.

In addition, Figure 1 shows that the US inflation rate series from 1973 to 2023 is characterized by non-linear dynamics. It is easy to see that the US inflation rate series is separated into two distinctive subsamples (possibly regimes). The period from 1983 to 2020 is marked by low levels of the inflation rate, while the rest of the sample, i.e. the periods of 1973 to 1982 and 2021 to 2023, shows a high level of the inflation rate. The fact that the inflation series differs from one subsample to another illustrates the potential presence of a regime-switching process in the US inflation rate series.

Two major changes are believed to have caused the separation of the US inflation rate series into these regimes. The first is linked to Paul Volcker's arrival at the Fed in 1979 and the resulting monetary policy reform. In October 1979, US President Jimmy Carter appointed Paul Volcker as chairman of the board of governors of the central bank. He was tasked with taming high inflation in the U.S. in the 1970s and 1980s, caused by the oil shocks of 1973 and 1979. To succeed in his mission, Volcker had to pursue a very aggressive restrictive monetary policy between 1980 and 1983. This monetary policy consisted in maintaining the Fed's key interest rate. The aim was clear: to subdue economic activity in order to dampen price growth. Paul Volcker's gamble paid off: The US inflation rate fell from 13.9% in 1980 to 3.2% in 1983. The year 1983 marked the break with the high-inflation regime and the transition to a low-inflation regime observed over the 1983-2019 period. Ahlgrim and D'Arcy (2012) mentioned that 1983 marks the start of the period of moderate levels of inflation for the insurance industry. The second change is linked to the COVID-19 pandemic shock. Appearing in early 2020, this shock marks the break with the low-inflation regime and the shift to a new high-inflation regime from 2021 to 2023.

In sum, our graphical analysis shows that the US inflation rate series observed over the 1973-2023 period can be characterized by a regime-switching process divided into two regimes: the low-inflation regime (State 1) and the high-inflation regime (State 2). Protecting insurers against the risks associated with regime shifts involving the transition (sudden or smooth) from a low-inflation regime to a high-inflation regime is now a necessity because inflation affects not only insurers' investment decisions (profitability of the investment business), but also the pricing of insurance products and claims management (profitability of the insurance business). However, Figure 1 may also contain three regimes. In this report, we investigate whether rising or falling inflation enhances or hinders insurance company performance, depending on whether the US economy is in a period of low, high, or moderate inflation period.

3. Literature review

3.1. Economic inflation

Economic inflation is the loss of purchasing power that results in a general and sustainable increase in prices. The inflation rate is the percentage change of a price index during a period, usually a year. Inflation can affect the real economy and the monetary policy.

There are two kinds of inflation originating from the real economy (Sowell, 2004). Demand pull inflation where workers with higher wages increase their demand for goods and services. Supply push inflation from natural resources exogenous shocks or other material supply shocks and labor shortage as we particularly observe in 2021 to 2023. The observed oil price shock explained by the current war in Ukraine is an example of such inflation driver. It could also be associated with the post COVID-19 economic environment. A poor local currency may create inflation in an open economy as imported goods and services will become more expensive (demand pull) while imported natural resources for production push prices (supply push). Finally, inflation can be caused by monetary policy, the other main causality link. A central bank may increase the money supply without having a corresponding increase in real output. This increase in money supply may then devaluate the local currency and increase prices of imported goods and services.

Deflation is another issue that must be considered. Deflation is a decline in the general price index explained by a lack of aggregate demand. Suppliers of goods and services must cut their selling prices and wages because demand is low. Deflation can induce unemployment and even a recession. Deflation may also be caused by a drop in the aggregate supply of money. On the converse we can have hyperinflation often explained by a large supply of money in the economy following important government deficits.

Social inflation is particular to insurance. It is defined as excessive growth in insurance settlements of claims often established by courts (Lynch and Moore, 2022). We do not consider social inflation in this report. See The Institutes (2020), Pain (2020), and Wellington (2023) for analyses.

The price index the most often used is the Consumer Price Index (CPI) of a large basket of goods (Bureau of Labor Statistics, BLS). Keeping a constant basket over the years may create a bias, because some goods may become less important for consumption and new goods from innovations may turn into high demand. Moreover, during an inflation period, customers may substitute goods with high inflation in the general basket and consume other goods with lower inflation rate. A US Senate committee concluded that the CPI overstated inflation by 1.1% in 1996 (Boskin et al., 1996; see also Gordon 2006). Since 1999, the BLS updates the index. We do not consider other measures of inflation in this study.

3.2. Causes of recent inflation

Inflation was not important over the 1983-2019 period. The 2007-2009 financial crisis did not accentuate price variations significantly although it affected financial markets. Particularly it increased default and liquidity risks in the banking sector.

The COVID-19 crisis had a different pattern on prices stability by creating shortage in many markets and inciting many governments to inject money into the economy. Following the recent COVID-19 pandemic, inflation became an international growing concern. The BLS reported that the CPI for all items in the US rose 7% from December 2020 to December 2021, the largest annual percent change since 1981. The annual inflation rate was 8.3% in April 2022 (6% in December 2022 and 3.3% in May 2024). The European Union annual inflation rate was 5.3% in December 2021 and 7.4% in April 2022 (10.4% in December 2022 and 2.4% in April 2024).

Many sources of the recent inflation are reported. Labor shortage in about all sectors is often mentioned as a primary source. The pandemic has triggered many workers to re-evaluate their priorities and discouraged many unemployed individuals from returning to the workforce. These labor shortages have led pressure for businesses and caused operational delays. Some employers had to increase their compensation packages to retain or attract workers. Such trends have increased overall labor costs. Supply chain disruptions represent another source of inflation during this period. They caused production slowdowns during pandemic-related closures and created scarcity. Finally, the Russia-Ukraine war is view as another cause of inflation for energy and food prices.

Used cars, houses replacement prices and skilled workers wages were particularly affected, values that are directly related to the severity of insurance claims. Moreover, the economic activity was restarting in the third quarter of 2021 which may have increased road accidents frequency and severity. Inflation also affected interest rates and consequently investments decisions and asset-liability risk management activities.

Blanchard and Bernanke (2023, 2024) analyze the causes of the post COVID-19 inflation. They show that, for the US, the recent inflation period was explained by strong increases in the prices of food and energy. Supply disruptions in key sectors is also a cause, as well labor supply became tight and contributed to wage inflation. They conclude that, for the United States, returning to price inflation target may require higher unemployment.

They estimate the relationships between four endogenous variables: wage inflation, price inflation, short-run inflation expectations, and long-run inflation expectations. Lag explanatory variables such as price inflation, wage inflation, commodity price shocks, sectoral shortages, and labor market tightness were used as explanatory variables over the period from 1990 to the start of the pandemic[1]. They then used their

[1] For example, wage inflation is function of lag of wage inflation, and lagged values of other determinants such as ratio of vacancies and the number of unemployed persons. Price inflation is

estimates to simulate the inflationary effects of the various shocks that affected the US economy from the beginning of 2020 to early 2023. The quarterly data used was for the period 1990Q1 to 2023Q2.

They find that energy prices, food prices, and price spikes due to shortages were the significant drivers of inflation in its early stages, although the second-round effects of these factors, through their effects on other prices and through higher inflation expectations and wages were limited. The contribution of labor market conditions to inflation was initially modest. But as product market shocks became less significant over time, the labor market conditions and the persistence in nominal wage increases have become the main factors behind wage and price inflation. These sources of inflation were unlikely to depart without macroeconomic policy intervention from the Fed.

The US response to the COVID-19 pandemic included a series of federal intervention plans which caused roughly $5 trillion in government spending. These programs contributed to strong consumer and business demand, which affected labor markets in mid-2021 and early 2022, causing upward pressure on wages and prices. In summary, rising commodity prices and supply chain disruptions were the principal triggers of the recent inflation. But when these factors became less significant, labor market conditions and wage increases became the main drivers of the rate of price increase.

3.3. The historical effect of inflation on the insurance industry

The main reference for this section is the excellent survey prepared by Ahlgrim and D'Arcy (2012) for the Casualty Actuary Society, the Canadian Institute of Actuaries, and the Society of Actuaries. Additional recent documents are also discussed although they are

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function of wage inflation and generic price shocks. Short-run inflation expectations are a weighted average of long-term inflation expectations and realized inflation. Long-run inflation expectations evolve as a weighted average of the previous link of long-run expectations and actual inflation. Different additional lags were added in the applications.

few because inflation has not been a popular research subject over the recent years. We also present recent industry documents.

The effect of inflation on the real economy depends on the fact that it was anticipated or not. For example, workers may ask for higher wages when they anticipate inflation. Not anticipated inflation by workers may cause increases in prices higher than wage increases and reduce the aggregate demand in the economy. Inflation could create a number of concerns for insurance policyholders and insurers. Inflation may also have redistributive effects (Blanchard, 1987).

Insurers should be proactive in managing inflation to keep profitability and reserves in adequate real values. Reinsurers must also be proactive in insulating their portfolios by conditioning and managing their treaty features in relation to inflation. Different financial hedging instruments (T-Bills and ETFs) can be used but the literature is very scarce on this subject.

During the 1951-1976 period, inflation had a negative correlation with underwriting margin profits and investment returns in the P&C insurance industry (D'Arcy, 1982). No significant correlation between levels of underwriting profits and inflation was observed during the 1977-2006 period (Krivo, 2009). A negative and significant correlation was observed between inflation and investment returns during that period.

Masterson (1968) measures the impact of inflation on insurers by isolating components that are related to inflation by line of business. Inflation did not have an isolated impact on insurer performance. While high inflation by itself may increase claim costs of insurers, the interaction with other economic and financial variables may lead to a more complex risk assessment. When an insurer may be experiencing higher automobile claims caused by inflation, these effects may be offset by lower employment which might influence negatively workers compensation claims.

Investment returns and change in underwriting profit margin were both significantly negatively correlated with inflation over the 1977-2006 period. More importantly, a positive relationship between T-Bill yields and inflation was estimated in the two 1951-1976 and 1977-2006 periods. In fact, D'Arcy (1981) recommends using T-Bills to immunize deteriorations in underwriting profit margins due to inflation. There is a trade-off here between return and coverage, and T-Bills represent a form of risk management during inflation period because of their very short duration.

Lowe and Warren (2010) describe the negative impact of inflation on property-casualty insurers' claim costs, loss reserves and asset portfolios. However, the article does not mention if the effects are statistically significant or not. The authors express concern that most current actuaries, underwriters and claim staff have never experienced severe inflation, so could be slow to adapt to any change in the economic environment.

In general, medical cost inflation for property-casualty insurers tends to exceed the general inflation rate. The Milliman Medical Index shows that the healthcare costs for workers and their health insurance companies have increased at a rate significantly in excess of the rate of inflation (Mayne et al, 2011).

Another major component of claim costs for property-casualty insurers is with liability claims for damage to property or injury to a person caused by an insured. In these cases, the claimant has little incentive to control costs when they will be paid by the party's insurer responsible. In fact, there is the perverse incentive to increase the cost of such items as medical care or loss of wages, to generate a larger settlement for non-economic losses such as pain-and-suffering (ex-post moral hazard, Dionne and St-Michel, 1991). As noted by Lowe and Warren (2010), when inflation spiked in the 1980s, a liability insurance crisis erupted, with claims costs increasing well in excess of the general inflation rate. Insurers are also likely to experience adverse development on loss reserves if inflation increases. As explained in D'Arcy et al. (2009), loss reserves are commonly set based on the inherent assumption that the inflation rate experienced in the recent past will continue until these claims are closed. For some liability insurance lines, it can take a decade for these losses to close.

Another impact of inflation is on the investment portfolio. As noted long ago by Fisher (1930) nominal interest rates (or money rates in insurance terminology) and inflation are closely related, as investors expect a return, over the inflation rate, as compensation for foregoing current consumption. An increase in interest rates reduces the value of long-term fixed income holdings, which make up a significant proportion of investments for property-casualty insurers. Insurance investment returns were significantly negatively correlated with inflation during the period 1933-1981 (D'Arcy, 1982) and that of 1977-2006 (Krivo, 2009). In addition, stock returns were significantly negatively correlated with inflation during the period 1933-1981 (D'Arcy, 1982), although not during the period 1977-2006 (Krivo, 2009). This discrepancy may be due to the level of inflation and whether it was expected. A return to a high level of inflation could reduce the value of stocks held in insurers' portfolios. If inflation rates were to increase sharply, the impact on property-casualty insurers would be significant. Earnings from both underwriting and investments will be reduced, in the short run, and policyholder surplus will decrease as a result of both increased liabilities and reduced asset values.

If inflation is bad for property-casualty insurers, is deflation good? During the Depression, 1930-1939, the US experience a deflation rate in six of the ten years. At the same time, the property-casualty insurance industry experienced underwriting losses in two of those years, but relatively high underwriting profits during the remainder of the period. In addition, investment returns were low, and stock returns extremely volatile, during most of the depression. The risk of default on bonds was high, creating a challenging investment environment for insurers.

The resurgence of inflation in 2020 was a surprise in insurance markets (Geneva Association, 2023). The immediate impact of inflation on non-life insurers' earnings should be negative according to the report, primarily through rising future claims costs on current insurance policies and the need to protect loss reserves with more capital.

The effect on life insurers' earnings should be more neutral. Most life insurance products, e.g. mortality, wealth accumulation and longevity protection, offer benefits that are nominally fixed. Rising interest rates may negatively affect insurers' balance sheets. Higher interest rates, however, could have a favorable effect on the net present value of future liabilities.

According to the Geneva Association (2023), there is a wide range of management actions insurers can take to respond to the recent macroeconomic environment. In terms of product design, insurers could offer more low-cost products with an increased focus on risk and loss prevention. With tight labor markets and increasing wage pressure, insurers can also improve operational cost efficiency and overall productivity. However, these activities take a long while to realize.

One underwriting response to inflation is to reset the insurance price of risks that exhibit high claims costs. This activity depends on the competitive environment in insurance markets, insurers' anticipation about central banks' ability to reduce inflation and the degree of public policy and regulatory constraints.

In investment management, there is some possibility for inflation protection on asset allocation by moving the investment portfolio away from bonds towards commodities, equities and real estate. For many insurers, however, such potential activity is constrained by their very high solvency capital requirements.

Every insurer should monitor price developments, focusing on insurance exposure, such as repair costs, construction prices or medical cost inflation. Insurers must react to anticipated cost increases by adjusting premiums. Moreover, the balance of an increase in premiums and potential losses of clients effects must always be considered. The same logic applies to reserving, especially in long-tail business. In this context, rising interest rates can mitigate selection issues by making it easier to finance long-term guarantees.

On the investment side, there are two divergent aspects, according to the Geneva Association report. On the one hand, rising interest rates are positive regarding investment yields. On the other hand, escalating anxiety of an economic recession can substantially affect market values and volatility.

In general, effective insurer responses to inflation would have to occur ex-ante, rather than ex-post. So, inflation anticipation remains a key issue. Once inflation has picked up, the value of inflation-linked securities and the level of interest rates reflect capital markets' inflation expectations, which drive up the cost of any hedging strategy. This means that the insurance industry must have models to anticipate inflation.

According to EIOPA (2023), the key determinants of P&C insurers' welfare sensitivity to inflation and corresponding higher interest rates are the exposure to interest rate sensitive assets, the relative duration of liabilities and the sensitivity of claims and expenses to inflation.

Inflation may also have an impact on regulated capital. A decrease in the value of fixed income assets leads to a decrease in market risks while an increase in exposure to future premiums might lead to a potential increase in underwriting risk. High inflation and interest rates could be beneficial for life and non-life insurers in the long run due to the reinvestment of assets at higher yields. In the short term, the impact should be negative mainly due to losses on interest rate sensitive investments.

When assessing the impact of inflation on profitability, the time horizon needs to be considered. In the short run, the impact of inflation on profitability may be negative, in particular for non-life insurers with higher share of business in competitive lines of business such as liability insurance. The impact is reflected in higher claims for which insurers must increase their reserves. Moreover, premiums need to be adjusted to maintain the equilibrium combine ratio. In the short run, under market competition, underwriting profitability is usually reduced.

Another important component of profitability is investment (EIOPA, 2023). If high inflation generates high interest rates this would result in higher investment returns on the fixed income portfolios. Better investment results would allow non-life insurers to compensate for lower premium increases and maintain overall profitability. In other words, considering that the pre-tax profitability of a non-life insurer is the sum of the underwriting result and the investment result, then higher investment results can provide at least a partial offset for the inability to increase premiums in line with inflation. This suggests that the potential partial offset from higher investment results should be significant for long-tail business.

Regarding the impact of inflation on insurance asset values, according to Swiss Re (2010, 2022), the impact of inflation on asset prices depends on time horizon. Insurers must consider short and long-term effects of inflation separately. Insurers can substitute bonds to commodities, equities, and real estate. In investigating the correlation between different asset classes returns and CPI in the US market between 1998 and 2009, the study showed that treasury bills and real estate were positively correlated while long-term bonds were negatively correlated.

One can examine the relationship between inflation and different variables such as underwriting profit margins, investment income, combined ratio, and capital, over an entire time period. What is important under a regime switching environment is the relationship within each regime, not across all regimes. Thus, we need to break the historical data into different regimes. Unfortunately, it is not possible to always identify particular regimes, even in retrospect. A deflation rate could be the result of a deflation regime, or an outlier value experienced during a normal, or even high inflation regime. Alternatively, an inflation rate in the normal range could occur even though the economy is experiencing a deflation or high inflation regime.

In this research we consider an inflation model that will have three potential regimes. One interpretation of these inflationary regimes is that when the economy is experiencing normal economic periods, the average inflation rate should be considered moderate. But two other economic regimes are possible. First, petroleum chocs may lead to sustained inflationary pressures. In this high inflation regime, there is a significantly higher average level of inflation than indicated from recent history. This may also correspond to the post-COVID 2019 economic situation. It is even plausible that, in this high inflation regime, inflation volatility may be higher. A final regime is one of continued worldwide economic stagnation with moderate government spending and central bank easing. This third regime incorporated in the inflation model reflects the possibility of deflationary pressures. The average level of inflation and its volatility should be low. This third potential regime should not be significant for the recent inflation period.

4. Insurance business performance indicators

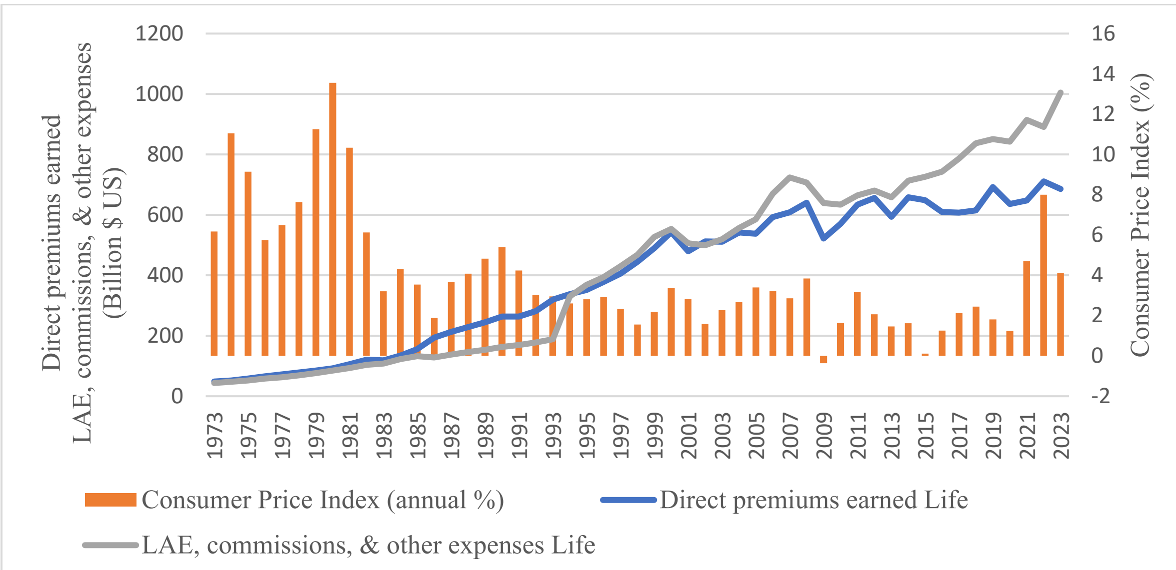
Two accounting indicators are often used by insurance professionals to measure insurance companies' performance: the combined ratio (indicator of efficiency in managing the operating costs of the insurance business) and the operating ratio (indicator of efficiency in managing the operating costs of the insurance business and investments). These two indicators, also known as loss ratios, are widely used in the insurance industry. In addition to these indicators of operating cost management efficiency, there is another indicator traditionally used in the literature to measure the performance of insurance companies: the ROA (Return on Assets), which measures the accounting profitability of insurers (Dionne and Harrington, 2014). Finally, insurers' capital and investment levels are indicators of their ability to cover more or less anticipated risks.

4.1. Management efficiency indicators for insurance business operating costs

- Influence of inflation on the combined ratio

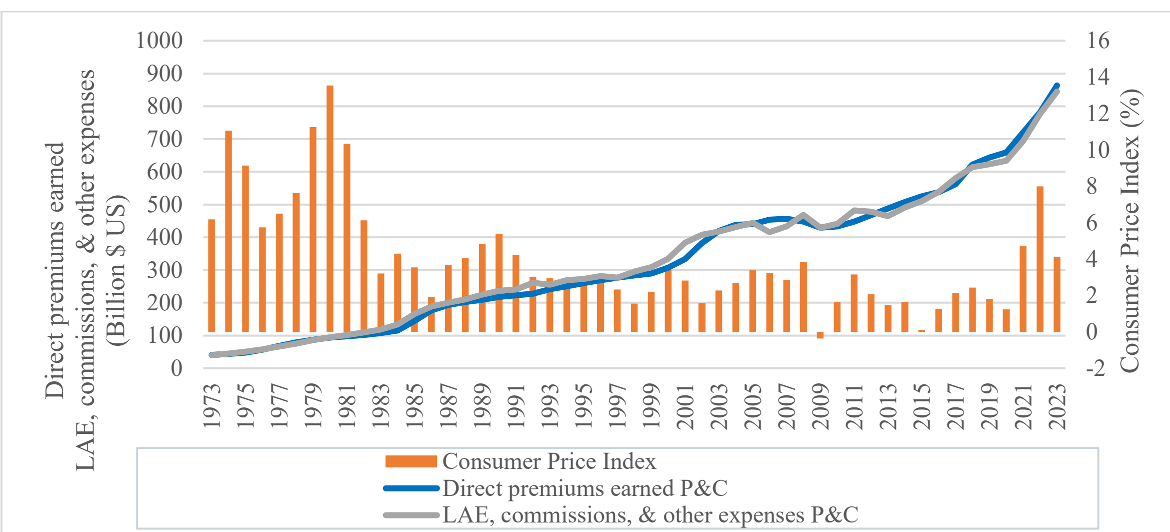
The combined ratio is measured by the ratio of total operating expenses (claims paid + management expenses) to premiums collected (insurance policies sold). This indicator shows whether premiums collected are sufficient to cover all operating expenses. Clearly, the most obvious risk for the insurer is that premiums collected are insufficient to pay policyholder claims and cover management expenses. The less sufficient premiums are to cover claims paid and management expenses, the higher the combined ratio will be, and the more the insurer will experience financial difficulties. Consequently, a high combined ratio will have a negative influence on the profitability of insurers' insurance business. A combined ratio below 100% means that the insurance company is in a profitable situation.

Figure 2: Trends in inflation (CPI), premiums collected and total operating expenses in the Life sector, 1973-2023 analysis period



Source: American Council of Life Insurers (ACLI).

Figure 3: Trends in inflation (CPI), premiums collected and total operating expenses in the P&C sector, 1973-2023 analysis period



Source: AM-Best.

Generally speaking, the two determinants of the combined ratio—total operating expenses (claims paid + management expenses) and premiums collected—follow the same rhythm, as shown in figures 2 and 3. Figure 2, however, points to some difficulties in the life insurance sector since the financial crisis of 2007-2009, despite the fact that inflation was at a low level before 2021. Inflation can affect each of the two determinants of the combined ratio. In fact, it is difficult to detect the precise influence of inflation on the combined ratio.

The P&C sector appears more stable than the Life sector over the same period, as shown in Figure 3. This difference can be explained by low interest rates, such as those observed in Figure 1 (Dionne et al., 2024). The life insurance sector has been more affected by the low interest rate policy of the Fed after the 2007-2009 financial crisis, a policy not related to inflation but to the lack of liquidity in different markets.

- Influence of inflation on the operating ratio

According to Ahlgrim and D'Arcy (2012), an insurance company has two main sources of revenue, namely premiums and net investment income, and two main sources of costs, namely claims paid and operating expenses (commissions and management fees or operating expenses). These two main sources of income and two main sources of costs (LAE)[2] are used to determine the operating ratio (Hull, 2018).

An insurance company can be profitable even with a combined ratio of over 100%. This is because the combined ratio does not consider the second source of income for insurance companies: net investment income, which comes from income earned on premiums invested in bonds, equities or other forms of longer-term investment. The inclusion of net investment income should reduce the level of the operating ratio in periods of high financial profitability, often associated with low inflation.

[2] Losses and adjustment expenses.

In the remainder of our analysis, we have chosen the operating ratio as the most reliable indicator for measuring the efficiency of operating cost management in the insurance business, since it considers the total level of revenue and the total level of operating expenses. As the operating ratio is an increasing function of the combined ratio, we can deduce that inflation can have a positive or negative influence on the operating ratio.

- Financial performance indicator for the insurance business

Until now, we have analyzed the performance of insurance companies simply by considering their operating activity, i.e. the net profit generated by their commercial activity, without considering the capital invested by shareholders and creditors to finance this activity. In fact, an insurer's real performance lies in its ability to create value or wealth for the shareholders and creditors who finance its activity. The impact of capital invested by shareholders and creditors on profitability is measured by the ROA (Return on Assets) indicator. ROA is obtained by taking the ratio between net income and total assets. This measure indicates profitability per dollar invested. In other words, the financial performance of the insurance business (ROA) is an increasing function of the profitability of the insurance business. We have just mentioned that inflation can exert a positive or negative influence on the profitability of the insurance business and that ROA is an increasing function of the profitability of the insurance business. It can then be argued that inflation can exert positive or negative effects on the performance of the insurance business.

- Insurers' capital or surplus (capital ratio)

The capital ratio, often measured by Capital and Surplus to Total assets, is determined by the ratio of shareholders' equity to total balance sheet assets (unadjusted for risk). It indicates insurance companies' efficiency in managing insolvency risk. Stronger capital means more reserve available to cover potential losses. Holding a high level of capital also lets insurance companies avoid an urgent need for capital and mitigate insolvency risk. This means that the best-capitalized insurance companies will be able to incur greater losses before becoming insolvent. Consequently, a high level of capitalization is a guarantee of the solidity of insurance companies. The level of capitalization can be affected by inflation when profitability is affected.

5. Properties of the U.S. inflation rate series

In this section we look at some empirical regularities in the US inflation rate series as measured by the annual rate of the consumer price index (CPI).

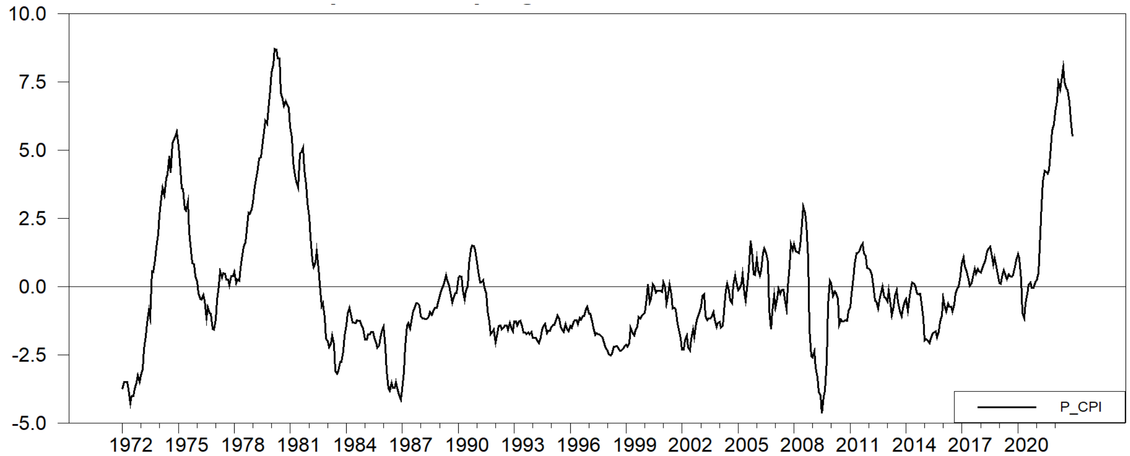
5.1. Non-stationarity

Figure 1 shows that the CPI annual rate series appears to be non-stationary. To verify this, we apply the Augmented Dickey-Fuller (ADF) stationarity test. We test the null hypothesis that the CPI variable is non-stationary (contains at least one unit root) against the alternative hypothesis of stationarity. Our ADF test on CPI, using a model with a constant and trend for an optimal lag equal to 3, gives us a *p*-value of Z(t) = 0.8039. As the *p*-value is above any significance level, the null hypothesis that CPI is non-stationary is not rejected. In this case, the use of the usual asymptotic properties to study the effect of inflation is not valid.

The non-stationary nature of the series may be linked to the presence of a deterministic linear trend or to the presence of a stochastic trend in the CPI series. To make the CPI series stationary, we will first assume the presence of a deterministic linear trend and perform a linear regression (OLS) of the series against a time trend variable. We will then extract the trend and recover the residuals.

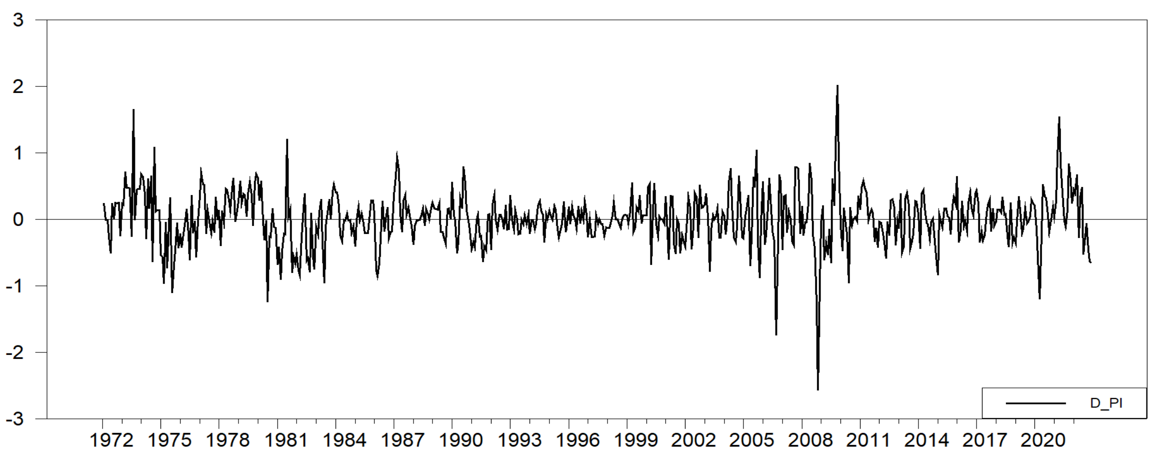
Figure 4 shows that the series still seems to retain its non-stationary character after the deterministic trend is extracted. This leads us to suspect the presence of a stochastic trend in place of the deterministic linear trend in the US CPI rate series. To verify this, we transformed the series into first-difference mode.

Figure 4: Evolution of the annual CPI rate after purging the deterministic trend, 1973-2023 analysis period



Source: World Bank.

Figure 5: Evolution of the CPI rate after purging the stochastic trend, 1973-2023 analysis period



Source: World Bank.

Figure 5 shows the variation of the CPI rate around a mean. In some periods, the CPI rate varies only slightly around its mean, while in others, the variations are very large. As can be seen in Figure 5, the downward trend in the CPI rate has been suppressed, and the series average appears to lie on a straight line parallel to the x-axis. In this case, the CPI rate variable is integrated of order 1, because it is made stationary after a difference. We check this graphical result using the Augmented Dickey-Fuller (ADF) test. Our application of the ADF test on the CPI rate, using a model with constant and trend for an optimal lag equal to

2, gives us a *p*-value Z(t) equal to 0.0003, which is well below the 5% significance level. Consequently, the null hypothesis that CPI inflation purged of the stochastic trend is non-stationary is rejected.

Our analysis enabled us to detect the presence of non-stationarity in the inflation series. In the presence of non-stationarity, a series has an infinite (long) memory or finite (short) memory depending on whether the CPI variable and the shock variable are integrated of order 1 and cointegrated or not. Consequently, a shock may have a permanent or short-term impact on the inflation series. The cases of the oil shocks of the 1970s (1973 and 1979), the 1980 monetary policy, and COVID-19 on the CPI rate may be illustrative. To demonstrate this, we will use VAR(c) processes, where *c* denotes the number of orders. VAR(l) models were introduced by Sims (1980) as alternatives to Keynesian-inspired macro-econometric models. In empirical applications, one of the main utilities of VAR processes is to analyze impulse responses of the variables under study.

5.2. VAR(l) processes and impulse responses

- Description of the Vector Autoregression (VAR(l)) model

VAR(l) processes are a generalization of autoregressive processes (AR) to the multivariate case (Sims, 1980). VAR(l) modeling is based on the assumption that the evolution of the economy is well described by the dynamic behavior of a vector of N variables that are linearly dependent on the past. The advantage of the VAR(1) model is that it is a powerful forecasting tool.

We use a VAR(l) model containing two variables, y_t and x_t. Each variable is a function of its own past values, but also of the past values of the other variable in the system of equations (1) and (2).

$$y_t = \beta_0 + \sum_{j=1}^{l} a_j y_{t-j} + \sum_{j=1}^{l} b_j x_{t-j} + u_{t,y} \tag{1}$$

$$x_t = \beta_0 + \sum_{j=1}^{l} a_j x_{t-j} + \sum_{j=1}^{l} b_j y_{t-j} + u_{t,x} \quad (2)$$

where y_t represents inflation (CPI), x_t our shock variable, $u_{t,y}$ is the unanticipated impact of inflation (innovation) on the inflation variable and $u_{t,x}$ is the unanticipated impact of the shock variable on the shock variable.

- Cointegration and VAR(l)

The VAR(l) model of order 1 is generally estimated on stationary variables. The VAR(l) model can also be estimated on non-stationary variables, provided they are integrated of order 1, i.e. they are non-stationary variables in the raw state that are made stationary after a difference. However, to estimate the VAR(l) model with non-stationary variables integrated of order 1, we need to distinguish between two possibilities for the VAR(l) model, depending on whether the variables y_t and x_t are cointegrated or not. The two special cases of the VAR(l) model are: 1) the VAR(l) level model, which is adapted to integrated variables of order 1 that are cointegrated, and 2), the VAR(l) difference model, which is adapted to integrated variables of order 1 that are not cointegrated.

The starting point for cointegration theory is the fact that many macroeconomic and financial series are non-stationary. Cointegration theory enables us to study non-stationary series of which one linear combination is stationary. It thus lets us specify stable long-term relationships. One of the fundamental properties of cointegration theory is that two non-stationary (I(1)) series, y_t and x_t, are cointegrated if there is a stationary linear combination (I(0)) of these two series.

According to Engle and Granger's (1987) approach, two non-stationary series I(1) of y_t and x_t are integrated if the residuals of the long-term relationship between these series are stationary. If two series y_t and x_t are cointegrated (stable long-term relationship between y_t and x_t,), the VAR(l) model can be estimated directly on the variables y_t and x_t. We thus estimate a level VAR(l) model. However, if the two series y_t and x_t are not cointegrated (short-term dynamics between y_t and x_t), we must consider the first difference of the variables, i.e. estimate a VAR(l) model in difference. To this end, it is therefore legitimate to test for the presence of cointegration to identify whether to use a *level* VAR(l) model or a VAR(l) model for our estimation. In short, we estimate a *level* VAR(l) model when we reject the null hypothesis (H_0) of no cointegration and estimate a VAR(l) model when we do not reject the null hypothesis of no cointegration.

- Two-step estimation method

Our approach to estimating the VAR(c) model is based on a two-stage estimation method proposed by Engle and Granger (1987). The advantage of this approach is that it is simple to implement. This technique is valid only for integrated series of order 1. The first step is to estimate the stable long-term relationship between the variables y_t and x_t. The second step consists in choosing one of the two special cases of the VAR(c) model best suited to the variables y_t and x_t.

- First step: Estimate the long-term relationship (static relationship between y_t and x_t)

Let the variables y_t and x_t be two I(1) variables. We estimate the following relationship:

$$y_t = \alpha + bx_t + v_t \tag{3}$$

where v_t is the error term. According to this equation, $v_t = y_t - \alpha - bx_t$, i.e. the error term v_t is a linear combination of y_t and x_t. In the special case where $b = 0$, v_t is I(1), since it is the sum of a variable y_t and the constant $-\alpha$. In contrast, if $b \neq 0$, it is possible that v_t is I(0). If we estimate (3) by OLS and find a high R^2, this indicates the presence of a long-run equilibrium relationship between the variables y_t and x_t. This relationship is called a cointegration relationship.

- Second step: Choosing and estimating the VAR(c) model

If the variables y_t and x_t are cointegrated, i.e. if the residuals of the long-run relationship in equation (3) are stationary, we proceed to estimating the *level* VAR(c) model in step 2. In the opposite case, we proceed to estimating the VAR(c) model in step 2.

5.3. Estimation of the VAR(c) model between inflation and the various shocks

5.3.1 VAR process for the 1970s Oil shocks variable and inflation

We represent the input, which is the oil shock variable of the '70s (positive inflation shock), by the x_t variable in our VAR(c) model. The variable 70s Oil shocks and inflation takes the value of 1 for each year of the period from 1973 to 1979, a period marked by various oil shocks during which inflation rose sharply. The CPI inflation output rate is represented by the variable y_t in our VAR(c) model.

Since Engle and Granger's (1987), we know the method is valid only for integrated series of order 1, i.e. I(1). We first need to determine the order of integration of each of our two variables: CPI and 70s Oil Shocks. We showed earlier that the CPI series is made stationary after a difference. It is therefore integrated of order 1(1). We will now check whether the 70s Oil Shocks variable is also integrated of order 1.

Table 1: ADF test on the 70s Oil Shocks variable,
1973-2023 analysis period

Z(t)	Test Statistic	1% Critical value	5% Critical value	10% Critical value	*p*-value
70s Oil shocks	-2.407	-4.159	-3.504	-3.504	0.376
D70s Oil shocks	-7.205	-4.159	-3.504	-3.182	0.000

Note: D stands for first difference.

Table 1 shows, in the first row, a *p*-value of Z(t) = 0.3756, which is above the 5% significance level. The null hypothesis that the 70s Oil shocks variable is non-stationary (presence of unit root) is therefore not rejected. We took the first difference of the 70s Oil shocks variable (D70s Oil shocks) and repeated the test. The result of the Augmented Dickey-Fuller (ADF) test on the variable D70s Oil shocks, shown in the second row of Table 1, indicates a *p*-value of Z(t) = 0.000, which is below the 1% significance level. Consequently, the null hypothesis, that the variable D70s Oil shocks is non-stationary, is rejected. In other words, the variable 70s Oil shocks is stationary after a difference and therefore integrated of order 1.

We now need to determine whether there is a stable long-term relationship between these two variables. To this end, we will estimate the static relationship between the 70s Oil shocks variable and the CPI variable. Next, we will recover the residuals of the static relationship and apply ADF tests on them.

Table 2: Estimation of the static relationship between 70s Oil Shock and CPI, 1973-2023 analysis period

Dependent variable	CPI
70s Oil shocks	4.874*** (0.901)
Constant	3.342*** (0.371)
Observations	51
R-squared	0.332
Adjusted R-squared	0.319

Notes: Robust standard errors in parentheses. *** p<0.01.

We mentioned that if we estimate the static relationship and $b \neq 0$, it is possible that the residuals of the static relationship v_t are I(0). This indicates the presence of a long-term equilibrium relationship between the variables y_t and x_t. The results of the estimation of the static relationship between the 70s Oil shocks variable and the CPI variable presented in Table 2 indicate that the coefficient of the 70s Oil shocks variable is statistically different from zero at 1%. It is therefore possible that the residuals (v_t) of the static relationship between 70s Oil shocks and CPI are stationary. We will check this by applying the ADF test to the residuals of the static relationship between the two variables. Table 3 shows the results of the ADF tests on the residuals of the static relationship.

Table 3: ADF test on the residuals of the static relationship between the 70s Oil shock and CPI variables, 1973-2023 analysis period

Z(t)	Test Statistic	1% Critical value	5% Critical value	10% Critical value	*p*-value
RES	-2.853	-3.600	-2.938	-2.604	0.051

Note: RES stands for residuals.

Table 3 shows a *p*-value of Z(t) = 0.051, which is below the 10% significance level. Consequently, the null hypothesis that the residuals of the static relationship between 70s Oil shocks and CPI are non-stationary is rejected. Consequently, the CPI and 70s Oil shocks series are cointegrated, i.e. there is a stable long-term relationship between these two variables. It is then possible to estimate the VAR(c) *level* model. To do this, we must first determine the order to retain. To this end, we have estimated various level VAR processes on our two CPI and 70s Oil shock series. For each model, we calculated the Akaike Information Criterion (AIC), the Schwarz Information Criterion (SIC) and the LR statistic. The LR statistic technique consists in estimating a constrained VAR(l) model and an unconstrained VAR(c+1) model, and computing the log likelihood ratio (LR). In other words, we can test the order *c* of the VAR model by considering the following equations:

$$\mathrm{H}_0\text{: } \Phi_{c+1} = 0\text{: VAR(c) process}$$

$$\mathrm{H}_1\text{: } \Phi_{c+1} \neq 0\text{: VAR (c+1) process}$$

where Φ is the optimal number of delays. VAR(c) represents the constrained model and VAR (c+1) the unconstrained model.

Under the null hypothesis, the LR statistic follows a chi-square distribution with *q* degrees of freedom. The *q* value is obtained by calculating the difference between the *c* of the unconstrained VAR (P_{H_1}) and that of the constrained VAR (P_{H_0}), which is the difference multiplied by the number of equations squared (N).

$$q = (P_{H_1} - P_{H_0})\, N^2$$

$$LR = 2\,(Log\_lik_{H_1} - Log\_lik_{H_0}).$$

The decision rule is as follows: If the value of the LR statistic is less than the critical value associated with a $\chi^2(q)$, H_0 is rejected (rejection of the constrained model). In this case, the LR test prefers the unconstrained model, namely the VAR(c+1) model.

We also use the BIC and AIC criteria. The BIC criterion is convergent and leads to asymptotically correct model selection, which is not the case with the AIC criterion. Further, the BIC criterion penalizes the results more severely than the AIC criterion does in terms of introducing too many variables into the model. This fits very well with the parsimony principle of Box and Jenkins (1970) and Box et al. (2015) in time series. According to this principle, when given a choice between two roughly equivalent models, we should choose the one involving the fewest parameters to be estimated. This is based on the principle that each parameter that we estimate represents one more possibility of making an error.

Table 4: Level VAR(l) model selection statistics,
1973-2023 analysis period

Var (p)	AIC	BIC	Log-likelihood
c = 1	2.5518	2.7812*	-57.7943*
c = 2	2.4365	2.8226	-49.6951
c = 3	2.4007	2.9464	-43.6162
c = 4	2.4473	3.1558	-39.5107
c = 5	2.2840	3.1586	-30.5318
c = 6	2.1336*	3.1774	-22.0049

Note: The asterisk indicates the model to be retained according to the selected criterion.

Table 4 shows the different statistics of interest for the choice of *c*. The AIC criterion chooses VAR (6) and BIC chooses VAR (1). The log-likelihood ratio statistic LR = 2 $(\text{Log\_lik}_{H_6} - \text{Log\_lik}_{H_1})$ confirms the choice with the BIC criterion. Indeed, calculation of the LR statistic gives us 71.57. This value is higher than the critical value for LR statistics, which comes from the distribution $\chi^2\ (20)$ since we have two equations ($N^2 = 4$) and the difference between the *c* of the unconstrained VAR (H_1) and the constrained VAR (H_0) is 5. The critical value at 5% is 31.41. In this case, H_0 is not rejected. Thus, based on the LR test, we prefer VAR (1) to VAR (6). We retain the level VAR (1) model to analyze the impulse response of inflation (CPI) to 70s Oil shocks.

5.3.2 Impulse response of inflation to the shock of the 1979 monetary policy reform

- VAR process between the variable 1979 Volcker shock and inflation

We represent the input, i.e. the 1979 Volcker shock variable, by the variable x_t in our VAR(c) model. Our 1979 Volcker shock variable takes the value of 1 for each of the years from 1980 to 1982, the period of implementation of the 1979 monetary policy reform led by Volcker. Once again, the CPI inflation rate is represented by the variable y_t.

We have previously shown that the CPI series is non-stationary and have made it stationary after a difference (D.CPI). We will now check the stationarity of the variable 1979 Volcker monetary reform shock before estimating our VAR model.

Table 5: ADF test on the 1979 Volcker shock variable,
1973-2023 analysis period

Z(t)	Test Statistic	1% Critical value	5% Critical value	10% Critical value	*p*-value
1979 Volcker shock	-3.262	-4.159	-3.504	-3.182	0.073
D1979 Volcker shock	-6.788	-4.159	-3.504	-3.182	0.000

Note: D stands for first difference.

Line 2 of Table 5 shows a *p*-value of Z(t) = 0.000, which is below the 1% significance level. Consequently, the null hypothesis that the variable D1979 Volcker shock is non-stationary is rejected. In other words, the D1979 Volcker shock variable is made stationary after a difference and is therefore integrated of order 1. Given that the two 1979 Volcker series and the CPI variables are integrated of order 1, we now need to check whether there is a stable long-term relationship between these two variables. To this end, we estimate the static relationship between the 1979 Volcker shock variable and the CPI variable.

Table 6: Estimation of the static relationship between 1979 Volcker shock and CPI, 1973-2023 analysis period

Dependent variable	CPI
1979 Volcker shock	6.844*** (1.409)
Constant	3.474*** (0.329)
Observations	51
Adjusted R-squared	0.388

Notes: Robust standard errors in parentheses. *** p<0.01.

Table 6 shows that the coefficient of the 1979 Volcker shock variable is statistically significant at 1%. It is therefore possible that the residuals of the static relationship between the 1979 Volcker shock and CPI variables are stationary. We will check this by applying an ADF test.

Table 7: ADF test on the residuals of the static relationship between 1979 Volcker shock and CPI, 1973-2023 analysis period

Z(t)	Test Statistic	1% Critical value	5% Critical value	10% Critical value	*p*-value
RES	-2.954	-3.600	-2.938	-2.604	0.040

Note: RES stands for residuals.

Table 7 shows a *p*-value of Z(t) = 0.040, which is below the 5% significance level. Consequently, the null hypothesis that the residuals of the static relationship between the 1979 Volcker shock and CPI variables are non-stationary is rejected. The CPI and Volcker Shock 1979 series are therefore cointegrated. It is then possible to estimate the level VAR(c) model. To do this, we first need to determine the order *c* to use for our estimation. To this end, we have estimated various level VAR processes on our two shock series, CPI and 1979 Volcker

Table 8: Level VAR(l) model selection statistics,
1973-2023 analysis period

Var (p)	AIC	BIC	Log-likelihood
c = 1	3.3940	3.6234	-78.8499
c = 2	3.2463	3.6324	-69.5339
c = 3	3.0111	3.5569	-58.2667
c = 4	3.5572	3.5572	-48.9438
c = 5	2.5699*	3.4445*	-37.1088
c = 6	2.6506	3.6945	-33.6391

Note: The asterisk indicates the model to be retained according to the selected criterion.

Table 8 shows that there is a consensus on the AIC and BIC criteria for the choice of VAR (5). We have therefore chosen the level VAR (5) model to analyze the impulse response of inflation (CPI) to the 1979 monetary policy reform shock from 1973 to 2023 (1979 Volcker shock).

5.3.3 Impulse response of inflation (CPI) to the shock of the COVID-19 pandemic

- VAR process between COVID-19 pandemic shock and inflation

We represent the input, namely the COVID-19 pandemic shock (positive inflation shock), by the variable x_t in our VAR(c) model. Our COVID-19 pandemic variable takes the value of 1 for each year in the period from 2020 to 2023 (even if the official end date is May 2023). The output represented by the y_t variable in our VAR(c) model remains the CPI inflation rate.

We begin by checking the stationarity of the COVID-19 pandemic variable before estimating our VAR model.

Table 9: ADF test on the COVID-19 shock variable,
1973-2023 analysis period

Z(t)	Test statistic	1% Critical value	5% Critical value	10% Critical value	*p*-value
COVID-19 shock	-0.825	-4.159	-3.504	-3.182	0.964
DCOVID-19 shock	-7.277	-4.159	-3.504	-3.182	0.000

Note: D stands for first difference.

Line 2 of Table 9 shows a *p*-value of Z(t) = 0.000, which is below the 1% significance level. Consequently, the null hypothesis that the DCOVID-19 shock variable is non-stationary is rejected.

Table 10: Estimation of the static relationship between COVID-19 shock and CPI, 1973-2023 analysis period

Dependent variable	CPI
COVID-19 shock	0.674
	(1.684)
Constant	3.971***
	(0.429)
Observations	51
Adjusted R-squared	-0.017

Notes: Robust standard errors in parentheses. *** p<0.01.

Table 10 shows that the coefficient of the COVID-19 shock variable is not statistically significant. The non-statistical significance of this coefficient suggests that the residuals of the static relationship between the COVID-19 shock and CPI variables are non-stationary. We will check this by applying the ADF test to the residuals of the static relationship between the COVID-19 shock and CPI variables.

Table 11: ADF test on the residuals of the static relationship between the variables COVID-19 shock and CPI, 1973-2023 analysis period

Z(t)	Test Statistic	1% Critical value	5% Critical value	10% Critical value	*p*-value
RES	-1.901	-3.600	-2.938	-2.604	0.331

Note: RES refers to residuals.

Table 11 shows a *p*-value of Z(t) = 0.331, which is above the 5% significance level. Consequently, the null hypothesis that the residuals of the static relationship between the COVID-19 shock and CPI variables are non-stationary is not rejected. Thus, there is no stable long-term relationship between these two variables. It is then necessary to estimate the VAR(c) model. To do this, we must first determine the order *c* to retain. To this end, we have estimated various VAR processes on our two CPI and COVID-19 shock series.

Table 12: VAR(l) difference model selection statistics,
1973-2023 analysis period

Var (p)	AIC	BIC	Log-likelihood
c = 1	3.0084	3.2423*	-66.2005*
c = 2	2.9511*	3.3447	-59.3506
c = 3	3.0340	3.5170	-57.9192
c = 4	3.0320	3.5941	-54.2199
c = 5	3.1389	3.7877	-53.0567
c = 6	3.1363	3.8735	-49.4300

Note: The asterisk indicates the model to be retained according to the selected criterion.

Table 12 shows the different statistics of interest for the choice of *c*. The AIC criterion chooses VAR(2) and the BIC chooses VAR(1). Calculation of the LR statistic gives us a value of 13.699. This value is higher than the critical value for LR statistics derived from the distribution χ^2 (4). The critical value at 5% is 9.94. In this case, H_0 is not rejected. Thus, according to the LR test, VAR(1) is preferable to VAR(2).

5.3.4 Orthogonalization of shocks

Our econometric approach enabled us to retain the VAR (1) model to analyze the impulse response of inflation to the '70s oil shocks and to COVID-19, and the VAR (5) model to analyze the impulse response of inflation (CPI) to the 1979 Volcker shock. We have retained the VAR (1) process to explain the notion of orthogonalization of shocks.

$$\mathrm{CPI}_t = a_{11}\mathrm{CPI}_{t-1} + a_{12}\mathrm{Shock}_{t-1} + u_{1t} \tag{4}$$

$$\mathrm{Shock}_t = a_{21}\mathrm{Shock}_{t-1} + a_{22}\mathrm{CPI}_{t-1} + u_{2t} \tag{5}$$

where CPI represents inflation, Shock represents our shock variable, u_{1t} represents the unanticipated impact of inflation (innovation) on inflation and u_{2t} is the unanticipated impact of the shock variable on the shock. We can clearly see that a shock to u_{1t} will immediately affect the present value of inflation (CPI_t). It will also affect future values of inflation and those of the shock variable, because past values of inflation are involved in both equations.

If the innovations u_{1t} and u_{2t} are uncorrelated, interpretation of the impulse response function is very straightforward. In this case, u_{1t} is the inflation innovation and u_{2t} is the innovation of the shock variable. In contrast, if the innovations u_{1t} and u_{1t} are correlated, they have a common component that cannot be associated with a specific variable. It is arbitrary to assume common effects for innovations in impulse response analysis. To put it plainly, assuming common effects between innovations leads to incorrect interpretation in impulse response analysis. The Cholesky decomposition method (Brezinski and Tournès, 2014) allows us to orthogonalize innovations u_{1t} and u_{1t} to make them uncorrelated.

Table 13: Calculation of innovation correlation coefficients, 1973-2023 analysis period

	70s Oil shocks innovation	1979 Volcker shock innovation	COVID-19 shock innovation
CPI innovation	0.576***	0.431***	0.050

Note: *** p<0.01.

Table 13 shows a statistically significant correlation coefficient at the 1% level between CPI innovation (u_{1t}) and innovation in the 70s Oil shocks variable (u_{2t}). It also indicates a statistically significant correlation coefficient at the 1% level between CPI innovation (u_{1t}) and innovation in the 1979 Volcker shock variable (u_{2t}). The correlation coefficient between CPI innovation (u_{1t}) and innovation in the COVID-19 variable indicates a non-statistically significant relationship.

On the one hand, the results show that innovation in CPI and in the 70s Oil shock variable are correlated. This suggests that we need to orthogonalize innovations u_{1t} and u_{2t} to make them uncorrelated, in order to interpret the impulse response analysis correctly. The same applies to the CPI and 1979 Volcker shock variable innovations. On the other hand, the statistical significance of the correlation coefficient between CPI innovations and the 70s oil shock variable suggests that CPI and 70s oil shock are endogenous variables in the VAR(1) model. The same is true of the CPI and Volcker shock variables in VAR(5) model. The non-statistical significance of the correlation coefficient between the CPI and COVID-19 shock innovations suggests that the CPI and COVID-19 shock variables are exogenous variables in the VAR(1) model. To validate these results, we used the weak exogeneity test and the strict exogeneity test of Durbin-Wu-Hausman. This test determines whether variables are endogenous or exogenous in the VAR(1) model.

5.3.5 Exogeneity

The graphical representation of impulse responses differs according to whether the variables in the VAR system are exogenous or endogenous. It also depends heavily on the order in which the variables are arranged in the VAR model. A good VAR model specification requires variables to be ordered from the most exogenous to the most endogenous. This is why it is essential to test the exogeneity of our variables. To this end, we have used the weak exogeneity test for the 70s Oil shock and COVID-19 variables. To test the endogeneity of the Volcker shock variable (monetary policy shock), we used the strict exogeneity test of Durbin-Wu-Hausman (with instrument) because there is a collinearity problem in the data. This result is explained by the high correlation between the Volcker shock variable and the error term.

Table 14: Weak exogenous test for Oil shocks and COVID-19 shock variables, 1973-2023 analysis period

	(1) CPI	(2) CPI
70s Oil shocks	0.000	0.000
COVID-19 shock	0.887	0.001

Note: CPI is the dependent variable and shock is the independent variable.

Table 14 shows that the *p*-value associated with the coefficient of the independent variable 70s Oil shocks is less than 1%. This indicates that the null hypothesis (H0) that the 70s Oil shocks variable is weakly exogenous is rejected. In other words, the 70s Oil shocks variable is endogenous in our VAR(1) model. The *p*-value associated with the coefficient of the independent variable COVID-19 is greater than 10%. This indicates that the null hypothesis (H0) that the COVID-19 shock variable is weakly exogenous is not rejected. In other words, the COVID-19 shock variable is exogenous in our VAR(1) model. Column (2) of Table 14 shows that the independent variable CPI is endogenous in our VAR(1) model for each of our two variables: 70s Oil shocks and COVID-19 shock. In sum, we can conclude that our two shock variables (70s Oil shocks and COVID-19 shock) are endogenous in our VAR(1) model, whereas the COVID-19 variable is exogenous in our VAR(1) model.

We now turn to the exogeneity test for the Volcker shock variable. Since we will be treating the Volcker shock variable as an endogenous regressor, we have used the Fed interest rate variable, which is correlated with the Volcker shock variable, but not necessarily with the error term, as the instrument for our Durbin-Wu-Hausman strict exogeneity test.

Table 15: Strict exogeneity test by Durbin, Wu and Hausman, 1973-2023 analysis period

Durbin chi2(1) = 24.815 (p = 0.0000)	Wu-Hausman F(1,48) = 45.489 (p = 0.0000)

Notes: Tests of endogeneity. H0: Variables are exogenous.

The Durbin-Wu-Hausman strict exogeneity test indicates a *p*-value of less than 1%. The null hypothesis (H0) that the CPI and Volcker shock variables are exogenous is therefore rejected. In other words, these two variables are endogenous in our VAR(1) model.

5.3.6 Impulse response and forecast error variance decomposition

In this section, we present the nature of the VAR(c) models specified in the previous section. We will focus on the inflation impulse response functions for the 1970s oil shocks, the 1979 monetary policy reform shock, the COVID-19 pandemic shock and on the forecast error variance decomposition. These two analyses allow us to synthesize the essential information contained in the dynamics of the estimated VAR(c) system. The variance decomposition allows us to indicate the relative importance of each shock in explaining inflation fluctuations. As for the shock reaction functions, they enable us to highlight the nature of the effects of the various shocks on inflation.

- Impulse response of inflation (CPI) to 70s Oil shocks

Figure 6 plots the impulse response of the inflation variable (CPI) to 70s Oil shocks. The gray area represents the 95% confidence interval. The amplitude of the shock is assumed to be equal to one standard deviation, and we are interested in the effects of the shock over 15 periods (i.e. 15 years, from 1973 to 1988). This horizon represents the maximum time required for the inflation variable to return to its normal level (pre-shock level). We have shown that there is a stable long-term relationship between inflation (CPI) and the 1970s oil shocks. It is therefore possible to estimate the *level* VAR model. Furthermore, the Cholesky decomposition of the variance-covariance matrix of canonical innovations, advocated by Sims (1980), suggests that when the dynamics are stationary, short-run constraints should be imposed. These constraints express the absence of instantaneous response.

Figure 6: Inflation impulse response function (CPI)
to the 70s oil shocks, 1973 to 1988 analysis period

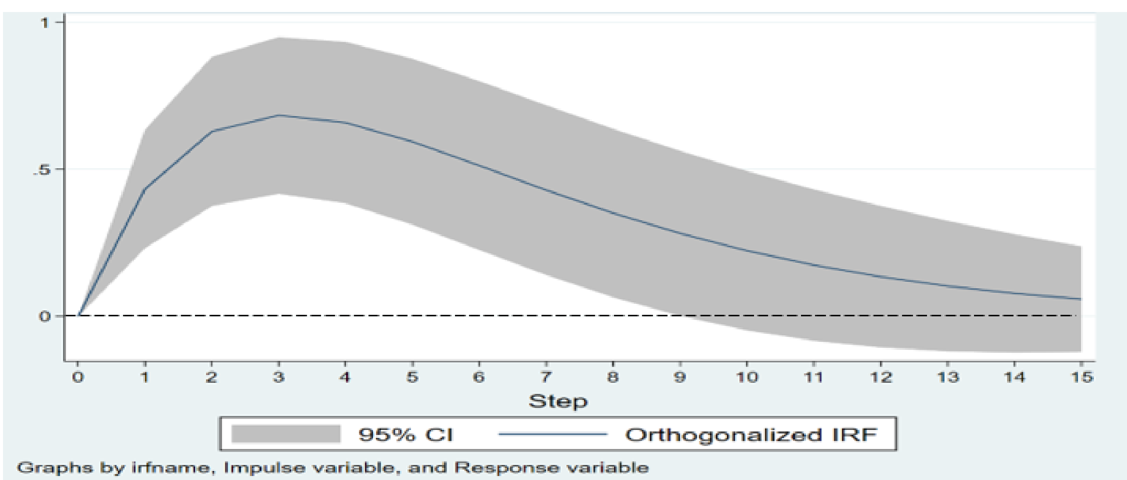


Figure 6 shows that the 70s Oil shocks variable has a positive effect on inflation. 70s Oil shocks have a marked impact on inflation, resulting in a maximum increase after 3 years, before the effects gradually disappear until period 9.

Impulse response results are often interpreted in terms of the size (amplitude) of the standard deviation of the shock and the contribution of the shock to the forecast error variance of the variable responding to the shock. Table 16 shows that the standard deviation of 70s oil shocks is 12.36% (response of 70s Oil shocks variable to its own innovations at time 0) and that the 70s Oil shocks variable has reached a maximum rise with an Oirf coefficient of 0.6839. Thus, the effects of 70s Oil shocks on annual inflation after three years can be calculated approximately as follows: 12.36%*0.6839 = 8.45 percentage points. In other words, the positive effects of the 70s oil shocks increased inflation by 8.45 percentage points after three years, before inflation gradually returned to its pre-shock level (convergence toward zero). Given that inflation returned to its pre-shock level after 9 periods following the 70s Oil shocks (transitory effect), it can be argued that inflation has a finite memory of the 70s Oil shocks.

To complete our analysis based on impulse response functions, we decompose the forecast error variance. The aim is to calculate the contribution of each of the innovations to the error variance. The results of the forecast error variance decomposition study are reported in Table 16. The results indicate that in period 3, 17.28% of the variance of the CPI forecast error is due to the innovations of the 70s Oil shocks variable and 82.72% to the innovations in inflation.

Table 16: Measuring the effect of 70s Oil shocks on inflation and forecast error variance decomposition, 1973-2023 analysis period

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Step	S.E.	CPI	70s Oil shocks	Lower	Oirf	Upper	Standard deviation	Amplitude of shock
0	0	0.00%	0.00%	0	0	0	12.36%	0.00%
1	0.1025	100.00%	0.00%	0.2323	0.4332	0.6340	11.23%	5.35%
2	0.1293	93.61%	6.39%	0.3758	0.6292	0.8826	9.75%	7.78%
3	0.1358	82.72%	17.28%	0.4177	0.6839	0.9501	8.20%	8.45%
4	0.1400	72.68%	27.32%	0.3847	0.6592	0.9336	6.73%	8.15%
5	0.1439	65.64%	34.36%	0.3122	0.5942	0.8762	5.42%	7.35%
6	0.1465	61.25%	38.75%	0.2260	0.5130	0.8000	4.30%	6.34%
7	0.1472	58.65%	41.35%	0.1410	0.4295	0.7180	3.36%	5.31%
8	0.1461	57.13%	42.87%	0.0652	0.3514	0.6377	2.60%	4.34%
9	0.1430	56.25%	43.75%	0.0020	0.2823	0.5626	1.99%	3.49%

Step	(1) S.E.	(2) CPI	(3) 70s Oil shocks	(4) Lower	(5) Oirf	(6) Upper	(7) Standard deviation	(8) Amplitude of shock
10	0.1380	55.75%	44.25%	-0.0471	0.2234	0.4939	1.51%	2.76%
11	0.1312	55.47%	44.53%	-0.0825	0.1745	0.4316	1.14%	2.16%
12	0.1227	55.31%	44.69%	-0.1056	0.1349	0.3753	0.85%	1.67%
13	0.1129	55.22%	44.78%	-0.1181	0.1032	0.3245	0.63%	1.28%
14	0.1023	55.17%	44.83%	-0.1223	0.0783	0.2789	0.47%	0.97%
15	0.0914	55.15%	44.85%	-0.1203	0.0589	0.2380	0.34%	0.73%

Notes: (1) standard error; (2) impulse = CPI and response = CPI; (3) impulse = 70s Oil shocks, and response = CPI; (4) Lower bound confidence interval; (5) CPI Orthogonalized Impulse Response Functions to 70s Oil shocks; (6) Upper bound confidence interval; (7) standard deviation 70s Oil shocks; (8) amplitude of shock = (5)*(7) first line.

5.3.7 Impulse response of inflation to the 1979 Volcker monetary policy shock

Figure 7 traces the impulse response of the inflation variable to the 1979 monetary policy reform shock. Again, the amplitude of the shock is considered a function of the standard deviation, and we are interested in the effects of the shock over 15 periods (i.e. 15 years, from 1979 to 1994). We have shown that there is a stable long-term relationship between inflation and the 1979 Volcker shock. This is why it is possible to estimate the *level* VAR model.

Figure 7: Impulse response function of inflation (CPI) to monetary policy reform shock (Volcker 1979), 1979 to 1994 analysis period

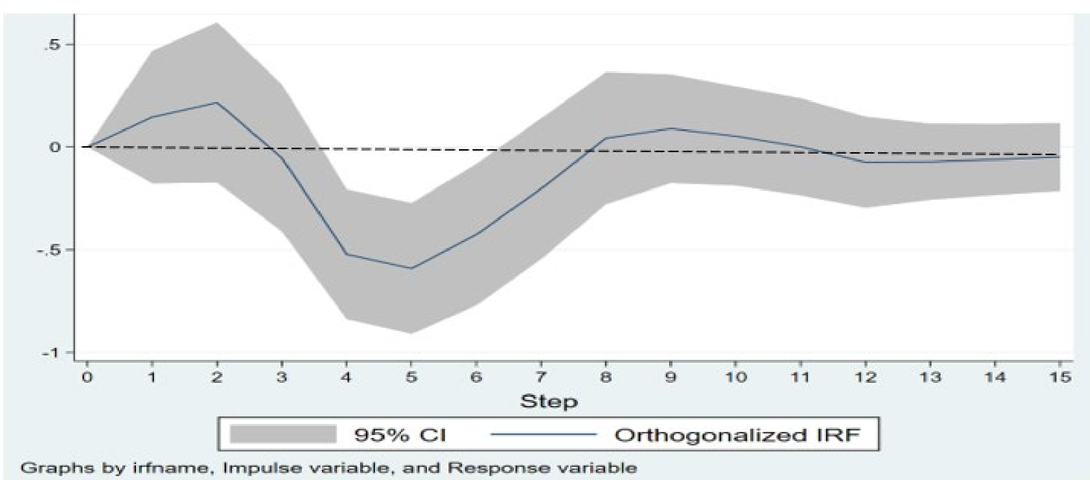


Figure 7 shows that a positive shock to interest rates in monetary policy (1979) has a negative effect on inflation. The Volcker shock has a marked impact on inflation, with a decline starting in the fourth year and peaking after five years, before the effects gradually disappear. In other words, the 1979 Volcker shock brought annual inflation down to a maximum level of -6.152 percentage points (10.40%*-0.5914) five years after the implementation of Volcker's monetary policy, before gradually returning to its pre-shock level (convergence towards zero). Since following the 1979 Volcker shock, inflation returns to its pre-shock level, it can be argued that inflation has a finite memory of the Volcker shock (transitory effect).

The results of the forecast error variance decomposition study are shown in Table 17. The results obtained indicate that at period 5, 11.79% of the variance of the CPI forecast error is due to the innovations of the 1979 Volcker shock variable and 88.21% to the innovations in inflation.

Table 17: Measuring the effect of the 1979 Volcker shock on inflation and forecast error variance decompositions, 1973-2023 analysis period

Step	(1) S.E.	(2) CPI	(3) Volcker shock	(4) Lower	(5) Oirf	(6) Upper	(7) Standard deviation	(8) Amplitude of shock
0	0	0.00%	0.00%	0	0	0	10.40%	0.000%
1	0.1647	100.00%	0.00%	-0.1772	0.1455	0.4683	4.47%	1.514%
2	0.1988	99.17%	0.83%	-0.1730	0.2166	0.6063	4.47%	2.254%
3	0.1821	97.40%	2.60%	-0.4111	-0.0542	0.3028	3.16%	-0.563%
4	0.1610	97.30%	2.70%	-0.8375	-0.5220	-0.2064	-4.63%	-5.430%
5	0.1625	88.21%	11.79%	-0.9098	-0.5914	-0.2729	-6.03%	-6.152%
6	0.1754	80.16%	19.84%	-0.7698	-0.4261	-0.0823	-7.02%	-4.432%
7	0.1745	78.09%	21.91%	-0.5448	-0.2028	0.1393	-4.69%	-2.109%
8	0.1640	78.09%	21.91%	-0.2782	0.0432	0.3646	-0.06%	0.449%
9	0.1350	78.33%	21.67%	-0.1754	0.0891	0.3537	0.54%	0.927%
10	0.1229	78.18%	21.82%	-0.1879	0.0530	0.2940	1.66%	0.552%
11	0.1204	78.13%	21.87%	-0.2354	0.0007	0.2368	1.11%	0.007%
12	0.1132	78.14%	21.86%	-0.2961	-0.0742	0.1476	-0.60%	-0.772%
13	0.0944	78.05%	21.95%	-0.2569	-0.0720	0.1130	-0.37%	-0.749%
14	0.0879	78.00%	22.00%	-0.2335	-0.0612	0.1111	-0.98%	-0.636%
15	0.0844	77.97%	22.03%	-0.2140	-0.0486	0.1167	-0.83%	-0.506%

Notes: (1) standard error; (2) impulse = CPI, and response = CPI; (3) impulse = Volcker shock, and response = CPI; (4) Lower bound confidence interval; (5) CPI Orthogonalized Impulse Response Functions to Volcker shock; (6) Upper bound confidence interval; (7) standard deviation Volcker shock; (8) amplitude of shock = (5)*(7) first line.

5.3.8 Impulse response of inflation to the COVID-19 pandemic shock

Figure 8 plots the impulse response of the inflation variable (CPI) to the COVID-19 pandemic shock. We have shown that there is a *short-term* relationship between inflation (CPI) and the COVID-19 variable. We then need to impose long-term constraints, which express the presence of an instantaneous response.

Figure 8: CPI impulse response function to COVID-19 pandemic shock, 2020 to 2035 analysis period

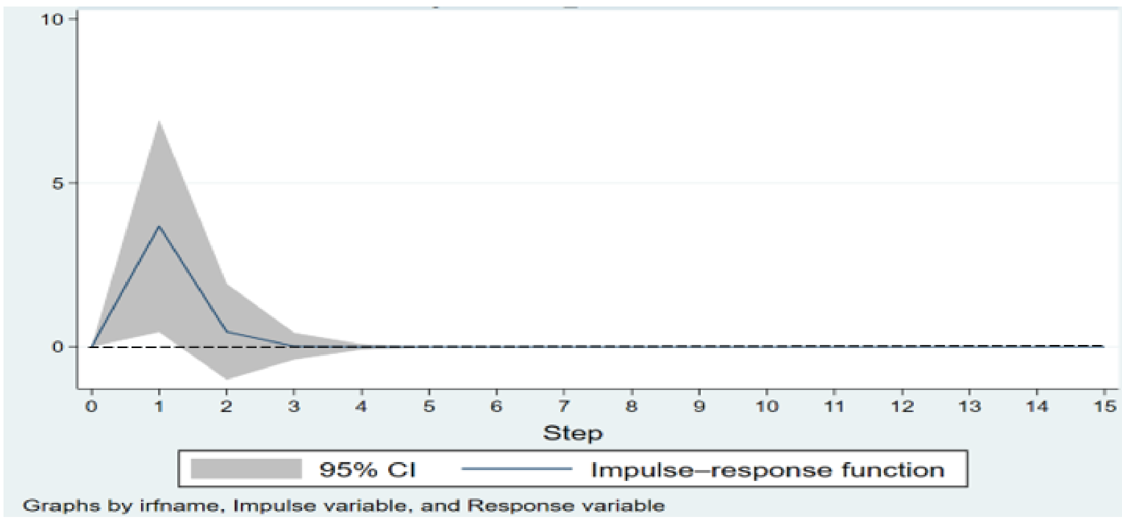


Figure 8 shows that the COVID-19 pandemic shock had a positive effect on inflation. The COVID-19 shock had a marked impact on inflation, resulting in a maximum increase after one year, before rapidly returning to its pre-shock level (convergence toward zero). In other words, the positive effects of the COVID-19 shock caused inflation to rise to a maximum level of 3.7 percentage points (3.69 × 1%) after one year, before returning abruptly to its pre-shock level (transitory effect). In statistical terms, we can see that the COVID-19 shock had a significant positive *short-term* impact on inflation, since the positive and significant effects of the COVID-19 shock on annual inflation lasted at most 15 months, i.e. ending in 2021. Unlike the 1970s oil shocks and the 1979 Volcker shock, where the significant effect observed was long-lasting, the effect of the COVID-19 shock was rather *short-lived*, as inflation responses became statistically insignificant after 1 year.

The results of the forecast error variance decomposition study are shown in Table 18. The results indicate that at period 2, 0.20% of the variance in the CPI forecast error is due to innovations in the COVID-19 shock variable and 99.80% to its own innovations.

Table 18: Measuring the effect of the COVID-19 shock on inflation and forecast error variance decomposition, 1973-2023 analysis

Step	(1) S.E.	(2) CPI	(3) COVID-19 shock	(4) Lower	(5) irf	(6) Upper	(7) Standard deviation	(8) Amplitude of shock
0	0	0.00%	0.00%	0	0	0	1%	0
1	0.0090	100.00%	0.00%	0.4512	3.6854	6.9197	-2.35%	3.69%
2	0.0780	99.80%	0.20%	-1.0052	0.4571	1.9194	-1.38%	0.46%
3	0.0789	99.80%	0.20%	-0.3921	0.0164	0.4249	-0.15%	0.02%
4	0.0789	99.80%	0.20%	-0.0840	-0.0030	0.0781	0.00%	0.00%
5	0.0789	99.80%	0.20%	-0.0090	-0.0005	0.0079	0.00%	0.00%
6	0.0789	99.80%	0.20%	-0.0007	0.0000	0.0006	0.00%	0.00%
7	0.0789	99.80%	0.20%	-0.0002	0.0000	0.0002	0.00%	0.00%
8	0.0789	99.80%	0.20%	0.0000	0.0000	0.0000	0.00%	0.00%
9	0.0789	99.80%	0.20%	0.0000	0.0000	0.0000	0.00%	0.00%
10	0.0789	99.80%	0.20%	0.0000	0.0000	0.0000	0.00%	0.00%
11	0.07897	99.80%	0.20%	0.0000	0.0000	0.0000	0.00%	0.00%
12	0.0789	99.80%	0.20%	0.0000	0.0000	0.0000	0.00%	0.00%
13	0.0789	99.80%	0.20%	0.0000	0.0000	0.0000	0.00%	0.00%
14	0.0789	99.80%	0.20%	0.0000	0.0000	0.0000	0.00%	0.00%
15	0.0789	99.80%	0.20%	0.0000	0.0000	0.0000	0.00%	0.00%

Notes: (1) standard error; (2) impulse = CPI, and response = CPI; (3) impulse = COVID-19 shock, and response = CPI; (4) Lower bound confidence interval; (5) CPI Orthogonalized Impulse Response Functions to COVID-19 shock; (6) Upper bound confidence interval; (7) standard deviation COVID-19 shock; (8) amplitude of shock = (5)*(7) first line.

Our analysis of the impulse response of inflation to the 1970s oil shocks, the 1979 monetary policy reform shock and the COVID-19 pandemic shock has yielded a number of observations. First, all three shocks have an instantaneous impact on inflation because the beginning is not at origin 0, as shown in figures 6, 7 and 8. The instantaneous magnitude of the shock is greater with the oil shocks. Second, we observed that the oil shocks and the 1979 monetary policy reform shock have permanent consequences (lasting effect) on inflation, whereas the COVID-19 pandemic shock has *short-term* consequences on inflation. Third, according to our forecast based on the COVID-19 pandemic shock, we should expect the decline in inflation observed in 2022 to continue in 2023 and 2024. The main difference of the COVID-19 pandemic shock on inflation with respect to the oil shocks is probably explained by the early intervention of the Fed in 2020.

5.4. Serial correlation of CPI_t

Empirical studies have shown that when serial correlation is present, financial series are frequently modeled using an ARMA (AutoRegressive Moving Average) model. The broad class of ARMA(1,q) processes includes the first-order autoregressive process, AR(l), and the *q*-order moving average process, MA(q). ARMA(l,q) processes are a natural extension of AR(l) and MA(q) processes. They are mixed processes in the sense that they simultaneously incorporate AR(l) and MA(q) components.

When serial correlation is present, financial series are frequently analyzed using a model of the three categories of the ARMA class (AR, MA and ARMA). To do this, we will first check whether serial correlation is present in our CPI rate data.

Table 19: Serial correlation of the inflation rate (CPI), 1973-2023 analysis period

Variable	(1)
(1) CPI_t	1.000
(2) $L.1.CPI_t$	0.787*** (0.000)
(3) $L.2.CPI_t$	0.567*** (0.000)
(4) $L.3.CPI_t$	0.468*** (0.001)
(5) $L.4.CPI_t$	0.441*** (0.002)

Notes: $L.i.CPI_t$ means CPI lagged *i* periods. Robust standard errors in parentheses. *** p<0.01.

Table 19 shows a strong presence of serial correlation between CPI and CPI lagged one period (L.1.CPI), CPI lagged 2 periods (L.2.CPI), CPI lagged 3 periods (L.3.CPI) and CPI lagged 4 periods (L.4.CPI). This result suggests that we can use the ARMA (l,q) to model the inflation series and apply the characteristics of the error term of the ARMA (l,q) CPI model as those of CPI_t.

5.5. Serial dependency of the CPI series

Table 20 shows that ${CPI_t}^2$ depends positively and strongly on its one-year and two-year lagged values. ${CPI_t}^2$ is an approximation of the variance of the CPI. This suggests that strong variations tend to be followed by strong variations, and weak variations by weak variations. Thus, the variance of CPI_t conditional on known events at time t-1 is not constant and depends on its past values. This points to a phenomenon of persistence in the variance of the conditional CPI_t variance. ARCH-type models take this phenomenon into account.

Table 20: Serial dependency of the CPI series,
1973-2023 analysis period

Variable	(1)
$L.1.{CPI_t}^2$	1.276***
	(0.343)
$L.2.{CPI_t}^2$	-0.868**
	(0.400)
$L.3.{CPI_t}^2$	0.384
	(0.389)
$L.4.{CPI_t}^2$	0.008
	(0.245)
Constant	3.222
	(2.311)
Observations	47
R-squared	0.711
Adjusted R-squared	0.684

Notes: $L.i.{CPI_t}^2$ means CPI lagged *i* periods. Robust standard errors in parentheses. *** p<0.01, ** p<0.05.

5.6. Distribution of the US inflation series

Table 21: Descriptive statistics for inflation
and Skewness/Kurtosis tests for Normality, 1973-2023 analysis period

	Mean	Median	Std.-dev.	Skewness	Kurtosis	Pr(Skewness)	Pr(Kurtosis)	*p*-value
CPI	4.0107	3.1568	2.9388	1.4437	4.7359	0.0002	0.0252	0.0006

Table 21 gives rise to several comments. First, the skewness coefficient is different from 0 and positive. This illustrates the presence of asymmetry, which may be an indicator of non-linearity, since we know that linear Gaussian models are necessarily symmetrical. The positive skewness coefficient suggests that the distribution is skewed to the right: Inflation thus reacts more to a positive shock than to a negative one. Second, the kurtosis coefficient is high, i.e. above 3. This excess kurtosis indicates a high probability of extreme points occurring. In other words, the distribution of the CPI series has thicker tails than the N (0, 1). Lastly, the *p*-value of the normality test is 0.0006. This indicates that the inflation series follows a normal distribution at the 5% threshold is rejected. To summarize, the inflation series is characterized by non-linear dynamics and a stochastic trend.

In the literature, stochastic non-linear processes take two forms: non-linear stochastic processes in variance (GARCH models) and non-linearity stochastic processes in the mean (regime-switching models such the Markov regime-switching model. We have just shown that the US inflation rate series is characterized, on the one hand, by a stochastic trend dynamic and, on the other hand, by a non-linear dynamic (high amplitude or low amplitude breaks). To take into account the presence of the stochastic (or random) trend and the presence of the non-linearity detected in our inflation rate data, we use non-linear stochastic processes in variance and non-linear stochastic processes in the mean to analyze the behavior of inflation.

6. Non-linear stochastic processes

In this section, we present nonlinear stochastic processes in variance, followed by nonlinear stochastic processes in the mean.

6.1. Nonlinear stochastic process in variance: ARCH, GARCH and EGARCH models

6.1.1 ARCH model

The ARCH model was introduced by Engle (1982). The null hypothesis tested is that of homoscedasticity $\alpha_0 = ... = \alpha_q = 0$ versus the alternative hypothesis of conditional heteroscedasticity: At least one coefficient α_i (i = 1, ..., q) is non-zero. If the null hypothesis is not rejected, the conditional variance is constant. Conversely, if the null hypothesis is rejected, the residuals follow an ARCH(q) process.

Let us assume that the mean equation is described by an ARMA process. Consider the series Y_t generated by the following system of equations:

$$\Phi(L)\, Y_t = \Theta(L)\, \tilde{e}_t \tag{6}$$

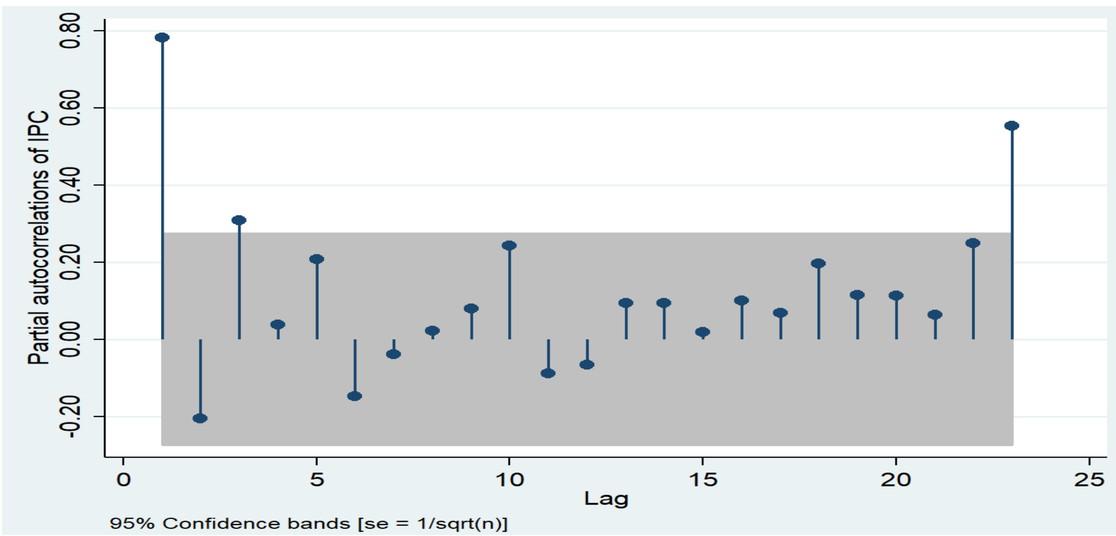
$$\sigma_t{}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \tilde{e}_t{}^2 \tag{7}$$

Y_t represents the inflation rate series and $\tilde{e}_t$ represents the residuals from estimating the mean equation. The parameter $\Phi(L)$ represents the lag polynomial of the inflation rate series (Y_t). Parameter $\Theta(L)$ represents the lag polynomial of the residuals from the estimation of the mean equation ($\tilde{e}_t$).

The ARCH test is implemented in three stages from the model presented in (6) and (7). The first step is to estimate the mean equation. We then recover the estimated residuals $\tilde{e}_t$ and calculate the series $\tilde{e}_t{}^2$. Second, we regress $\tilde{e}_t{}^2$ on a constant and its *q* past values (only significant lags are retained). Third, we calculate the TR^2 statistic, where T is the number of observations and R^2 is the coefficient of determination associated with the regression in step 2. Under the null hypothesis of homoscedasticity, the TR^2 statistic follows a chi-square distribution with *q* degrees of freedom. The decision rule is as follows: If $TR^2 \leq \chi^2(q)$, the null hypothesis is not rejected. In other words, there is no ARCH effect. Conversely, if $TR^2 > \chi^2(q)$, the null hypothesis is rejected in favor of the alternative hypothesis of conditional heteroscedasticity.

To select the ARMA (c,q) model for our estimation, we apply the method of Box and Jenkins (1970) and Box, Jenkins et al. (2015). The Box and Jenkins method consists, first, in selecting the number of lags *c* and *q* using visual inspection of sampled autocorrelations and partial autocorrelations. As mentioned earlier, ARMA(c,q) processes are a natural extension of AR(c) and MA(q) processes. For an AR(l) process, the partial autocorrelations cancel out from rank c+1. This property is used to identify the order *c* of AR processes. For an MA(q) process, the autocorrelations cancel out from rank q+1. This second property is used to identify the order *q* of MA processes.

Figure 9: Partial CPI autocorrelations, 1973-2023 analysis period

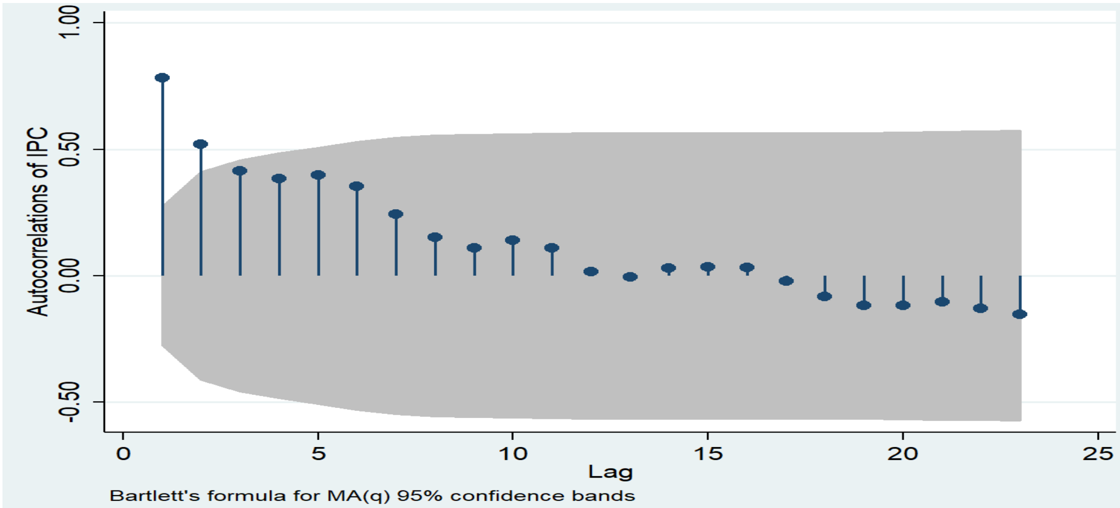


Source: World Bank and our calculations.

The fact that the first partial autocorrelation in Figure 9 is highly statistically significant while the others are not could indicate an AR(1) process, i.e., c = 1. Moreover, Figure 10 implies that we could choose MA(2) because the autocorrelations are not statistically significant starting from order 3.

To summarize, visual inspection of the sampled autocorrelations and partial autocorrelations enabled us to select the AR(1) and MA(2) models. The AR(2), MA(1), ARMA(1,1), ARMA(1,2), ARMA(2,1) and ARMA(2,2) models, derived from the combination of *c* and *q* with a maximum number of lags equal to 2, may also be logical candidates.

Figure 10: CPI autocorrelations, 1973-2023 analysis period



Source: World Bank and our calculations.

Table 22: Information criteria for estimated models, 1973-2023 analysis period

	AIC	BIC
AR (1)	211.3436	217.1391
AR (2)	211.0094	218.7367
MA (1)	218.4029	224.1984
MA (2)	210.4831	218.2104
ARMA (1,1)	207.1818*	214.9091*
ARMA (1,2)	207.6114	217.2706
ARMA (2,1)	215.2440	224.9031
ARMA (2,2)	209.0835	220.6745

Note: The asterisk indicates the model to be retained according to the selected criterion.

A comparison of the selection criteria between the different models estimated is shown in Table 22. This leads us to select the ARMA(1,1) process for the CPI inflation rate. The estimation of this process is shown in Table 23.

Table 23: Estimation of the mean equation: ARMA (1, 1) process, 1973-2023 analysis period

Variable	CPI
L.ar	0.556***
	(0.151)
L.ma	0.596***
	(0.183)
Constant	3.913***
	(0.927)
Sigma	1.683***
	(0.132)
Adjusted R-squared	0.133
Observations	51

Notes: L.ar and L.ma represent respectively the AR (1) and MA(1) components of the ARMA(1,1) model. Robust standard errors in parentheses. *** p<0.01.

The second stage of our ARCH test consists in recovering the residuals $\tilde{e}_t$ from the estimation of the ARMA(1,1) mean equation and regressing $\tilde{e}_t^{\,2}$ on a constant and its q past values. To estimate the second-stage regression, we first need to determine the number of q lags to be considered. To do this, we selected the number of q lags from the graph of partial autocorrelations shown in Figure 11.

Figure 11: Partial autocorrelations of squared residuals ($\tilde{e}_t^{\,2}$) 1973-2023 analysis period

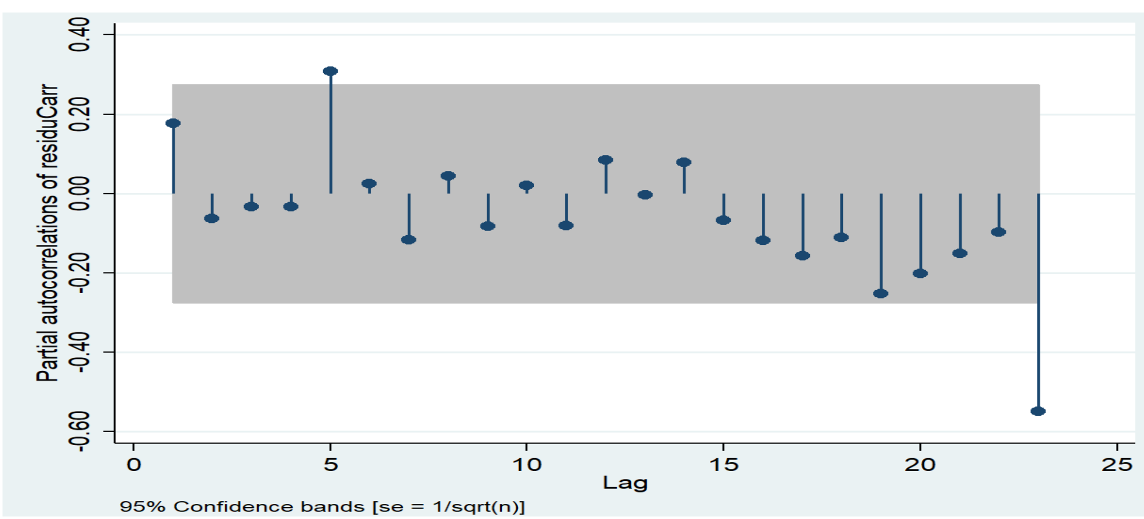


Figure 11 shows that only the fifth partial autocorrelation is significantly different from zero. We therefore use a number of q lags equal to 5 to perform the ARCH test. The results are shown in Table 24.

Table 24: ARCH test results, 1973-2023 analysis period

Variable	RES_t^2
L.1. RES_t^2	0.293*** (0.048)
L.2. RES_t^2	-0.039 (0.101)
L.3. RES_t^2	-0.050 (0.054)
L.4. RES_t^2	-0.085 (0.059)
L.5. RES_t^2	0.308 (0.215)
Constant	1.360 (0.989)
Observations	46
R-squared	0.230
Adjusted R-squared	0.133

Notes: RES_t^2 represents the squared residuals from estimating the mean equation. Robust standard errors in parentheses. *** p<0.01.

The results in Table 24 allow us to calculate a TR^2 statistic of 10.58 and a $\chi^2(5)$, which gives us a value of 9.236 at the 10% threshold. Given that $TR^2 \geq \chi^2(5)$, we reject the null hypothesis in favor of the alternative hypothesis of conditional heteroscedasticity. We find that the autoregressive coefficient associated with one-period lagged squared residuals is significantly different from zero. In other words, there is an ARCH effect in our CPI inflation series.

ARCH(q) applications are often used in finance to account for this ARCH effect. However, certain criticisms have been leveled at ARCH models. According to Nelson (1991), ARCH models may prove inadequate for two main reasons. The first is that the choice of a quadratic form for the conditional variance has important consequences for the time path of the series.

Choosing a symmetrical quadratic form for the conditional variance does not allow us to model the phenomenon of asymmetry. The second reason is that ARCH models remain strongly constrained to a positive conditional variance. This implies that a shock, whatever its sign, always has a positive effect on current volatility: the impact increases with the size of the shock.

These criticisms led to the development of the EGARCH (Exponential GARCH) model. The EGARCH model (Nelson, 1991) takes into account the possibility that variance responds asymmetrically to positive and negative shocks.

6.1.2. EGARCH (c,q) model

An EGARCH process is given by:

$$y_t = \mu_t + \sigma_t \varepsilon_t \qquad \varepsilon_t \sim N(0, 1) \tag{8}$$

where μ_t and $\sigma_t{}^2$, respectively, denote the conditional mean and variance of y_t (the CPI series) for a set of information consisting of the variables observed up to time[3] $t-1$ (Ω_{t-1}). ε_t represents the innovation (shock) of an ARMA-type process fitted to the series under study y_t. Nelson (1991) proposed the following model:

$$\ln \sigma_t{}^2 = \alpha_0 + \sum_{j=1}^{c} \beta_j \ln \sigma_{t-j}{}^2 + \sum_{i=1}^{q} \alpha_i\, g(z_{t-i}),\ z_{t-i} = \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \sim \mathrm{iid}(0,1). \tag{9}$$

where z_{t-i} represents normalized innovations and g(.) is a function of normalized innovations (z_{t-i}). β_j is the coefficient associated with the EGARCH(c) part and α_i is the coefficient associated with the ARCH(q) part of the EGARCH (c,q) model.

Unlike GARCH models, whose specialization concerns the quadratic nature of the conditional variance, the specification of the EGARCH model concerns the logarithm of the

[3] $\Omega_{t-1} = [y_1, y_2 \dots \dots \dots, y_{t-1}]$.

conditional variance and thus avoids positivity constraints on the coefficients α_i and β_j of equation (9).

6.1.3 Estimation with the maximum likelihood method

Since the data are stochastic, the maximum likelihood method must be applied. Table 25 shows the estimation of the ARMA(1,1)-EGARCH(1,1) model. The table suggests that the negative and statistically significant coefficient of the variable ($\beta_j < 0$) implies that a shock with a negative effect on inflation will have a greater impact on volatility than would a shock with an equivalent positive effect. In other words, inflation reacts more strongly to a negative shock than to a positive one, reflecting the asymmetry effect. Table 25 shows that all the coefficients of the variables in the variance equation are significantly different from zero. Furthermore, the coefficients of the variance equation β_j^+ and α_i^- are statistically different from zero, indicating the presence of asymmetry. The significance of these two coefficients indicates that the EGARCH(1,1) model indeed takes into account the asymmetry observed in the inflation series.

Table 25: ARMA(1,1)-EGARCH(1,1) model estimates
1973-2023 analysis period

Dependent variable	CPI
L1.ar	0.462**
	(0.204)
L1.ma	0.434*
	(0.259)
Constant	2.820***
	(0.394)
Variance equation (σ_t^2)	
L1.egarch (β_j)	-0.696***
	(0.131)
L1.arch (α_i)	0.180***
	(0.057)
Constant	0.940***
	(0.364)
Observations	51

Notes: L1.ar and L1.ma represent respectively the AR(1) and MA(1) components of the ARMA(1,1) model. L1.egarch and L1.arch respectively represent the EGARCH(1) and ARCH(1) components of the EGARCH (1,1) model. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6.2. Stochastic non-linear processes in the mean: Markov regime-switching model

For the application of non-linear processes in the mean, we have chosen the Markov regime-switching model because the Markov model seems to fit our inflation data if we refer to the graphical analysis in Figure 1. This figure clearly shows that the US inflation rate series observed over the 1973-2023 period is characterized by a regime-switching process, possibly split into two different sub-samples or even three.

6.2.1 Regime detection

To detect the presence of regimes, we used the Markov model approach (Hamilton, 1994). This procedure identifies regimes in the levels (constant) and volatility (lnsigma) of the inflation series. These two moments are estimated simultaneously. In the remainder of our analysis, we will focus on level regimes (controlling for volatility) because the Markov regime-switching model we propose to use for inflation analysis seems more appropriate. The process under study is a non-linear stochastic process in the mean of the insurance variables of interest.

Graphically, it can be argued that the two-regime Markov model is best suited to our inflation series. Indeed, Figure 1 shows that the U.S. inflation series underwent a structural change due to a monetary policy led by Paul Volcker at the Fed in 1979. It has also undergone two major changes linked to the oil shocks of the 1970s and the COVID-19 pandemic shock of 2020-2023. These non-linearities suggest that inflation rate dynamics in the United States differ from one sub-sample (regime) to the next. Figure 1 indicates that the period from 1983 to 2020 was marked by a low level of inflation rate, while the rest of the sample (periods of 1973 to 1982 and 2021 to 2023) displays a high level of the inflation rate. This suggests that a two-state model seems reasonable. A three-regime model may also be a potential candidate, as there may be a very low or even negative level of the inflation rate (deflation), as in 2009. To properly test our two-regime hypothesis, we ask the following question: Would the three-regime Markov model be better than the two-regime Markov model suggested by our graphical analysis?

6.2.2 Two-regime model vs. three-regime model

We propose here a Markov model of regimes with a constant. The existence of two states of the world st ∈ (1, 2) is assumed to be the two-regime model and st ∈ (1, 2, 3) is assumed for the three-regime model. It is also supposed that, in each regime, the dynamics are potentially different.

- Two-regime model

We assume the existence of two states of the world st ∈ (1, 2) for the two-regime model; μ_1 is the mean in the low inflation state and μ_2 is the mean in a high-inflation state.

$$y_{st} = \mu_{st} + \sigma_{st} z_t \text{ , } z_t \sim N\,(0,\,1) \tag{10}$$

where y_{st} is the inflation rate, the index st designates the regime and μ_{st} is the average for each regime.

The hypothesis tested is that the dynamics of the CPI data in our two subsamples (regimes) are potentially different. The null hypothesis H_0 ($\mu_1 = \mu_2$) means no change in regime levels. In other words, our approach is to test the null hypothesis (H0) that the average CPI rate estimated in State 1 and the average CPI rate estimated in State 2 are statistically the same, where State 2 is the high-inflation regime. The data used is observed annual data over the 1973-2023 period (51 periods).

The results in Table 26 show that the low-inflation regime (State 1) has an estimated average inflation rate of 2.87%, while the high-inflation regime (State 2) has an average inflation rate of 8.82%. The results clearly show that the estimated average CPI rate in State 1 and the estimated average CPI rate in State 2 are not statistically the same.

Table 26: Two-regime model with constant inflation
1973-2023 analysis period

Variable	CPI
Constant (State 1)	2.870*** (0.278)
Constant (State 2)	8.820*** (0.102)
lnsigma	1.726 (0.176)
p11	0.980** (0.022)
p21	0.044** (0.065)
Observations	51

Notes: Insigma is a volatility parameter. *** $p<0.01$, ** $p<0.05$.

The parameter p11 is the estimated probability of remaining in State 1. The value 0.98 implies that State 1 is highly persistent. This means that a year of low inflation is followed 98% of the time by a year of low inflation. Parameter p21, which is the probability of moving from State 1 to State 2 (transition), is 0.04. The probability of remaining in State 2 (p22) is therefore $1 - 0.04 = 0.96$, which implies that State 2 is also persistent. This result indicates that a year of high inflation is followed 96% of the time by a year of high inflation. Table 26 also shows that the estimated inflation volatility (Insigma) is not statistically significant. The results obtained indicate that the data segmentation determined by the Markov regime-switching model is largely influenced by the behavior of the inflation rate series. In other words, the two-regime Markov model takes into account the presence of the stochastic (or random) trend and non-linearity detected in the inflation rate series, since we have already documented the presence of the stochastic trend and non-linearity that give rise to the asymmetry phenomenon observed in the inflation series.

- Three-regime model

We assume the existence of three states st ∈ (1, 2 ,3) for the three-regime model; μ_1 is the mean in the low inflation state, μ_2 is the mean in the moderate inflation state and μ_3 is the mean in the high inflation state.

The hypothesis tested is that the dynamics of the CPI data in our three sub-samples (regimes) are potentially different. The three potential sub-samples analyzed in the three-regime model can be identified by reading Figure 1. Indeed, Figure 1 indicates that the periods from 1973 to 1982 and from 2021 to 2023 display a high inflation rate (State 3), the 1983 to 1991 period displays a moderate inflation rate (State 2) while the rest of the sample, i.e. the 1992 to 2020 period, is marked by a low inflation rate (State 1). Table 27 shows the estimation results for the three-regime model.

Table 27: Three-regime model with constant inflation
1973-2023 analysis period

Variable	CPI
Constant (State 1)	2.593*** (0.281)
Constant (State 2)	6.038*** (0.786)
Constant (State 3)	11.070*** (0.786)
lnsigma	11.069** (0.551)
p11	0.930** (0.051)
p12	0.007** (0.051)
p21	0.213** (0.170)
p22	0.550** (0.232)
p31	8.32e-31 (.)

Variable	CPI
p32	0.422
	(.)
Observations	51

Notes: Insigma is a volatility parameter. *** $p<0.01$, ** $p<0.05$.

The transition probabilities in the three-regime model indicate a parameter p11, i.e. the estimated probability of remaining in State 1, of 0.93 (State 1 is highly persistent); and a parameter p22, i.e. the estimated probability of remaining in State 2, of 0.55 (State 2 is moderately persistent). The probability of remaining in State 3 (p33) is therefore $1 - 8.3e - 31 - 0.422 = 0.58$, implying that State 3 is also moderately persistent. These results indicate that a year of low inflation is followed 93% of the time by a year of low inflation, a year of moderate inflation is followed 55% of the time by a year of moderate inflation, and a year of high inflation is followed 58% of the time by a year of high inflation. The results in Table 27 indicate that the three-regime model also appears to be a potential candidate for modeling the non-linearity of the U.S. inflation rate. However, the strong persistence of the two states (State 1 and State 2) of the two-regime model seems to better capture the non-linearity of the US inflation rate than does the three-regime model. We use the AIC, SBIC (Singular BIC) and LL information criteria to separate the two-regime model from the three-regime model.

Table 28: Comparison criteria for estimated models, 1973-2023 analysis period

	AIC	SBIC	LL
2 States	4.1436	4.3709*	-99.6630*
3 States	4.0940*	4.4728	-94.3981

Note: The asterisk indicates the model to be retained according to the selected criterion.

Table 28 shows the different statistics of interest for regime selection. The AIC criterion selects the three-regime Markov model and the SBIC criterion selects the two-regime Markov model. The log-likelihood ratio statistic confirms the result of the SBIC test. Calculating the LR statistic gives us 10.52. This value is higher than the critical value derived from the distribution χ^2 (1) since we have only one constraint (k =1). The critical value at 5% is 5.99. In this case, H_0 is not rejected. Thus, according to the LR test, we choose the two-regime Markov model over the 3-regime Markov model.

Figure 12: Evolution of probabilities of being in the high-inflation regime detected from January 1972 to December 2023

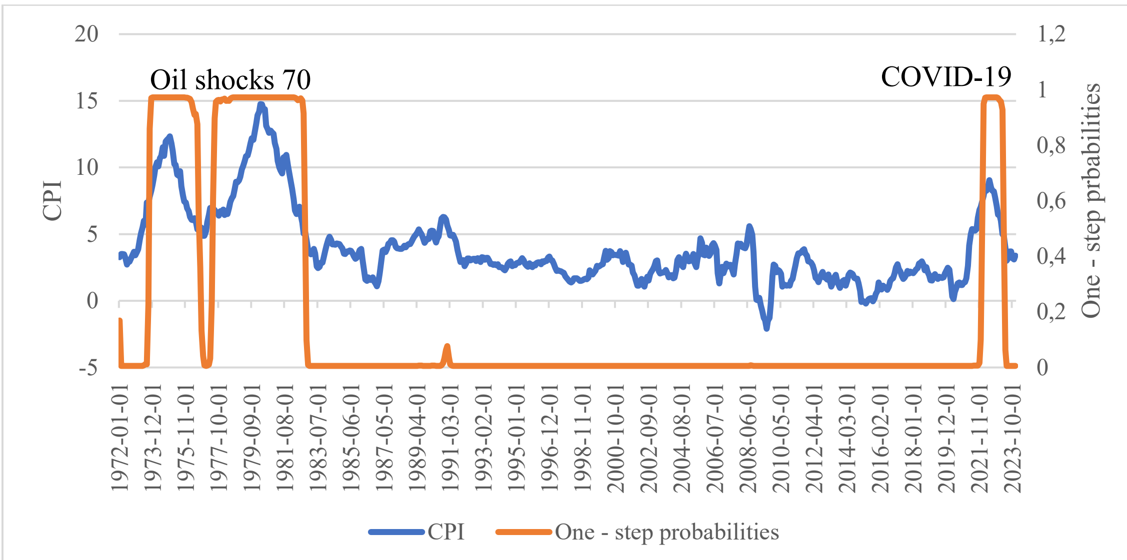


Figure 12 shows three periods of high-inflation states and two periods of low-inflation states. The high-inflation regime is detected during the 1970s oil shocks (1973 to 1982) and during the COVID-19 period. Note that the 1970s oil shock period was a longer period of high and sustained inflation rates, compared with the COVID-19 period. In contrast, the low-inflation regime was detected over the rest of the sample.

6.3. Comparison of nonlinear stochastic processes in variance (EGARCH SV) and nonlinear stochastic processes in the mean (Markov SV)

The results show that the two forms of nonlinear stochastic process, namely the nonlinear stochastic process in variance (EGARCH (1, 1) model) and the nonlinear stochastic process in the mean (two-regime Markov model), are well suited to capture the asymmetry observed in the US inflation series. To select the process best suited to our data, we use the selection criteria shown in Table 29 to distinguish between the two forms of nonlinear stochastic process.

Table 29: Comparison criteria for estimated models, 1973-2023 analysis period

	EGARCH	Markov
LL	-93.8176	-87.4665*
AIC	199.6351	188.9331*
BIC	211.2261	202.3172*

Notes: LL is the log-likelihood value at the optimum, AIC and BIC are the information criteria of Akaike (1969) and Schwarz (1978) respectively. The asterisk indicates the model to be retained according to the selected criterion.

A comparison of the selection criteria shows, first, that the results obtained differ very little, suggesting that the two EGARCH models of the GARCH class (nonlinear stochastic process in variance) and Markov (nonlinear stochastic process in the mean) are relevant for modeling the inflation series. However, the comparison shows a slight advantage for the Markov regime-switching model over the EGARCH model. All three information criteria (LL, AIC and BIC) lead us to select the Markov regime-switching model.

Despite their many empirical successes, EGARCH models share two major weaknesses. First, they fail to produce unconditional distributions of CPI_t with tails as thick as those observed in reality, even when replacing $z_t \sim N(0, 1)$ by a distribution with thicker tails than N (0, 1), such as the *t*-distribution. Second, in EGARCH SV models, the conditional variance of the CPI (σ_t^2) is non-random, as shown in equation (9). This is a problem because financial theoretical models assume that volatility is a random process. The class of models known as random volatility models, such as the case of the Markov SV model where the conditional variance of the CPI (σ_{st}^2) is random because it depends on the state of the regime $st \in (1, 2)$ (see equation 10), solves both of these problems.

7. Estimating the effect of inflation on insurance industry

In this section, we analyze the impact of inflation on different fundamental indicators of insurance company performance in the United States. We verify the impact of inflation on insurers performance indicators such as operating cost management efficiency, measured by the operating ratio; and financial profitability, measured by the ROA indicator. Other indicators are analyzed. The Markov regime-switching model is estimated. Given that the data are stochastic, the maximum likelihood method is applied to estimate the parameters.

7.1. Data on insurance company performance measurement variables

The database used to analyze the performance of the insurance industry corresponds to sector-aggregated data observed in the two main sectors of American insurance industry (P&C and Life insurance) over a 51-year period. These are time series composed of annual data, for the 1973-2023 period, on variables such as Premiums collected, Claims costs, Net investment income, Profitability (ROA), Capital and Surplus to Total assets, and operating cost management efficiency, measured by the Combined ratio, and the Operating ratio. Data for fundamental indicators of insurance company performance in the P&C insurance sector are all sourced from AM Best. Data on the fundamental indicators of performance for insurance companies in the Life insurance sector are all taken from the American Council of Life Insurers (ACLI) database, with the exception of ROA (own estimation). Finally, CPI data is obtained from the World Bank database.

7.2. Mean and standard-deviation of insurance company performance variables in both regimes

Tables 30 and 31 present the descriptive statistics for the main variables analyzed. Descriptions of the different variables are in the Appendix.

Table 30: Mean and standard-deviation (P&C sector) for both regimes, analysis period 1973 to 2023

	State 1(N=37)		State 2 (N=14)	
P&C sector	Mean	Std.-dev.	Mean	Std.-dev.
Combined ratio (%)	103.9892	5.8670	100.9286	3.7070
Net investment income to Total assets (ratio)	0.0425	0.0131	0.0440	0.0153
Operating ratio (%)	91.6329	4.9405	91.4500	3.1683
ROA (ratio)	0.0215	0.0160	0.0294	0.0176
Capital and Surplus to Total assets (ratio)	0.3154	0.0514	0.2874	0.0642

Notes: State 1: low inflation; State 2: high inflation.

The mean and standard-deviation of the five P&C insurer performance measurement variables in Table 30 show different trends between the two states of inflation for some variables. We also note that the mean and standard-deviation of the five variables that measure the performance of Life insurance companies in Table 31 show different trends for some variables.

Table 31: Mean and standard-deviation (Life sector) in both regimes, analysis period 1973 to 2023

	State 1 (N=37)		State 2 (N=14)	
Life sector	Mean	Std. Dev.	Mean	Std. Dev.
Combined ratio (%)	98.4554	21.2245	102.5142	22.7429
Net investment income to Total assets (ratio)	0.0578	0.0165	0.0567	0.0147
Operating ratio (%)	58.5830	21.6838	66.1706	16.6773
ROA (ratio)	0.0224	0.0378	0.0078	0.0070
Capital and Surplus to Total assets (ratio)	0.0620	0.0049	0.0669	0.0067

Note: State 1: low inflation; State 2: high inflation.

Note that the inflation rate in the United States is exposed to the risks associated with regime changes involving a shift from a low-inflation to a high-inflation regime. In this section, we analyze, instead, inflation effects of insurers' investment decisions (investment portfolio), pricing of insurance products, and claims management inside each regime. This methodology suggests a better way to consider short-run management of inflation.

7.3. Main predictions from literature

This table summarizes the main predictions discussed in the literature review.

Table 32: Main predictions of inflation effect from literature

Effect	Reference
Positive effect of inflation on claims costs in P&C sector	Geneva Association, 2023; EIOPA, 2023
During inflation periods, premiums must increase to maintain the combined ratio at an equilibrium level	EIOPA, 2023; Geneva Association, 2023
Positive effect of inflation on interest rates, including T-Bills	Masterson, 1968
Positive effect of inflation on long-run investment returns	D'Arcy, 1981; EIOPA, 2023
Negative impact on short-run investment returns because inflation reduces bond values	D'Arcy et al, 2009; EIOPA, 2023; Krivo, 2009
Negative impact of inflation on loss reserves in P&C sector	Lowe and Warren, 2010; D'Arcy et al., 2009
Short-run effect of inflation should be negative on earnings	Geneva Association, 2023
Inflation may affect capital	EIOPA, 2023

The effects on claims management should be more neutral for life insurance activities because many variables are long-run activities measured in nominal terms (Geneva Association, 2023). Investment activities may represent less neutral effects for life insurers (EIOPA, 2023).

7.4. Results of estimates of the impact of inflation on insurance company performance (P&C and Life)

7.4.1 Impact of inflation on premiums and total operating expenses

Table 33: Estimated impact of inflation on premiums collected and operating expenses (P&C sector), 1973-2023 analysis period

Dependent variable	Expense P&C		Premium P&C	
Independent variables	Coefficient	Std. error	Coefficient	Std. error
CPI (State1)	-23.09***	(5.28)	-21.98***	(5.23)
Constant (State1)	304.20***	(33.29)	290.00***	(32.12)
CPI (State2)	36.83***	(10.73)	36.82***	(10.96)
Constant (State2)	434.20***	(33.14)	443.50***	(32.12)
Lnsigma	84.63**	(8.49)	86.03**	(8.62)
p11	0.98**	(0.02)	0.98**	(0.02)
p21	0.02**	(0.03)	0.02**	(0.03)
Observations	51	51	51	51

Notes: Lnsigma: parameter of volatility. Robust standard errors in parentheses. ***: $p<0.01$, ** $p<0.05$.

Table 33 shows that inflation has a negative and statistically significant influence on both premiums and total operating expenses for the P&C sector in periods of low inflation (State 1). It also indicates that inflation exerts a positive and statistically significant influence on premiums and total operating expenses in periods of high inflation (State 2). In other words, premiums and total operating expenses seem to be influenced in the same way in periods of low inflation as in periods of high inflation, but in the opposite sign between the two states.

The results suggest that a reduction in the P&C combined ratio should be expected in periods of low inflation, since total operating expenses seem to fall by more than the volume of premiums collected. This suggests that, in a low-inflation environment, premiums collected are sufficient to cover total operating expenses, resulting in a lower P&C combined ratio. Under the high-inflation regime, we would expect the P&C combined ratio to remain constant because total operating expenses seem to rise as premiums collected. It is then difficult to anticipate the net effect of inflation on the combined ratio in periods of high inflation.

Table 34: Estimated impact of inflation on premiums collected and operating expenses (Life sector), 1973-2023 analysis period

Dependent variable	Expense Life		Premium Life	
Independent variable	Coefficient	Std. error	Coefficient	Std. error
CPI (State1)	-20.99***	(7.75)	-24.54***	(7.10)
Constant (State1)	271.60***	(52.21)	328.90***	(47.91)
CPI (State2)	30.27**	(14.12)	-12.50	(11.95)
Constant (State2)	612.30***	(43.32)	603.80***	(38.83)
Lnsigma	112.38**	(11.24)	104.08**	(10.42)
p11	0.98**	(0.02)	0.96**	(0.04)
p21	0.02**	(0.02)	2.71e-16	−
Observations	51	51	51	51

Notes: Lnsigma: parameter of volatility. Robust standard errors in parentheses. ***: $p<0.01$, ** $p<0.05$.

Table 34 shows that inflation has a negative and statistically significant influence on both premiums and total operating expenses in periods of low inflation. The impact of these two effects on the Life combined ratio suggests that an increase in the Life combined ratio should be expected in a period of low inflation, given that premiums collected fall by more than operating expenses. As a result, premiums collected may not sufficiently cover total operating expenses in a low-inflation environment. Table 34 also shows that inflation exerts a positive and statistically significant influence on total operating expenses in periods of high inflation, and a non-statistically significant influence on premiums in periods of high inflation. The non-statistically significant influence of inflation on premiums allows us to anticipate a net positive influence of inflation on the Life combined ratio in periods of high inflation.

To summarize, higher inflation in a low-inflation environment keeps total operating expenses and premiums low, while higher inflation in a high-inflation environment keeps total operating expenses and premiums high. Our analysis of the impact of inflation on premiums and total operating expenses also lets us predict the following three main outcomes. First, the P&C combined ratio is expected to fall in periods of low inflation. Second, the P&C combined ratio is expected to remain constant in periods of high inflation. Third, the Life combined ratio is expected to increase in both periods of inflation.

7.4.2 Impact of inflation on the combined ratio

The combined ratio is closely monitored in the insurance industry to ensure that premiums collected are at least equal to total operating expenses. When an insurance contract is sold, the expected cost of claims is unknown. This means that when selling insurance contracts, the insurance company takes the risk that the premiums it collects will not be sufficient to pay claims and expenses. This risk is greater in a high inflation context, because inflation represents an additional random dimension. Thus, it may be difficult for insurers to incorporate anticipated inflation into their pricing calculations for insurance policies during periods of high inflation. Competition may also limit premium increases. Inflation can lead to errors in the assessment of the actual pricing of insurance policies, which can cause insurers to underestimate the risk they accept to bear with the premiums they collect, or to underprice the risk they take. In both cases, there is a breach of equality between the premiums collected and the claims payable.

Table 35: Estimated impact of inflation on insurers' operating cost management efficiency (P&C and Life) measured by the combined ratio, 1973-2023 analysis period

	P&C sector		Life sector	
Dependent variable	Combined ratio		Combined ratio	
Independent variable	Coefficient	Std. error	Coefficient	Std. error
CPI (State 1)	-0.6180***	(0.1140)	0.3710**	(0.1520)
Determinants				
Premium	-0.4580***	(0.0269)	-0.3150***	(0.0112)
Total expense	0.4130***	(0.0250)	0.3540***	(0.0164)
Constant	113.1000***	(1.2420)	85.7500***	(1.7030)
CPI (State 2)	0.2110**	(0.0963)	-0.4000*	(0.2180)

	P&C sector		Life sector	
Dependent variable	Combined ratio		Combined ratio	
Independent variable	Coefficient	Std. error	Coefficient	Std. error
Determinants				
Premium	-0.1950***	(0.0141)	-0.1680***	(0.0083)
Total expense	0.2030***	(0.0143)	0.1580***	(0.0048)
Constant	96.0030***	(0.7600)	107.3000***	(2.4370)
Lnsigma	1.0870**	(0.1100)	1.6810**	(0.1692)
p11	0.9030**	(0.0570)	0.9790**	(0.0265)
p21	0.0630**	(0.0460)	0.0180**	(0.0225)
Observations	51	51	51	51

Notes: Lnsigma: parameter of volatility. Robust standard errors in parentheses. *** p<0.01, ** p<0.05. State 1 = low inflation; State 2 = high inflation.

The results in Table 35 indicate that the coefficients of each of our two determinants, Premiums and Total expenses, have the expected signs and are statistically significant in each of the two states for each of the two sectors. Table 11 also shows that inflation has a statistically significant impact on the combined ratio of P&C and Life insurers in each of the two states, but only at 10% in State 2 for the Life sector.

On the one hand, the results shown in Table 35 point to a positive and statistically significant coefficient at the 5% threshold in the high-inflation regime for the P&C sector. This result suggests that the upward variation in inflation during periods of high inflation increases the P&C combined ratio, which signals performance difficulties in the P&C insurance business.

In periods of high inflation, total P&C operating expenses (claims and management costs) rise sharply because repair and other claim costs increase with inflation. Management costs should also increase. Premiums must then rise in periods of high inflation to maintain the combined ratio at an equilibrium level. However, an increase in inflation during a period of high inflation leads to a rise in the price of P&C insurance policies, which increases the cost of insurance for policyholders, who are already weakened by the reduction in their purchasing power induced by high inflation. This rise in insurance premiums may prompt policyholders to consider cancelling their coverage or trying to reduce their coverage in order to lower the premiums they have to pay. The direct consequence will be a drop in demand for P&C insurance policies. This, in turn, will slow the growth in sales that insurers should be reaping from the rising price of P&C insurance policies in times of high inflation. This slowdown in the growth of premiums collected by insurers, which may have underestimated the effect of anticipated inflation, may result in insufficient premiums being collected to cover total operating expenses, and hence a rise in the combined ratio. A higher combined ratio impedes insurers' ability to generate returns in the P&C insurance business, especially during periods of high inflation.

On the other hand, the results obtained in Table 35 show a negative and statistically significant coefficient at the 1% level in State 1 for the P&C sector. This result suggests that the upward variation in inflation during periods of low inflation reduces the P&C combined ratio. In periods of low inflation, the increase in total P&C operating expenses (claims and management expenses) will be lower with low inflation than with high inflation. Premium increases can also be managed more easily to maintain the combined ratio at an equilibrium level. Further, in periods of low inflation, demand for P&C insurance policies should keep pace with consumer need, and a smaller drop in demand for coverage than in periods of high inflation.

To summarize, in a low-inflation environment, higher inflation seems to enhance P&C insurers' insurance business performance because premiums volumes are sufficient to cover losses incurred. This suggests that P&C insurers seem to anticipate inflation better when it is low. In contrast, the results indicate that higher inflation seems to be detrimental to P&C insurance business performance in a high-inflation environment because premium volumes are insufficient to cover loss increases.

In the case of Life insurers, the results presented in Table 35 indicate a positive and statistically significant coefficient at the 5% threshold in the low-inflation regime and a negative and statistically significant coefficient at only 10% in the high-inflation regime, which seems to confirm that Life insurance business would be less sensitive to inflation, as predicted in the literature.

7.4.3 Impact of inflation on net investment income

The results in Table 36 indicate that the coefficients of each of our two determinants, Net investment income and Total assets, have the expected signs and are statistically significant in each of the two regimes for each of the two sectors.

The results in Table 36 show a negative and statistically significant coefficient at the 5% level in the low-inflation regime for the Life sector. This result suggests that the upward variation in inflation in periods of low inflation reduces Life insurers' net investment income. In other words, rising inflation in periods of low inflation does not cover the risks associated with low interest rate rises, which reduces bond values.

Table 36: Estimated impact of inflation on net investment income to Total assets (P&C and Life), 1973-2023 analysis

	P&C sector		Life sector	
Dependent variable	Net investment income to Total assets		Net investment income to Total assets	
Independent variable	Coefficient	Std. error	Coefficient	Std. error
CPI (State 1)	0.0005	(0.0003)	-0.0005**	(0.0002)
Determinants				
Net investment income	0.0006**	(0.0002)	0.0005***	(7.66e-05)
Total assets	-5.06e-05***	(9.75e-06)	-3.75e-05***	(4.48e-06)
Constant	0.0649***	(0.0027)	0.0767***	(0.00269)
CPI (State 2)	0.0012***	(0.0001)	0.0008***	(0.0002)
Determinants				
Net investment income	0.0003***	(5.29e-05)	0.0001***	(2.18e-05)
Total assets	-1.46e-05***	(1.28e-06)	-6.12e-06***	(8.06e-07)
Constant	0.0370***	(0.0014)	0.0501***	(0.0018)
Lnsigma	0.0019**	(0.0002)	0.0024**	(0.0438)

p11	0.9384**	(0.0498)	0.9452**	(0.9452)
p21	0.0246**	(0.0257)	0.0262**	(0.0278)
Observations	51	51	51	51

Notes: Lnsigma: parameter of volatility. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. State 1 = low inflation; State 2 = high inflation. Lnsigma: parameter of volatility.

On the other hand, Table 36 shows a positive and statistically significant coefficient at the 1% level in the high-inflation regime for the Life sector. This result suggests that the upward variation in inflation during periods of high inflation increases insurers' net investment income during periods of high inflation. In other words, rising inflation sufficiently covers the risks incurred, which can be explained by the rising interest rates observed during periods of high inflation.

Third, for the P&C insurance sector, the results show that in periods of low inflation, inflation variation does not have a statistically significant impact on insurers' investment performance. However, the results also indicate that the variation in inflation has a significant impact on the investment performance of P&C insurers during periods of high inflation. Thus, Table 36 shows a positive and statistically significant coefficient at the 1% threshold in the high-inflation regime for the P&C sector, an effect further explained by significant increases in interest rates.

In conclusion, insurers' investment performance is positively linked to inflation, especially in periods of high inflation. This may represent a natural hedge against inflation risk for insurers. The results of the operating ratio should reflect this conjecture.

7.4.4 Impact of inflation on operating ratio

First, the results in Table 37 indicate that the coefficients of each of our two determinants, Combined ratio and Net investment income, broadly have the expected signs. According to the definition of operating cost efficiency in the insurance business, Operating ratio is an increasing function of Combined ratio and a decreasing function of Net Investment Income**.** Table 13 shows that the coefficient of the Combined ratio variable is statistically significant and has the expected sign in each of the two regimes, for each of the two sectors. The coefficient of the Net investment income variable has the expected sign in State 1 for both sectors but is not statistically significant. However, it is negative and statistically significant in State 2 for the Life sector. Second, the results show that variation in inflation has a statistically significant impact on the operating ratio of Life insurers in both states.

Table 37: Estimated impact of inflation on insurers' operating cost management efficiency (P&C and Life) measured by the operating ratio, 1973-2023 analysis period

	P&C sector		Life sector	
Dependent variable	Operating ratio		Operating ratio	
Independent variable	Coefficient	Std. error	Coefficient	Std. error
CPI (State 1)	0.0529	(0.1180)	0.3620*	(0.2120)
Determinants				
Combined Ratio	0.8380***	(0.0650)	1.0310***	(0.0292)
Net investment income	-0.0146	(0.0337)	-0.0043	(0.0119)
Constant	3.6810	(8.1180)	-44.2600***	(2.5190)
CPI (State 2)	0.2400**	(0.1000)	-0.4400**	(0.2180)
Determinants				
Combined ratio	0.8450***	(0.0498)	0.8050***	(0.0529)
Net investment income	0.0007	(0.0124)	-0.0356***	(0.0100)
Constant	5.3590	(4.9920)	-7.4260*	(4.3990)
Lnsigma	1.0110**	(0.1040)	2.1120**	0.2151
p11	0.9090**	(0.0530)	0.9400**	0.0483
p21	0.0690**	(0.0510)	0.0279**	0.0301
Observations	51	51	51	51

Notes: Lnsigma: parameter of volatility. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. State 1 = low inflation; State 2 = high inflation.

On the one hand, the results in Table 37 indicate that the coefficient of the CPI variable is positive and statistically significant at the low threshold of 10% in the low-inflation regime for the Life sector. This suggests that in periods of low inflation, inflation exerts a positive influence on the operating ratio of Life insurers. In short, higher inflation in periods of low inflation appears to be detrimental to the overall performance (insurance business plus investment activity) of Life insurers. The effect of investment hedging on the operating ratio is inconclusive.

On the other hand, the results obtained indicate a negative and statistically significant coefficient at the 5% threshold in the high-inflation regime for the Life sector. Thus, in periods of high inflation, investments have a hedging effect on the operating ratio of Life insurers, since the coefficient is higher in absolute value in Table 37 than in Table 35.

In conclusion, the results indicate that the variation in inflation has a statistically significant impact on the P&C operating ratio only in the high-inflation regime. The results in Table 13 indicate that, in the P&C sector, the coefficient of the CPI variable is positive and statistically significant at the 5% threshold in the high-inflation regime. The investment hedging effect is inconclusive.

Our analysis of the impact of inflation on insurers' operating cost management efficiency, as measured by the operating ratio, yields four main conclusions.

First, the increase in inflation during periods of low inflation appears to be detrimental to the overall performance of insurers in the Life sector. Tables 35, 36 and 37 suggest that the poor performance observed when inflation rises in periods of low inflation seems to be attributable to the poor performance of the Life sector's investment activity.

Second, rising inflation during periods of high inflation appears to improve the overall performance of Life insurers. Tables 35, 36 and 37 show that the good performance of Life insurers when inflation rises during periods of high inflation seems to be attributable to the good performance of Life investment activity, which confirms the natural risk management interpretation.

Third, rising inflation during periods of high inflation appears to impede the overall performance of P&C insurers. Tables 35, 36 and 37 show that the poor overall performance of P&C insurers when inflation rises during periods of high inflation seems to be attributable to the performance of the insurance business. Further, Table 36 shows that rising inflation exerts positive effects on the investment activity performance (positive and statistically significant effect of CPI on the net investment income ratio) of P&C insurers in periods of high inflation. However, the positive effects from the investment business did not offset the trend of negative effects from the insurance business: Table 37 shows that rising inflation still exerts negative effects on overall performance (positive and statistically significant effect of CPI on the operating ratio) in periods of high inflation.

In conclusion, the results show that inflation positively affects the overall performance of Life insurers through their investment activities, while inflation negatively affects the overall performance of P&C insurers, mainly through their underwriting business.

7.4.5 Impact of inflation on financial profitability measured by the ROA indicator

Our analysis of the impact of inflation on insurers' operating cost management efficiency as measured by the operating ratio has shown that inflation exerts a statistically significant positive influence on the P&C operating ratio in periods of high inflation. Given that the profitability of the insurance business is a decreasing function of the operating ratio, we would expect inflation to exert a negative influence on the financial profitability of P&C insurers in periods of high inflation. The coefficient is not significant in Table 38. The impact of inflation on the ROA of the P&C sector in periods of low inflation is also inconclusive: The coefficient obtained is not statistically significant. In the Life sector, our analysis of the impact of inflation on insurers' operating cost management efficiency as measured by the operating ratio shows that inflation has a statistically significant positive influence (at 10%) on the Life operating ratio in periods of low inflation, and a statistically significant negative influence on the Life operating ratio in periods of high inflation (at 5%). In other words, inflation should have a negative influence on the financial profitability of the Life insurance business in periods of low inflation, and a positive influence on the financial profitability of the Life insurance business in periods of high inflation.

Table 38: Estimated impact of inflation
on financial profitability measured by the ROA indicator, 1973-2023 analysis period

	P&C sector		Life sector	
Dependent variable	ROA		ROA	
Independent variable	Coefficient	Std. error	Coefficient	Std. error
CPI (State 1)	-0.0007	(0.0006)	-0.0004*	(0.0002)
Determinants				
Pretax Operating Income	0.0056***	(0.0004)	0.0002***	(1.73e-05)
Capital and Surplus to Total assets	-0.1060	(0.0813)	0.7260***	(0.1760)
Log Total assets	-0.0116***	(0.0032)	-0.0035***	(0.0010)
Reserves to Total assets	-0.3610***	(0.1200)	-0.0800***	(0.0209)
Constant	0.3430***	(0.0933)	0.0501**	(0.0232)
CPI (State 2)	0.0004	(0.0006)	0.0078***	(0.0026)
Determinants				
Pretax Operating Income	0.0007***	(4.82e-05)	0.0002***	(7.87e-05)
Capital and Surplus to Total assets	0.0054	(0.0276)	2.9960**	(1.235)
Log Total assets	-0.0256***	(0.0069)	-0.0331***	(0.0045)
Reserves to Total assets	-0.0444	(0.0471)	-0.0743**	(0.0321)
Constant	0.2010***	(0.0728)	0.1310	(0.106)
Lnsigma	0.0047**	(0.0005)	0.0027**	(0.0008)
p11	0.9702**	(0.0405)	0.9517**	(0.0340)
p21	0.0170**	(0.0192)	0.1798**	(0.1087)
Observations	51	51	51	51

Notes: Lnsigma: parameter of volatility. Robust standard errors in parentheses. *** p<0.01, ** p<0.05. State 1: low inflation; State 2: high inflation.

The impact of inflation on financial profitability proved to be statistically significant in the Life sector in the two regimes. Table 38 shows that the CPI variable presents a statistically significant negative coefficient at the 10% threshold and a statistically significant positive coefficient at the 1% threshold for State 1 and State 2 respectively. The results in Table 38 also suggest that, in the Life sector, the coefficients of each of our four determinants, Pretax Operating Income (which measures operating profit), Capital and Surplus to Total assets, Total assets (in log) and Reserves to Total assets have the expected signs and are all statistically significant in each of the two states. They are less significant in the P&C sector.

To summarize, our analysis of the impact of inflation on financial profitability as measured by the ROA indicator validated our finding that inflation would detract from the financial profitability of the Life insurance business in periods of low inflation, and enhance the financial profitability of the Life insurance business in periods of high inflation. The impact of inflation on the ROA of the P&C sector in periods of low inflation and high inflation was inconclusive, given the non-statistical significance of the coefficient obtained in each of the two regimes.

7.4.6 Impact of inflation on capital measured by the variable Capital to Total assets

Our analysis of the impact of inflation on financial profitability shows that inflation is detrimental to the financial profitability of the Life insurance business in periods of low inflation, and beneficial to the financial profitability of the Life insurance business in periods of high inflation. Since, in theory, capital should increase with companies' financial performance, we would expect the Life capital to fall in periods of low inflation and to rise in periods of high inflation.

Table 39: Estimated results for the impact of inflation on capital measured by the variable Capital and Surplus to Total assets, 1973-2023 analysis period

	P&C sector		Life sector	
Dependent variable	Capital and Surplus to Total assets		Capital and Surplus to Total assets	
Independent variable	Coefficient	Std. error	Coefficient	Std. error
CPI (State 1)	0.0005	(0.0015)	-0.0002**	(9.40e-05)
Determinants				
Capital and Surplus	0.0003***	(2.19e-05)	2.99e-05***	(3.31e-06)
Log Total assets	-0.0237***	(0.0070)	-0.0100***	(0.0006)
Constant	0.3730***	(0.0420)	0.1350***	(0.0040)
CPI (State 2)	-0.0010	(0.0015)	0.0005***	(0.0002)
Determinants				

	P&C sector		Life sector	
Dependent variable	Capital and Surplus to Total assets		Capital and Surplus to Total assets	
Independent variable	Coefficient	Std. error	Coefficient	Std. error
Capital and Surplus	-7.60e-05**	(3.58e-05)	0.0001**	(5.40e-05)
Log Total assets	0.0687***	(0.0119)	-0.0058*	(0.0034)
Constant	-0.0777	(0.0645)	0.0956***	(0.0184)
Lnsigma	0.0128**	(0.0013)	0.0010**	(0.0001)
p11	0.9181**	(0.0476)	0.9511**	(0.0347)
p21	0.1614**	(0.0962)	0.1920**	(0.1140)
Observations	51	51	51	51

Notes: Lnsigma: parameter of volatility. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. State 1 = low inflation; State 2 = high inflation.

The results in Table 39 show that inflation had no statistically significant impact on the value of capital for P&C insurers, as observed in the ROA analysis. In contrast, the results obtained for the Life sector suggest that the CPI variable has a negative and statistically significant coefficient at the 5% threshold in periods of low inflation and a positive and statistically significant coefficient at the 1% threshold in periods of high inflation. In other words, the impact of inflation on the value of capital is statistically significant in the Life sector in both regimes. The results in Table 39 also indicate that, in both sectors, the coefficients of each of our two determinants, Capital and Surplus and Total assets (in log), are all statistically significant in each of the two states.

To summarize, our analysis of the impact of inflation on the value of capital confirms the result that Life capital should increase in periods of high inflation and decrease in periods of low inflation. This result is explained by the positive relationship between companies' financial performance and the value of capital.

8. Conclusion

The objective of this research is to analyse the effect of inflation on US insurance markets. The study is based initially on a VAR (Vector AutoRegressive) model. We used this model to analyze the impulse response functions of inflation to shocks observed in the United States over the last 51 years (1973-2023 period), namely the oil shocks of the 1970s, the 1979 monetary policy reform led by Paul Volcker, and the COVID-19 pandemic. We show that the shock of the COVID-19 pandemic, by comparison to previous oil shocks, had a significant positive *short-term* impact on inflation, probably explained by the recent contractionary of the Fed monetary policy against inflation.

We then analyzed the characteristics of the U.S. inflation rate series observed over the 1973-2023 period in order to capture and model the effect of inflation on the insurance industry. Two important conclusions emerge from this analysis: The US inflation rate series is characterized by non-linear dynamics (asymmetry) and a random trend. These results led us to select the two-regime Markov model for analysing the effect of inflation on different performance indicators of the insurance industry.

In the third part of our study, we analyzed the impact of inflation on various fundamental determinants of insurance company performance in the US. Our results show that premiums and claims for P&C and Life insurers are negatively and positively affected by inflation in periods of low inflation and high inflation respectively, with one exception for the Life sector (no significant effect on premiums in State 2). Regarding the performance of the insurance business as measured by the Combined ratio indicator, we found that inflation has a negative influence (beneficial effects) on the P&C Combined ratio indicator in periods of low inflation, and a positive influence (harmful effects) on the P&C Combined ratio indicator in periods of high inflation. In the Life sector, the effects obtained are the opposite of those seen in the P&C sector. The results show that inflation has a detrimental effect on the Life Combined ratio indicator in periods of low inflation, and a beneficial effect on the Life Combined ratio indicator in periods of high inflation. In terms of the performance of insurers' investment activity, the results show that insurers' net investment income is higher in periods of high inflation in each of the two sectors. Conversely, in periods of low inflation, insurers' net investment income is lower in the Life sector, and higher in the P&C sector.

Furthermore, the results show that in the P&C sector, inflation has no statistically significant impact on the other performance measurement indicators (ROA and capital) in either of the two regimes, except for the Operating ratio indicator, where a positive and statistically significant influence was observed at 5% in the high-inflation regime. In contrast, in the Life sector, the results show that inflation has a statistically significant impact on the other performance measurement indicators (Operating ratio, ROA and Capital and Surplus to Total assets) in both regimes.

In the Life sector, the results obtained with the Operating ratio indicator show that inflation has both harmful and beneficial effects on the overall cost efficiency of Life insurers in periods of low inflation and high inflation respectively. Regarding the financial profitability of Life insurers, measured by the ROA indicator, the results are the opposite of those obtained with the Operating ratio indicator. This seems logical given that financial profitability is negatively related to overall cost efficiency as measured by the Operating ratio indicator. Thus, the results indicate that Life insurers are likely to achieve lower financial returns in periods of low inflation, and higher financial returns in periods of high inflation. Finally, the results obtained for the performance of invested capital indicate that invested capital is likely to be lower in periods of low inflation and higher in periods of high inflation. All in all, the results suggest that both sectors were exposed differently to the risks associated with changes in inflation regimes.

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