MASTERARBEIT | MASTER'S THESIS

Titel | Title

Markup and Price Responses to Supply-Side Shocks: The Case of the Italian Manufacturing Sector

verfasst von | submitted by

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angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien | Vienna, 2024

Studienkennzahl lt. Studienblatt | Degree programme code as it appears on the student record sheet:	UA 066 913
Studienrichtung lt. Studienblatt | Degree programme as it appears on the student record sheet:	Masterstudium Applied Economics
Betreut von | Supervisor:	Univ.-Prof. i.R. Dipl.-Ing. Dr. Robert Kunst

ABSTRACT

The recent surge in inflation and its associated economic challenges highlight the necessity of understanding the intricate dynamics of global supply chains, energy markets, and firms' pricing behavior. Italy, heavily dependent on fossil fuels, has faced considerable production challenges and energy price volatility. This thesis contributes to applied macro-econometric research by employing multivariate time series techniques to analyze the dynamic behavior of markups and price levels in response to supply-side shocks, focusing on the Italian manufacturing sector. The study uses Vector Autoregression (VAR) models to explore the dynamic relationships between markups, price levels, and supply-side shocks, employing Granger causality tests, impulse response functions, and forecast error variance decomposition. This thesis provides insights that contribute to a deeper understanding of the factors influencing pricing behavior in the manufacturing sector amidst supply-side disruptions. The findings indicate that all examined supply-side shocks threaten price stability, with varying impacts, delays in pass-through effects, and persistence levels. Specifically, we observe evidence of excess cost pass-through with domestic energy price indices, particularly electricity prices, and supply chain constraints, notably delivery times. Additionally, liquid fuels have the most pronounced effect on the output deflator and its variance, so firms tend to absorb part of a liquid fuel cost shock by reducing their markup. Imported energy, imported intermediate goods, and capacity constraints similarly threaten price stability.

ZUSAMMENFASSUNG

Der jüngste Inflationsanstieg und die damit verbundenen wirtschaftlichen Herausforderungen machen deutlich, wie wichtig es ist, die komplexe Dynamik der globalen Lieferketten, der Energiemärkte und des Preissetzungsverhaltens der Unternehmen zu verstehen. Italien, das stark von fossilen Brennstoffen abhängig ist, sah sich mit erheblichen Produktionsproblemen und Energiepreisschwankungen konfrontiert. Diese Arbeit leistet einen Beitrag zur angewandten makroökonometrischen Forschung, indem sie multivariate Zeitreihentechniken einsetzt, um das dynamische Verhalten von Preisaufschlägen und Preisniveaus als Reaktion auf angebotsseitige Schocks zu analysieren, wobei der Schwerpunkt auf dem italienischen verarbeitenden Gewerbe liegt. Unter Verwendung von Vektor-Autoregressions-Modellen (VAR) werden in der Studie die dynamischen Beziehungen zwischen Preisaufschlägen, Preisniveaus und angebotsseitigen Schocks untersucht, wobei Granger-Kausalitätstests, Impuls-Antwort-Funktionen und Varianzdekomposition von Prognosefehlern eingesetzt werden. Diese Arbeit liefert Erkenntnisse, die zu einem tieferen Verständnis der Faktoren beitragen, die das Preisverhalten im verarbeitenden Gewerbe inmitten von Störungen auf der Angebotsseite beeinflussen. Die Ergebnisse deuten darauf hin, dass alle untersuchten angebotsseitigen Schocks die Preisstabilität bedrohen, wobei die Auswirkungen, die Verzögerungen bei der Weitergabe von Effekten und das Ausmaß der Persistenz variieren. Insbesondere gibt es Hinweise auf eine übermäßige Kostenüberwälzung bei inländischen Energiepreisindizes, insbesondere bei den Strompreisen, und bei Beschränkungen in der Lieferkette, vor allem bei den Lieferzeiten. Darüber hinaus wirken sich flüssige Brennstoffe am stärksten auf das Preisniveau und seine Varianz aus, sodass die Unternehmen dazu neigen, einen Teil des Kostenschocks durch eine Senkung ihrer Preisaufschläge aufzufangen. Importierte Energie, importierte Zwischenprodukte und Kapazitätsengpässe bedrohen die Preisstabilität in ähnlicher Weise.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS

ARCH – Autoregressive conditional heteroskedasticity

BOWI – Backlogs of Work Index

CUSUM – Cumulative sum

FEVD – Forecast error variance decomposition

IRF – Impulse response function

IFAPI – Imports from Abroad Price Index

IFAPI IG – Imports from Abroad Price Index: Intermediate Goods

MA – Moving average

OIRF – Orthogonal impulse response function

PMI – Purchasing Managers' Index

SDTI – Suppliers' Delivery Times Index

UVC – Unit variable costs

VAR – Vector autoregression

1 INTRODUCTION

The recent spike in inflation and the associated economic challenges have underscored the critical importance of understanding the intricate dynamics of global supply chains and energy markets. Economists widely agree that the recent price increases are primarily due to disruptions in the worldwide supply chain, where demand has outpaced supply following pandemic-related lockdowns. For instance, shipping times from China have dramatically increased due to the zero-COVID strategy implemented by the Chinese government. Another momentous disruption was the microchip shortage, which severely impacted the automotive industry. Additionally, the escalation of the Russian-Ukrainian conflict has caused steep increases in gas and oil prices, consequently raising electricity prices. These factors have collectively led to a cost-of-living crisis, declining real incomes for households, and a severe risk of economic stagnation.

Italy's manufacturing sector operates within a highly dynamic environment characterized by various bottlenecks in supply chains, fluctuations in production capacity, and energy and import price volatility. The sector has been demonstrably affected by recent global events. According to the International Energy Agency (2024), Italy's industrial energy use in 2021 was heavily reliant on fossil fuels. Natural gas accounted for 42.2 percent, oil for 7.1 percent, and coal for 3.1 percent of the total final energy consumption. Heat, accounting for 7 percent of total final energy consumption, and electricity, comprising 37.9 percent of total final energy consumption, were also predominantly generated from fossil fuels. Despite a 36-percentage point reduction in manufacturing energy intensity since 2000, it remained at 3.18 MJ per 2015 USD PPP in 2021. Italy has substantially developed its natural gas pipeline and LNG infrastructure. Consequently, Italy remains highly dependent on fossil fuels and vulnerable to imported energy price fluctuations, with net energy imports comprising 83.7 percent of the total energy supply in 2022. Supply shocks in 2021 are estimated to have lowered Italy's manufacturing output by approximately 6 percent, and GDP was lowered by more than 2 percent (Kemp, Portillo, and Santoro 2023).

Economists have been diligently analyzing the mechanisms behind inflation, particularly how energy price increases and supply chain bottlenecks contribute to inflationary pressures. Some studies suggest firms have exploited the altered competitive landscape to raise profits. Stiglitz and Regmi (2023) argue that the excess aggregate demand theory cannot fully explain the recent inflationary period. Instead, an increase in market power and concentration combined with the ability to raise markups provide a more empirically accurate explanation for the recent inflation. This has led to unprecedented policy implications. In the US and the EU, less orthodox inflation-fighting policies such as windfall profit taxes, price gouging policies, and anti-trust measures have emerged in response to the recent inflation crisis (Weber et al. 2022).

While numerous studies examine the effect of profits or markups on inflation, they typically rely on static regression analysis and focus on short periods. This approach overlooks the dynamic effects of supply-side shocks on markups and price levels. There is a scarcity of literature that explores how these factors interact over time, particularly in response to supply-side disruptions. We argue that it is essential to analyze markups and price levels together, as their dynamic interplay provides a more comprehensive understanding than static regressions, which often yield a single coefficient for the effect. Additionally, the existing literature has scarcely utilized multivariate time series analysis, a powerful method for examining the persistency of shock responses and pass-through dynamics.

The primary research question guiding this study is: how do markups and prices dynamically react to various supply-side shocks in the Italian manufacturing sector? This thesis aims to enhance the understanding of how global supply chain disruptions and energy market dynamics influence inflation. We investigate the complex relationships between supply chain bottlenecks, capacity constraints, energy price fluctuations, import price fluctuations, and their impact on aggregate markups and price levels. By thoroughly examining these interdependencies, this thesis provides insights into the factors shaping manufacturing firms' collective pricing behavior in response to different shocks.

To achieve our research objectives, we have gathered time series data spanning 18 to 26 years to ensure a comprehensive long-term perspective of the manufacturing sector. We employ Vector Autoregression (VAR) models at the sector level, which are well-suited to capture the dynamic interdependencies among multiple time series variables. This approach allows us to analyze the temporal relationships between markups, price levels, and various supply-side shocks. Our analysis includes time series plots, Granger causality tests, impulse response functions (IRFs), and forecast error variance decomposition (FEVD) to investigate these dynamics thoroughly. Additionally, we compare our findings with recent literature to contextualize our results and highlight their contributions to the existing body of knowledge.

Our findings indicate that all examined supply-side shocks pose significant risks to price stability, with varying magnitudes of impact, delays in pass-through effects, and persistence levels. Specifically, there is evidence of excess cost pass-through with domestic energy price indices, particularly electricity prices, and supply chain constraints, notably delivery times. Additionally, liquid fuels have the most pronounced effect on the output deflator and its variance, to the extent that firms tend to absorb part of a liquid fuel cost shock by reducing their markup. We also found that imported energy, imported intermediate goods, and capacity constraints similarly threaten price stability.

The structure of this thesis is as follows: First, we summarize the current state of the literature and theoretical background. Next, we detail our data sample and empirical methodology. Next, we present our findings. Finally, we discuss limitations and conclude with implications and future research directions.

2 LITERATURE REVIEW

This chapter aims to provide a comprehensive overview of the existing literature. We achieve this by summarizing the methodologies and key findings of studies focusing on energy and import price shocks, supply chain disruptions, capacity bottlenecks, and their impacts on markups and prices.

Weber et al. (2022) used an input-output model to simulate price shocks and identify critical sectors crucial for monetary stability in the US, focusing on inflation from the Ukraine war and COVID-19. According to their study, recent US inflation originates from specific crucial sectors, affecting overall price stability through sectoral linkages. The authors argue that this type of inflation is microeconomic in origin, and thus, monetary policy is not an effective tool to counter commodity-specific price shocks. Utilizing a Leontief price model, they studied cost-price structures and simulated how price shocks in specific industries cascade through the economy, influencing the general price level. They identified the most inflationary sectors by analyzing shocks to 71 industries in the input-output table published by the U.S. Bureau of Economic Analysis. The authors note that the sectors systematically relevant before the pandemic remain crucial today, albeit with tripled inflation impact post-shutdown and during the Ukraine war. They concluded that energy, basic production inputs (excluding energy), necessities, and commercial and financial infrastructure are the most systematically relevant sectors. Furthermore, fossil energy sources such as petroleum and coal, oil and gas, chemical and agricultural products, housing, utilities, and wholesale trade exhibit strong price-amplifying properties. The findings highlight pre-existing price stability vulnerabilities exacerbated by recent global events.

Stiglitz and Regmi (2023) have also analyzed the causes of recent US inflation. The primary sources of inflation in the US since the pandemic have been energy, food, rents, supply chain interruptions, inelastic demand, and manifestations of market power. Two unanticipated shocks, the Russian-Ukrainian war and the Omicron variant, amplified and prolonged inflation. The war caused spikes in food and energy prices, while China's zero-COVID policy led to further supply chain disruptions. The authors argue that the lack of resilience in production can be attributed to just-in-time inventory systems, excess capacity avoidance, supply chain diversification, and reliance on interdependent production processes. These cost-cutting strategies, effective in stable times, appeared vulnerable during overlapping crises. In the US, firms' markups over marginal costs averaged around 26 percent between 1969 and 1980, rising steadily to 72 percent by 2021. This increase is attributed to rising market concentration, particularly in sectors driving the recent inflation. Firms may raise markups during overlapping crises due to uncertainty, even if it risks future losses. Supporting these findings, Baioni (2023a) demonstrates that markups have a positive and statistically significant impact on producer prices in the US. Also, markups were found to Granger cause producer inflation. Looking at the Austrian case, Reiner and Bellak (2023) demonstrate that estimated markups in Austria increased by 35 to 44 percent between 1980 and 2016. Except for a period of stagnation following the EU accession in 1995, the markups have been increasing steadily.

Arquié and Thie (2023) aimed to validate Weber and Wasner's (2023) Sellers' inflation theory using firm-level balance sheet data from the French manufacturing sector from 2020 to 2023. They estimated individual firm markups and aggregated them at the sector level to examine the role of market power in the transmission of shocks. Through regression analysis of a shift-share measure of exposure to energy cost shocks and the producer price index (PPI), with an interaction term for markups, they found that energy cost increases were passed through to prices. Notably, in sectors with less competition and higher sales-weighted average markups, up to 110 percent of the cost shock was passed through, indicating that greater market concentration allows firms to increase markups. Additionally, the pass-through was most pronounced in sectors with low dispersion of markups, where competition had incentives to raise prices. This excess pass-through implies that firms' profit-seeking behavior fueled inflation.

Bräuning, Fillat, and Joaquim (2022) employed an approach that combines industry-level data on producer prices and industry concentration, measured by sales, with firm-level data. They discovered that the US economy has seen a 50 percent increase in industry concentration since 2005. This rise in concentration has resulted in a 25-percentage point increase in the pass-through of costs to prices. On average, price growth above the trend lasts for four quarters. The study indicates that increased industry concentration can amplify inflation, particularly during supply chain disruptions.

Franzoni, Giannetti, and Tubaldi (2023) present empirical evidence indicating that supply chain shortages benefit large firms, allowing them to leverage their market power to increase markups and profitability, while smaller firms suffer the most. Superstar firms, being key customers of suppliers, are prioritized, putting small firms at a double disadvantage: they are hit hardest by input scarcity and lack the power to raise prices. Supply chain backlogs account for 19 percent of US inflation in industries with more asymmetric firm size distribution, with higher inflation observed in sectors heavily impacted by shortages and those with greater market concentration. Using firm-level financial data from Worldscope, the authors show that superstar firms gain market share and profitability during backlogs relative to the bottom 90 percent of firms. Superstar firms also tend to partner with other superstar firms, minimizing their exposure to backlogs and further strengthening their competitive edge. The study's findings, supported by regression analysis, highlight the sizable increase in the ability of superstar firms to raise their markups during supply chain disruptions.

Kemp, Portillo, and Santoro (2023) examined the supply disruptions that hindered the recovery from the Covid-19 pandemic. Using a sign-restricted Bayesian VAR model and the IMF's G20 model, they discovered that these disruptions caused global core inflation to be 1 percent higher in 2021. Global core inflation would have been below pre-Covid projections without these supply shocks. The core inflation was estimated to be around 0.5 percent higher for Italy due to the supply disruptions in 2021. Analyzing the *suppliers' delivery times* and *new orders* subindices of the Purchasing Managers' Index (PMI) to identify supply shocks, they found that these disruptions impeded manufacturing recovery. This slowdown had a ripple effect, impacting other sectors and reducing overall economic value added.

Hansen, Toscani, and Zhou (2023) conduct an innovative decomposition of the consumption deflator, highlighting the critical role of imports in driving inflation. Their findings indicate that profits surged most in sectors facing demand-supply mismatches, with price increases surpassing simple cost pass-throughs despite markups not rising broadly. In the Euro area, import prices contributed approximately 40% to inflation, domestic firms' profits around 45%, and labor costs about 25% in 2022, while net taxes had a disinflationary effect. Firms have been more insulated from adverse terms of trade shocks than wage earners, as prices can be adjusted more flexibly than wages, as seen during the oil price shocks of 1973 and 1979. The sectors with the highest increases in unit profits in the Euro area were agriculture, construction, manufacturing, mining and utilities, and services. This resilience or increase in profitability is attributed to temporary pricing power, capacity constraints, or market structures that allow windfall profits.

Lafrogne-Joussier, R., Martin, J., and Mejean, I. (2023) investigate how import price pressures and energy cost hikes influenced producer prices in the French manufacturing sector from 2018 to mid-2022. Using micro-level data and measures of exposure to imported inputs and energy cost shocks, they found that while 100 percent of energy cost changes were passed through to producer prices, only 30 percent of imported input price increases were reflected. The pass-through rates were asymmetric, with positive shocks resulting in higher pass-throughs than adverse shocks. Specifically, the pass-through rate for positive energy price shocks exceeded 100 percent, while 58 percent for adverse shocks. Each firm's exposure to external shocks varied, leading to heterogeneous contributions to inflation. Imported input prices added 1.9 percentage points to the producer price index, whereas energy contributed 1.6 percentage points, with the chemical and metal industries being the most affected. Despite the varied exposure to shocks, firms responded uniformly to cost changes.

In the case of Italy, Baioni (2023b) employed an impulse-response approach on a dataset spanning from 1996 to 2023. He found that, across the entire economy, markups increased during the COVID-19 pandemic but remained below the average levels observed from 1996 to 2019. To test the sellers' inflation theory from Weber and Wasner (2023), Baioni examined the responses of headline inflation to a shock in markups. He discovered that such shocks had a statistically insignificant impact on post-pandemic inflation when focusing on the period after 2010. Using Granger causality tests, he inferred that inflation Granger causes markups, but not vice versa. Additionally, the effect of markups on inflation was significant in the manufacturing and mining sectors, although the impact was negative.

According to Loecker, Eeckhout, and Unger (2020), markups in the US have been rising since 1980. The distribution of markups has shifted considerably, with the upper percentiles growing substantially while the median remains constant. This markup increase is accompanied by a reallocation of firm activity favoring large firms. In the US, market power and markups have risen from 21 percent above marginal costs in 1980 to 61 percent in 2020, while average profitability has increased from 1 to 8 percent. Most of the gains in markups are found in the upper tail of the markup distribution, reflecting a redistribution of market share from more minor to larger corporations. The authors demonstrate that this markup increase is not merely a response to higher overhead costs. Following these findings, Palazzo (2023) shows that profit margins of the top 20 percent of firms in the US have increased between 2010 and 2019, while others stagnated or declined.

This trend is not unique to the United States. Leigh, Tambunlertchai, and Diez (2018) show that since the 1980s, markups in 33 advanced countries have steadily risen. This increase is evident across industries and is primarily driven by a small group of large 'superstar' corporations. When markups are low, investments tend to be higher, and conversely, high markups are associated with low levels of investment and innovation, especially in sectors with high market concentration. Additionally, there is a negative relationship between markups and the firm-level labor share. The authors also demonstrate a robust positive relationship between markups and profitability at the firm level, measured by either the dividends-to-sales ratio or the market capitalization-to-sales ratio.

3 THEORETICAL BACKGROUND

This chapter establishes the theoretical foundation for our empirical analysis, which primarily adopts a data-driven approach. We explain concepts such as markup pricing, cost pass-through, and supply-side-induced inflation.

3.1 Markup pricing

The following theoretical considerations are based on the principle of markup pricing. Markup pricing, also known as cost-plus pricing, is a pricing strategy where a business sets the selling price of a product by adding a specific markup to its cost. This markup is typically a percentage of the product's cost and is intended to cover the business's expenses and generate a profit. The basic formula for markup pricing is:

$$Selling\ Price = Cost + (Cost * \ Markup\ Percentage)$$

Markups play a crucial role in macroeconomics, reflecting both production technology and the efficient allocation of resources among firms. They are a vital component in the benchmark New Keynesian and standard endogenous growth models. Understanding markups helps illuminate the trade-offs between dynamic and static efficiency, shedding light on how pricing strategies impact overall economic performance and resource distribution. (Loecker, Eeckhout, and Unger 2020, 565)

Following the definitions from Istat – Istituto nazionale di statistica (2024a) and adapting the accounting approach used by Loecker, Eeckhout, and Unger (2020), the markup at the firm level is defined as

$$\mu_{it} \equiv \frac{P_{it}}{c_{it}}$$

i.e., the ratio between the output price P_{it} and unit variable costs c_{it}. At the sector level, the following variables are utilized. The output price is measured by the output deflator at factor costs, calculated as the ratio between the current price production at factor costs and the chain-linked production (measured at factor costs), with the reference year for this analysis being 2015. Unit variable costs are defined as the ratio between the sum of unit labor costs and intermediate consumption and production. For the whole sector, the aggregate markup is calculated as

$$\mu_t = \sum_i m_{it}\mu_{it}$$

where m_{it} is the weight of each firm, e.g., the share of sales. This analysis focuses exclusively on aggregate markup in the manufacturing sector, as provided by *Istat*. Therefore, whenever the term "markup" is used, it refers to this aggregate variable. Loecker, Eeckhout, and Unger (2020) also introduced a novel method for calculating markups using a production approach. However, for our example, the accounting approach is sufficient. In the same paper, they demonstrate that the evolution of markups is closely related to an increase in market concentration. Markups can also be high due to high overhead or fixed costs. However, the authors demonstrate that these factors cannot fully explain the rise in markups in the US case. This suggests that markups are indeed a measure of profitability. In addition, larger firms can set higher markups than smaller firms. This follows the paper of Autor et al. (2020), who state that larger firms have larger markups, resulting in the size-weighted average markup rising more than its unweighted counterpart. These patterns can be observed across OECD countries. As an accompanying trend, the labor share in value-added has decreased. This is due to the reallocation of sales between firms, which is also linked to increased market concentration.

Recent ECB, IMF, and World Bank publications have popularized profit shares, profit margins, and unit profits as proxies for markups. This approach is favored due to the straightforward method of GDP deflator decomposition and the timely availability of national account data, e.g. Hahn (2019), Hahn (2023), Arce, Hahn, and Koester (2023), Hansen, Toscani, and Zhou (2023), Palazzo (2023), and The World Bank (2023). Because markups are challenging to monitor in practice, profit shares are often used as a proxy. If profit shares rise, it is assumed that markups rise accordingly. However, as discussed by Colonna, Torrini, and Viviano (2023), the profit share in value-added and markup are similar only if production follows a Cobb-Douglas function. While profit shares are widely used as a proxy for markups, there are instances where the profit shares can increase while markups remain constant. This can occur when intermediate input costs grow faster than labor costs and input substitutability is limited. Under a constant markup assumption, profits and revenues increase proportionally, the so-called cost pass-through. Cost pass-through measures the ability and willingness of firms to adjust their prices in response to changes in costs. Since the profit share is relative to value-added, which excludes intermediate goods, an increase in the price of intermediate goods can lead to value-added growing less than total revenues. Consequently, profit shares might rise even if firms' pricing strategies remain unchanged.

Intuitively, the response of markups to cost shocks can manifest in three distinct ways. First, markups may contract in response to higher input costs, a short-term necessity as firms may delay price changes due to associated costs and wait until the next feasible adjustment period to recover absorbed losses. Another reason markups may contract is that smaller firms, lacking the market power to raise prices, face intense competitive pressure. Consequently, these firms cannot pass higher input costs to consumers and must absorb the cost increases, leading to reduced markups. Second, markups may remain constant if firms' pricing strategies stay unchanged, reflecting a straightforward pass-through of costs to prices without altering the markup percentage. Third, markups may expand as firms with increased market power seek to maximize profits. This could occur if firms benefit from reduced input costs while maintaining constant prices or strategically accumulate reserves in anticipation of future economic challenges or wage negotiations, particularly after inflation rises. Firms have an incentive to raise markups if they expect input prices to hike soon so they can pursue a more smoothed-out pricing strategy over time (Glover, Mustre-del-Río, and Ende-Becker 2023, 24).

3.2 Sellers' inflation

The idea of firms' pricing decisions driving inflation goes back to Lerner (1958), who called it seller-induced inflation. He theorized that the wage and profit elements in product prices can equally offset inflation. The power relations in the economy determine the balance between those elements. Powerful firms can protect or increase their margins, raising their products' prices as a result.

Kaldor (1985) pointed out that the only market in which firms are *price takers* are commodity markets, which are fully competitive with flexible prices governed by demand and supply. However, prices are not in equilibrium as they frequently fluctuate with the global industrial production growth that determines global demand, while the supply side holds inventories. In all other concentrated markets, firms are *price makers* and set their supply according to changes in orders or inventories. The resulting prices are 'list prices,' with less frequent fluctuations than commodity prices. Competition still plays a role in firms' pricing decisions through strategic interactions between firms with large market shares.

Weber and Wasner (2023) present a novel theoretical framework on sellers' inflation, highlighting large firms' ability to raise prices during emergencies. Their work distinguishes itself by examining the drivers of inflation and the limitations of traditional theories, which often overlook supply-side origins and firms' market power. Traditional New Keynesian and Monetarist views attribute inflation to excess aggregate demand or excessive money supply, with minimal emphasis on supply-side factors beyond high labor costs. In contrast, Weber and Wasner argue that firms' strategic pricing primarily aims to protect profit margins. Prices result from path-dependent strategic interactions between firms and are not necessarily optimal or market-clearing. In stable price periods, firms can increase margins by reducing costs but face competitive pressure to prevent price hikes. They only raise prices when introducing innovative products that create a new market segment or when they expect competitors to follow. Firms already part of a market avoid lowering prices as the competitors' response would lead to a price war, posing a threat to profits. The following theory is based on the idea that the coordination in a market can either be a cartel or implicitly based on common knowledge about exogenous shocks that affect the sector equally. To explain why firms in concentrated industries could hike prices during the pandemic, the authors developed a three-stage model of the inflation process following a period of prolonged price stability: First, in the 'impulse' stage, bottlenecks and commodity price upswings induce rising margins and prices in systematically relevant upstream sectors. In the 'propagation and amplification' stage, firms want to protect their margins against input cost increases and raise prices. In the 'conflict' stage, workers and labor unions try to negotiate higher wages to offset the loss in real wages. In this case, increased wages are not the origin of inflation (the classical wage-price-spiral case) but a consequence. The essence of this theory is that external shocks, such as supply chain bottlenecks and energy price increases, act as implicit coordination mechanisms between firms. Firms have an incentive to raise prices to protect their profit margins simultaneously. The threat of being undercut by competitors is temporarily suspended because not increasing prices would decrease profitability. Hence, the ability of competition to fight for market shares declines. When supply chain bottlenecks affect the whole sector, demand can outpace supply, which enables firms to gain temporary monopoly power and increase their profit margins. This is further fueled by inelastic demand and consumer acceptance of price increases. Supply-chain bottlenecks and energy cost shocks can lead consumers to accept price increases, e.g., when inflation coverage in the media makes them expect price increases. Another implication is that market shares are protected, as consumers have little incentive to switch to competitors when all firms increase their prices simultaneously. While the incentive for adjusting prices is equal sector-wide, firms' motivation may vary depending on their size. Large firms face the threat of investors selling off shares if they do not stick with a more aggressive pricing strategy. Evidence from the US retail market from 2021 shows that investors can sanction corporations with a sell-off of shares if they pursue a strategy to absorb price increases rather than protect margins. Small firms generally have lower revenues, market shares, and pricing power. Their maneuver room for lowering margins is narrow; hence, they cannot absorb large cost increases. They face the threat of market exit if they do not follow the market in increasing prices. To summarize, a market in which all agents are incentivized to increase prices can increase profits when firms exploit this situation to increase margins. In the long run, too high prices in a given sector can raise the possibility of new entrants starting a price competition. Analogously, too low prices can lead to a withdrawal of capital, leading to market exits and increased concentration. Weber and Wasner's analysis of earnings calls from major US firms supports their model, showing that firms exploited the pandemic-induced situation to increase margins and protect market shares.

4 DATA

We use sector-level aggregated time series data in quarterly frequency for the empirical analysis, which is seasonally adjusted unless stated otherwise. The following data can be obtained from quarterly national accounts at Istat – Istituto nazionale di statistica (2024a) and is available from 1997 quarter two until 2023 quarter 4 (indices, reference base = 2015, 107 quarterly data points) for the Italian manufacturing sector. The ratio between the sum of unit labor costs and intermediate consumption and production gives *unit variable costs (UVC)*. The ratio between the output deflator and unit variable costs gives the *markup*. We use the *output deflator* from the same source to measure the price level in the manufacturing sector.

To have a measure for energy prices, we use the *Harmonized Index of Consumer Prices (HICP)* for *total energy*, *electricity*, *gas*, and *liquid fuels* (reference base = 2015, Q1 2001 – Q4 2023, 92 quarterly data points). (Istat – Istituto nazionale di statistica 2024b)

Given the increased relevance of imported energy due to the recent gas and oil shortages, we also consider import prices from abroad for *intermediate goods* and *energy* (reference base = 2015, Q1 2005 – Q4 2023, 76 quarterly data points). All of these price indices are not seasonally adjusted. (Istat – Istituto nazionale di statistica 2024c)

With permission from S&P Global Market Intelligence (2024), we obtained the Purchasing Managers' Index™ (PMI®) time series data. The PMI is a survey-based indicator that includes the subindex output, new orders, employment, input and output prices, export orders, purchasing activity, suppliers' performance, backlogs of work, and inventories. Respondents are asked to report changes in these variables compared to the previous month, indicating improvement, deterioration, or no change. The subindices are so-called diffusion indices, which signal improvements if the index is above the natural level of 50 and deterioration if the index is below 50. The further the index level is from 50, the greater the rate of change. For this analysis, we use the *Suppliers' Delivery Times Index (SDTI)*, which can reveal supply chain bottlenecks, and the *Backlogs of Work Index (BOWI)*, which is a measure of production capacity, but also equipment breakdowns, labor shortages, etc. The SDTI data spans from quarter two 1997 to quarter four 2023 (107 quarterly data points), while the BOWI starts in quarter four 2002 (85 quarterly data points). Because it aims to signal improvements when the index value exceeds 50, the PMI includes the inverse of suppliers' delivery times. That is because when delivery times are shorter, which signals an improvement, the SDTI value lies below 50, and vice versa. For this analysis, we use the variant of the SDTI that signals improvement when below 50, i.e., delivery times are shorter, and deterioration above 50, i.e., delivery times are longer.

5 EMPIRICAL STRATEGY

This thesis investigates how markups and prices react to economic shocks in the Italian manufacturing sector. To achieve this, we gather time series data at the sector level and employ a Vector Autoregression (VAR) model. This approach was chosen because VAR models effectively capture the dynamic interdependencies among multiple time series variables. Given that markup and price levels are likely influenced by various economic factors, a data-driven approach that avoids strict theoretical restrictions is ideal. This flexibility is crucial when theoretical relationships are complex and existing theories are scarce.

We consider VAR models to be adequate for this analysis. They provide flexibility and simplicity, allowing us to capture the dynamics and feedback loops among the variables in the system. This is particularly relevant for prices and markups, regularly adjusted as firms adapt to volatile economic conditions. The dynamic approach of VAR, combined with impulse response analysis, enables us to observe how markups and prices respond to shocks over time, potentially revealing patterns of collective firm behavior in the manufacturing sector. The use of impulse response analysis and forecast error variance decomposition, as pioneered by Sims (1980, 1981), allows for a nuanced understanding of these dynamics without imposing rigid a priori restrictions on the data generation process.

One noteworthy drawback of using VAR models is the risk of overfitting, which can lead to inefficient estimates if the sample size is not sufficiently large. This is relevant since our data has a quarterly frequency and limited observations. Additionally, without additional constraints and assumptions, VAR models are not well-suited for identifying underlying structural relationships, limiting their ability to uncover causality. To mitigate the risk of overfitting, we restrict the number of variables in the model to those most essential to firms' pricing decisions: unit variable costs, markup, and output price indices, along with one variable to introduce a shock into the system. This helps ensure more efficient estimates.

Many variables show trending behavior that violates the stationarity assumption of VAR models. To address this, we use first-differenced time series to remove trends and ensure the stability of the VAR models. Additionally, seasonality is addressed by using seasonally adjusted data, further enhancing the reliability of the results.

VAR models are generally not well-suited for studying contemporaneous effects directly because they focus on how past values of variables affect current and future values. To address this, we apply Cholesky decomposition, which enables the use of orthogonal impulse response functions to capture contemporaneous effects. However, a potential concern with this method is that the results can be sensitive to the chosen ordering of variables, necessitating careful justification and robustness checks. This issue is thoroughly explained in the impulse response analysis chapter.

By carefully addressing these challenges, this thesis aims to provide a robust analysis of how markups and prices in the manufacturing sector respond to economic shocks, contributing valuable insights into the dynamic behavior of these key economic variables. In the following subchapters, we explain the VAR model and the structural methods, including Granger causality analysis, impulse response analysis, and forecast error variance decomposition.

5.1 Vector Autoregression Model

The notation of the VAR model follows that used in Lütkepohl (2005). We use finite-order, stationary, reduced-form vector autoregression (VAR) models, which are convenient due to their simplicity and suitability for applications such as forecasting. Our analysis focuses solely on endogenous variables, given the reasonable assumption of a relationship between input costs, markup, and output prices. We use the definition of the $VAR(p)$ model according to Lütkepohl (2005, 13):

$$y_t = \nu + A_1 y_{t-1} + A_2 y_{t-2} + \dots + A_p y_{t-p} + u_t,$$

where $y_t = (y_{1t}, \dots, y_{Kt})'$ is a $(K \times 1)$ vector containing the variables, A_i are coefficient matrices of the dimension $(K \times K)$, $\nu = (\nu_1, \dots, \nu_K)'$ is the fixed $(K \times 1)$ intercept vector, and $u_t = (u_{1t}, \dots, u_{Kt})'$ is a K-dimensional white noise process. The variables vector is

$$y_t = \begin{pmatrix} \boldsymbol{Impulse\ variable} \\ Unit\ Variable\ Costs \\ Markup \\ Output\ Deflator \end{pmatrix}.$$

Including all impulse variables that introduce shocks into the system in a single model would lead to overidentification, rendering the results meaningless. Therefore, we construct several similarly structured models. Each model contains the three core variables: unit variable costs, markup, and output deflator, along with one unique impulse variable selected from Table 1.

Table 1: Impulse Variables by Category

Category	Impulse Variable
Energy Price Indicators	HICP Energy
	HICP Electricity
	HICP Gas
	HICP Liquid Fuels
Import Price Indicators	Imports from Abroad Energy
	Imports from Abroad Intermediate Goods
Operational and Supply Chain Bottlenecks	SDTI
	BOWI

A critical decision when constructing a VAR model is selecting the lag length, also known as the VAR order. Choosing an excessively large VAR(p) order can diminish the model's forecast precision and the impulse responses' estimation precision. Fortunately, statistical methods are available to help determine a suitable VAR order, balancing the need for accuracy with the penalty of higher lag lengths, which reduce the effective length of our time series and potentially limit the significance of our results. The following criteria are used to determine an appropriate VAR order:

Akaike's Information Criterion (AIC)

$$AIC(m) = \ln\left|\tilde{\Sigma}_u(m)\right| + \frac{2}{T}mK^2,$$

Hannan-Quinn criterion

$$HQ(m) = \ln\left|\tilde{\Sigma}_u(m)\right| + \frac{2\ln(\ln(T))}{T}mK^2,$$

Schwarz criterion

$$SC(m) = \ln\left|\tilde{\Sigma}_u(m)\right| + \frac{\ln(T)}{T}mK^2,$$

and the Final Prediction Error (FPE) criterion

$$FPE(m) = \left(\frac{T+m^*}{T-m^*}\right)^K \left|\tilde{\Sigma}_u(m)\right|,$$

where K denotes the dimension of the time series, T is the sample size, m is the order of the VAR model fitted to the data, and $\tilde{\Sigma}_u(m)$ is the maximum likelihood estimator of the white noise covariance matrix Σ_u. The VAR order m which minimizes a criterion is an estimate of the VAR order p. All four criteria are examined to determine the VAR order. If all have the same optimal VAR order, it is chosen for the model. If they have different results, there is no clear strategy for selecting an adequate VAR order, as one criterion is not, per se, superior to another; it depends on the context. The strength of the criteria, such as AIC, is a weighted criterion function that includes penalty terms. On the one hand, AIC and FPE asymptotically overestimate the true VAR order p with positive probability. Yet, they may have better properties in small samples and produce superior forecasts. On the other hand, SC has the strong property of being consistent for the true lag order. We look at all criteria when determining an adequate VAR order and use statistical tests to help our decision if necessary. (Lütkepohl 2005, 147–57)

After setting up each VAR(p) model, we test for serially correlated errors using the multivariate Portmanteau test, heteroskedasticity using the multivariate ARCH-LM test, normal distributions of the residuals using the multivariate Jarque-Bera test, and structural stability, structural breaks in the residuals, because ideal VAR models fulfill the stability condition.

5.2 Granger Causality Tests

First, we conduct Granger causality tests to uncover potential links between the chosen variables, i.e., which could have a Granger causal relationship in at least one direction. Granger causality tests uncover if a set of variables contains valuable information for predicting another set of variables. When using VAR models, the concept of Granger causality, established by Granger (1969), is straightforward. The cause must come before the effect and not afterward. Hence if variable x_t affects variable z_t, x_t must improve the prediction of z_t. For a stationary, stable VAR(p) process

$$y_t = \begin{pmatrix} z_t \\ x_t \end{pmatrix} = \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} + \begin{pmatrix} A_{11,1} & A_{12,1} \\ A_{21,1} & A_{22,1} \end{pmatrix} \begin{pmatrix} z_{t-1} \\ x_{t-1} \end{pmatrix} + \cdots + \begin{pmatrix} A_{11,p} & A_{12,p} \\ A_{21,p} & A_{22,p} \end{pmatrix} \begin{pmatrix} z_{t-p} \\ x_{t-p} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

the condition for Granger Noncausality

$$z_t(h|\{y_s|s \leq t\}) = z_t(h|\{z_s|s \leq t\}) \Leftrightarrow \Phi_{12,i} = 0 \text{ for } i = 1,2,\dots, \text{ and } h = 1,2,\dots,$$

with $\Phi(z)$ being the canonical MA operator is satisfied if and only if

$$A_{12,i} = 0 \text{ for } i = 1, \dots, p.$$

Hence, we can accept the null, z_t is not Granger caused by x_t, if all coefficients $A_{12,i}$ linking those two variables are zero. Likewise, we can accept the null, x_t is not Granger caused by z_t, if all coefficients $A_{21,i}$ are zero. Note that Granger causality tests do not uncover contemporaneous relationships. For this, the concept of instantaneous causality is frequently used. Further, it is essential not to confuse Granger causality with actual causality. The former can be present without the latter and the other way round. The actual direction of causation between variables must be derived using other tools, such as economic theory. (Lütkepohl 2005, 41–51)

5.3 Impulse Response Analysis

Insights into the dynamic behavior of a VAR model and the effects' direction and magnitude can be derived from impulse response analyses. The goal is to simulate shocks to an impulse variable that could affect firms' pricing decisions and investigate their influence on aggregate markup and prices. The basic idea is an exogenous effect or innovation in one variable affects some or all other variables. Impulse response functions (IRFs) show how variables in a system react to a one standard deviation shock in one variable. Since VAR models do not reflect contemporaneous effects, we must find a circumvention to include those effects in the impulse response analysis. In addition, basic impulse response functions assume that a shock occurs only in one variable at a time, i.e., setting the innovations of all other variables to zero. However, this may be misleading, as shocks to variables may depend on each other. For these reasons, impulse response analysis often uses the moving average representation,

$$y_t = \mu + \sum_{i=0}^{\infty} \Theta_i \omega_{t-i}$$

where white noise errors $\omega_t = (\omega_{1t}, \dots, \omega_{Kt})'$ are uncorrelated, have unit variance, and are thus called *orthogonal* residuals or innovations. Hence, a unit innovation has the size of one standard deviation. The elements of Θ_i are the system's responses to such innovations, i.e., we assume $\theta_{jk,i}$ is the effect of the variable j on a unit innovation in the k-th variable, which occurred i periods ago. Our VAR(p) process can be rewritten so that the residuals of different equations are uncorrelated. To do so, we apply the Cholesky decomposition,

$$\mathrm{A} y_t = c + A_1^* y_{t-1} + A_2^* y_{t-2} + \dots + A_p^* y_{t-p} + \epsilon_t$$

where $A_i^* = AA_i$, $i = 1, \dots, p$, and $\epsilon_t = (\epsilon_{1t}, \dots, \epsilon_{Kt})' := Au_t$ has a diagonal covariance matrix. Note that A is a lower triangular matrix with a unit diagonal. The multiplication with matrix A allows us to assume the cross-correlation among error terms is zero. The graphical representation is called the *orthogonal impulse response function (OIRF)*. However, applying this method increases the importance of the ordering of variables in our model, often called *Wold causal ordering*, because it may largely determine the impulse responses. The order cannot be determined by statistical methods but must be chosen by the analyst. The first variable to enter our model y_{1t} is assumed to be the only one with a potential immediate impact on all other variables. The second variable y_{2t} can have an immediate impact on all remaining $K - 2$ components of y_t except y_{1t}. (Lütkepohl 2005, 58–63)

In our case, the impulse variable that represents the shocks to the Manufacturing sector enters the model first, and thus, it is assumed to immediately affect unit variable costs, markup, and output price level. The second variable is unit variable costs, which we assume cannot immediately affect the impulse variable but markup and output price. In that sense, an individual firm has to know its variable costs first and choose markup and output price accordingly, ideally above the costs, to make a profit. The variable costs are the sum of all individual input costs, including energy and transport costs. Assuming only a shock is occurring in the impulse variable and holding the production, energy, and transport demand constant while the shock appears, the variable costs result from impulse variable changes, not vice versa. Considering the remaining pair of variables, the ordering depends on firms' pricing strategies. If the firm has a target price in mind and lets the markup be determined solely by variable costs and the target price, the output price should enter first and markup last. Since we consider a markup pricing strategy in this thesis, we assume that firms have target markups and choose the price according to variable costs plus markup. Hence, we put the markup as the third variable and the output price as the last variable. Given the numerous possible variations in variable orderings and the multitude of models being considered, conducting robustness checks for all potential orderings exceeds the scope and depth intended for this thesis. As illustrated above, assuming a theoretical linkage between the variables in the specified order is reasonable. However, we acknowledge the potential sensitivity of our results to the chosen order of variables.

One critique of impulse response analysis is that we usually work with lower-dimensional VAR systems that may be incomplete. Thus, we assume that the effects of omitted variables are part of the innovations. If essential variables are missing in the system, this may introduce distortions to the impulse responses, which limits interpretability. Despite this, our system can still be helpful for predictions. (Lütkepohl 2005, 62)

5.4 Forecast Error Variance Decomposition

Here, we again consider orthogonal white noise innovations and the MA representation of our model from above. The Decomposition of the forecast error variance (FEVD) allows us to quantify the amount of information each variable contributes to the autoregressions of all other variables. Thus, conducting an FEVD aids in comprehending the factors contributing to variability in a time series, as well as indicating interdependence and spillovers. Given that the $\omega_{k,t}$'s are uncorrelated and have unit variances, we can write the mean squared error (MSE) of $y_{j,t}(h)$ as:

$$MSE\left[y_{j,t}(h)\right] = E\left(y_{j,t+h} - y_{j,t}(h)\right)^2 = \sum_{k=1}^{K}(\theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2).$$

The contribution of innovations in variable k to the forecast error variance (MSE of the h-step ahead forecast of variable j) is

$$\theta_{jk,0}^2 + \cdots + \theta_{jk,h-1}^2 = \sum_{i=0}^{h-1}\left(e_j{}'\Theta_i e_k\right)^2$$

where e_k is the k-th column of the identity matrix I_K. We can divide this expression by the forecast error variance, which gives us

$$\omega_{jk,h} = \frac{\sum_{i=0}^{h-1}\left(e_j{}'\Theta_i e_k\right)^2}{MSE\left[y_{j,t}(h)\right]}.$$

Given that we can associate $\omega_{k,t}$ with variable k, $\omega_{k,t}$ is the proportion of the h-step forecast error variance accounted for by innovations in variable k. Conveniently, the proportions of all variables sum up to 1, allowing for an interpretation in percentage terms. Note that seasonal adjustment, measurement errors, and the use of aggregates might contaminate FEVD. (Lütkepohl 2005, 63–66).

6 RESULTS

This chapter explains the procedure for VAR order selection and the accompanying statistical tests. We then present time series plots of all variables and detail the results of the Granger causality tests, orthogonal impulse response functions, and forecast error variance decomposition for both the base and augmented VAR models.

The four aforementioned selection criteria are computed and compared to determine the optimal VAR order for each model. The results and a description of the decisive factors can be found in Table 2. The resulting VAR models differ in terms of their impulse variables, time series length, and VAR order, which limits the comparability between them. The time series length is constrained by data availability; therefore, models with fewer observations per time series use more recent data points. For example, the VAR model with the SDTI as the impulse variable (106 data points) includes older data points than the model with the Energy Import Price Index as the impulse variable (75 data points). This difference of 31 quarters, equivalent to over seven years, means that each model's implications are specific to their respective observation periods. Fortunately, models incorporating the HICP indices and the Import Price Indices have the same time series length, allowing for direct comparison within the same time frame

We conduct several tests to ensure the reliability of the models. First, we use the multivariate ARCH-Lagrange Multiplier test to check for autoregressive conditional heteroskedasticity (ARCH) in the errors. This test showed no significant heteroskedasticity, indicating that the models are unaffected by this issue. We also employed Cumulative Sum (CUSUM) tests to check for structural breaks in our VAR models. These tests provide a graphical representation of the cumulative sum of standardized recursive residuals over time. If this cumulative sum exceeds a critical threshold, it indicates the presence of a structural break. However, the CUSUM tests showed no evidence of such breaks for our models. In addition, we perform the multivariate Portmanteau test to check for serially correlated errors. The choice of VAR order is crucial for this test, and all VAR orders were selected to ensure no serial correlation among the error terms. Lastly, we test for the normal distribution of the residuals using the multivariate Jarque-Bera test, which was significant in each case. Thus, we cannot assume normally distributed error terms.

Not normally distributed residuals can be a signal for omitted variables, structural breaks, or nonlinearity. This is somewhat to be expected, given the tradeoff between the number of included variables and VAR model accuracy. This issue is addressed using bootstrapped confidence intervals for impulse response functions (IRFs). Bootstrapping is a non-parametric resampling technique that does not rely on specific distributional assumptions about the residuals. By repeatedly resampling from the observed data (with replacement), bootstrapping can generate an empirical distribution of the IRFs, which inherently captures the characteristics of the original data, including any non-normality. Since bootstrapping uses the empirical distribution of the data, it naturally incorporates the actual distributional properties of the residuals. This makes the resulting confidence intervals more robust to deviations from normality than analytical methods assuming normally distributed errors. When residuals are not normally distributed, standard asymptotic confidence intervals for IRFs may be misleading. On the other hand, bootstrapped confidence intervals are based on the observed data and better reflect the genuine uncertainty and variability in the IRFs. However, non-normality can affect the accuracy and reliability of statistical inferences derived from FEVD. Hence, we must be careful when interpreting the FEVD results and focus on the results from orthogonal IRFs.

The resulting VAR models differ in terms of their impulse variables, time series length, and VAR order, which limits the comparability between them (see Table 2). The time series length is constrained by data availability; therefore, models with fewer observations per time series use more recent data points. For example, the VAR model with the SDTI as the impulse variable (106 data points) includes older data points than the model with the Energy Import Price Index as the impulse variable (75 data points). This difference of 31 quarters, equivalent to over seven years, means that each model's implications are specific to their respective observation periods. Fortunately, models incorporating the HICP indices and the Import Price Indices have the same time series length, allowing for direct comparison within the same time frame.

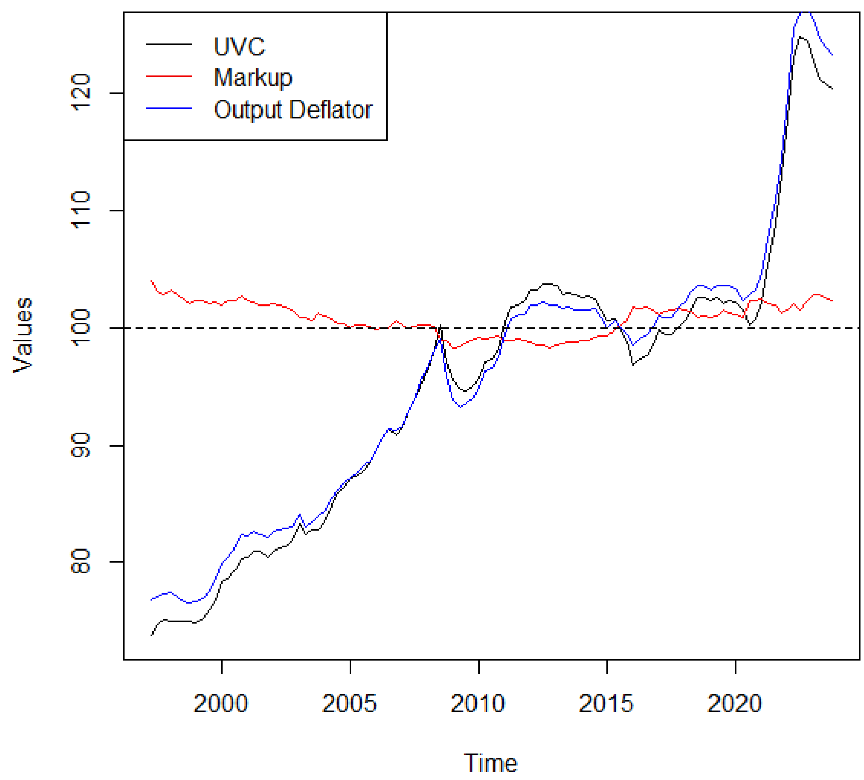
Table 2: VAR Order Selection Criteria and Decisions

Time series length	Impulse variable	Base year	AIC(n)	HQ(n)	SC(n)	FPE(n)	Decision	Decisive factors
106	*None* (Base Model)	2015	1	1	1	1	**1**	
106	SDTI	/	4	1	1	2	**4**	More significant coefficients for p=2 and p=4, visual inspection
91	HICP Energy	2015	2	2	1	2	**2**	For p=2, better result of the serial correlation test and more significant coefficients
91	HICP Electricity	2015	6	2	1	2	**2**	P=6 questionable results, for p=2 more significant coefficients, visual inspection
91	HICP Gas	2015	2	2	1	2	**2**	for p=2 more significant coefficients, p=2 performs better in the portmanteau test, visual inspection
91	HICP Liquid Fuels	2015	3	1	1	3	**1**	visual inspection
84	BOWI	/	1	1	1	1	**1**	
75	IFAPI Energy	2015	10	1	1	1	**1**	For p=10 serial correlation (portmanteau test sign.)
75	IFAPI Intermediate Goods	2015	2	2	1	2	**2**	p=2 more sign coefficients

Note: The time series consist of the first differences of the respective variables. Figures with VAR orders different from those selected can be found in the Annex.

Now, we interpret the results of the VAR model estimations. We provide time series plots for each model and examine the Granger causality, orthogonal impulse response functions, and forecast error variance decomposition. First, we look at the base model, consisting of the core variables UVC, markup, and output deflator. This allows us to understand the linkages and dynamics between these variables, which is essential for the augmented model analysis.

Figure 1: Time Series Plot: UVC, Markup, and Output Deflator



Note: Indices are equal to 100 in 2015. Changes in the respective indices must be interpreted relative to this base year.

Figure 1 shows the time series plots of UVC (unit variable costs), markup, and output deflator from 1996 to 2023. UVC and the output deflator exhibit similar courses throughout the observation period. From 1996 to 2008, both indices steadily increased, peaking around the onset of the financial crisis. Following this peak, they maintained a relatively horizontal trajectory until the onset of the COVID-19 pandemic, after which they experienced a sharp increase. The markup time series represents the ratio between the output deflator and UVC. When the markup index is above 100, the output deflator exceeds UVC, and vice versa, relative to the 2015 baseline. The markup was constantly above its 2015 level before 2008 and after 2015, with a noticeable increase during the COVID-19 pandemic.

Table 3: Granger Causality Test Results: Base Model

	Markup	UVC	Output deflator
Markup		1,2(***) 3,4,8-10 (**) 5(*)	8,9,10 (**)
UVC	-		8(**) 9,10(*)
Output deflator	-	1(***) 2-4,8(**) 9(*)	

Note: Time series represent the first differences of displayed variables with length n=106. Cause variables are in the left column; response variables are in the upper row. The listed numbers are the lags for which the Granger causality test was significant. Significance levels: 0.01 (***), 0.05 (**), 0.1 (*), "-" indicates no significant test result.

We conducted Granger causality tests to investigate the causal relationship between the time series that comprise the base model for our analysis: markup, UVC, and output deflator (Table 3). The null hypothesis for each direction (X does not Granger cause Y, and Y does not Granger cause X, respectively) was evaluated using p-values obtained from the tests. We tested Granger causality for up to 10 lags in both directions. The Granger causality test results for the base model, reveal significant relationships among the variables markup, UVC, and output deflator. Specifically, markup Granger causes UVC at multiple lags, including 1 and 2 with a high significance level, and at lags 3, 4, 8, 9, and 10 with moderate significance. This suggests markup's robust and durable influence on UVC across several periods. Conversely, UVC does not exhibit any significant causality towards markup, indicating a one-way Granger causality from markup to UVC. The markup also Granger causes the output deflator at lags 8, 9, and 10 with moderate significance. Conversely, the output deflator does not Granger cause markup. The output deflator significantly Granger causes UVC at lag 1, 2, 3, 4, and 8 with moderate significance. UVC does Granger the output deflator at lags 8, 9, and 10, showing a delayed effect.

These findings highlight intricate dynamic relationships in the base model, implying that forecasts of one variable can be improved by adding the other variable to the model. The output deflator seems to be significantly affected by UVC and markups only after a delay of 2 years (8 quarters). This could imply that prices may not instantaneously react to variable cost and markup changes and are somewhat sticky. However, we see that the impulse response functions do suggest a more short-term connection between these variables. The role of markup is unique in this regard since it can improve the forecasts of the other two variables, but not vice versa. This could imply that markup choices are complex and may consider variables other than UVC and the output deflator.

Granger causality is a valuable tool for understanding the connections between variables and the potential information one variable can provide for predicting another. However, it's important to note that these results do not present the complete picture. Impulse response analysis offers valuable insights into how variables interact when the system is shocked, allowing for straightforward visual inspection.

We want to clarify the interpretation of the orthogonal impulse response functions. The variables are represented by dimensionless indices, meaning they do not have units. These indices should be understood as the level of the variable relative to a base year, where the index is equal to 100. For example, an index with a value of 105 indicates a 5-percentage point increase relative to the base year.

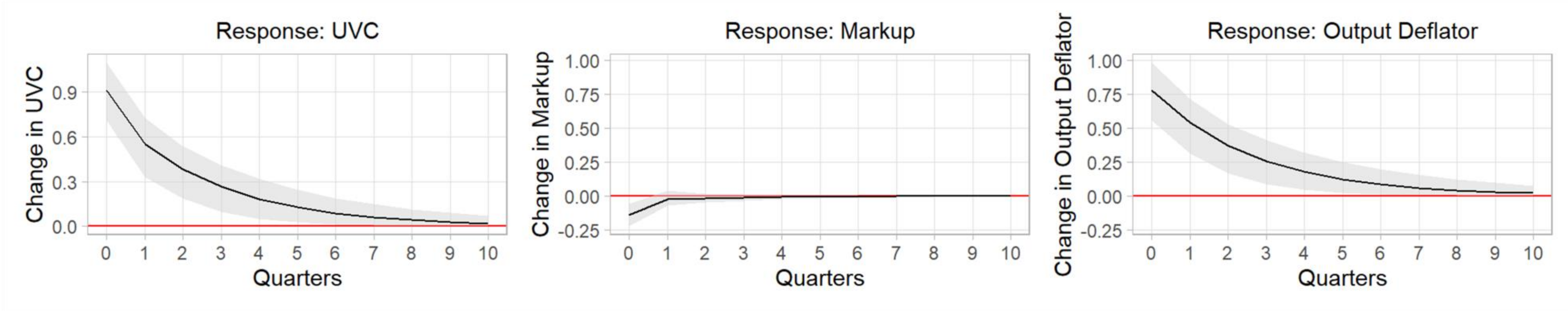
If an index moves from 105 to 107, it represents a 2-percentage point increase relative to the base year. The primary focus of this thesis is to understand how variables interrelate in a system rather than to derive specific numerical effects. Understanding the direction and relative magnitude of the relationships is more crucial. The orthogonal impulse response functions initiate at period zero, which signifies the contemporaneous reaction of the variables.

Note that the y-axis always shows the change in the respective variable. When the point estimate is above the zero line, the variable grows. On the other hand, if it's below the zero line, the variable is shrinking. The distance from the zero line indicates the magnitude of the deviation. Therefore, if the graph is above the zero line and declining over time, the variable grows, but the growth rate decreases. Conversely, if the graph is below the zero line and increasing over time, it implies that the variable is shrinking, but the rate of shrinkage is decreasing. If the bootstrapped 95 percent confidence interval for a specific point estimate does not include the zero line, the point estimate is significant at the 5 percent level. The complexity of the Impulse Response Functions (IRFs) increases with an increasing VAR order.

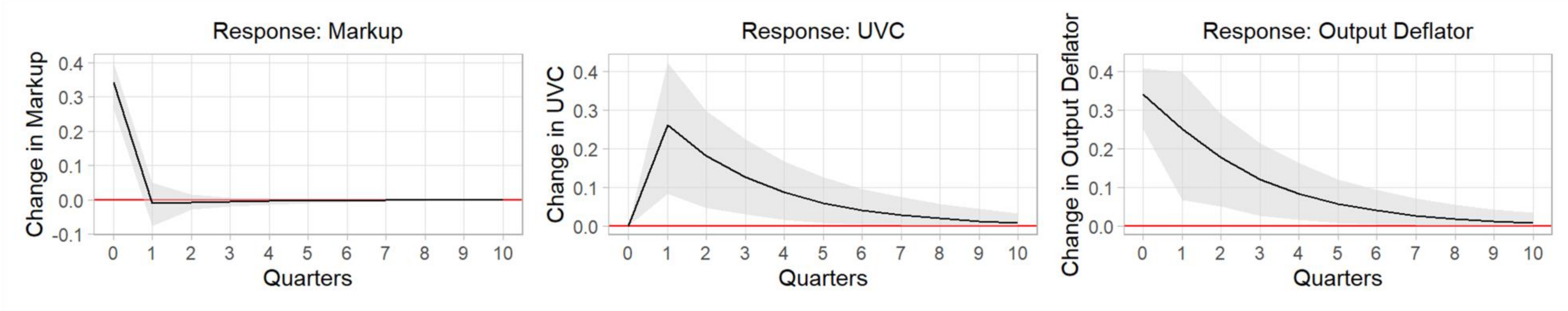
Figure 2 displays the base model's orthogonal impulse response functions with UVC, markup, and output deflator. It is interesting to see how these variables react without specific shocks that only influence parts of production costs. The first three plots show the reference model reactions of each variable after an impulse from UVC. UVC grows significantly for five periods after the impulse, with declining growth rates. Markup absorbs part of the UVC impulse significantly in the first period, after which it stabilizes at zero growth rate quite rapidly. The output deflator graph can be interpreted as the result of the UVC and markup graph. When UVC and markup grow in different directions, as in this case, the change in the output deflator is smaller than in UVC. This property is in accordance with the time series plot (see Figure 1). After the impulse, the output deflator is pushed upwards for the first five quarters. The first three graphs mark the reference model for the models augmented with impulse variables. The other six graphs reveal how the model is set up. The second variable that enters the system, markup, can only affect the output deflator contemporaneously, not the UVC. Hence, UVC shows a point estimate of zero in period zero. The output deflator grows positively due to a positive markup impulse, but the magnitude is smaller than the UVC impulse case. The duration until the effect becomes insignificant is similar to the first case. Change in markup shows only a significant deviation from zero in period 0, after which it returns to zero instantly. To conclude, shocks in UVC tend to destabilize the system longer, while shocks in markup are usually not sustained for so long. The last case with an impulse in output deflator leads to no significant reaction in UVC and markup despite introducing more volatility to the former versus the latter. This is, again, to be expected due to how the model is set up. Because the output deflator enters the system as the last variable, there are no contemporaneous effects on either of the other variables.

Figure 2: Orthogonal Impulse Response Functions for the Base Model

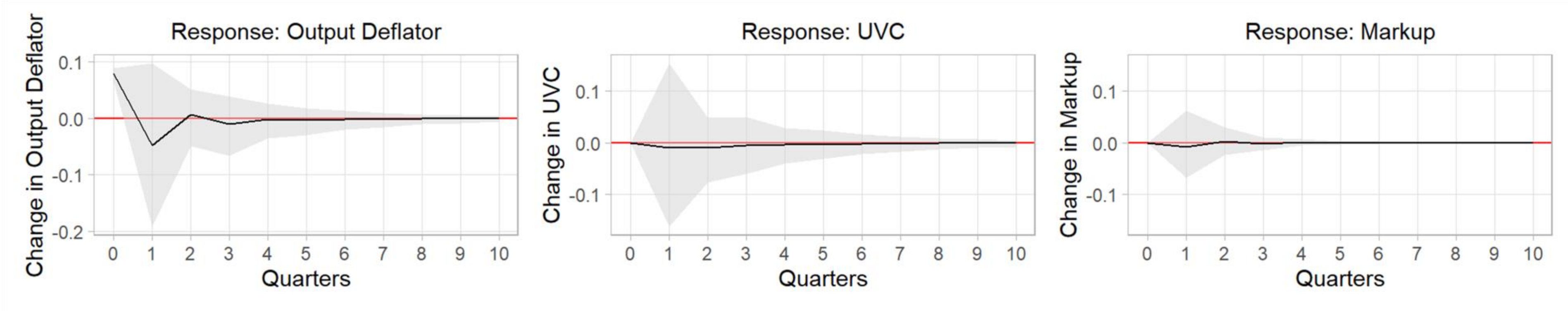
Impulse: UVC



Impulse: Markup

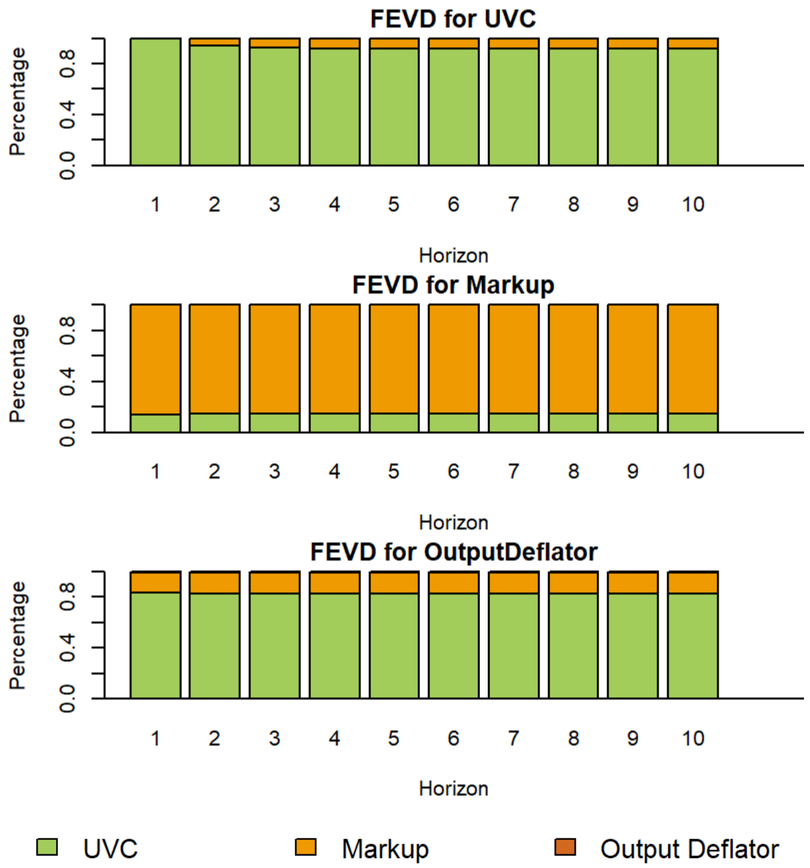


Impulse: Output Deflator



Note: Note: The chosen VAR order for this model is 1. The grey area marks the 95% bootstrap confidence interval, computed with 1000 runs.

Figure 3: Forecast Error Variance Decomposition for the Base Model



Note: The FEVD starts with the immediate effect in Horizon 1, which corresponds to lag 0 (Quarter 0, see IRFs).

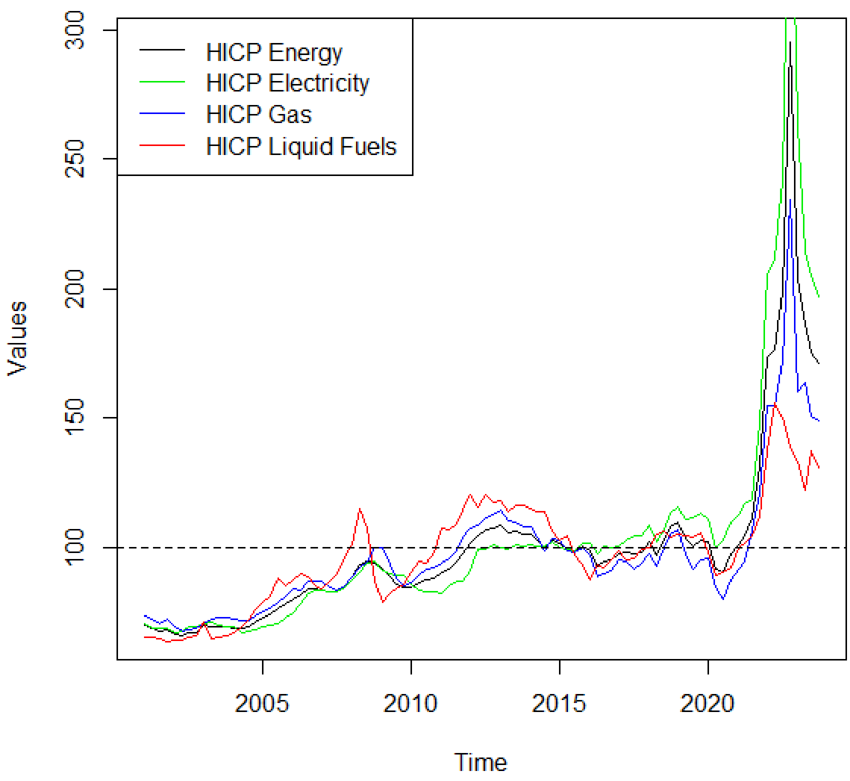
Figure 3 presents the Forecast Error Variance Decomposition (FEVD) results for the base model across the three core variables, unit variable costs (UVC), markup, and output deflator, over a 10-period horizon. Each bar in the graph represents the proportion of the forecast error variance attributable to UVC, markup, and output deflator at different time horizons. In the first panel, FEVD for UVC, the variance is predominantly explained by UVC across all horizons, with a minor contribution from markup starting one period after the immediate effect. In the second panel, FEVD for markup, the forecast error variance is mostly explained by markup, with minor contributions from UVC and negligible impact from the output deflator. The third panel, FEVD for output deflator, shows that the variance is initially primarily attributed to the UVC, with a small but durable contribution from markup over time. UVC explains most of its forecast error variance and considerably contributes to the output deflator's variance. Markup mainly explains its variance and has a minor but stable effect on the UVC and output deflator. This indicates that UVC has a dominant influence across the model, while markup maintains a more specific, self-contained impact.

To contextualize these results, it is essential to recall that Baioni (2023b) also analyzed the case of Italy over a similar observation period. Baioni concluded that inflation caused markups, not vice versa, contrasting our findings. Our analysis suggests that markups Granger cause the output deflator (a measure of inflation), not vice versa. This discrepancy may be attributed to our exclusive focus on the manufacturing sector rather than the entire economy. Baioni also found that while the effect of markups on inflation was significant in the manufacturing sector, the impact was negative. In contrast, our base model Orthogonal Impulse Response Functions (OIRFs) reveal a significant positive response, indicating that an impulse in markup leads to an increase in the output deflator for several periods.

6.1 Energy Price Indices

This chapter begins by analyzing the augmented VAR models, i.e., the four-variable models that each include one impulse variable. We start with the Harmonized Index of Consumer Prices (HICP) for Energy and subsequently distinguish between the three main types of energy: electricity, natural gas, and liquid fuels.

Figure 4: Time Series Plot: HICP Indices



Note: Indices are equal to 100 in 2015. Changes in the respective indices must be interpreted relative to this base year.

The time series plots of the HICP indices in Figure 4 reveal that, relative to 2015, energy prices were lower before the financial crisis in 2008. After the crisis, liquid fuels and gas became the primary drivers of energy price increases, as indicated by their higher growth than the electricity index. This pattern shifted after 2015, with electricity prices exhibiting higher growth. The underlying reasons for this shift are multifaceted and complex, given that a large portion of electricity generation in Italy still relies on fossil fuels. The most striking finding from this plot is the sharp and unprecedented rise in all energy price indices following the 2022 Russian invasion of Ukraine. As a major natural gas and liquid fuel supplier, Russia crucially influenced European energy prices, which surged as supply decreased. In Italy, electricity prices increased by more than 200 percentage points, accompanied by a 130-percentage point increase in gas prices and a 60-percentage point increase in liquid fuel prices relative to 2015. Notably, liquid fuel prices declined even as gas and electricity prices rose. According to the International Energy Agency (2024), natural gas is Italy's dominant energy and heating source, which explains its severe impact on the HICP energy index.

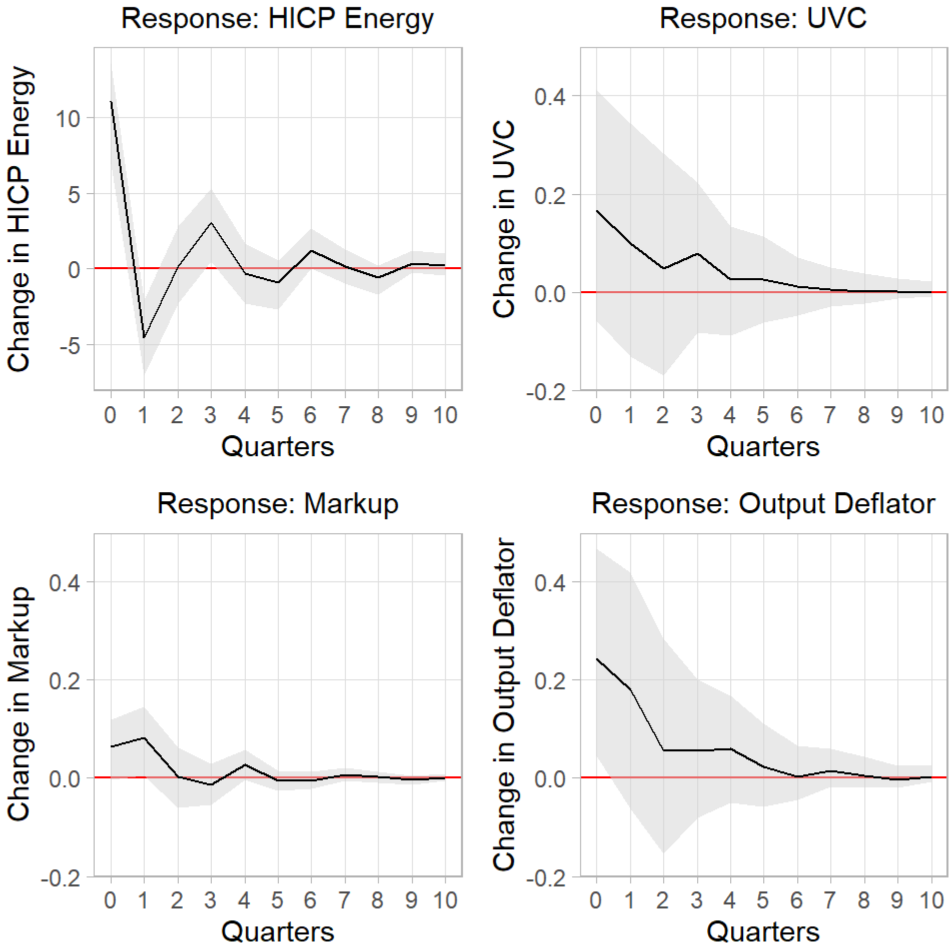
Table 4: Granger Causality Test Results: Energy Price Indices

	Markup	UVC	Output deflator	HICP Energy	HICP Electricity	HICP Gas	HICP Liq. Fuels
Markup		1(***) 2,3,8,9(**) 4,10(*)	8-10(**)	1,6-10(***) 2-5(**)	1,6,8-10(***) 2-5,7(**)	1,2,10(***) 3-9(**)	-
UVC	-		8(*)	1-10(***)	1-7(***) 8-10(**)	1-10(***)	4-6(***) 3,7,10(**) 8,9(*)
Output deflator	-	1(***) 2(**) 3,4,8(*)		1-10(***)	1-10(***)	1-10(***)	4-8(***) 3,9,10(**) 2(*)
HICP Energy	-	-	-				
HICP Electricity	1,2(*)	-	-				
HICP Gas	-	-	-				
HICP Liq. Fuels	1(**) 2(*)	1-6,9,10(***) 7,8(**)	2-10(***)				

Note: Time series represent the first differences of displayed variables with length n=91. Cause variables are in the left column; response variables are in the upper row. The listed numbers are the lags for which the Granger causality test was significant. Significance levels: 0.01 (***), 0.05 (**), 0.1 (*), "-" indicates no significant test result.

When looking at the results of the Granger causality tests in Table 4, the significance of the UVC – Output deflator relation became weaker, which is to be expected because an additional impulse variable captures a part of the influence UVC had on the output deflator. HICP Energy and HICP Gas do not significantly Granger cause UVC and output deflator. The most important finding is that HICP Electricity and HICP Liquid Fuels Granger cause markup at lags 1 and 2. This highlights the unique role electricity and liquid fuels have in pricing decisions. Furthermore, the HICP Liquid Fuels granger causes UVC at all ten lags and the output deflator from lag two onwards. It is already evident that HICP Energy represents an average energy mix and may show a diffuse or muted influence in this analysis. In contrast, the individual energy type prices react somewhat differently and may show a more pronounced response in markup and Output deflator. Conversely, markup, UVC, and output deflator Granger cause almost all HICP subindices, except for the markup - HICP Liquid Fuels relation. Overall, the influence of Energy prices on the model's core variables may be limited to specific periods, with bi-directional Granger causality. Despite this, the number of lags with significant Granger causality tests is high, providing a good foundation for further analysis.

Figure 5: Orthogonal Impulse Response Functions for the HICP Energy Model

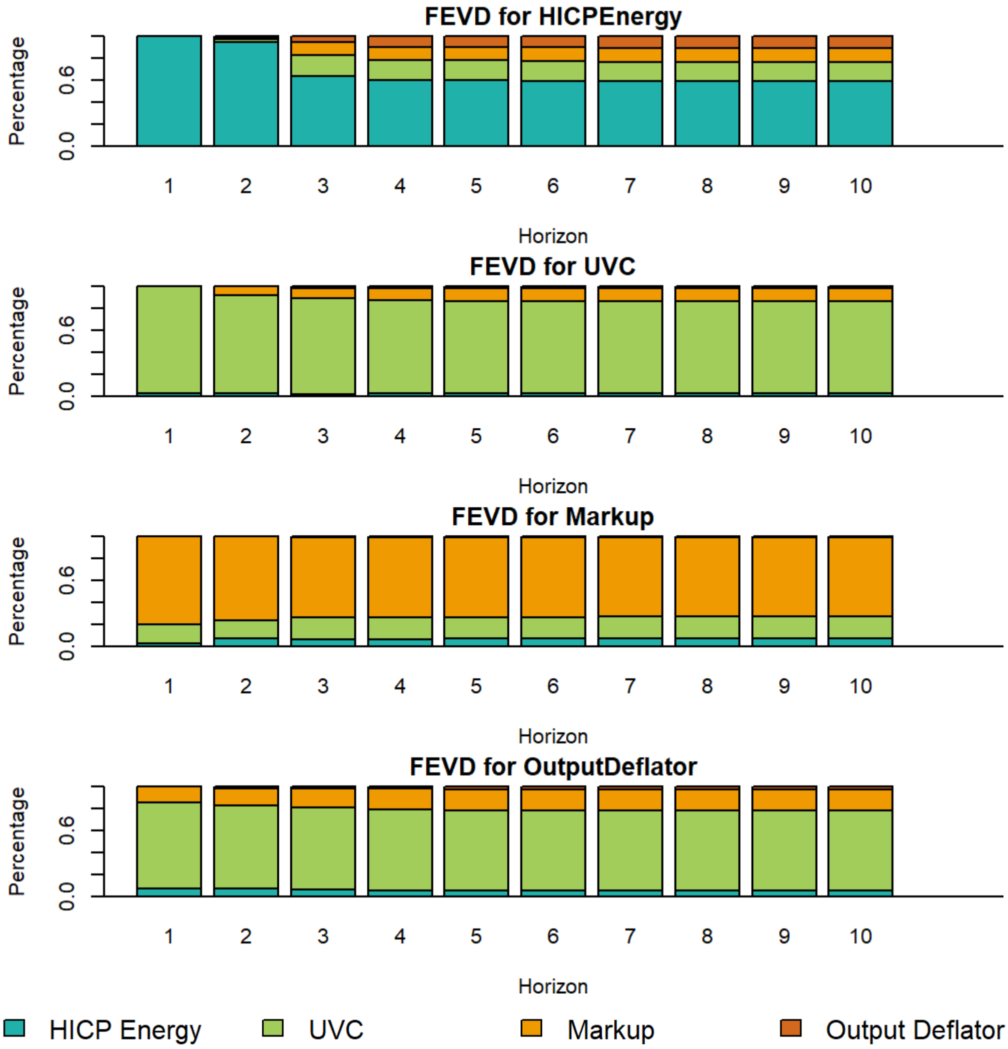


Note: This model's chosen VAR order is 2. The grey area marks the 95% bootstrap confidence interval, computed with 1000 runs.

In Figure 5, we observe the OIRFs following an impulse in the HICP Energy. The HICP Energy experiences oscillations for ten quarters after being impacted by the impulse, with alternating periods of growth and contraction (significant in periods 0,1 and 3) that gradually converge to zero. The response of UVC displays initially positive and then declining point estimates. However, the dispersion of bootstrap functions results in a wide confidence interval, rendering the overall effect statistically insignificant. There is an immediate positive change in markup, which lasts for one quarter and then returns to zero. In quarter 1, this effect is statistically significant. Regarding the output deflator, the positive response to an impulse in HICP Energy is most prominent in quarter 0 (significant at the 5% level). Comparing these results to the same model at VAR order 1, we find that the significance for markup and output deflator in the respective periods is not established. Nevertheless, the point estimates and system stabilization speed are comparable.

The change in the core variables is small compared to the base model. This is expected because energy only represents a fraction of variable costs, and each company's energy mix may vary. We examine Electricity, Gas, and Liquid Fuels separately later in this chapter. However, the markup response is different from the base model. Companies in the manufacturing sector appear to increase markups when energy prices rise. In contrast, the standard response to a cost increase (as seen in the base model) is for the markup to decrease to cushion the output price level temporarily.

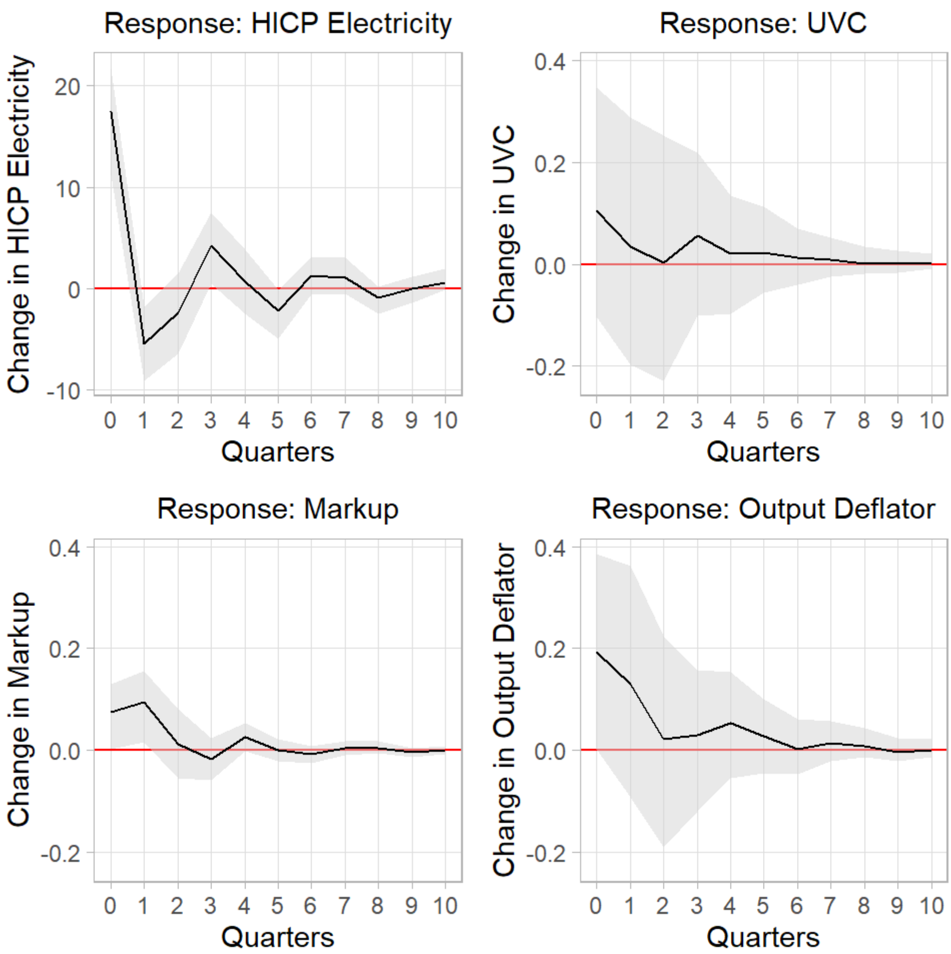
Figure 6: Forecast Error Variance Decomposition for the HICP Energy Model



Note: The FEVD starts with the immediate effect in Horizon 1, which corresponds to lag 0 (Quarter 0, see IRFs).

In Figure 6, in the first panel, the FEVD for HICP Energy, the forecast error variance is initially almost entirely explained by HICP Energy itself. Over time, the contributions from UVC, markup, and output deflator increased mainly in the second quarter after the immediate reaction. They remain roughly the same level for the rest of the time horizon, but HICP Energy remains the dominant factor. The second panel, FEVD for UVC, shows that UVC predominantly explains the forecast error variance for UVC across all horizons. Markup and output deflator contributions are minimal, with a minimal effect from HICP Energy. The third panel, FEVD for markup, indicates that the forecast error variance is mainly driven by markup itself across all periods, with minor contributions from UVC, a negligible impact of output deflator, and a weak impact from HICP Energy, which broadly establishes itself one quarter after the immediate reaction. The fourth panel, FEVD for output deflator, reveals that the forecast error variance is explained mainly by UVC throughout all horizons, followed by contributions from markup. HICP Energy and output deflator have minimal impacts. The shares stay primarily unchanged for all horizons. Overall, the FEVD results highlight that each variable predominantly explains its forecast error variance. HICP Energy has a substantial self-explanatory power, with slight influences from the other variables over time. UVC plays a major role in explaining its variance, comparable to markup. The output deflator's variance is primarily driven by UVC and markup, with a minimal contribution from HICP Energy.

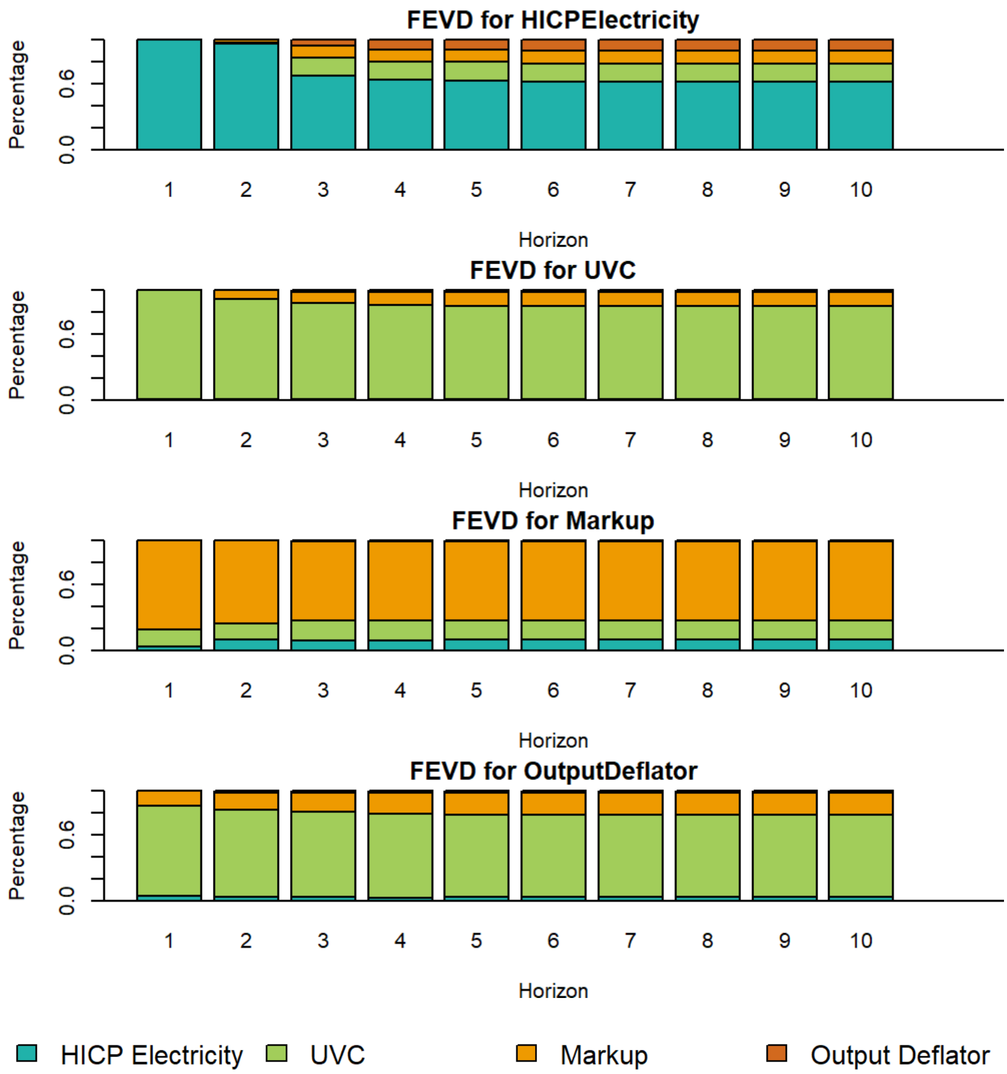
Figure 7: Orthogonal Impulse Response Functions for the HICP Electricity Model



Note: This model's chosen VAR order is 2. The grey area marks the 95% bootstrap confidence interval, computed with 1000 runs.

The results of the impulse response analysis for the HICP Electricity (Figure 7) are somewhat similar to those of the HICP Energy model. After the initial impulse, the HICP Electricity oscillates around the zero line, indicating alternating periods of growth and decline before converging to zero. The effect is statistically significant in quarters 0,1,3 and 5. The response of UVC is positive but relatively small, with a large variance and insignificant for all quarters. The markup response is positive and significant for the immediate effect, and quarter 1 is opposite the direction in the reference model. The Output deflator shows significant positive growth in quarter 0, after which the effect becomes insignificant. For reference, the point estimates and the direction and duration of the impulse response functions are comparable but insignificant in the VAR model at VAR order 1. The results for the VAR model at VAR order six do not reasonably depict the responses (see the Annex). Overall, the HICP Electricity Model is comparable with the HICP Energy model in terms of effect direction and size, with one major difference being the significance of the response of markup.

Figure 8: Forecast Error Variance Decomposition for the HICP Electricity Model

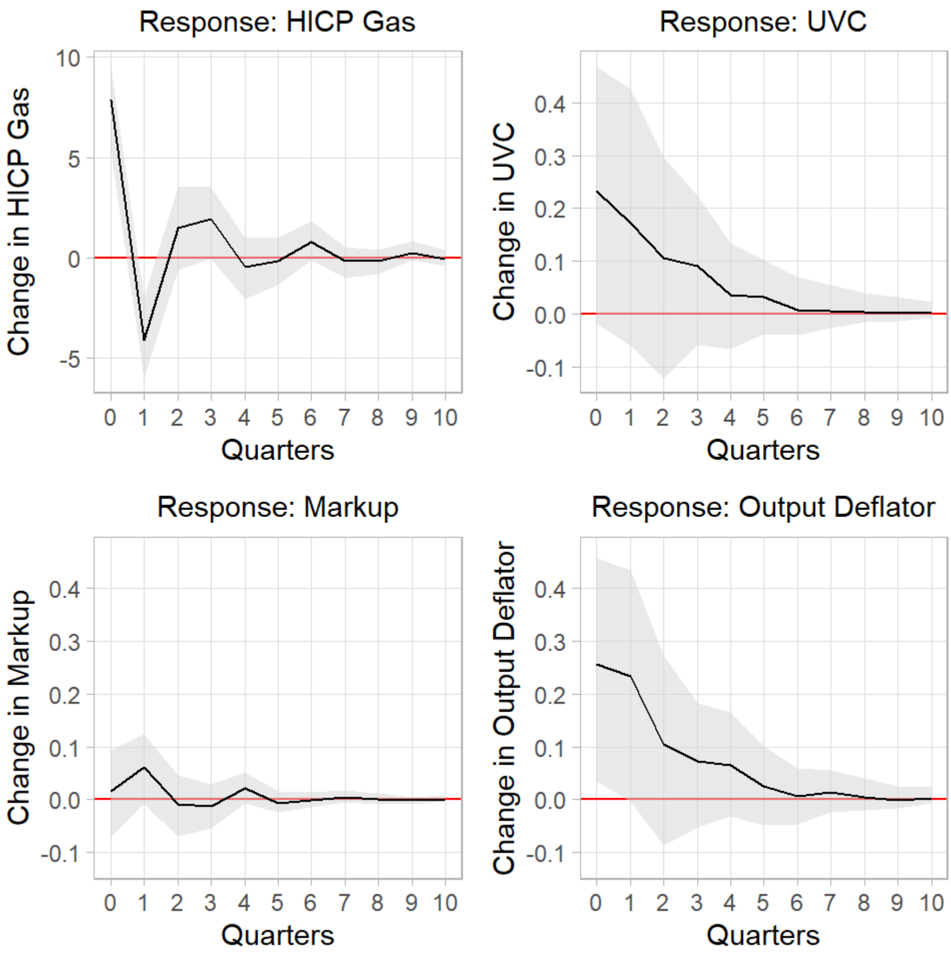


Note: The FEVD starts with the immediate effect in Horizon 1, which corresponds to lag 0 (Quarter 0, see IRFs).

Figure 8 shows the FEVD for the HICP Electricity model. In the first panel, the FEVD for HICP Electricity shows that its forecast error variance is primarily explained by HICP Electricity itself across all horizons, with increasing contributions from UVC, markup, and output deflator over time. Starting from the second quarter after the immediate reaction, those three variables take up roughly a third of the variance in HICP Electricity. The second panel, depicting the FEVD for UVC, reveals that UVC predominantly explains the forecast error variance throughout all periods. Contributions from output deflator are durable yet minimal, and HICP Electricity has a minimal effect. Markup's share increased from quarter one after the immediate effect but stabilized quickly at that level. In the third panel, the

FEVD for markup indicates that its forecast error variance is mainly driven by markup across all horizons. It has a sizable contribution from UVC and negligible impacts from the output deflator. HICP Electricity takes up a small share, which increases for one quarter and stabilizes on that level. The fourth panel, showing the FEVD for output deflator, highlights that the forecast error variance is mostly explained by UVC across all periods, with steady but smaller contributions from markup. The impacts of HICP Electricity and output deflator are minimal. Again, each variable predominantly explains its forecast error variance. HICP Electricity has its most prominent influence on the variance of markup, followed by its influence on the output deflator.

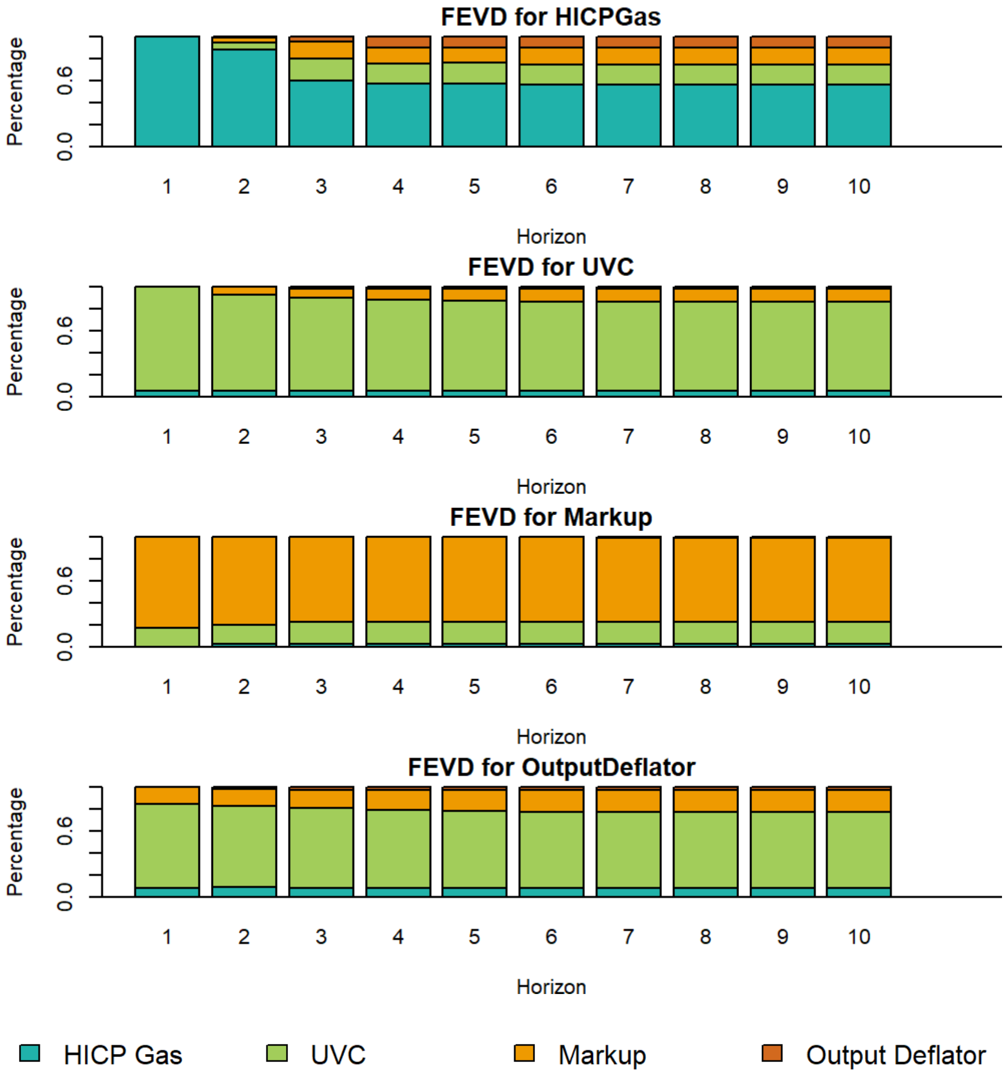
Figure 9: Orthogonal Impulse Response Functions for the HICP Gas Model



Note: This model's chosen VAR order is 2. The grey area marks the 95% bootstrap confidence interval, computed with 1000 runs.

Looking at Figure 9, the HICP Gas exhibits a response after experiencing a shock similar to the HICP indices discussed earlier. The immediate response is strongly positive, followed by a significant swing below the zero line, displaying an oscillating behavior and eventually fading out. The response of unit variable costs (UVC) is positive yet not statistically significant at the 5% level, as indicated by the confidence interval. The response of markup is nearly zero without reaching statistical significance. The output deflator reacts in line with the UVC response, displaying a strongly positive and significant instantaneous reaction, implying a substantial growth in the output deflator that decelerates over time and becomes insignificant from quarter one onwards. Compared to the two HICP indices discussed earlier, the markup response is more minor and insignificant, while the point estimates for UVC and output deflator are higher for HICP Gas. For reference, when examining the same VAR model but at VAR order 1, the instantaneous output deflator effect is insignificant, yet the course of the response functions are comparable.

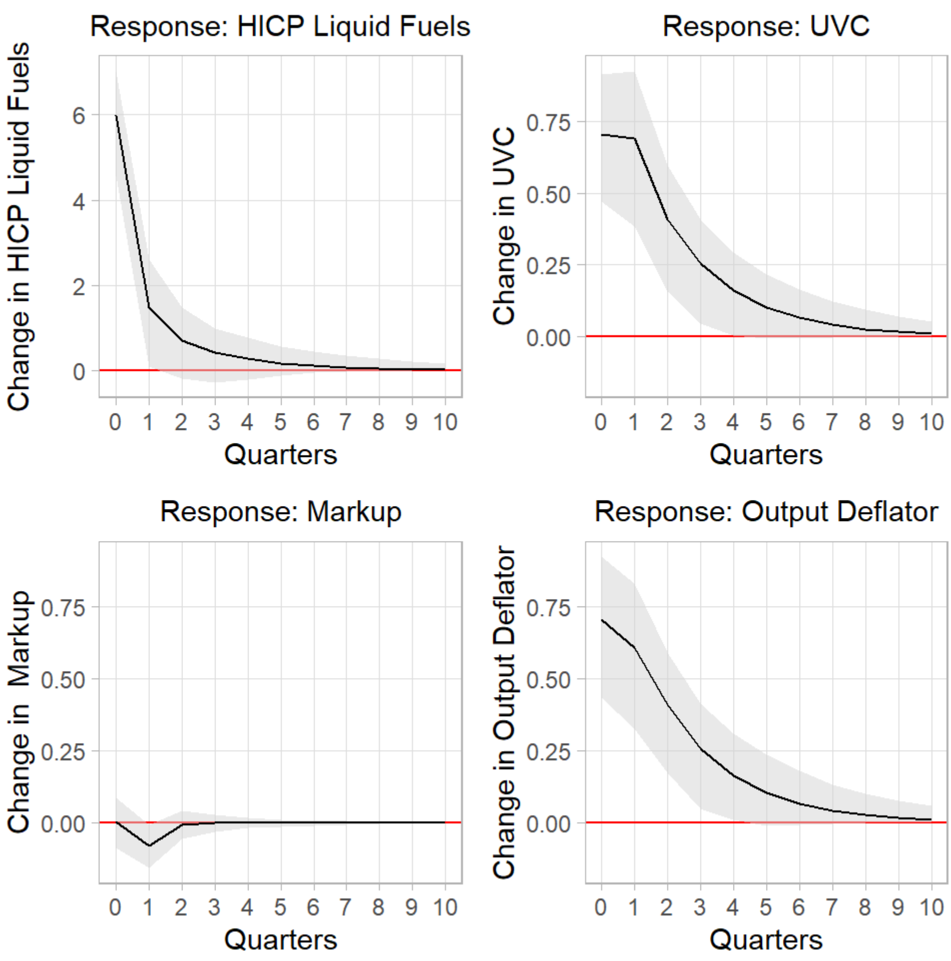
Figure 10: Forecast Error Variance Decomposition for the HICP Gas Model



Note: The FEVD starts with the immediate effect in Horizon 1, which corresponds to lag 0 (Quarter 0, see IRFs).

The FEVD results of the HICP Gas model can be seen in Figure 10. In the first panel, the FEVD for HICP Gas reveals that its forecast error variance is primarily explained by HICP Gas throughout all horizons, with increasing but still modest contributions from UVC, markup, and output deflator over time. The shares of the other variables start increasing one quarter after the immediate reaction and approximately reach their final level one quarter after. The second panel, depicting the FEVD for UVC, shows that UVC largely explains the forecast error variance across all periods. Contributions from markup increase from quarter one onwards and stabilize quickly, while HICP Gas has a minimal effect, and the contribution of the output deflator stays negligible. In the third panel, the FEVD for markup indicates that the forecast error variance is predominantly driven by markup at all horizons, with minor contributions from UVC and negligible impacts from HICP Gas and output deflator. The fourth panel, showing the FEVD for output deflator, highlights that the forecast error variance is mainly explained by UVC throughout all periods, with durable yet smaller contributions from markup. The impacts of HICP Gas and output deflator are minimal. Overall, each variable primarily explains its forecast error variance.

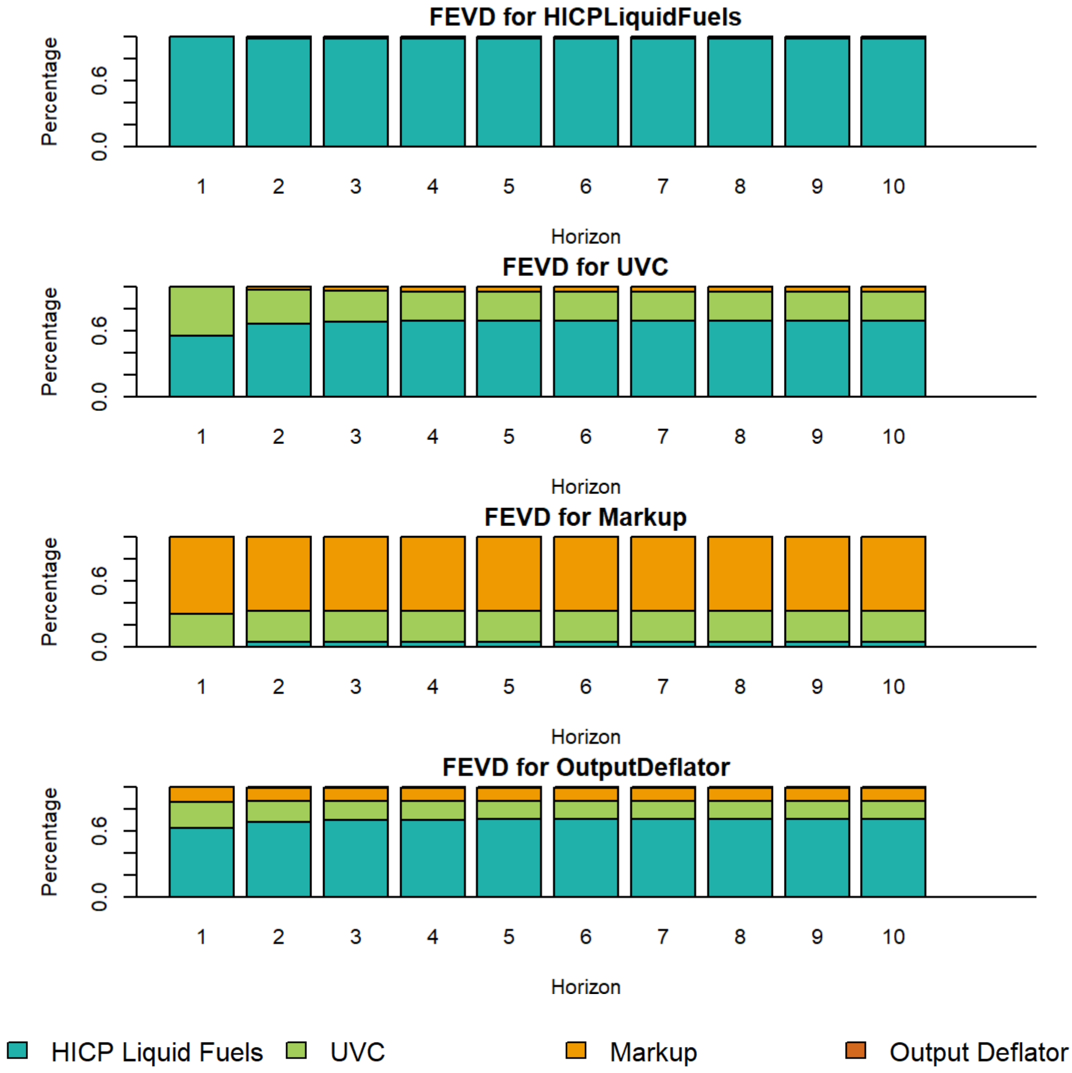
Figure 11: Orthogonal Impulse Response Functions for the Liquid Fuels Model



Note: This model's chosen VAR order is 1. The grey area marks the 95% bootstrap confidence interval, computed with 1000 runs.

The last model in this section is the HICP Liquid Fuels (Figure 11), which stands out from the previous three models. The response function of HICP Liquid Fuels has a smoother positive course. In quarters 0 and 1, this effect is significant. The impact of both UVC and output deflator response is nearly double that of the other HICP indices, with more significant periods (significance at the 5% level from period 0 to period 4). Interestingly, the markup response is almost zero in quarter 0 and significantly negative in quarter 1. This deviation from the previous HICP impulse effects aligns more with the base model. Firms seem unwilling or unable to increase markup when liquid fuels become more expensive. Instead, markup experiences a negative impact in absorbing some of the input cost increases. Note that the impulse in HICP Liquid Fuels is comparable in size to the HICP gas and even smaller than that of HICP Electricity. Thus, the larger and more significant response of UVC and output deflator cannot be explained by a higher standard deviation of HICP Liquid Fuels. For reference, the oscillating effect of the HICP Liquid Fuels is more noticeable in the Model with VAR order 3. In the same model, the HICP and UVC are only significant in quarters 0 and 1, with a slight rebound effect in quarter 4. The reaction of markup is sustained for a more extended period and is insignificant.

Figure 12: Forecast Error Variance Decomposition for the HICP Liquid Fuels Model



Note: The FEVD starts with the immediate effect in Horizon 1, which corresponds to lag 0 (Quarter 0, see IRFs).

The graph in Figure 12 presents the FEVD of the HICP Liquid Fuels model. Compared to the three previous HICP model FEVDs, this one marks a major deviation from the patterns we have seen before. In the first panel, the FEVD for HICP Liquid Fuels reveals that its forecast error variance is almost entirely explained by HICP Liquid Fuels across all horizons, indicating a solid self-explanatory power with negligible influence from the other variables. The share of HICP Liquid Fuels takes up more than half of the forecast error variance in quarter 0, and the share increases to about two-thirds in the second quarter afterward, remaining at that level. The second panel, depicting the FEVD for UVC, shows that the forecast error variance is predominantly explained by the HICP Liquid Fuels, which is a novelty. UVC itself takes the second-largest share of the variance. Contributions from markup and output deflator are minimal. In the third panel, the FEVD for markup indicates that the forecast error variance is primarily driven by markup itself at all horizons, with small but steady contributions from UVC and negligible impacts from HICP Liquid Fuels and output deflator, which is compatible with the previous models. The fourth panel, showing the FEVD for the output deflator, highlights that the forecast error variance is mainly explained by HICP Liquid Fuels, with steady but smaller contributions from UVC. The impacts of markup and output deflator itself are minimal. The fact that the output deflator's variance is heavily influenced by HICP Liquid Fuels, taking up to two-thirds of the total variance, marks a major difference from the other Energy price indices.

To sum up, the findings of this chapter, differentiating between energy types, have turned out to be an effective strategy for uncovering their distinct impacts on markup and prices; specifically, only the HICP Electricity and Gas indices significantly Granger cause markup at low lags. In contrast, the HICP Liquid Fuels index is the only one that Granger causes the output deflator. When examining the impulse response functions (IRFs) for markup, impulses from HICP Energy and HICP Electricity led to significant short-term growth in markup. This suggests that companies in the manufacturing sector tend to increase markups when energy and electricity prices rise, thereby not absorbing parts of the cost shock but rather exacerbating its influence on inflation. However, an increase in the HICP Gas index did not elicit a significant reaction in the markup. Interestingly, increases in the HICP Liquid Fuels index resulted in a one-quarter delayed yet significant short-term decrease in the markup. This indicates that firms may absorb some input cost increases by lowering their markups in response to liquid fuel price shocks. The FEVD for the markup variable showed minimal impacts from HICP index shocks, with the greatest influence coming from electricity prices. All HICP indices led to a significant immediate response in the output deflator, with the deviation being larger for gas than for electricity price shocks. Notably, the response of the output deflator was highest for a liquid fuels price shock, exhibiting nearly double the magnitude compared to other energy types and remaining significant for four quarters after the impulse. The FEVD analysis revealed that nearly two-thirds of the variance in the output deflator can be attributed to shocks in liquid fuels, while the effects from other energy types were much smaller. Overall, liquid fuels appear to play a pivotal role in the manufacturing sector, substantially influencing firms' pricing decisions.

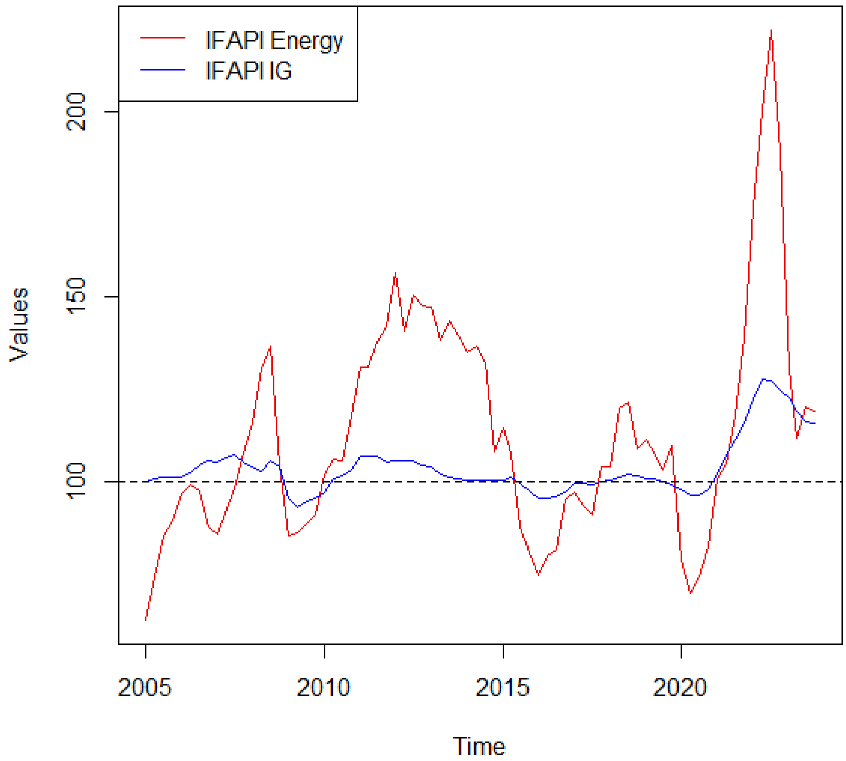
These findings align with Weber et al. (2022), who concluded that the energy sector exhibits strong price-amplifying properties, particularly fossil fuels like coal, gas, and oil. Italy's high dependence on fossil fuels makes it especially vulnerable to energy price fluctuations. When comparing our findings on energy and electricity price increases to those in the French manufacturing sector, as studied by Arquié and Thie (2023), we also observe that firms' exposure to energy cost shocks leads to excess pass-through, resulting in increased markups. However, our analysis does not observe this effect on price increases for gas and liquid fuels. Regarding the energy price hikes induced by the Ukraine war, our

VAR model predicts an excess pass-through of energy price shocks, particularly electricity. While the price shock for liquid fuels was more minor than other energy types, our model still predicts a significant increase in output prices due to the pronounced response of output prices to liquid fuel cost shocks. In practice, firms often have contracts with energy suppliers that fix prices for specific periods, shielding them from immediate market disruptions. This allows firms some time to evaluate their pricing decisions and adjust markup and output prices in anticipation of future energy price increases, leading to price stickiness. This means that firms can strategically plan their pricing adjustments, smoothing out the immediate impact of energy price fluctuations on their costs and final product prices.

6.2 Import Price Indices

In this chapter, we analyze the role of import prices in firms' pricing decisions.

Figure 13: Time Series Plot: Import Price Indices



Note: Indices are equal to 100 in 2015. Changes in the respective indices must be interpreted relative to this base year.

In Figure 13, the time series plot illustrates the course of imported energy (IFAPI Energy) and intermediate goods (IFAP IG) prices. While both indices generally move in similar directions, the energy price index demonstrates higher volatility than the intermediate goods price index. The most notable increase in both indices occurred during the onset of the Russian invasion of Ukraine in 2022, highlighting the substantial impact of geopolitical events on import prices.

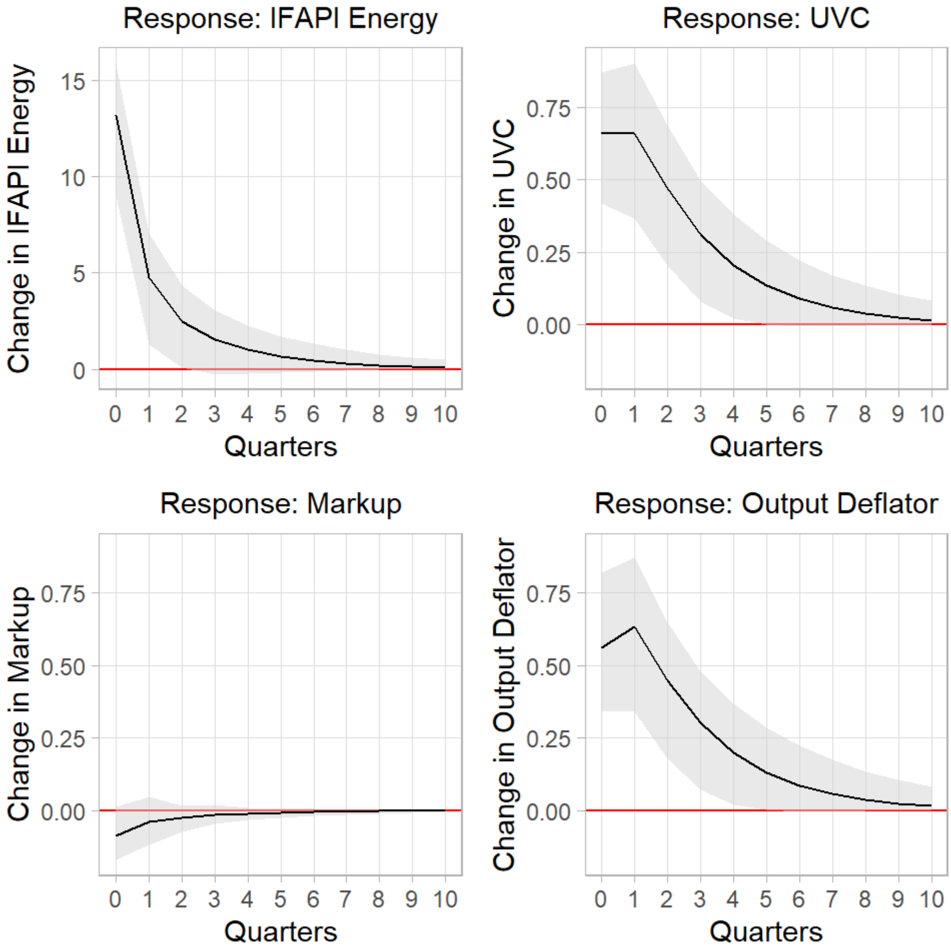
Table 5: Granger Causality Test Results: Import Price Indices

	Markup	UVC	Output deflator	IFAPI Energy	IFAPI IG
Markup		1,2,9(**) 3,8,10(*)	8,9(**) 10(*)	-	-
UVC	-		-	6,7(***) 3-5,8(**) 9(*)	2-6(***) 1,7-10(**)
Output deflator	-	1,2(**)		3-7,9(***) 2,8,10(**)	2-5(***) 1,6,7(**) 8,9(*)
IFAPI Energy	-	1(**) 2(*)	1,2(**) 3(*)		
IFAPI IG	-	8,9(**) 2-4,10(*)	3,4,7(**) 5,6(*)		

Note: Time series represent the first differences of displayed variables with length n=75. Cause variables are in the left column; response variables are in the upper row. The listed numbers are the lags for which the Granger causality test was significant. Significance levels: 0.01 (***), 0.05 (**), 0.1 (*), "-" indicates no significant test result.

When examining the Granger causality tests in Table 5, markup, IFAPI Energy, and Intermediate Goods do not have a significant Granger causal relationship. The focus is on the relationship between import prices, UVC, and the Output deflator. IFAPI Energy causes UVC at lags 1 and 2, while for lags 3 to 9, the causation is in the opposite direction. The imported energy price causes the output deflator with a lag of 1; for lags 2 and 3, the relationship is bidirectional. However, from 4 lags onwards, the causality direction shifts from the output deflator to the imported energy price. Looking at the import price index of intermediate goods, the Granger causation relationship with UVC is more pronounced in both directions for lags 8 and 9. In contrast, the remaining lags suggest Granger causation from UVC to the IFAPI intermediate goods. As for the output deflator and the imported intermediate goods price index, the Granger causation seems to go in both directions, with the significance level for the lags suggesting that the causation is more substantial in the opposite direction.

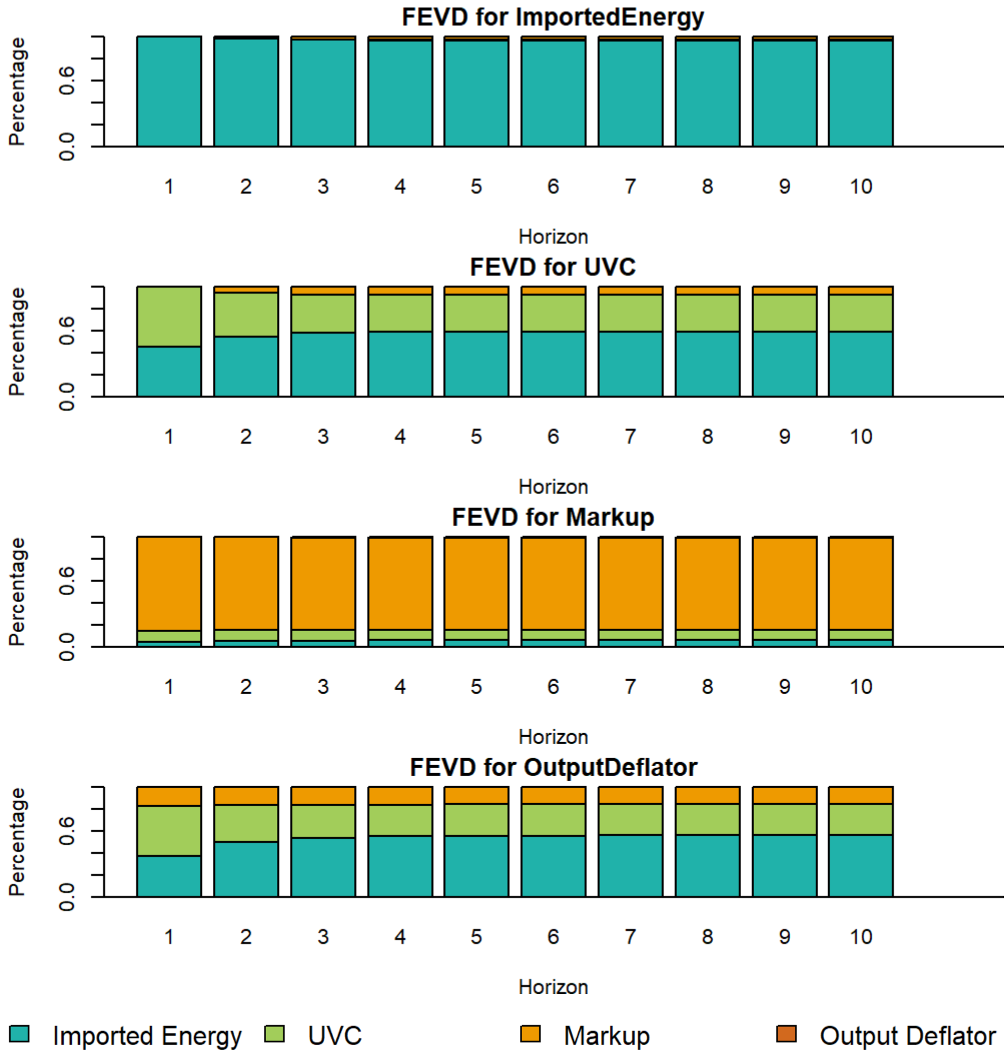
Figure 14: Orthogonal Impulse Response Functions for the IFAPI Energy Model



Note: This model's chosen VAR order is 1. The grey area marks the 95% bootstrap confidence interval, computed with 1000 runs.

In Figure 14, we observe the orthogonal impulse response functions of the *Imports from Abroad Price Index* Energy. The shock in IFAPI Energy results in sustained and decelerating growth, with significant impacts in periods 0, 1, and 2. The response from markup is insignificant. UVC and output deflator show similar responses, reflecting the little effect captured by markup. Both variables display immense positive growth as an instantaneous response, followed by a slow convergence to zero growth (both functions are significant until and including quarter 5). The shock in imported energy prices appears to lead to sustained cost and price increases in the manufacturing sector. This is no surprise since Italy is a net importer of energy on a large scale.

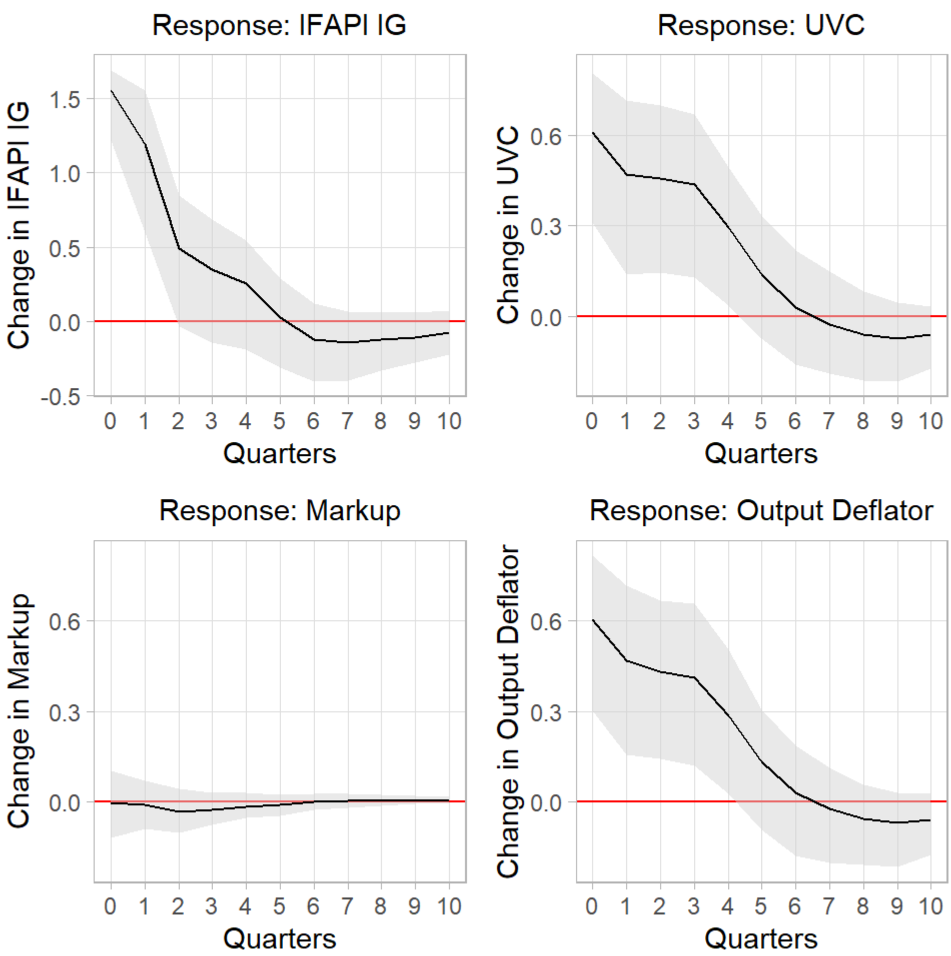
Figure 15: Forecast Error Variance Decomposition for the IFAPI Energy Model



Note: The FEVD starts with the immediate effect in Horizon 1, which corresponds to lag 0 (Quarter 0, see IRFs).

Figure 15 displays the FEVD of the IFAPI Energy Model, showing the proportion of forecast error variance attributable to each variable over time. In the first panel, the FEVD for *Imports from Abroad Price Index: Energy* indicates that its forecast error variance is almost entirely self-explained across all horizons, suggesting a dominant influence from Imported Energy with negligible contributions from the other variables. The second panel, showing the FEVD for UVC, reveals that the forecast error variance is mainly explained by UVC only in quarter 0, with a growing contribution from Imported Energy over time, of which the share takes up more than half from quarter one onwards. The influence from markup grows in quarters 1 and 2, after which it stabilizes at a small share of the variance, while the output deflator has minimal influence throughout the periods. In the third panel, the FEVD for markup demonstrates that the forecast error variance is overwhelmingly driven by markup across all horizons, with minor and relatively durable contributions from UVC and Imported Energy. At the same time, the impact of the output deflator is minimal. The fourth panel, depicting the FEVD for output deflator, shows that its forecast error variance is primarily influenced by Imported Energy, followed by UVC, with smaller contributions from markup. The share of the forecast error variance for the output deflator is dominated by UVC and markup only in quarter 0. From quarter one onwards, imported energy takes over as the dominant driver.

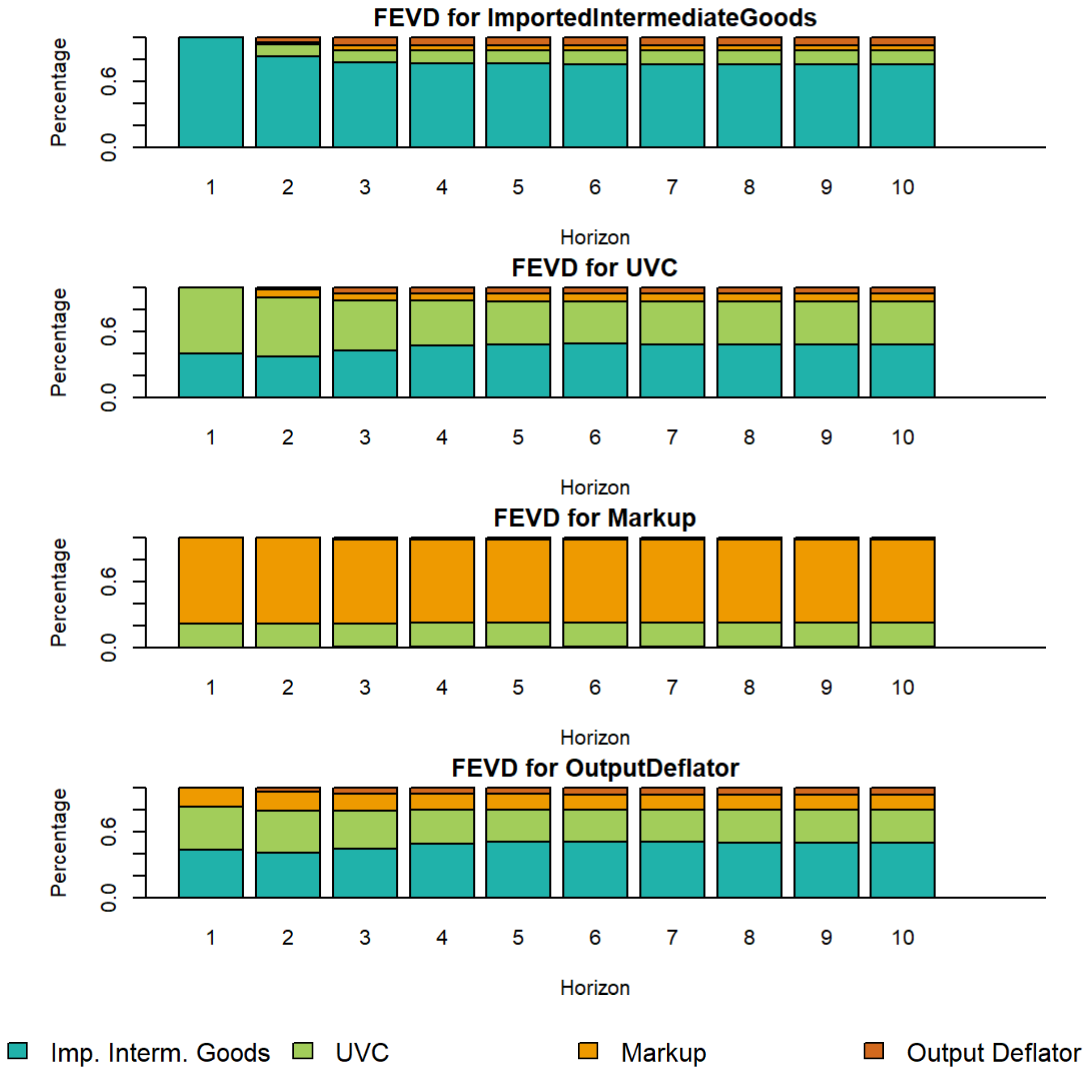
Figure 16: Orthogonal Impulse Response Functions for the IFAPI IG Model



Note: This model's chosen VAR order is 2. The grey area marks the 95% bootstrap confidence interval, computed with 1000 runs.

The graph in Figure 16 shows the orthogonal impulse response functions for the *Imports from Abroad Price Index: Intermediate Goods*. After an initial increase in the price of intermediate goods, the index shows growth significantly different from zero in the instantaneous effect and period 1. The markup shows a weak reaction to the impulse, with the response function staying close to the zero line and having insignificant point estimates. UVC and output deflator demonstrate a similar course, showing four quarters of significant positive and decelerating growth after the impulse. Comparing these results to those of the same model with VAR order 1, the number of significant periods for the IRFs is robust for UVC. In contrast, the output deflator only has significant point estimates in quarters 0 to 2. The IFAPI IG response is significant for a more extended period, from quarters 0 to 4. When comparing IFAPI Energy to IFAPI Intermediate Goods, it is observed that the impulse from IFAPI Intermediate Goods leads to a similar response in UVC and output deflator. Additionally, all variables, except markup, show a reversal of the initially positive increase from the impulse after a certain period. This can be seen in the response functions, which eventually go below the zero line. This behavior can be attributed to differing VAR orders for the import indices models. It has been established that VAR order 1 shows a smoother reaction with minimal variation in the point estimates.

Figure 17: Forecast Error Variance Decomposition for the IFAPI Intermediate Goods Model



Note: The FEVD starts with the immediate effect in Horizon 1, which corresponds to lag 0 (Quarter 0, see IRFs).

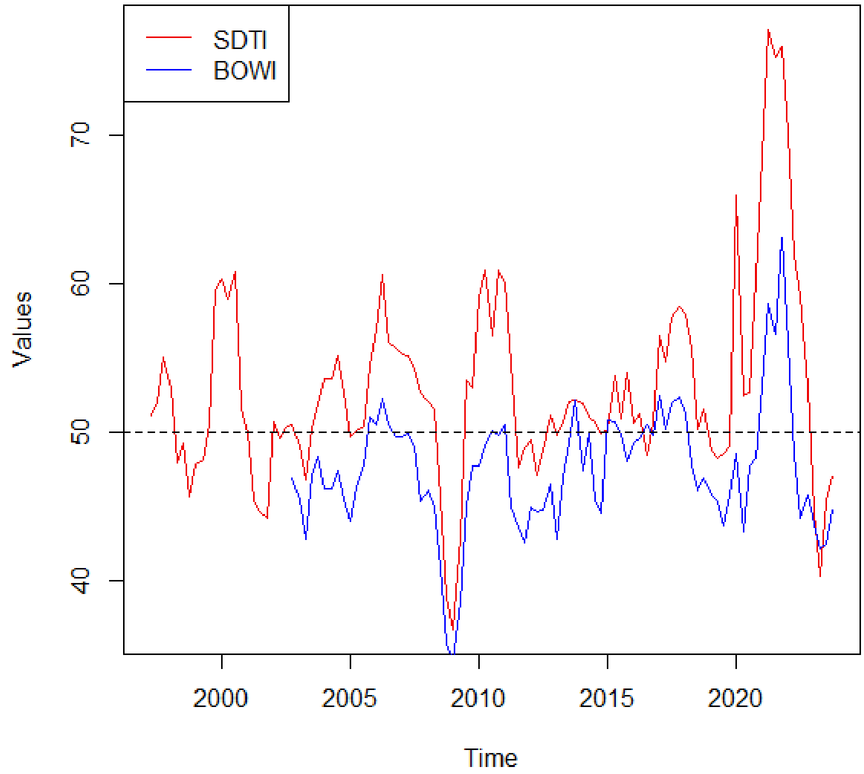
Figure 17 shows the forecast error variance decomposition of the IFAPI Intermediate Goods Model. In the first panel, the FEVD for *Imports from Abroad Price Index: Intermediate Goods* indicates that its forecast error variance is explained predominantly by Imported Intermediate Goods across all horizons, with the other three variables taking a small share from quarter one after the immediate effect. The second panel, showing the FEVD for UVC, reveals that the forecast error variance is mainly explained by UVC only in quarter 0, with a growing contribution from Imported Energy over time, of which the share takes up about half of the total variance from quarter four onwards. The influence of markup and output deflator starts being obvious from quarter one onwards, with a small yet persistent share. In the third panel, the FEVD for markup demonstrates that the forecast error variance is overwhelmingly driven by markup across all horizons, with a sizable and steady contribution from UVC. At the same time, the impact from output deflator and imported intermediate goods is minimal. The fourth panel, depicting the FEVD for output deflator, shows that its forecast error variance is influenced by all other variables, with the largest share stemming from UVC initially, followed by imported energy and markup. The output deflator only starts to influence its forecast error variance from quarter one onwards. Over time, the IFAPI IG increases its influence to about half the share of total variance. When comparing the FEVD plots of imported energy and imported intermediate goods, it becomes evident that imported energy has more influence on the error variance in UVC and output deflator than imported intermediate goods.

To summarize, the IFAPI Energy and IFAPI Intermediate Goods indices do not exhibit any Granger causal relationship with markup. However, imported energy prices Granger causes the output deflator at short lags, while imported intermediate goods prices Granger causes the output deflator with a higher lag. In both models, the OIRFs reveal no significant response in markup. The output deflator response is significant until the fifth quarter following an imported energy impulse and until the fourth quarter for imported intermediate goods. The magnitudes of the responses are comparable across models. When considering the FEVD, imported energy accounts for a small share of the variance in markup but a dominant share of the variance in the output deflator. Similarly, imported intermediate goods show a dominant share of variance in the output deflator but no effect on markup variance. Overall, the response function of imported energy is more similar to the HICP liquid fuels case, although different observation periods prevent a direct comparison. The shock in imported energy prices appears to lead to sustained cost and price increases in the manufacturing sector. This is unsurprising, given that Italy is a large-scale net importer of fossil energy. For the import price shocks starting in 2022, our models predict no change in markups but a sizable response in output prices. The importance of import prices predicted by our models aligns with findings from Hansen, Toscani, and Zhou (2023), which indicated that import prices substantially contributed to inflation and that firms adjust quickly to import price changes. The authors found that the manufacturing sector experienced one of the highest unit profit increases in the euro area. Our findings do not support this, given the insignificant markup response in our predictions. However, this does not necessarily represent a contradiction, as profits can still rise even without a constant markup if the cost pass-through is 100 percent (see Colonna, Torrini, and Viviano 2023). Compared with the French manufacturing sector, Lafrogne-Joussier, R., Martin, J., and Mejean, I. (2023) found evidence for excess pass-through for imported energy and noted that firms passed on only a fraction of the cost increase from imported intermediate goods. In our case, we do not find evidence of the pass-through being different from 100 percent, as the markup shows no significant response to imported energy or intermediate goods.

6.3 Operational and Supply Chain Bottlenecks

In this chapter, we analyze the impact of suppliers' delivery times and backlogs of work on firms' pricing behavior.

Figure 18: Time Series Plot: Suppliers' Delivery Times Index and Backlogs of Work Index



Note: The Suppliers' Delivery Times Index and the Backlogs of Work Index are so-called diffusion indices, which signal deterioration if the index is above the natural level of 50 and improvement if the index is below 50, compared to the previous month. The further the index level is from 50, the greater the rate of change. See the Data chapter. Source: S&P Global PMI

The time series plot in Figure 18 illustrates the course of two indices over time: the Suppliers' Delivery Times Index (SDTI) in red and the Backlogs of Work Index (BOWI) in blue. Notably, the SDTI and the BOWI show similar movements. Throughout this period, the SDTI and BOWI exhibit fluctuations around the neutral level of 50. Notably, the SDTI shows several pronounced peaks, particularly around the years 2001, 2005, 2007, and 2010, and a large spike around 2020-2021, indicating periods of substantial delivery delays. The BOWI, on the other hand, demonstrates less extreme but still notable oscillations, particularly with sharp declines around the same periods, suggesting varying levels of backlogs. The most prominent observation is that both indices signal a remarkable deterioration during the COVID-19 pandemic, particularly in 2020 and 2021. Delivery times were negatively impacted by disruptions in maritime trade, mainly due to the strict anti-COVID measures in China. Concurrently, multiple lockdowns affected production capacity, with producers struggling to keep up with demand after restrictions were lifted. The time required to ramp up production exacerbated these issues, resulting in prolonged delivery times and substantial backlogs.

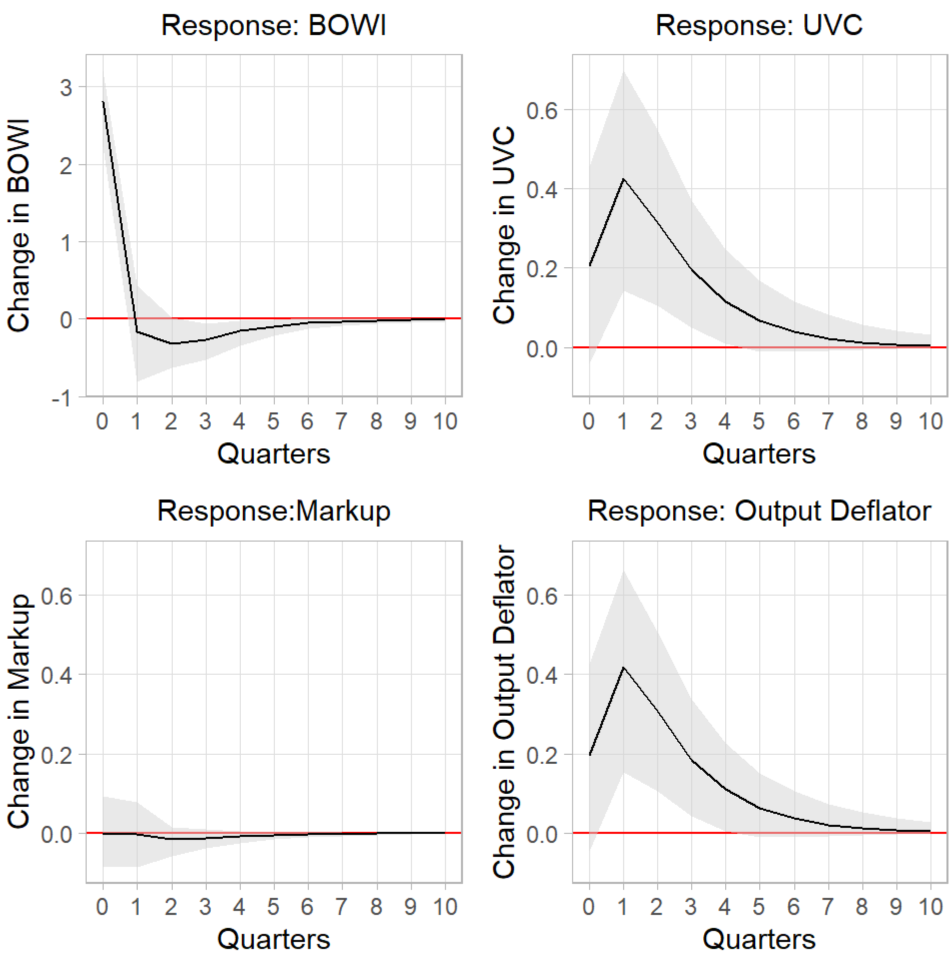
Table 6: Granger Causality Test Results: Backlogs of Work Index

	Markup	UVC	Output deflator	BOWI
Markup		1(***) 2,8(**) 3,4,9(*)	8(**) 9,10(*)	-
UVC	-		-	1-5(***) 6,7(*)
Output deflator	-	1,2(**) 3,4,8(*)		1-5(***) 6(**) 7(*)
BOWI	-	2(***) 1,3-5(**) 6(*)	1-6(***) 7-8(**) 9(*)	

Note: Time series represent the first differences of displayed variables with length n=84. Cause variables are in the left column; response variables are in the upper row. The listed numbers are the lags for which the Granger causality test was significant. Significance levels: 0.01 (***), 0.05 (**), 0.1 (*), "-" indicates no significant test result.

In the results of the Granger causality test (Table 6), including the backlogs of work index, there appears to be no evidence of Granger causation between markup and BOWI. However, there is a significant Granger causation relationship in both directions between BOWI and UVC for up to 6 lags. Likewise, when examining the output deflator and BOWI, the relationship shows bidirectionality for lags 1 to 7, with lags 8 and 9 being significant only for the BOWI to output deflator direction.

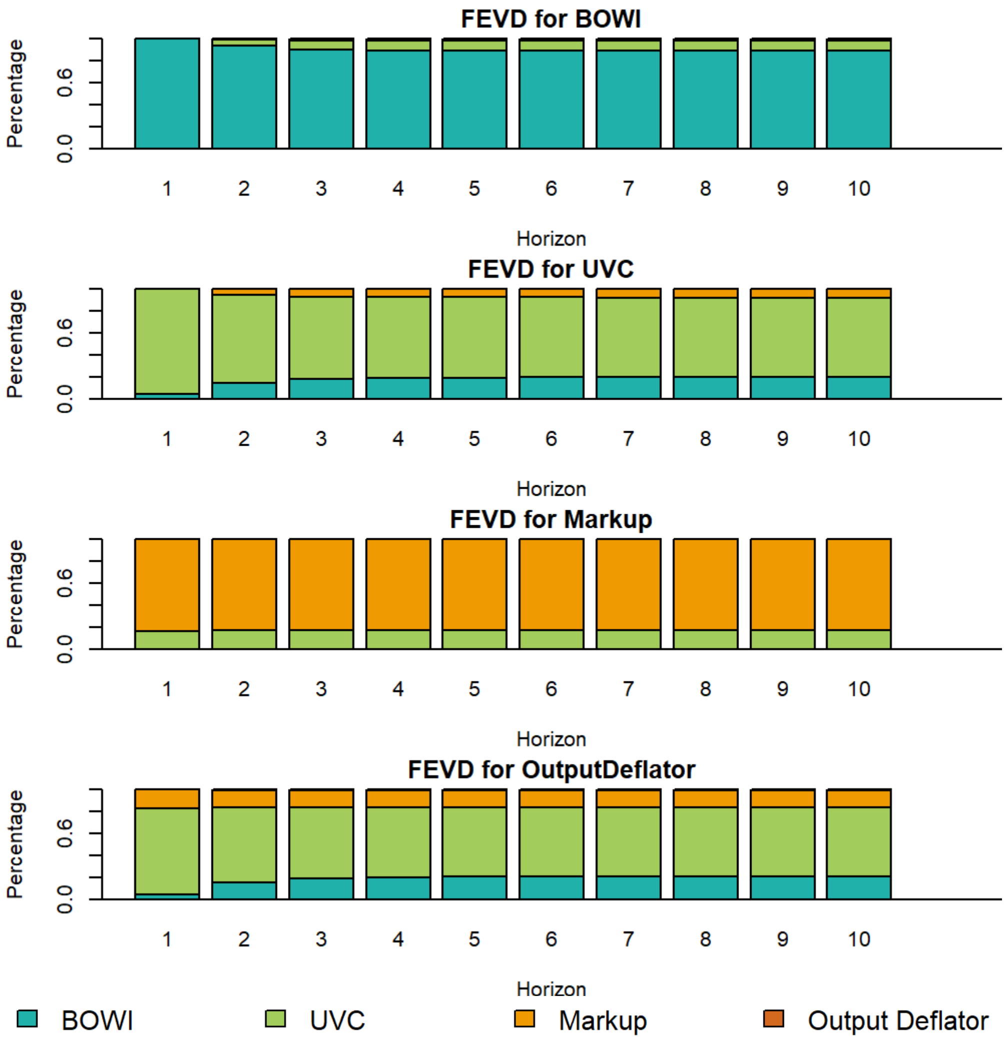
Figure 19: Orthogonal Impulse Response Functions for the BOWI Model



Note: This model's chosen VAR order is 1. The grey area marks the 95% bootstrap confidence interval, computed with 1000 runs.

In Figure 19, the response functions following an impulse in the Backlogs of Work Index are depicted. The BOWI shows a rapid negative change after the impulse, remaining steadily low and negative in relation to the zero line for the duration, particularly in quarters two to five. Markup shows little reaction with insignificant estimates. UVC and output deflator exhibit nearly identical response functions, showing an initially insignificant immediate reaction to the impulse, followed by a peak change in the variables in period one. This is then followed by a steady decline in the response functions, with significant point estimates observed in quarters one to four.

Figure 20: Forecast Error Variance Decomposition for the BOWI Model



Note: The FEVD starts with the immediate effect in Horizon 1, which corresponds to lag 0 (Quarter 0, see IRFs).

Figure 20 shows the FEVD of the BOWI Model. In the first panel, the FEVD for the *Backlogs of Work Index* indicates that its forecast error variance is explained predominantly by itself across all horizons, with the other three variables taking a small share from quarter one after the immediate effect, among which UVC is the most noticeable. The second panel, showing the FEVD for UVC, reveals that the forecast error variance is primarily explained by UVC across periods, with an initially growing contribution from BOWI leading to a noticeable share that stays roughly unchanged for the rest of the horizon. The influence from markup is small, and the output deflator is negligible. In the third panel, the

FEVD for markup demonstrates that the forecast error variance is overwhelmingly driven by markup across all horizons, with a noteworthy contribution from UVC. At the same time, the impact of the other variables is negligible. The fourth panel, depicting the FEVD for output deflator, shows that its forecast error variance is mainly influenced by UVC, followed by markup and an initially rising BOWI share that plateaus over time. The output deflator's share is tiny.

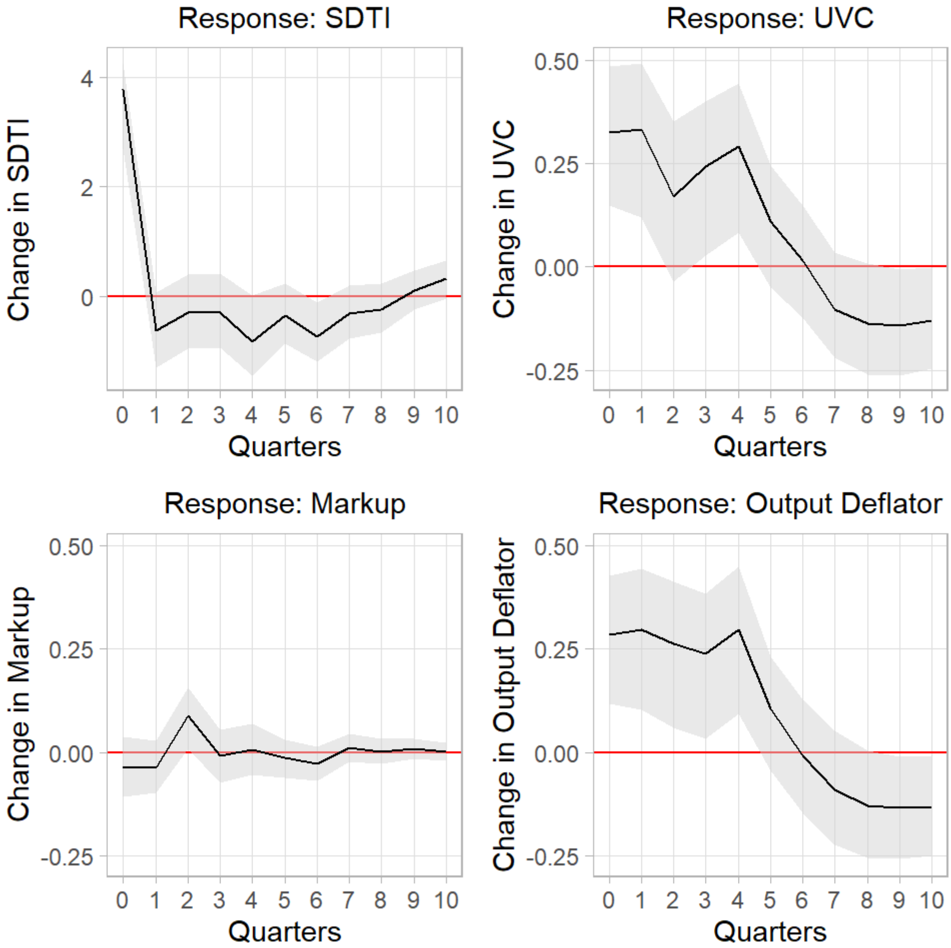
Table 7: Granger Causality Test Results: Suppliers' Delivery Times Index

	Markup	UVC	Output deflator	SDTI
Markup		1,2(***) 3,4,8-10 (**) 5(*)	8,9,10 (**)	4(**) 5(*)
UVC	-		8(**) 9,10(*)	1-6(***) 7,8(**) 9,10(*)
Output deflator	-	1(***) 2-4,8(**) 9(*)		1-8(***) 9,10 (**)
SDTI	2,10(*)	10(***) 1-5,9(**) 6,7(*)	9,10(***) 1,2,4(**) 3,5-8(*)	

Note: Time series represent the first differences of displayed variables with length n=106. Cause variables are in the left column; response variables are in the upper row. The listed numbers are the lags for which the Granger causality test was significant. Significance levels: 0.01 (***), 0.05 (**), 0.1 (*), "-" indicates no significant test result.

The results of the Granger causality tests for the model, including SDTI, can be seen in Table 7. SDTI Granger causes markup at lags 2 and 10, albeit at a 10 percent significance level. Conversely, SDTI significantly causes markup at lags 4 and 5. The relationship between SDTI and UVC is highly significant in both directions for all ten lags. Similarly, the SDTI and output deflator also appear to have a close relationship.

Figure 21: Orthogonal Impulse Response Functions for the SDTI Model

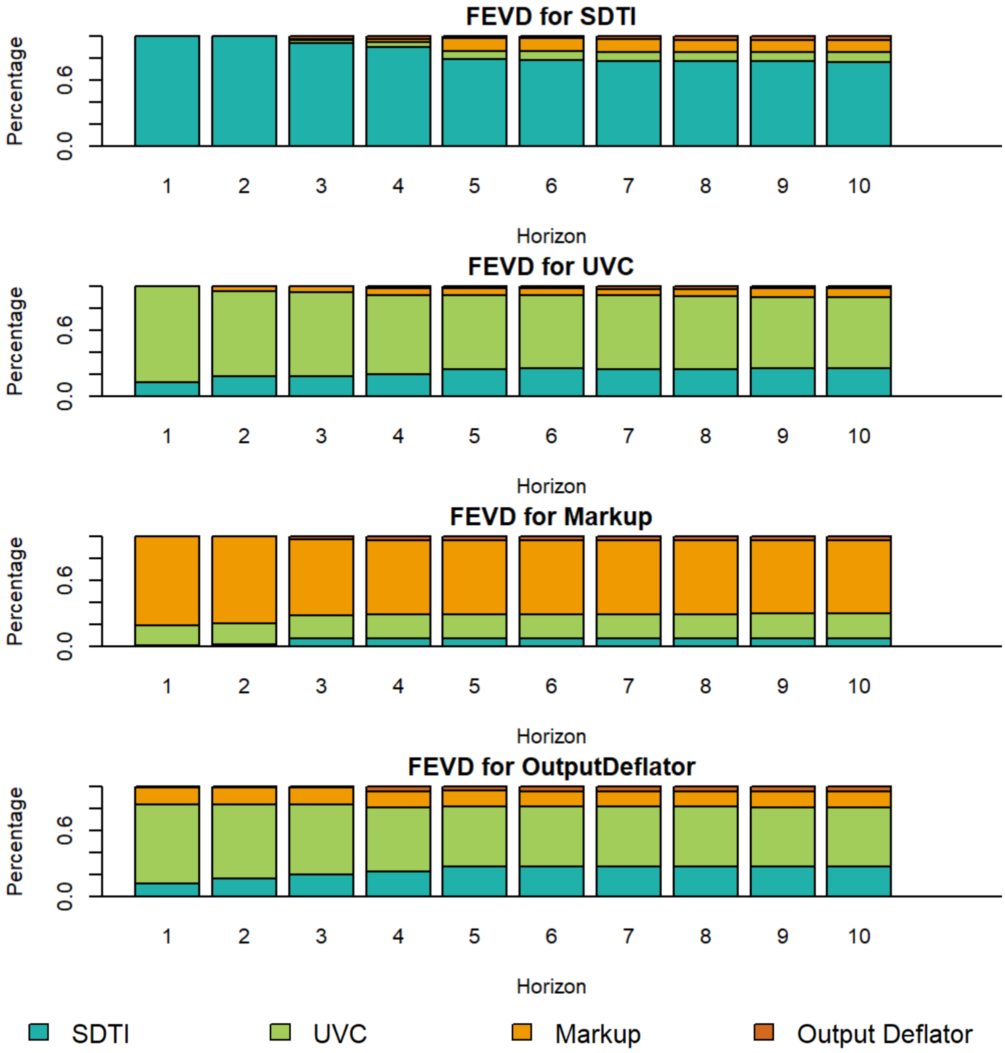


Note: This model's chosen VAR order is 4. The grey area marks the 95% bootstrap confidence interval, computed with 1000 runs.

Figure 21 illustrates the orthogonal impulse response functions for the Suppliers Delivery Times Index (SDTI) model. Following the initial impulse in SDTI, the index quickly decreases and becomes insignificant, except for a significant adverse effect in quarter six. The UVC react with an immediate increase. The rate of change is the highest and most significant in quarters 0 and 1, then it reaches a low point (insignificant) in quarter two before increasing significantly for two quarters again. As a result, some of the cost increases are compensated for around two years after the impulse. The point estimates are significant for periods 0, 1, 3, 4, 9, and 10. Markup's initial reaction is insignificant. There is a notable and significant peak in quarter two, after which it returns to insignificance. It appears that during supply chain disruptions, firms raise the markup after two quarters to recover their losses. The output deflator increases significantly for the first four quarters, with the growth rate remaining nearly constant. The output deflator decreases again significantly in quarters nine and ten. The direction and magnitude of the impulse response functions are comparable across different VAR orders for this model. For VAR order 1, the response functions were relatively simple. For VAR order 2, UVC and the output deflator

IRFs are significant up to quarter three. Markup estimates are significant for VAR orders 2 and 4 in quarter two.

Figure 22: Forecast Error Variance Decomposition for the SDTI Model



Note: The FEVD starts with the immediate effect in Horizon 1, which corresponds to lag 0 (Quarter 0, see IRFs).

Figure 22 depicts the forecast error variance decomposition of the SDTI Model. In the first panel, the FEVD for the *Suppliers' Delivery Times Index* indicates that its forecast error variance is explained predominantly by itself across all horizons, with the other three variables starting to take a small share in quarter two after the immediate effect, among which markup is the most noticeable. The second panel, showing the FEVD for UVC, reveals that the forecast error variance is primarily explained by UVC across periods, with an initially growing sizable contribution from SDTI. The influence from markup is small, and the output deflator's share is negligible. In the third panel, the FEVD for markup demonstrates that the forecast error variance is overwhelmingly driven by markup across all horizons, with a noteworthy contribution from UVC. SDTI plays a minor role in markup's error variance. The fourth panel, depicting the FEVD for the output deflator, shows that UVC mainly influences its forecast error variance. Initially, markup took the second largest share, but it was taken over by SDTI in quarter two after the immediate effect. The output deflator's share is minimal.

To summarize, the Backlogs of Work Index (BOWI) appears to have a weak connection to markup, as indicated by the Granger causality tests, OIRFs, and FEVD. However, the relationship between BOWI and the output deflator is well-established, with Granger causality tests showing significance at multiple lags. The FEVD and OIRFs demonstrate that BOWI affects the output deflator with a delay. In the OIRFs, the output deflator shows significant growth in quarters 1 to 4 after an initially insignificant response. The FEVD attributes a sizable share of variance in the output deflator to BOWI. Hansen, Toscani, and Zhou (2023) argue that Euro area inflation was driven by increased profitability following capacity constraints. While our model indicates that output prices react accordingly, we find no evidence of a corresponding increase in markup.

The Suppliers' Delivery Times Index (SDTI) significantly positively impacts markup two quarters after the impulse, aligning with a weakly significant Granger causality test for the same lag. The share of SDTI in the error variance of markup is small and becomes established with a delay. The relationship between SDTI and the output deflator is stronger, as the Granger causality tests suggested. The output deflator is significantly Granger caused by SDTI at multiple lags. The OIRFs reveal that the output deflator exhibits almost constant growth for one year after the impulse. Lastly, the FEVD shows that SDTI accounts for a sizable share of the output deflator's variance, with the effect growing more potent over time. Similar to Kemp, Portillo, and Santoro (2023), we used the PMI subindex for suppliers' delivery times to measure supply chain disruptions in Italy. The authors estimated that core inflation was approximately 0.5 percent higher due to supply disruptions in 2021. This is compatible with our findings, as output prices grew following a shock in delivery times. Furthermore, Franzoni, Giannetti, and Tubaldi (2023) claimed that supply chain disruptions cause inflation and that superstar firms can raise markups during such disruptions. We confirm that output prices rise significantly for one year after a supply chain shock and provide some evidence that markups also increase significantly in response.

7 LIMITATIONS

Our study's findings are subject to several limitations, primarily data frequency and availability. The quarterly frequency and short length of the time series data necessitate using smaller models, as the inclusion of more variables may translate into the loss of statistical significance of our estimates. Additionally, the availability of time series data restricts our choice of variables. While our model addresses the recent energy cost crisis and inflationary period, it is designed for the manufacturing sector over a longer timeframe. It may not capture the immediate impacts that higher-frequency data might reveal, especially post-COVID-19. Each model should be interpreted individually, given the varying time series lengths corresponding to different observational periods. Moreover, our analysis is limited to the sectoral level, preventing us from asserting individual firm behavior or distributional effects. Consequently, we cannot account for differences in how large and small firms respond to economic shocks nor assess competition dynamics or performance disparities between superstar firms and smaller enterprises.

Our empirical approach, which primarily employs Vector Autoregression (VAR) analysis, has some inherent limitations. Firstly, VAR models are not ideally suited for identifying underlying structural relationships, which restricts their ability to establish true causality. The sensitivity of our results to the ordering of variables further complicates this issue, as conducting robustness checks for all potential orderings is beyond the scope of this thesis. Additionally, the shocks modeled in our analysis are considered one-time increases to a variable, whereas, in reality, factors like energy prices and supplier delivery times might stay elevated for several quarters. We also face challenges with the distribution of error terms, as they do not exhibit normality. While we mitigate this issue using bootstrapped confidence intervals for the Impulse Response Functions, the non-normality can still affect the accuracy and reliability of statistical inferences derived from Forecast Error Variance Decomposition. Consequently, it is crucial to interpret FEVD results with caution. Another limitation is the tradeoff between overfitting and omitted variable bias, which influences our decisions on variable inclusion. Moreover, potential non-linearity in the relationships among variables poses a drawback, given that VAR models assume linear relationships. If the true relationships are non-linear, this assumption leads to biased and inconsistent parameter estimates, less accurate forecasts, and distorted impulse response functions. These limitations underscore the need for careful interpretation of our empirical findings.

8 CONCLUSION

This thesis investigates the dynamic relationships between energy prices, import prices, supply chain bottlenecks, capacity constraints, and their impact on aggregate markups and price levels within Italy's manufacturing sector. Our empirical analysis yields several key findings that offer valuable insights into the factors driving inflation and pricing behavior in the manufacturing sector.

In the absence of specific shocks, our model signals that firms in the Italian manufacturing sector absorb part of the increase in unit variable costs by instantly lowering markups. In addition, an impulse in markup leads to an increase in the output deflator for several periods. Differentiating between energy types turns out to be effective in uncovering their distinct impacts on markup and prices.

Specifically, the Harmonized Index of Consumer Prices (HICP) Electricity and Gas indices significantly Granger cause markups at low lags. Impulses from HICP Energy and HICP Electricity led to significant short-term growth in markup, suggesting that companies tend to increase markups when energy and electricity prices rise. This excess pass-through exacerbates the cost shock's influence on inflation. However, an increase in the HICP Gas index does not elicit a significant reaction in markup. Interestingly, increases in the HICP Liquid Fuels index result in a one-quarter delayed yet significant short-term decrease in markup. This indicates that firms may absorb some input cost increases by lowering their markups in response to liquid fuel price shocks. These findings contrast with imported energy and intermediate goods prices, which show neither a significant Granger causal relationship with markups nor any significant impulse response of markup. Moreover, the Suppliers' Delivery Times Index (SDTI) significantly impacts markup two quarters after the impulse, which coincides with significant Granger causality at this lag. On the other hand, the Backlogs of Work Index (BOWI) shows no significant Granger causal relationship with markup or any significant impulse response.

The responses of the output deflator to supply-side shocks reveal distinct patterns across various variables. All HICP indices - Energy, Electricity, Gas, and Liquid Fuels - prompt immediate and significant responses in the output deflator, with liquid fuels exhibiting the most pronounced effect persisting for up to four quarters post-impulse. Notably, the HICP Liquid Fuels stands out as the sole driver that Granger causes changes in the output deflator. The Forecast Error Variance Decomposition (FEVD) analysis indicates that nearly two-thirds of the variance in the output deflator can be attributed to shocks in liquid fuels. At the same time, the effects from other energy types were much smaller. Following an impulse in imported energy prices, the output deflator increases significantly up to the fifth quarter and the fourth quarter for imported intermediate goods. Notably, imported energy prices exhibit a shorter Granger causal influence on the output deflator than imported intermediate goods prices. The FEVD highlights a substantial share of output variance attributed to both import price indices. Moreover, the Backlogs of Work Index shows a robust Granger causal relationship with the output deflator, with capacity constraints impacting output prices with a noticeable delay, as evidenced in both the OIRFs and FEVD. An impulse in capacity constraints increased the output deflator significantly from quarter one to quarter four post-impulse. Lastly, suppliers' delivery times are significantly linked to output prices, with constant growth in the output deflator expected for one year following an increase in delivery times. Granger causation tests and FEVD underline this strong relation.

Understanding sector-wide pricing behavior is crucial in shaping inflationary trends. This thesis highlights that while firms typically absorb cost increases by adjusting markups, supply-side shocks can disrupt this behavior, leading to collective increases in markups across the sector. Even when markups remain stable, firms may still capitalize on sector-wide shocks as inflation makes demand inelastic and disrupts competitive dynamics. Italy's heavy reliance on fossil fuels exacerbates vulnerability to price instability, emphasizing the need to transition to domestically produced renewable energy sources. Such a transition could enhance economic stability and resilience amidst fluctuating energy markets. Strengthening supply chain resilience and implementing strategic inventory management strategies are critical to mitigating inflationary pressures. Ultimately, effective industry regulation should aim to prevent widespread price increases and excess pass-through. This could include implementing price gouging policies, anti-trust measures, and initiatives to reduce market concentration, fostering a more stable and competitive economic environment.

Researchers should consider exploring firm-level data on markups to gain insights into individual firm behavior and distributional effects. Existing studies suggest that large and small firms respond differently to economic shocks, with larger firms often better positioned to raise markups during crises. Our study infers that increased pricing power likely results from disruptions in competition dynamics and aligned incentives among firms within a sector. Investigating these competition dynamics during sector-wide shocks could provide valuable insights. Understanding how competition is altered in these contexts would enrich our comprehension of market behavior and firms’ pricing strategies in response to economic disruptions.

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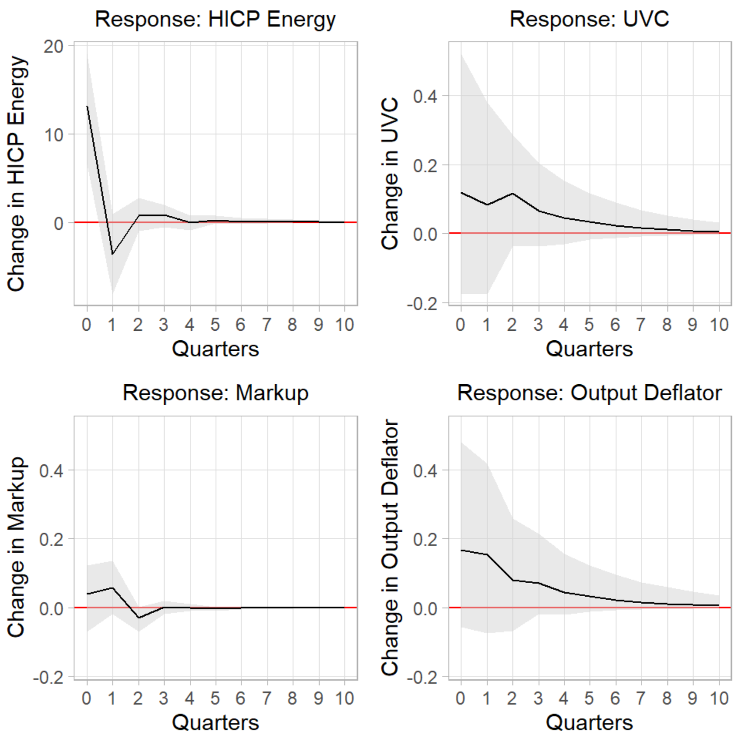
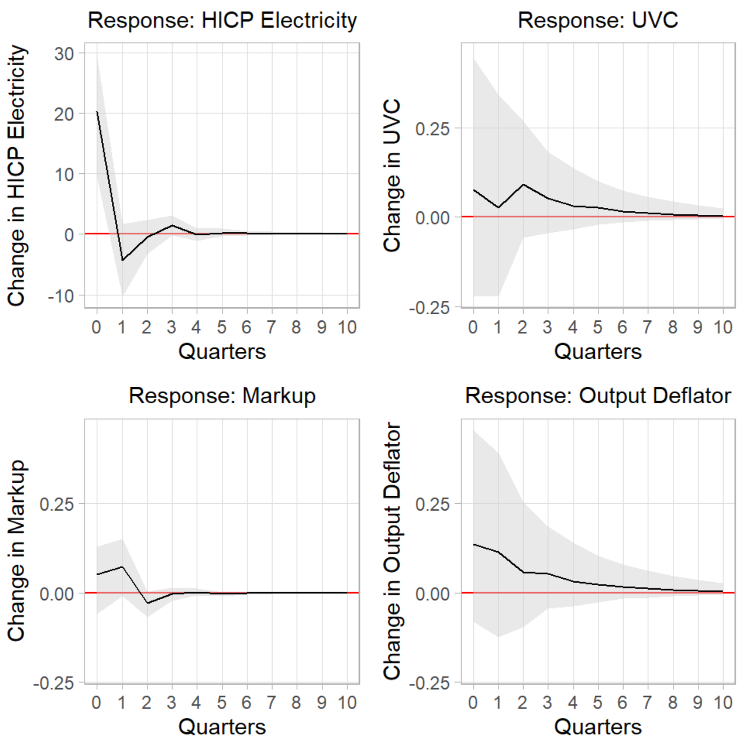
APPENDIX

Figure 23: Orthogonal Impulse Response Functions for the HICP Energy Model: VAR Order 1



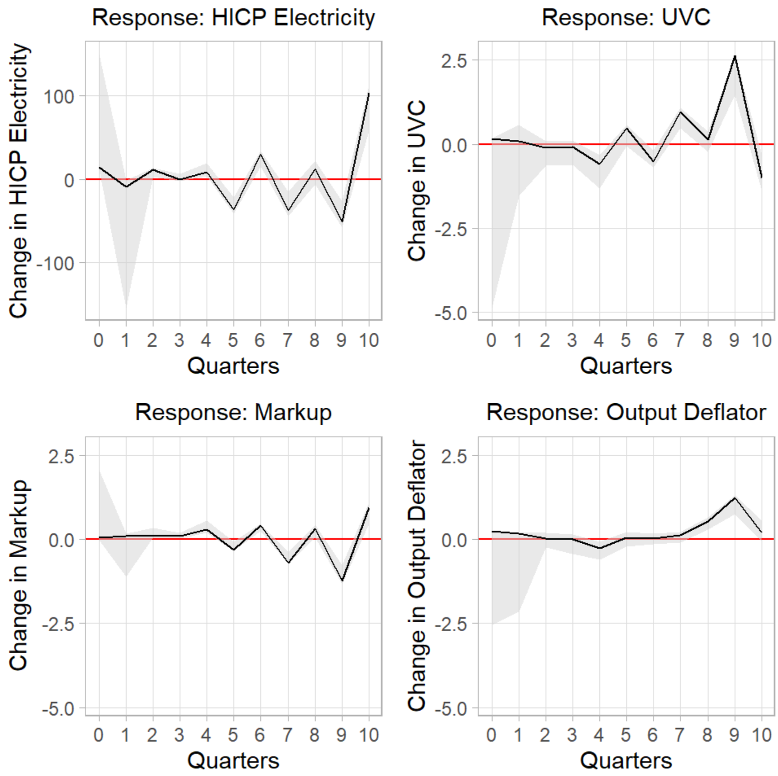
Note: The VAR order for this version of the model is 1. The grey area marks the 95% bootstrap confidence interval, computed with 1000 runs.

Figure 24: Orthogonal Impulse Response Functions for the HICP Electr. Model: VAR Order 1



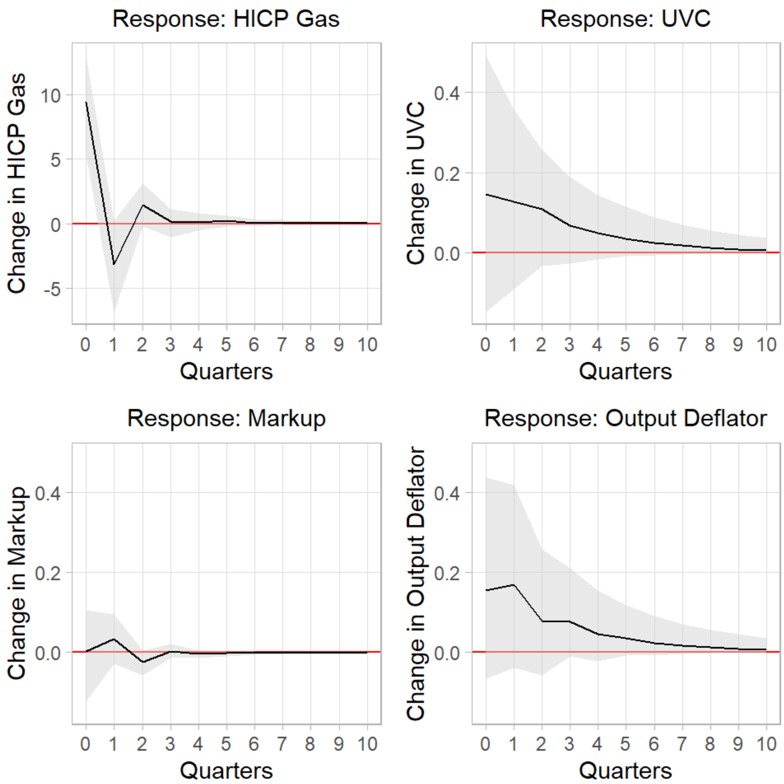
Note: The VAR order for this version of the model is 1. The grey area marks the 95% bootstrap confidence interval, computed with 1000 runs.

Figure 25: Orthogonal Impulse Response Functions for the HICP Electr. Model: VAR Order 6



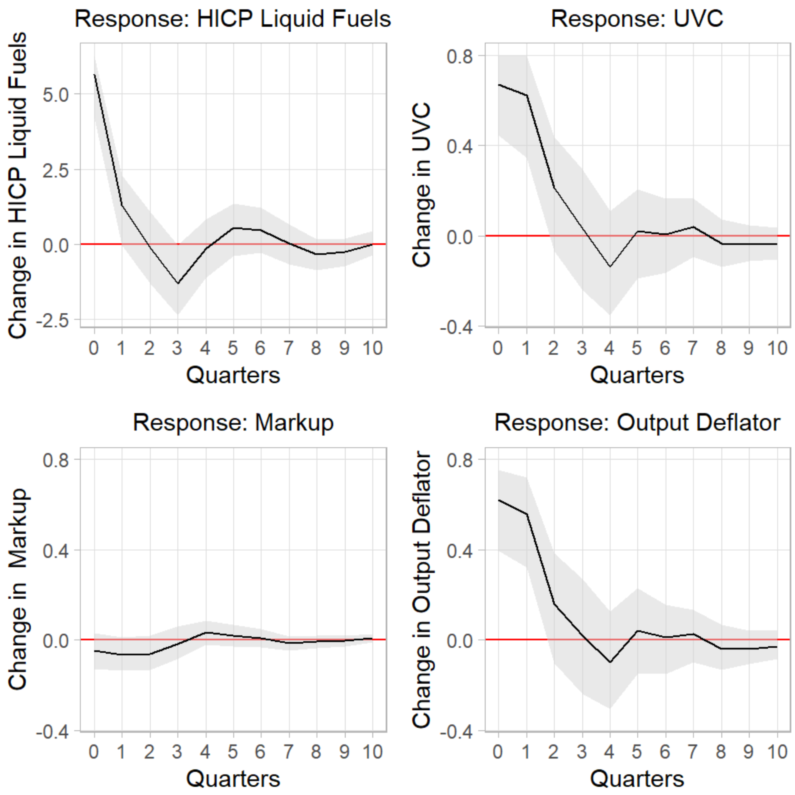
Note: This version of the model has a VAR order of 6. The grey area marks the 95% bootstrap confidence interval computed with 1000 runs.

Figure 26: Orthogonal Impulse Response Functions for the HICP Gas Model: VAR Order 1



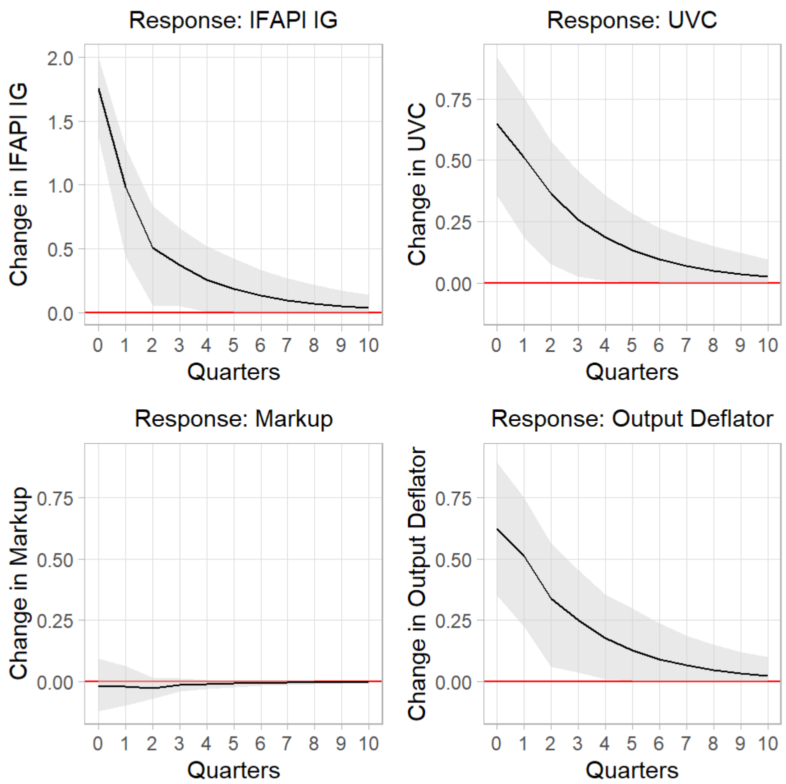
Note: The VAR order for this version of the model is 1. The grey area marks the 95% bootstrap confidence interval, computed with 1000 runs.

Figure 27: Orthogonal Impulse Response Functions for the HICP Liq. Fuels Model: VAR Order 3



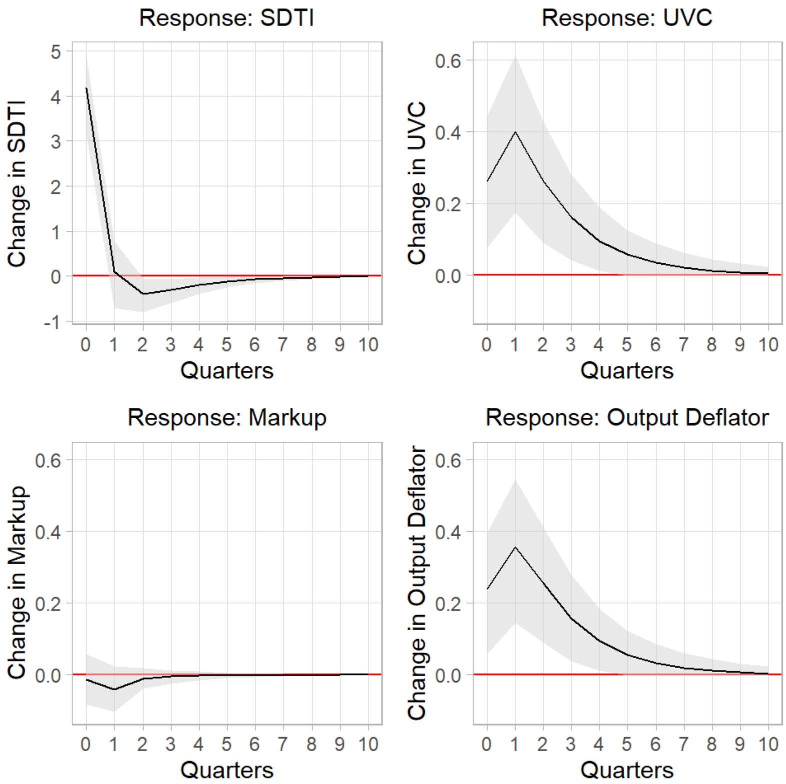
Note: This version of the model has a VAR order of 3. The grey area marks the 95% bootstrap confidence interval computed with 1000 runs.

Figure 28: Orthogonal Impulse Response Functions for the IFAPI IG Model: VAR Order 1



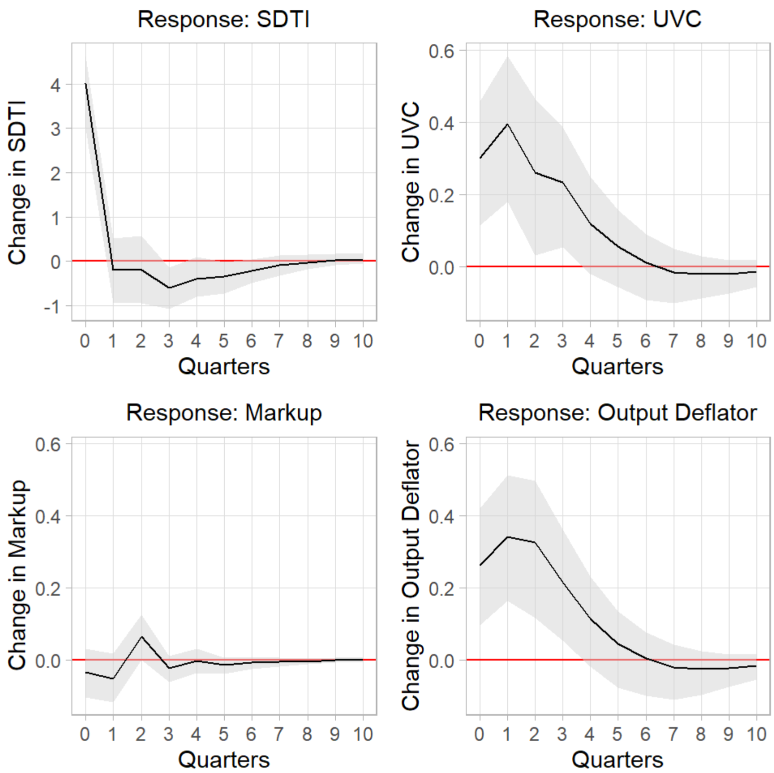
Note: The VAR order for this version of the model is 1. The grey area marks the 95% bootstrap confidence interval, computed with 1000 runs.

Figure 29: Orthogonal Impulse Response Functions for the SDTI Model: VAR Order 1



Note: The VAR order for this version of the model is 1. The grey area marks the 95% bootstrap confidence interval, computed with 1000 runs.

Figure 30: Orthogonal Impulse Response Functions for the SDTI Model: VAR Order 2



Note: This version of the model has a VAR order of 2. The grey area marks the 95% bootstrap confidence interval computed with 1000 runs.